

# NSW Dynamic Life Cycle and Stimulus Checks Code Companion

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# Preface

This is a work-in-progress Matlab package consisting of functions that solve the dynamic life cycle model in [Nygård, Sørensen and Wang \(2021\)](#). The paper is titled [Optimal allocations to heterogeneous agents with an application to the COVID-19 stimulus checks](#). [Nygård, Sørensen and Wang \(2021\)](#) supersedes two prior papers, [Nygård, Sørensen and Wang \(2020\)](#) as well as [Wang \(2020\)](#). The code companion presents solutions to the dynamic life-cycle problem, and methods for evaluating the marginal gains from allocating additional stimulus checks. Tested with [Matlab 2020a \(The MathWorks Inc, 2019\)](#).

All functions are parts of a matlab toolbox that can be installed:

Download and install the Matlab toolbox: [PrjOptiSNW.mltbx](#)

The Code Companion can also be accessed via the bookdown site and PDF linked below:

[bookdown pdf](#), [MathWorks File Exchange](#)

This bookdown file is a collection of mlx based vignettes for functions that are available from [PrjOptiSNW](#). Each Vignette file contains various examples for invoking each function.

The package relies on [MEconTools](#), which needs to be installed first. The package does not include allocation functions, only simulation code to generate the value of each stimulus check increments for households. Allocation functions rely the R optimal allocation package [PrjOptiAlloc](#).

The files below largely document contents in the Matlab-based [PrjOptiSNW](#) folder of the repository. The [AllocateR](#) folder contains additional documentation for various functions and files that solve allocation problems based on functions in the R [PrjOptiAlloc](#) package and solutions csv files generated by the dynamic programming files from the Matlab-based [PrjOptiSNW](#) folder. Some additional results for the paper are included in the [additional\\_results](#) folder.

The site is built using [Bookdown \(Xie, 2020\)](#).

Please contact [FanWangEcon](#) for issues or problems.



# Chapter 1

## Introduction

### 1.1 Household Problem and Distributions

In [Nygaard, Sorensen and Wang \(2020\)](#), we study the optimal allocation of COVID-19 stimulus checks as well as the 2008 Bush era stimulus checks. Congress spent \$250 billion sending checks to individuals in March 2020 to provide economic stimulus. In the summer of 2008, the Bush administration sent stimulus checks (in the form of tax rebates) to 150 million American households.

Could the same amount of stimulus have been achieved for less money? Using a life-cycle consumption-saving model with heterogeneous consumers, we calculate the consumption responses to cash transfers for, e.g., couples and singles with different levels of income and number of children. We calculate the aggregate consumption response for all feasible allocations of a stimulus checks program billion and, using a new algorithm that allows for the ranking of an arbitrarily large number of allocations, we find the optimal allocation under alternative constraints. The optimal policy allocates more toward low-income and younger consumers and can achieve the same stimulus effect at almost half the cost.

This Matlab based programming guide, package, and associated vignettes, provide examples and instructions on how the dynamic programming problem in Nygaard, Sorensen and Wang (2020) is solved. The R optimal allocation package [PrjOptiAlloc](#) takes inputs from the dynamic programming problems and solves for optimal allocations given varying planner objectives and constraints.

#### 1.1.1 Flat Script and Code Package

There are two broad versions of the code. A number of files are included in the [zflat](#) folder, including the operation gateway file [main](#). Files in the [zflat](#) folder provides a linear, easier to understand illustration/demonstration of the overall code structure. It is useful to review the overall algorithm design. However, it should not be called to implement the programs. Programs in the folder were written to help test out algorithm ideas.

The rest of the files inside [PrjOptiSNW](#) form a matlab [package](#) that can be downloaded and installed. Each component of the overall code program is programmed up separately with its own testing vignette and default parameter structure. Various solution algorithms are provided at each step, with the final checks problem relying on efficient and precise solution methods.

#### 1.1.2 Dynamic Programming Solution Structure COVIDless World

First we solve for the optimal consumption/savings problem in the COVID-less world:

- **83:** 2020 or 2008 age groups, age 18 to 100 age groups
- **65:** grid of savings state-space grid, and exact continuous optimal savings choices using the [FF\\_VFI\\_AZ\\_BISEC\\_VEC](#) function from [MEconTools](#).
- **6650 shocks:** 1330 productivity shocks for household head and spouse and 5 kids transition count shocks

- 2 permanent education states
- 2 permanent marital states

The state-space has:  $2 \times 2 \times 6650 \times 65 \times 83 = 143,507,000$  elements. The choice-space is continuous. Two important things to note:

1. The large number of shocks are needed to obtain accurate group-specific marginal propensity effects for small income bins that define the choice-set of the allocation problem.
2. While a choice-grid-based solution algorithm might sufficiently approximate the value function, but its policy function zig-zags. For the stimulus checks problem, where stimulus checks come in small increments, the zig-zags lead to fluctuating (negative and positive) marginal propensities to consume as resource availability increases for very small amounts of check increments. To deal with this challenge, we rely on the `FF_VFI_AZ_BISEC_VEC` function from `MEconTools` to provide efficient exact savings choices.

Solving this dynamic life-cycle programming problem requires approximately 10 to 20 minutes on a home-pc depending on computer speed. There are no processor requirements. Memory requirement is approximately 20GB. There are two core associated functions vignettes that solve the dynamic programming problem to obtain value/policy and distributions induced by exogenous processes and the policy function:

- Core dynamic programming code: `snwx_vfi_bisec_vec`
- Core distribution code: `snwx_ds_bisec_vec`

Small testing vignettes of alternative solution algorithms for policy/value:

- Small test using matlab minimizer (very slow but identical results as core program): `snwx_vfi_test`
- Small test using grid-search-based solution algorithm (insufficiently precise for stimulus checks): `snwx_vfi_test_grid_search`
- Small test of core dynamic programming code: `snwx_vfi_test_bisec_vec`
- Small test of core dynamic programming code with spousal shock: `snwx_vfi_test_bisec_vec_spousalshock`

Testing vignettes for alternative solution algorithm for distribution:

- Grid search distributional code (insufficiently precise): `snwx_ds_grid_search`
- Core solution distribution code (vectorized for policy/value, looped for dist): `snwx_ds_bisec_vec_loop`
- Core solution distribution code (vectorized fully): `snwx_ds_bisec_vec`

### 1.1.3 Dynamic Programming Solution Structure during COVID Year

During the COVID year, we use the value function from the COVID-less world as the continuation value, and solve for consumption-savings policy/value functions during the COVID year. We solve once for households facing realized COVID surprise unemployment shocks, one more time for households who do not experience COVID unemployment shocks.

We solve for the marginal consumption differences and value given 244 increments of checks (\$100) each check. This is done again by using the `FF_VFI_AZ_BISEC_VEC` function from `MEconTools`. While checks could be viewed as an additional state variable, we evaluate the marginal effects of check by solving for the equivalent household-specific variation in savings state that has the same effect as a stimulus check transfer. The process takes into account the nonlinear tax-schedule that households face as well as return on savings.

Overall:

- 286 billion: Solve 143 billion state-space points twice under COVID unemployment and COVID employment world
- 70 billion: Solve at the 143 billion state-space elements  $244 + 1$  times for all possible check levels (244 checks + no check value/consumption) to arrive at 70 billion marginal propensity to consume



for households with heterogeneities in education level, marital status, children below 18 count (0 to 4), age, savings levels, household head and spouse shocks.

Associated functions vignettes: the core dynamic programming code: `snwx_vfi_bisec_vec`, has a third input which is the existing future value function. When this is provided, the dynamical programming problems solves for one period given already computed future value, and so the dynamic programming solution solves forward. When it is not provided, solves for value/policy backwards.

- `snwx_vfi_unemp_bisec_vec` provides the vignette given unemployment shock.
- `snwx_a4chk_wrk_bisec_vec` computes the marginal impacts of a particular stimulus check increment for those without unemployment shock in COVID year.
- `snwx_a4chk_unemp_bisec_vec` computes the marginal impacts of a particular stimulus check increment for those with unemployment shock in COVID year.
- `snwx_evuvw20_jaeemk` considers probabilities for getting hit with the COVID shock and considers the expected value conditional on age, savings level, shocks, educational status, kids count and marital status in 2020.

### 1.1.4 Dynamic Programming Solution Structure Bush Stimulus Checks

The Bush era stimulus checks problem is similar to the Covid problem, but there are some key differences.

1. The Bush `stimulus were tax rebate`, and had a more complicated schedule that is based on `tax-liability`.
2. The Bush stimulus were sent out prior to the unemployment shock, and hence in expectation of forthcoming shocks. In our setting, households can receive unemployment shock in 2009, and they optimize their savings/consumption decision in 2008 given this expectation. Computationally, this means the stimulus check effects do not need to be solved separately for unemployment and employed individuals as under the COVID stimulus. Instead, we solve the effects of stimulus checks on households in 2008, prior to shock realization.

More generally, stimulus checks can be given based on realized shocks or ex-ante state-space information prior to shocks. Given the information available to the IRS, which comes from the prior tax year, it seems that stimulus checks have been sent out during the Bush and Trump/Biden era based not on realized shocks, but on ex-ante information. Additionally, stimulus can be received during the period of crisis (COVID) or prior to it (Great Recession).

Our 2020 and 2008 programs rely on the same set of underlying dynamic programming and distributional functions, however there are also some functions that are specific to each program year that are shown on the project webpage under headings with differing dates.

## 1.2 Values of Checks Conditional on 2019 Information

Eligibility for the stimulus checks was tied to each household's income and family size in the year prior to COVID-19. Consistent with this, we focus on the optimal allocation of stimulus checks given household characteristics in 2019.

### 1.2.1 Expected Outcomes given 2019 Information

In the actual stimulus checks allocation policy setting, 2020 realized individual level COVID shocks and other productivity shocks were not used by the IRS to determine allocation eligibility. Instead, the IRS used information available from 2019. Given the persistence of productivity shocks, as well as the correlation between surprised COVID shock and household income and age from 2019, 2019 information are good predictors of household status in 2020.

We compute the expected outcomes from 2019 perspective conditional on household attributes that are observed to the IRS in 2020 given information they gathered in 2019. The planner does not observe the full state-space so we intergrate from 2019 perspective given 2019 to 2020 COVID transition probabilities (conditional on state-space) and kids and shock transitions.

- 82 age groups: Age 18 to 99
- 5 kids groups: Children 0 to 4
- 2 marital groups: Marital Status 0 or 1
- 509 Income Groups: 476 bins below max actual phaseout: solved at \$500 intervals between \$0 and \$238,000, and 33 bins after max actual phaseout: solved at \$5000 interval after \$238,000, where the 33rd final bin is between \$401,130 and Maximum.

Together, these are:  $5 \times 2 \times 83 \times 509 = 422,470$  groups/bins in 2019. We have  $(244+1)$  marginal average consumption gain, and value gain for each of the groups, so from 2019 planner perspective, we have 103.5 million expected MPCs (and expected value changes):  $422470 \times (244+1) = 103,505,150$ .

Each income group is composed of individuals of with different 2019 productivity shocks and savings levels. Given the transition probabilities, policy functions, and covid-less distributions across household types, we can compute the joint distribution of education type, shocks, and savings levels condition on income bins, marital status, kids count and age. This joint distribution is only well approximated when sufficient number of shocks were used when solving for value/policy in the covid-less world and covid-year world.

- [snwx\\_evuvw19\\_jaeemk](#) provides the expected outcomes conditional on 2019 age, savings levels, shocks, educational status, marital status and kids under 18 count, given the transition probabilities that incorporate the surprise COVID shock. Households do not optimize in 2019 given COVID shock probabilities, the shock is a surprise. But expected value in 2019 given 2019 state-space for consumption and value depends on COVID shock and the non-covid households dynamic consumption/savings choices in 2019.
- [snwx\\_evuvw19\\_jmky](#) provides the expected value in 2019 given not the full state-space, but the state-space that is potentially known to the IRS in 2019: age, marital status, kids count and 2019 household income. Household income is a function of savings, shock and educational status.
- [snwx\\_evuvw19\\_jmky\\_allchecks](#) solves for the marginal incremental effects of a vector of checks for all household types, and stores the results to file. This operation is fully parallelizable.

Given the solution, [snwx\\_evuvw19\\_jaeemk\\_mky](#) shows key overall distributional statistics, and distributional statistics by kids, marital and income bins.

### 1.2.2 Dynamic Programming Timing

Overall time requirements for solving the checks problem on a standard (\$1000) dollar desktop with 4 cores:

- 30 minutes to 1 hour: solving the dynamic programming problem 3 times for covid-less world, for covid-world with unemployment shock and without.
- 3 hours: derive the distributions induced by policy functions and shock processes.
- 650 seconds: the time it takes to compute the marginal effects of one check. This step is fully scalable. With a cloud computer with larger memory and cores, the problem over all checks could be solved fully parallelly.

Due to the large state-space, especially the large shock-grid, the memory requirement for storing the various multi-dimensional matrixes is high. Solving the problem requires 20GB of memory.

On a workstation with 12 cores with 190 GB of memory (12 workers same time), the computer is able to fully solve the problem from start to finish for 244 check increments in less than 24 hours. On a computer with 4 to 6 cores and 36 GB of memory, the computer is able to fully solve the problem from start to finish for 244 check increments in about 48 hours.

## 1.3 The Stimulus Check Planning Problem

The planner chooses the amount of stimulus checks for each group, where groups are defined by marital status, number of children, income, and age in 2019.

### 1.3.1 2019 Information Planning Problem

Given the expected outcomes we computed conditional on 2019 information, we can solve the planning problem. We have a number of different planning problems that we solve given different individual level constraints and what the planner can condition allocations on.

For FEASIBLE allocation, there are  $970=5*2*97$  types/cells of households:

- 5 children groups
- 2 spousal groups
- 97 income bins: the allocation planner sees approximately \$2500 income bins between \$0 and \$238,800, and 1 bin after \$238,800. There are 97 bins

for OPTIMAL G4 (4 age groups 18 to 64) allocation, there are  $3880=5*2*97*4$  types/cells of households:

- 5 children groups
- 2 spousal groups
- 4 age groups
- 97 income bins

for OPTIMAL G47 (47 age groups) allocation, there are  $45590=5*2*97*47$  types/cells of households:

- 5 children groups
- 2 spousal groups
- 47 age groups
- 97 income bins

Optimal G4 has a + 1 version where we allocate for a fifth age group of individuals older than 64 years of age. Optimal G47 has a + 35 version where optimal allocation for all age groups are determined.

### 1.3.2 Allocation Functions

Functions in the [AllocateR/alloc\\_discrete\\_fun\\_R](#) folder of the project repository page is responsible for feeding the dynamic programming results into the allocation functions. The functions in this folder call the [ffp\\_snw\\_process\\_inputs](#) function to solve the allocation problems and compute REV, and call the [ffp\\_snw\\_graph\\_feasible](#) function to generate allocation graphs. These two functions are a part of the [PrjOptiAlloc](#) package.



# Chapter 2

## Parameters

### 2.1 Model Parameters

This is the example vignette for function: [snw\\_mp\\_param](#) from the [PrjOptiSNW Package](#). This function sets and gets different parameters.

#### 2.1.1 Parameters Used for Test Simulation

Rather than solving for all ages between 18 to 100, this solves for age groups, and has limited shocks and asset levels. Used for testing.

```
mp_params = snw_mp_param('default_small', true, 100, 6);
```

```
-----  
XXXXXXXXXXXXXXXXXXXXXXXXXXXXXXXXXXXXXXXXXXXXXXXXXXXX  
CONTAINER NAME: mp_params_preftechpricegov Scalars  
XXXXXXXXXXXXXXXXXXXXXXXXXXXXXXXXXXXXXXXXXXXXXXXXXXXX  
          i      idx      value  
          --      ---      -  
Bequests          1      1          0  
a0                2      2      0.258  
a1                3      3      0.768  
a2                4      4      1.5286  
a2_bushchkyr_2008 5      5      1.5286  
a2_covidyr        6      6          NaN  
a2_covidyr_manna_heaven 7      7      1.5286  
a2_covidyr_tax_fully_pay 8      8      12.718  
a2_greatrecession_2009 9      9      1.5286  
bequests_option   10     10          1  
beta              11     11      0.86389  
cons_allocation_rule 12     12          2  
g_cons            13     13      0.17576  
g_n               14     14      0.05101  
gamma             15     15          2  
invbtlock         16     16          1  
it_yrs_per_period 17     17          5  
jret              18     18          13  
r                 19     19      0.21665  
theta             20     20      0.56523  
throw_in_ocean    21     21          1  
-----
```

```

XXXXXXXXXXXXXXXXXXXXXXXXXXXXXXXXXXXXXXXXXXXXXXXXXXXX
CONTAINER NAME: mp_params_intlen Scalars
XXXXXXXXXXXXXXXXXXXXXXXXXXXXXXXXXXXXXXXXXXXXXXXXXXXX

```

	i	idx	value
	-	---	-----
n_agrid	1	1	25
n_educgrid	2	2	2
n_eta_H_grid	3	3	5
n_eta_S_grid	4	4	1
n_etagrid	5	5	5
n_jgrid	6	6	18
n_kidsgrid	7	7	3
n_marriedgrid	8	8	2

```

-----
XXXXXXXXXXXXXXXXXXXXXXXXXXXXXXXXXXXXXXXXXXXXXXXXXXXX
CONTAINER NAME: mp_params_covid_unemploy ND Array (Matrix etc)
XXXXXXXXXXXXXXXXXXXXXXXXXXXXXXXXXXXXXXXXXXXXXXXXXXXX

```

	i	idx	ndim	numel	rowN	colN	sum	mean	st
	-	---	----	-----	----	----	-----	-----	----
inc_grid	1	7	2	201	201	1	578.5	2.8781	1.
pi_unemp	2	10	2	240	48	5	47.034	0.19598	0.09
pi_unemp_2009_edu_age	3	11	2	96	48	2	6.6005	0.068755	0.04
pi_unemp_2020_april	4	12	2	240	48	5	47.034	0.19598	0.09
pi_unemp_2020_juneadj	5	13	2	240	48	5	16.17	0.067373	0.03

```

xxx TABLE:inc_grid XXXXXXXXXXXXXXXXXXXXXXXX
c1

```

```

-----
r1      0
r2    0.026667
r3    0.053333
r4     0.08
r5    0.10667
r6    0.13333
r7     0.16
r8    0.18667
r9    0.21333
r10   0.24
r11   0.26667
r12   0.29333
r13   0.32
r14   0.34667
r15   0.37333
r16   0.4
r17   0.42667
r18   0.45333
r19   0.48
r20   0.50667
r21   0.53333
r22   0.56
r23   0.58667
r24   0.61333
r25   0.64
r26   0.66667

```

r27	0.69333
r28	0.72
r29	0.74667
r30	0.77333
r31	0.8
r32	0.82667
r33	0.85333
r34	0.88
r35	0.90667
r36	0.93333
r37	0.96
r38	0.98667
r39	1.0133
r40	1.04
r41	1.0667
r42	1.0933
r43	1.12
r44	1.1467
r45	1.1733
r46	1.2
r47	1.2267
r48	1.2533
r49	1.28
r50	1.3067
r152	4.06
r153	4.12
r154	4.18
r155	4.24
r156	4.3
r157	4.36
r158	4.42
r159	4.48
r160	4.54
r161	4.6
r162	4.66
r163	4.72
r164	4.78
r165	4.84
r166	4.9
r167	4.96
r168	5.02
r169	5.08
r170	5.14
r171	5.2
r172	5.26
r173	5.32
r174	5.38
r175	5.44
r176	5.5
r177	5.56
r178	5.62
r179	5.68
r180	5.74
r181	5.8
r182	5.86
r183	5.92
r184	5.98
r185	6.04

```

r186      6.1
r187      6.16
r188      6.22
r189      6.28
r190      6.34
r191      6.4
r192      6.46
r193      6.52
r194      6.58
r195      6.64
r196      6.7
r197      6.76
r198      6.82
r199      6.88
r200      6.94
r201      7

```

```
xxx TABLE:pi_unemp xxxxxxxxxxxxxxxxxxxxxx
```

	c1	c2	c3	c4	c5
	-----	-----	-----	-----	-----
r1	0.36194	0.22237	0.17262	0.14265	0.083133
r2	0.36194	0.22237	0.17262	0.14265	0.083133
r3	0.36194	0.22237	0.17262	0.14265	0.083133
r4	0.36194	0.22237	0.17262	0.14265	0.083133
r5	0.36194	0.22237	0.17262	0.14265	0.083133
r6	0.36194	0.22237	0.17262	0.14265	0.083133
r7	0.36194	0.22237	0.17262	0.14265	0.083133
r8	0.36194	0.22237	0.17262	0.14265	0.083133
r9	0.36194	0.22237	0.17262	0.14265	0.083133
r10	0.36194	0.22237	0.17262	0.14265	0.083133
r11	0.36194	0.22237	0.17262	0.14265	0.083133
r12	0.36194	0.22237	0.17262	0.14265	0.083133
r13	0.36194	0.22237	0.17262	0.14265	0.083133
r14	0.3534	0.21383	0.16408	0.13411	0.074592
r15	0.3534	0.21383	0.16408	0.13411	0.074592
r16	0.3534	0.21383	0.16408	0.13411	0.074592
r17	0.3534	0.21383	0.16408	0.13411	0.074592
r18	0.3534	0.21383	0.16408	0.13411	0.074592
r19	0.3534	0.21383	0.16408	0.13411	0.074592
r20	0.3534	0.21383	0.16408	0.13411	0.074592
r21	0.3534	0.21383	0.16408	0.13411	0.074592
r22	0.3534	0.21383	0.16408	0.13411	0.074592
r23	0.3534	0.21383	0.16408	0.13411	0.074592
r24	0.34917	0.2096	0.15984	0.12988	0.070361
r25	0.34917	0.2096	0.15984	0.12988	0.070361
r26	0.34917	0.2096	0.15984	0.12988	0.070361
r27	0.34917	0.2096	0.15984	0.12988	0.070361
r28	0.34917	0.2096	0.15984	0.12988	0.070361
r29	0.34917	0.2096	0.15984	0.12988	0.070361
r30	0.34917	0.2096	0.15984	0.12988	0.070361
r31	0.34917	0.2096	0.15984	0.12988	0.070361
r32	0.34917	0.2096	0.15984	0.12988	0.070361
r33	0.34917	0.2096	0.15984	0.12988	0.070361
r34	0.35656	0.21699	0.16723	0.13727	0.077749
r35	0.35656	0.21699	0.16723	0.13727	0.077749
r36	0.35656	0.21699	0.16723	0.13727	0.077749
r37	0.35656	0.21699	0.16723	0.13727	0.077749



r38	0.35656	0.21699	0.16723	0.13727	0.077749
r39	0.35656	0.21699	0.16723	0.13727	0.077749
r40	0.35656	0.21699	0.16723	0.13727	0.077749
r41	0.35656	0.21699	0.16723	0.13727	0.077749
r42	0.35656	0.21699	0.16723	0.13727	0.077749
r43	0.35656	0.21699	0.16723	0.13727	0.077749
r44	0.40989	0.27032	0.22056	0.1906	0.13108
r45	0.40989	0.27032	0.22056	0.1906	0.13108
r46	0.40989	0.27032	0.22056	0.1906	0.13108
r47	0.40989	0.27032	0.22056	0.1906	0.13108
r48	0.40989	0.27032	0.22056	0.1906	0.13108

xxx TABLE:pi\_unemp\_2009\_edu\_age xxxxxxxxxxxxxxxxxxxxxxx

	c1	c2
	-----	-----
r1	0.17919	0.12517
r2	0.17919	0.12517
r3	0.17919	0.12517
r4	0.17919	0.12517
r5	0.17919	0.12517
r6	0.17919	0.12517
r7	0.17919	0.12517
r8	0.086103	0.032088
r9	0.086103	0.032088
r10	0.086103	0.032088
r11	0.086103	0.032088
r12	0.086103	0.032088
r13	0.086103	0.032088
r14	0.086103	0.032088
r15	0.086103	0.032088
r16	0.086103	0.032088
r17	0.086103	0.032088
r18	0.086103	0.032088
r19	0.086103	0.032088
r20	0.086103	0.032088
r21	0.086103	0.032088
r22	0.086103	0.032088
r23	0.086103	0.032088
r24	0.086103	0.032088
r25	0.086103	0.032088
r26	0.086103	0.032088
r27	0.086103	0.032088
r28	0.086103	0.032088
r29	0.086103	0.032088
r30	0.086103	0.032088
r31	0.086103	0.032088
r32	0.086103	0.032088
r33	0.086103	0.032088
r34	0.086103	0.032088
r35	0.086103	0.032088
r36	0.086103	0.032088
r37	0.086103	0.032088
r38	0.06902	0.015005
r39	0.06902	0.015005
r40	0.06902	0.015005
r41	0.06902	0.015005
r42	0.06902	0.015005

r43	0.06902	0.015005
r44	0.06902	0.015005
r45	0.06902	0.015005
r46	0.06902	0.015005
r47	0.06902	0.015005
r48	0.06902	0.015005

xxx TABLE:pi\_unemp\_2020\_april xxxxxxxxxxxxxxxxxxxxxx

	c1	c2	c3	c4	c5
	-----	-----	-----	-----	-----
r1	0.36194	0.22237	0.17262	0.14265	0.083133
r2	0.36194	0.22237	0.17262	0.14265	0.083133
r3	0.36194	0.22237	0.17262	0.14265	0.083133
r4	0.36194	0.22237	0.17262	0.14265	0.083133
r5	0.36194	0.22237	0.17262	0.14265	0.083133
r6	0.36194	0.22237	0.17262	0.14265	0.083133
r7	0.36194	0.22237	0.17262	0.14265	0.083133
r8	0.36194	0.22237	0.17262	0.14265	0.083133
r9	0.36194	0.22237	0.17262	0.14265	0.083133
r10	0.36194	0.22237	0.17262	0.14265	0.083133
r11	0.36194	0.22237	0.17262	0.14265	0.083133
r12	0.36194	0.22237	0.17262	0.14265	0.083133
r13	0.36194	0.22237	0.17262	0.14265	0.083133
r14	0.3534	0.21383	0.16408	0.13411	0.074592
r15	0.3534	0.21383	0.16408	0.13411	0.074592
r16	0.3534	0.21383	0.16408	0.13411	0.074592
r17	0.3534	0.21383	0.16408	0.13411	0.074592
r18	0.3534	0.21383	0.16408	0.13411	0.074592
r19	0.3534	0.21383	0.16408	0.13411	0.074592
r20	0.3534	0.21383	0.16408	0.13411	0.074592
r21	0.3534	0.21383	0.16408	0.13411	0.074592
r22	0.3534	0.21383	0.16408	0.13411	0.074592
r23	0.3534	0.21383	0.16408	0.13411	0.074592
r24	0.34917	0.2096	0.15984	0.12988	0.070361
r25	0.34917	0.2096	0.15984	0.12988	0.070361
r26	0.34917	0.2096	0.15984	0.12988	0.070361
r27	0.34917	0.2096	0.15984	0.12988	0.070361
r28	0.34917	0.2096	0.15984	0.12988	0.070361
r29	0.34917	0.2096	0.15984	0.12988	0.070361
r30	0.34917	0.2096	0.15984	0.12988	0.070361
r31	0.34917	0.2096	0.15984	0.12988	0.070361
r32	0.34917	0.2096	0.15984	0.12988	0.070361
r33	0.34917	0.2096	0.15984	0.12988	0.070361
r34	0.35656	0.21699	0.16723	0.13727	0.077749
r35	0.35656	0.21699	0.16723	0.13727	0.077749
r36	0.35656	0.21699	0.16723	0.13727	0.077749
r37	0.35656	0.21699	0.16723	0.13727	0.077749
r38	0.35656	0.21699	0.16723	0.13727	0.077749
r39	0.35656	0.21699	0.16723	0.13727	0.077749
r40	0.35656	0.21699	0.16723	0.13727	0.077749
r41	0.35656	0.21699	0.16723	0.13727	0.077749
r42	0.35656	0.21699	0.16723	0.13727	0.077749
r43	0.35656	0.21699	0.16723	0.13727	0.077749
r44	0.40989	0.27032	0.22056	0.1906	0.13108
r45	0.40989	0.27032	0.22056	0.1906	0.13108
r46	0.40989	0.27032	0.22056	0.1906	0.13108
r47	0.40989	0.27032	0.22056	0.1906	0.13108

	0.40989	0.27032	0.22056	0.1906	0.13108
xxx TABLE:pi_unemp_2020_juneadj	xxxxxxxxxxxxxxxxxxxxxx				
	c1	c2	c3	c4	c5
	-----	-----	-----	-----	-----
r1	0.11257	0.062283	0.046026	0.036173	0.035471
r2	0.11257	0.062283	0.046026	0.036173	0.035471
r3	0.11257	0.062283	0.046026	0.036173	0.035471
r4	0.11257	0.062283	0.046026	0.036173	0.035471
r5	0.11257	0.062283	0.046026	0.036173	0.035471
r6	0.11257	0.062283	0.046026	0.036173	0.035471
r7	0.11257	0.062283	0.046026	0.036173	0.035471
r8	0.11257	0.062283	0.046026	0.036173	0.035471
r9	0.11257	0.062283	0.046026	0.036173	0.035471
r10	0.11257	0.062283	0.046026	0.036173	0.035471
r11	0.11257	0.062283	0.046026	0.036173	0.035471
r12	0.11257	0.062283	0.046026	0.036173	0.035471
r13	0.11257	0.062283	0.046026	0.036173	0.035471
r14	0.11994	0.069654	0.053397	0.043545	0.042842
r15	0.11994	0.069654	0.053397	0.043545	0.042842
r16	0.11994	0.069654	0.053397	0.043545	0.042842
r17	0.11994	0.069654	0.053397	0.043545	0.042842
r18	0.11994	0.069654	0.053397	0.043545	0.042842
r19	0.11994	0.069654	0.053397	0.043545	0.042842
r20	0.11994	0.069654	0.053397	0.043545	0.042842
r21	0.11994	0.069654	0.053397	0.043545	0.042842
r22	0.11994	0.069654	0.053397	0.043545	0.042842
r23	0.11994	0.069654	0.053397	0.043545	0.042842
r24	0.11038	0.060097	0.04384	0.033988	0.033285
r25	0.11038	0.060097	0.04384	0.033988	0.033285
r26	0.11038	0.060097	0.04384	0.033988	0.033285
r27	0.11038	0.060097	0.04384	0.033988	0.033285
r28	0.11038	0.060097	0.04384	0.033988	0.033285
r29	0.11038	0.060097	0.04384	0.033988	0.033285
r30	0.11038	0.060097	0.04384	0.033988	0.033285
r31	0.11038	0.060097	0.04384	0.033988	0.033285
r32	0.11038	0.060097	0.04384	0.033988	0.033285
r33	0.11038	0.060097	0.04384	0.033988	0.033285
r34	0.12326	0.072969	0.056712	0.04686	0.046157
r35	0.12326	0.072969	0.056712	0.04686	0.046157
r36	0.12326	0.072969	0.056712	0.04686	0.046157
r37	0.12326	0.072969	0.056712	0.04686	0.046157
r38	0.12326	0.072969	0.056712	0.04686	0.046157
r39	0.12326	0.072969	0.056712	0.04686	0.046157
r40	0.12326	0.072969	0.056712	0.04686	0.046157
r41	0.12326	0.072969	0.056712	0.04686	0.046157
r42	0.12326	0.072969	0.056712	0.04686	0.046157
r43	0.12326	0.072969	0.056712	0.04686	0.046157
r44	0.16597	0.11568	0.099422	0.08957	0.088867
r45	0.16597	0.11568	0.099422	0.08957	0.088867
r46	0.16597	0.11568	0.099422	0.08957	0.088867
r47	0.16597	0.11568	0.099422	0.08957	0.088867
r48	0.16597	0.11568	0.099422	0.08957	0.088867

-----  
 xxx  
 CONTAINER NAME: mp\_params\_covid\_unemploy Scalars

```
XXXXXXXXXXXXXXXXXXXXXXXXXXXXXXXXXXXXXXXXXXXXXXXXXXXXXXXXXXXX
```

	i	idx	value
	---	---	-----
TR	1	1	0.0015999
b	2	2	1
fl_stimulus_adult_first	3	3	1200
fl_stimulus_adult_second	4	4	600
fl_stimulus_child_first	5	5	500
fl_stimulus_child_second	6	6	600
n_incgrid	7	8	201
n_welfchecksgrid	8	9	45
scaleconvector	9	14	62502
xi	10	16	0.75

```
XXXXXXXXXXXXXXXXXXXXXXXXXXXXXXXXXXXXXXXXXXXXXXXXXXXXXXXXXXXX
```

```
CONTAINER NAME: mp_params_covid_unemploy String
```

```
XXXXXXXXXXXXXXXXXXXXXXXXXXXXXXXXXXXXXXXXXXXXXXXXXXXXXXXXXXXX
```

	i	idx	string
	---	---	-----
st_biden_or_trump	"1"	"15"	"st_biden_or_trump_undefined"

```
XXXXXXXXXXXXXXXXXXXXXXXXXXXXXXXXXXXXXXXXXXXXXXXXXXXXXXXXXXXX
```

```
CONTAINER NAME: mp_params_statesgrid ND Array (Matrix etc)
```

```
XXXXXXXXXXXXXXXXXXXXXXXXXXXXXXXXXXXXXXXXXXXXXXXXXXXXXXXXXXXX
```

	i	idx	ndim	numel	rowN	colN	sum	mean	std
	-	---	----	-----	----	----	-----	-----	-----
agrid	1	1	2	25	25	1	878.91	35.156	41.372
eta_H_grid	2	2	2	5	5	1	-2.2204e-16	-4.4409e-17	1.4543
eta_S_grid	3	3	2	5	5	1	0	0	0

```
xxx TABLE:agrid XXXXXXXXXXXXXXXXXXXXXXX
```

```
c1
```

```
-----
```

r1	0
r2	0.0097656
r3	0.078125
r4	0.26367
r5	0.625
r6	1.2207
r7	2.1094
r8	3.3496
r9	5
r10	7.1191
r11	9.7656
r12	12.998
r13	16.875
r14	21.455
r15	26.797
r16	32.959
r17	40
r18	47.979
r19	56.953

```
r20      66.982
r21      78.125
r22      90.439
r23     103.98
r24     118.82
r25      135
```

```
xxx TABLE:eta_H_grid xxxxxxxxxxxxxxxxxxxxxxxx
      c1
```

```
-----
r1     -1.8395
r2     -0.91976
r3         0
r4      0.91976
r5      1.8395
```

```
xxx TABLE:eta_S_grid xxxxxxxxxxxxxxxxxxxxxxxx
      c1
```

```
--
r1      0
r2      0
r3      0
r4      0
r5      0
```

```
-----
xxxxxxxxxxxxxxxxxxxxxxxxxxxxxxxxxxxxxxxxxxxxx
CONTAINER NAME: mp_params_exotrans ND Array (Matrix etc)
xxxxxxxxxxxxxxxxxxxxxxxxxxxxxxxxxxxxxxxxxxxxx
```

	i	idx	ndim	numel	rowN	colN	sum	mean	std
	-	---	----	-----	-----	----	-----	-----	-----
cl_mt_pi_jem_kidseta	1	2	2	1	1	1	0	0	
pi_H_eta	2	3	2	25	5	5	5	0.2	0.3851
pi_eta	3	5	2	25	5	5	5	0.2	0.3851
pi_kids	4	6	5	648	3	216	216	0.33333	0.3561
psi	5	7	2	18	18	1	14.251	0.79171	0.3125

```
xxx TABLE:cl_mt_pi_jem_kidseta xxxxxxxxxxxxxxxxxxxxxxxx
      c1
```

```
--
r1      0
```

```
xxx TABLE:pi_H_eta xxxxxxxxxxxxxxxxxxxxxxxx
      c1      c2      c3      c4      c5
```

```
-----
r1      0.925      0.075001      4.8068e-10      0      0
r2      0.0026569      0.96788      0.029459      2.602e-11      0
r3      1.1558e-12      0.0096913      0.98062      0.0096913      1.1559e-12
r4      1.28e-29      2.602e-11      0.029459      0.96788      0.0026569
r5      2.8504e-54      1.8802e-27      4.8068e-10      0.075001      0.925
```

```
xxx TABLE:pi_eta xxxxxxxxxxxxxxxxxxxxxxxx
      c1      c2      c3      c4      c5
```

```

-----
r1      0.925      0.075001      4.8068e-10      0      0
r2      0.0026569      0.96788      0.029459      2.602e-11      0
r3      1.1558e-12      0.0096913      0.98062      0.0096913      1.1559e-12
r4      1.28e-29      2.602e-11      0.029459      0.96788      0.0026569
r5      2.8504e-54      1.8802e-27      4.8068e-10      0.075001      0.925
    
```

xxx TABLE:pi\_kids xxxxxxxxxxxxxxxxxxxxxxx

```

      c1      c2      c3      c214      c215      c216
-----
r1      0.88584      0.11137      0.0027905      1      0      0
r2      0.051343      0.66234      0.28632      1      0      0
r3      0.0015025      0.063309      0.93519      1      0      0
    
```

xxx TABLE:psi xxxxxxxxxxxxxxxxxxxxxxx

```

      c1
-----
r1      0.99935
r2      0.99623
r3      0.99635
r4      0.99537
r5      0.99299
r6      0.98956
r7      0.98547
r8      0.98022
r9      0.96914
r10     0.95071
r11     0.92082
r12     0.87772
r13     0.81394
r14     0.70638
r15     0.54032
r16     0.34767
r17     0.18848
r18      0
    
```

-----

xxx  
CONTAINER NAME: mp\_params\_exotrans Scalars  
xxx

```

           i      idx      value
           -      ---      -----
bl_store_shock_trans      1      1      0
pi_S_eta      2      4      1
    
```

-----

xxx  
CONTAINER NAME: mp\_params\_typerlife ND Array (Matrix etc)  
xxx

```

           i      idx      ndim      numel      rowN      colN      sum      mean      std      coefvari
           -      ---      ---      -----      ---      ---      -----      ---      ---      ---
SS      1      1      2      36      18      2      2.916      0.081      0.11695      1.4439
epsilon      2      2      2      36      18      2      39.526      1.0979      0.85451      0.77828
    
```

xxx TABLE:SS xxxxxxxxxxxxxxxxxxxxxxxx

	c1	c2
	----	-----
r1	0	0
r2	0	0
r3	0	0
r4	0	0
r5	0	0
r6	0	0
r7	0	0
r8	0	0
r9	0	0
r10	0	0
r11	0	0
r12	0	0
r13	0.22	0.266
r14	0.22	0.266
r15	0.22	0.266
r16	0.22	0.266
r17	0.22	0.266
r18	0.22	0.266

xxx TABLE:epsilon xxxxxxxxxxxxxxxxxxxxxxxx

	c1	c2
	-----	-----
r1	1	1
r2	1.0778	1.1836
r3	1.2546	1.6124
r4	1.397	1.9418
r5	1.5022	2.1452
r6	1.5712	2.2394
r7	1.6064	2.2588
r8	1.6097	2.2341
r9	1.5815	2.182
r10	1.5204	2.1034
r11	1.4243	1.9846
r12	1.2917	1.8041
r13	0	0
r14	0	0
r15	0	0
r16	0	0
r17	0	0
r18	0	0

-----  
 xxx  
 CONTAINER NAME: mp\_params\_stat ND Array (Matrix etc)  
 xxx

	i	idx	ndim	numel	rowN	colN	sum	mean	std
	-	---	----	-----	-----	-----	-----	-----	-----
Pop	1	1	2	18	18	1	9.8945	0.54969	0.31889
stat_distr_educ	2	3	2	2	1	2	1	0.5	0.2786
stat_distr_eta	3	4	2	5	1	5	1	0.2	0.24003
stat_distr_kids	4	5	3	12	2	6	4	0.33333	0.33166

stat\_distr\_married 5 6 2 4 2 2 2 0.5 0.073381

xxx TABLE:Pop xxxxxxxxxxxxxxxxxxxxxxxx  
c1

```

-----
r1      1
r2     0.95085
r3     0.90129
r4     0.85442
r5     0.80919
r6     0.76452
r7     0.71982
r8     0.67493
r9     0.62947
r10    0.58044
r11    0.52505
r12    0.46001
r13    0.38416
r14    0.29751
r15    0.19995
r16    0.1028
r17    0.034004
r18    0.006098
    
```

xxx TABLE:stat\_distr\_educ xxxxxxxxxxxxxxxxxxxxxxxx  
c1 c2

```

-----
r1  0.697  0.303
    
```

xxx TABLE:stat\_distr\_eta xxxxxxxxxxxxxxxxxxxxxxxx  
c1 c2 c3 c4 c5

```

-----
r1  0.0069316  0.19567  0.59479  0.19567  0.0069316
    
```

xxx TABLE:stat\_distr\_kids xxxxxxxxxxxxxxxxxxxxxxxx  
c1 c2 c3 c4 c5 c6

```

-----
r1  0.75801  0.44877  0.1564  0.32041  0.08559  0.23083
r2  0.97627  0.7604  0.023626  0.2173  0.00010011  0.022305
    
```

xxx TABLE:stat\_distr\_married xxxxxxxxxxxxxxxxxxxxxxxx  
c1 c2

```

-----
r1  0.5635  0.4365
r2  0.4364  0.5636
    
```

```

-----
xxxxxxxxxxxxxxxxxxxxxxxxxxxxxxxxxxxxxxxxxxxxxxxxxxxxxxxxxxxxxxxxxxxxxxxx
CONTAINER NAME: mp_params_stat String
xxxxxxxxxxxxxxxxxxxxxxxxxxxxxxxxxxxxxxxxxxxxxxxxxxxxxxxxxxxxxxxxxxxxxxxx
    
```

```

i      idx      string
-----
    
```



```
st_old_age_depend    "1"    "2"    "Old-age dependency ratio (ratio of 65+/(18-64))=0.1155"
```

### 2.1.2 Documentation Run Parameters Docdense

Parameters used for documentation vig. "docdense" uses less shocks than the version of the model used to implement the allocation problems in the [Nygaard, Sorensen and Wang \(2020\)](#).

```
mp_params = snw_mp_param('default_docdense', true, 100, 6);
```

```
-----
XXXXXXXXXXXXXXXXXXXXXXXXXXXXXXXXXXXXXXXXXXXXXXXXXXXX
CONTAINER NAME: mp_params_preftechpricegov Scalars
XXXXXXXXXXXXXXXXXXXXXXXXXXXXXXXXXXXXXXXXXXXXXXXXXXXX
          i      idx      value
          --      ---      -
Bequests          1      1          0
a0                 2      2      0.258
a1                 3      3      0.768
a2                 4      4      1.5286
a2_bushchkyr_2008  5      5      1.5286
a2_covidyr         6      6          NaN
a2_covidyr_manna_heaven  7      7      1.5286
a2_covidyr_tax_fully_pay  8      8      12.718
a2_greatrecession_2009  9      9      1.5286
bequests_option   10     10          1
beta              11     11      0.97116
cons_allocation_rule 12     12          2
g_cons            13     13      0.17576
g_n               14     14          0.01
gamma             15     15          2
invbtlock         16     16          1
it_yrs_per_period 17     17          1
jret              18     18          48
r                 19     19          0.04
theta             20     20      0.56523
throw_in_ocean    21     21          1
-----
```

```
-----
XXXXXXXXXXXXXXXXXXXXXXXXXXXXXXXXXXXXXXXXXXXXXXXXXXXX
CONTAINER NAME: mp_params_intlen Scalars
XXXXXXXXXXXXXXXXXXXXXXXXXXXXXXXXXXXXXXXXXXXXXXXXXXXX
          i      idx      value
          -      ---      -
n_agrid           1      1      65
n_educgrid        2      2          2
n_eta_H_grid      3      3      81
n_eta_S_grid      4      4          5
n_etagrid         5      5      405
n_jgrid           6      6      83
n_kidsgrid        7      7          5
n_marriedgrid     8      8          2
-----
```

```
-----
XXXXXXXXXXXXXXXXXXXXXXXXXXXXXXXXXXXXXXXXXXXXXXXXXXXX
CONTAINER NAME: mp_params_covid_unemploy ND Array (Matrix etc)
XXXXXXXXXXXXXXXXXXXXXXXXXXXXXXXXXXXXXXXXXXXXXXXXXXXX
          i      idx      ndim      numel      rowN      colN      sum      mean      st
```

	-	---	----	-----	-----	-----	-----	-----	-----
inc_grid	1	7	2	201	201	1	578.5	2.8781	1.
pi_unemp	2	10	2	415	83	5	47.034	0.11333	0.1
pi_unemp_2009_edu_age	3	11	2	166	83	2	6.6005	0.039762	0
pi_unemp_2020_april	4	12	2	415	83	5	47.034	0.11333	0.1
pi_unemp_2020_juneadj	5	13	2	415	83	5	16.17	0.038963	0.04

xxx TABLE:inc\_grid xxxxxxxxxxxxxxxxxxxxxx  
c1

	-----
r1	0
r2	0.026667
r3	0.053333
r4	0.08
r5	0.10667
r6	0.13333
r7	0.16
r8	0.18667
r9	0.21333
r10	0.24
r11	0.26667
r12	0.29333
r13	0.32
r14	0.34667
r15	0.37333
r16	0.4
r17	0.42667
r18	0.45333
r19	0.48
r20	0.50667
r21	0.53333
r22	0.56
r23	0.58667
r24	0.61333
r25	0.64
r26	0.66667
r27	0.69333
r28	0.72
r29	0.74667
r30	0.77333
r31	0.8
r32	0.82667
r33	0.85333
r34	0.88
r35	0.90667
r36	0.93333
r37	0.96
r38	0.98667
r39	1.0133
r40	1.04
r41	1.0667
r42	1.0933
r43	1.12
r44	1.1467
r45	1.1733
r46	1.2

r47	1.2267
r48	1.2533
r49	1.28
r50	1.3067
r152	4.06
r153	4.12
r154	4.18
r155	4.24
r156	4.3
r157	4.36
r158	4.42
r159	4.48
r160	4.54
r161	4.6
r162	4.66
r163	4.72
r164	4.78
r165	4.84
r166	4.9
r167	4.96
r168	5.02
r169	5.08
r170	5.14
r171	5.2
r172	5.26
r173	5.32
r174	5.38
r175	5.44
r176	5.5
r177	5.56
r178	5.62
r179	5.68
r180	5.74
r181	5.8
r182	5.86
r183	5.92
r184	5.98
r185	6.04
r186	6.1
r187	6.16
r188	6.22
r189	6.28
r190	6.34
r191	6.4
r192	6.46
r193	6.52
r194	6.58
r195	6.64
r196	6.7
r197	6.76
r198	6.82
r199	6.88
r200	6.94
r201	7

xxx TABLE:pi\_unemp xxxxxxxxxxxxxxxxxxxxxxx

c1	c2	c3	c4	c5
-----	-----	-----	-----	-----

r1	0.36194	0.22237	0.17262	0.14265	0.083133
r2	0.36194	0.22237	0.17262	0.14265	0.083133
r3	0.36194	0.22237	0.17262	0.14265	0.083133
r4	0.36194	0.22237	0.17262	0.14265	0.083133
r5	0.36194	0.22237	0.17262	0.14265	0.083133
r6	0.36194	0.22237	0.17262	0.14265	0.083133
r7	0.36194	0.22237	0.17262	0.14265	0.083133
r8	0.36194	0.22237	0.17262	0.14265	0.083133
r9	0.36194	0.22237	0.17262	0.14265	0.083133
r10	0.36194	0.22237	0.17262	0.14265	0.083133
r11	0.36194	0.22237	0.17262	0.14265	0.083133
r12	0.36194	0.22237	0.17262	0.14265	0.083133
r13	0.36194	0.22237	0.17262	0.14265	0.083133
r14	0.3534	0.21383	0.16408	0.13411	0.074592
r15	0.3534	0.21383	0.16408	0.13411	0.074592
r16	0.3534	0.21383	0.16408	0.13411	0.074592
r17	0.3534	0.21383	0.16408	0.13411	0.074592
r18	0.3534	0.21383	0.16408	0.13411	0.074592
r19	0.3534	0.21383	0.16408	0.13411	0.074592
r20	0.3534	0.21383	0.16408	0.13411	0.074592
r21	0.3534	0.21383	0.16408	0.13411	0.074592
r22	0.3534	0.21383	0.16408	0.13411	0.074592
r23	0.3534	0.21383	0.16408	0.13411	0.074592
r24	0.34917	0.2096	0.15984	0.12988	0.070361
r25	0.34917	0.2096	0.15984	0.12988	0.070361
r26	0.34917	0.2096	0.15984	0.12988	0.070361
r27	0.34917	0.2096	0.15984	0.12988	0.070361
r28	0.34917	0.2096	0.15984	0.12988	0.070361
r29	0.34917	0.2096	0.15984	0.12988	0.070361
r30	0.34917	0.2096	0.15984	0.12988	0.070361
r31	0.34917	0.2096	0.15984	0.12988	0.070361
r32	0.34917	0.2096	0.15984	0.12988	0.070361
r33	0.34917	0.2096	0.15984	0.12988	0.070361
r34	0.35656	0.21699	0.16723	0.13727	0.077749
r35	0.35656	0.21699	0.16723	0.13727	0.077749
r36	0.35656	0.21699	0.16723	0.13727	0.077749
r37	0.35656	0.21699	0.16723	0.13727	0.077749
r38	0.35656	0.21699	0.16723	0.13727	0.077749
r39	0.35656	0.21699	0.16723	0.13727	0.077749
r40	0.35656	0.21699	0.16723	0.13727	0.077749
r41	0.35656	0.21699	0.16723	0.13727	0.077749
r42	0.35656	0.21699	0.16723	0.13727	0.077749
r43	0.35656	0.21699	0.16723	0.13727	0.077749
r44	0.40989	0.27032	0.22056	0.1906	0.13108
r45	0.40989	0.27032	0.22056	0.1906	0.13108
r46	0.40989	0.27032	0.22056	0.1906	0.13108
r47	0.40989	0.27032	0.22056	0.1906	0.13108
r48	0.40989	0.27032	0.22056	0.1906	0.13108
r49	0	0	0	0	0
r50	0	0	0	0	0
r51	0	0	0	0	0
r52	0	0	0	0	0
r53	0	0	0	0	0
r54	0	0	0	0	0
r55	0	0	0	0	0
r56	0	0	0	0	0
r57	0	0	0	0	0

r58	0	0	0	0	0
r59	0	0	0	0	0
r60	0	0	0	0	0
r61	0	0	0	0	0
r62	0	0	0	0	0
r63	0	0	0	0	0
r64	0	0	0	0	0
r65	0	0	0	0	0
r66	0	0	0	0	0
r67	0	0	0	0	0
r68	0	0	0	0	0
r69	0	0	0	0	0
r70	0	0	0	0	0
r71	0	0	0	0	0
r72	0	0	0	0	0
r73	0	0	0	0	0
r74	0	0	0	0	0
r75	0	0	0	0	0
r76	0	0	0	0	0
r77	0	0	0	0	0
r78	0	0	0	0	0
r79	0	0	0	0	0
r80	0	0	0	0	0
r81	0	0	0	0	0
r82	0	0	0	0	0
r83	0	0	0	0	0

xxx TABLE:pi\_unemp\_2009\_edu\_age xxxxxxxxxxxxxxxxxxxxxxx

	c1	c2
	-----	-----
r1	0.17919	0.12517
r2	0.17919	0.12517
r3	0.17919	0.12517
r4	0.17919	0.12517
r5	0.17919	0.12517
r6	0.17919	0.12517
r7	0.17919	0.12517
r8	0.086103	0.032088
r9	0.086103	0.032088
r10	0.086103	0.032088
r11	0.086103	0.032088
r12	0.086103	0.032088
r13	0.086103	0.032088
r14	0.086103	0.032088
r15	0.086103	0.032088
r16	0.086103	0.032088
r17	0.086103	0.032088
r18	0.086103	0.032088
r19	0.086103	0.032088
r20	0.086103	0.032088
r21	0.086103	0.032088
r22	0.086103	0.032088
r23	0.086103	0.032088
r24	0.086103	0.032088
r25	0.086103	0.032088
r26	0.086103	0.032088
r27	0.086103	0.032088

r28	0.086103	0.032088
r29	0.086103	0.032088
r30	0.086103	0.032088
r31	0.086103	0.032088
r32	0.086103	0.032088
r33	0.086103	0.032088
r34	0.086103	0.032088
r35	0.086103	0.032088
r36	0.086103	0.032088
r37	0.086103	0.032088
r38	0.06902	0.015005
r39	0.06902	0.015005
r40	0.06902	0.015005
r41	0.06902	0.015005
r42	0.06902	0.015005
r43	0.06902	0.015005
r44	0.06902	0.015005
r45	0.06902	0.015005
r46	0.06902	0.015005
r47	0.06902	0.015005
r48	0.06902	0.015005
r49	0	0
r50	0	0
r51	0	0
r52	0	0
r53	0	0
r54	0	0
r55	0	0
r56	0	0
r57	0	0
r58	0	0
r59	0	0
r60	0	0
r61	0	0
r62	0	0
r63	0	0
r64	0	0
r65	0	0
r66	0	0
r67	0	0
r68	0	0
r69	0	0
r70	0	0
r71	0	0
r72	0	0
r73	0	0
r74	0	0
r75	0	0
r76	0	0
r77	0	0
r78	0	0
r79	0	0
r80	0	0
r81	0	0
r82	0	0
r83	0	0

xxx TABLE:pi\_unemp\_2020\_april xxxxxxxxxxxxxxxxxxxxxx

	c1	c2	c3	c4	c5
	-----	-----	-----	-----	-----
r1	0.36194	0.22237	0.17262	0.14265	0.083133
r2	0.36194	0.22237	0.17262	0.14265	0.083133
r3	0.36194	0.22237	0.17262	0.14265	0.083133
r4	0.36194	0.22237	0.17262	0.14265	0.083133
r5	0.36194	0.22237	0.17262	0.14265	0.083133
r6	0.36194	0.22237	0.17262	0.14265	0.083133
r7	0.36194	0.22237	0.17262	0.14265	0.083133
r8	0.36194	0.22237	0.17262	0.14265	0.083133
r9	0.36194	0.22237	0.17262	0.14265	0.083133
r10	0.36194	0.22237	0.17262	0.14265	0.083133
r11	0.36194	0.22237	0.17262	0.14265	0.083133
r12	0.36194	0.22237	0.17262	0.14265	0.083133
r13	0.36194	0.22237	0.17262	0.14265	0.083133
r14	0.3534	0.21383	0.16408	0.13411	0.074592
r15	0.3534	0.21383	0.16408	0.13411	0.074592
r16	0.3534	0.21383	0.16408	0.13411	0.074592
r17	0.3534	0.21383	0.16408	0.13411	0.074592
r18	0.3534	0.21383	0.16408	0.13411	0.074592
r19	0.3534	0.21383	0.16408	0.13411	0.074592
r20	0.3534	0.21383	0.16408	0.13411	0.074592
r21	0.3534	0.21383	0.16408	0.13411	0.074592
r22	0.3534	0.21383	0.16408	0.13411	0.074592
r23	0.3534	0.21383	0.16408	0.13411	0.074592
r24	0.34917	0.2096	0.15984	0.12988	0.070361
r25	0.34917	0.2096	0.15984	0.12988	0.070361
r26	0.34917	0.2096	0.15984	0.12988	0.070361
r27	0.34917	0.2096	0.15984	0.12988	0.070361
r28	0.34917	0.2096	0.15984	0.12988	0.070361
r29	0.34917	0.2096	0.15984	0.12988	0.070361
r30	0.34917	0.2096	0.15984	0.12988	0.070361
r31	0.34917	0.2096	0.15984	0.12988	0.070361
r32	0.34917	0.2096	0.15984	0.12988	0.070361
r33	0.34917	0.2096	0.15984	0.12988	0.070361
r34	0.35656	0.21699	0.16723	0.13727	0.077749
r35	0.35656	0.21699	0.16723	0.13727	0.077749
r36	0.35656	0.21699	0.16723	0.13727	0.077749
r37	0.35656	0.21699	0.16723	0.13727	0.077749
r38	0.35656	0.21699	0.16723	0.13727	0.077749
r39	0.35656	0.21699	0.16723	0.13727	0.077749
r40	0.35656	0.21699	0.16723	0.13727	0.077749
r41	0.35656	0.21699	0.16723	0.13727	0.077749
r42	0.35656	0.21699	0.16723	0.13727	0.077749
r43	0.35656	0.21699	0.16723	0.13727	0.077749
r44	0.40989	0.27032	0.22056	0.1906	0.13108
r45	0.40989	0.27032	0.22056	0.1906	0.13108
r46	0.40989	0.27032	0.22056	0.1906	0.13108
r47	0.40989	0.27032	0.22056	0.1906	0.13108
r48	0.40989	0.27032	0.22056	0.1906	0.13108
r49	0	0	0	0	0
r50	0	0	0	0	0
r51	0	0	0	0	0
r52	0	0	0	0	0
r53	0	0	0	0	0
r54	0	0	0	0	0
r55	0	0	0	0	0

r56	0	0	0	0	0
r57	0	0	0	0	0
r58	0	0	0	0	0
r59	0	0	0	0	0
r60	0	0	0	0	0
r61	0	0	0	0	0
r62	0	0	0	0	0
r63	0	0	0	0	0
r64	0	0	0	0	0
r65	0	0	0	0	0
r66	0	0	0	0	0
r67	0	0	0	0	0
r68	0	0	0	0	0
r69	0	0	0	0	0
r70	0	0	0	0	0
r71	0	0	0	0	0
r72	0	0	0	0	0
r73	0	0	0	0	0
r74	0	0	0	0	0
r75	0	0	0	0	0
r76	0	0	0	0	0
r77	0	0	0	0	0
r78	0	0	0	0	0
r79	0	0	0	0	0
r80	0	0	0	0	0
r81	0	0	0	0	0
r82	0	0	0	0	0
r83	0	0	0	0	0

xxx TABLE:pi\_unemp\_2020\_juneadj xxxxxxxxxxxxxxxxxxxxxxx

	c1	c2	c3	c4	c5
	-----	-----	-----	-----	-----
r1	0.11257	0.062283	0.046026	0.036173	0.035471
r2	0.11257	0.062283	0.046026	0.036173	0.035471
r3	0.11257	0.062283	0.046026	0.036173	0.035471
r4	0.11257	0.062283	0.046026	0.036173	0.035471
r5	0.11257	0.062283	0.046026	0.036173	0.035471
r6	0.11257	0.062283	0.046026	0.036173	0.035471
r7	0.11257	0.062283	0.046026	0.036173	0.035471
r8	0.11257	0.062283	0.046026	0.036173	0.035471
r9	0.11257	0.062283	0.046026	0.036173	0.035471
r10	0.11257	0.062283	0.046026	0.036173	0.035471
r11	0.11257	0.062283	0.046026	0.036173	0.035471
r12	0.11257	0.062283	0.046026	0.036173	0.035471
r13	0.11257	0.062283	0.046026	0.036173	0.035471
r14	0.11994	0.069654	0.053397	0.043545	0.042842
r15	0.11994	0.069654	0.053397	0.043545	0.042842
r16	0.11994	0.069654	0.053397	0.043545	0.042842
r17	0.11994	0.069654	0.053397	0.043545	0.042842
r18	0.11994	0.069654	0.053397	0.043545	0.042842
r19	0.11994	0.069654	0.053397	0.043545	0.042842
r20	0.11994	0.069654	0.053397	0.043545	0.042842
r21	0.11994	0.069654	0.053397	0.043545	0.042842
r22	0.11994	0.069654	0.053397	0.043545	0.042842
r23	0.11994	0.069654	0.053397	0.043545	0.042842
r24	0.11038	0.060097	0.04384	0.033988	0.033285
r25	0.11038	0.060097	0.04384	0.033988	0.033285



r26	0.11038	0.060097	0.04384	0.033988	0.033285
r27	0.11038	0.060097	0.04384	0.033988	0.033285
r28	0.11038	0.060097	0.04384	0.033988	0.033285
r29	0.11038	0.060097	0.04384	0.033988	0.033285
r30	0.11038	0.060097	0.04384	0.033988	0.033285
r31	0.11038	0.060097	0.04384	0.033988	0.033285
r32	0.11038	0.060097	0.04384	0.033988	0.033285
r33	0.11038	0.060097	0.04384	0.033988	0.033285
r34	0.12326	0.072969	0.056712	0.04686	0.046157
r35	0.12326	0.072969	0.056712	0.04686	0.046157
r36	0.12326	0.072969	0.056712	0.04686	0.046157
r37	0.12326	0.072969	0.056712	0.04686	0.046157
r38	0.12326	0.072969	0.056712	0.04686	0.046157
r39	0.12326	0.072969	0.056712	0.04686	0.046157
r40	0.12326	0.072969	0.056712	0.04686	0.046157
r41	0.12326	0.072969	0.056712	0.04686	0.046157
r42	0.12326	0.072969	0.056712	0.04686	0.046157
r43	0.12326	0.072969	0.056712	0.04686	0.046157
r44	0.16597	0.11568	0.099422	0.08957	0.088867
r45	0.16597	0.11568	0.099422	0.08957	0.088867
r46	0.16597	0.11568	0.099422	0.08957	0.088867
r47	0.16597	0.11568	0.099422	0.08957	0.088867
r48	0.16597	0.11568	0.099422	0.08957	0.088867
r49	0	0	0	0	0
r50	0	0	0	0	0
r51	0	0	0	0	0
r52	0	0	0	0	0
r53	0	0	0	0	0
r54	0	0	0	0	0
r55	0	0	0	0	0
r56	0	0	0	0	0
r57	0	0	0	0	0
r58	0	0	0	0	0
r59	0	0	0	0	0
r60	0	0	0	0	0
r61	0	0	0	0	0
r62	0	0	0	0	0
r63	0	0	0	0	0
r64	0	0	0	0	0
r65	0	0	0	0	0
r66	0	0	0	0	0
r67	0	0	0	0	0
r68	0	0	0	0	0
r69	0	0	0	0	0
r70	0	0	0	0	0
r71	0	0	0	0	0
r72	0	0	0	0	0
r73	0	0	0	0	0
r74	0	0	0	0	0
r75	0	0	0	0	0
r76	0	0	0	0	0
r77	0	0	0	0	0
r78	0	0	0	0	0
r79	0	0	0	0	0
r80	0	0	0	0	0
r81	0	0	0	0	0
r82	0	0	0	0	0
r83	0	0	0	0	0

```

-----
XXXXXXXXXXXXXXXXXXXXXXXXXXXXXXXXXXXXXXXXXXXXXXXXXXXX
CONTAINER NAME: mp_params_covid_unemploy Scalars
XXXXXXXXXXXXXXXXXXXXXXXXXXXXXXXXXXXXXXXXXXXXXXXXXXXX
          i      idx      value
          --      ---      -
TR          1      1      0.0015999
b           2      2           1
fl_stimulus_adult_first  3      3      1200
fl_stimulus_adult_second 4      4       600
fl_stimulus_child_first   5      5       500
fl_stimulus_child_second  6      6       600
n_incgrid          7      8       201
n_welfchecksgrid   8      9        45
scaleconvector     9     14     62502
xi                10     16       0.75

```

```

-----
XXXXXXXXXXXXXXXXXXXXXXXXXXXXXXXXXXXXXXXXXXXXXXXXXXXX
CONTAINER NAME: mp_params_covid_unemploy String
XXXXXXXXXXXXXXXXXXXXXXXXXXXXXXXXXXXXXXXXXXXXXXXXXXXX
          i      idx      string
          ---      ---      -
st_biden_or_trump  "1"    "15"  "st_biden_or_trump_undefined"

```

```

-----
XXXXXXXXXXXXXXXXXXXXXXXXXXXXXXXXXXXXXXXXXXXXXXXXXXXX
CONTAINER NAME: mp_params_statesgrid ND Array (Matrix etc)
XXXXXXXXXXXXXXXXXXXXXXXXXXXXXXXXXXXXXXXXXXXXXXXXXXXX
          i      idx      ndim      numel      rowN      colN      sum      mean      std
          -      ---      ----      -
agrid          1      1      2      65      65      1      2228      34.277      39.432
eta_H_grid     2      2      2     405     405      1     9.015e-14     2.2259e-16     1.5783
eta_S_grid     3      3      2     405     405      1    -1.7764e-14    -4.3861e-17     2.2103

```

```

xxx TABLE:agrid XXXXXXXXXXXXXXXXXXXXXXX
      c1

```

```

-----
r1          0
r2      0.00051498
r3      0.0041199
r4      0.013905
r5      0.032959
r6      0.064373
r7      0.11124
r8      0.17664
r9      0.26367
r10     0.37542
r11     0.51498
r12     0.68544
r13     0.88989
r14     1.1314
r15     1.4131

```

r16	1.7381
r17	2.1094
r18	2.5301
r19	3.0034
r20	3.5323
r21	4.1199
r22	4.7693
r23	5.4836
r24	6.2658
r25	7.1191
r26	8.0466
r27	9.0514
r28	10.136
r29	11.305
r30	12.56
r31	13.905
r32	15.342
r33	16.875
r34	18.507
r35	20.241
r36	22.08
r37	24.027
r38	26.085
r39	28.258
r40	30.548
r41	32.959
r42	35.493
r43	38.154
r44	40.945
r45	43.868
r46	46.928
r47	50.126
r48	53.467
r49	56.953
r50	60.587
r51	64.373
r52	68.313
r53	72.411
r54	76.669
r55	81.091
r56	85.68
r57	90.439
r58	95.371
r59	100.48
r60	105.77
r61	111.24
r62	116.89
r63	122.74
r64	128.77
r65	135

xxx TABLE:eta\_H\_grid xxxxxxxxxxxxxxxxxxxxxx  
c1

r1	-2.6968
r2	-2.6294
r3	-2.562

r4	-2.4945
r5	-2.4271
r6	-2.3597
r7	-2.2923
r8	-2.2249
r9	-2.1574
r10	-2.09
r11	-2.0226
r12	-1.9552
r13	-1.8878
r14	-1.8203
r15	-1.7529
r16	-1.6855
r17	-1.6181
r18	-1.5507
r19	-1.4832
r20	-1.4158
r21	-1.3484
r22	-1.281
r23	-1.2136
r24	-1.1461
r25	-1.0787
r26	-1.0113
r27	-0.94388
r28	-0.87646
r29	-0.80904
r30	-0.74162
r31	-0.6742
r32	-0.60678
r33	-0.53936
r34	-0.47194
r35	-0.40452
r36	-0.3371
r37	-0.26968
r38	-0.20226
r39	-0.13484
r40	-0.06742
r41	2.2204e-16
r42	0.06742
r43	0.13484
r44	0.20226
r45	0.26968
r46	0.3371
r47	0.40452
r48	0.47194
r49	0.53936
r50	0.60678
r356	-0.60678
r357	-0.53936
r358	-0.47194
r359	-0.40452
r360	-0.3371
r361	-0.26968
r362	-0.20226
r363	-0.13484
r364	-0.06742
r365	2.2204e-16
r366	0.06742

r367	0.13484
r368	0.20226
r369	0.26968
r370	0.3371
r371	0.40452
r372	0.47194
r373	0.53936
r374	0.60678
r375	0.6742
r376	0.74162
r377	0.80904
r378	0.87646
r379	0.94388
r380	1.0113
r381	1.0787
r382	1.1461
r383	1.2136
r384	1.281
r385	1.3484
r386	1.4158
r387	1.4832
r388	1.5507
r389	1.6181
r390	1.6855
r391	1.7529
r392	1.8203
r393	1.8878
r394	1.9552
r395	2.0226
r396	2.09
r397	2.1574
r398	2.2249
r399	2.2923
r400	2.3597
r401	2.4271
r402	2.4945
r403	2.562
r404	2.6294
r405	2.6968

xxx TABLE:eta\_S\_grid xxxxxxxxxxxxxxxxxxxx  
c1

r1	-3.122
r2	-3.122
r3	-3.122
r4	-3.122
r5	-3.122
r6	-3.122
r7	-3.122
r8	-3.122
r9	-3.122
r10	-3.122
r11	-3.122
r12	-3.122
r13	-3.122
r14	-3.122

r15	-3.122
r16	-3.122
r17	-3.122
r18	-3.122
r19	-3.122
r20	-3.122
r21	-3.122
r22	-3.122
r23	-3.122
r24	-3.122
r25	-3.122
r26	-3.122
r27	-3.122
r28	-3.122
r29	-3.122
r30	-3.122
r31	-3.122
r32	-3.122
r33	-3.122
r34	-3.122
r35	-3.122
r36	-3.122
r37	-3.122
r38	-3.122
r39	-3.122
r40	-3.122
r41	-3.122
r42	-3.122
r43	-3.122
r44	-3.122
r45	-3.122
r46	-3.122
r47	-3.122
r48	-3.122
r49	-3.122
r50	-3.122
r356	3.122
r357	3.122
r358	3.122
r359	3.122
r360	3.122
r361	3.122
r362	3.122
r363	3.122
r364	3.122
r365	3.122
r366	3.122
r367	3.122
r368	3.122
r369	3.122
r370	3.122
r371	3.122
r372	3.122
r373	3.122
r374	3.122
r375	3.122
r376	3.122
r377	3.122

```

r378    3.122
r379    3.122
r380    3.122
r381    3.122
r382    3.122
r383    3.122
r384    3.122
r385    3.122
r386    3.122
r387    3.122
r388    3.122
r389    3.122
r390    3.122
r391    3.122
r392    3.122
r393    3.122
r394    3.122
r395    3.122
r396    3.122
r397    3.122
r398    3.122
r399    3.122
r400    3.122
r401    3.122
r402    3.122
r403    3.122
r404    3.122
r405    3.122
    
```

```

-----
XXXXXXXXXXXXXXXXXXXXXXXXXXXXXXXXXXXXXXXXXXXXXXXXXXXX
CONTAINER NAME: mp_params_exotrans ND Array (Matrix etc)
XXXXXXXXXXXXXXXXXXXXXXXXXXXXXXXXXXXXXXXXXXXXXXXXXXXX
    
```

	i	idx	ndim	numel	rowN	colN	sum	mean
	-	---	----	-----	----	----	-----	-----
cl_mt_pi_jem_kidseta	1	2	2	1	1	1	0	0
pi_H_eta	2	3	2	6561	81	81	81	0.012346
pi_S_eta	3	4	2	25	5	5	5	0.2
pi_eta	4	5	2	1.6403e+05	405	405	405	0.0024691
pi_kids	5	6	5	8300	5	1660	1660	0.2
psi	6	7	2	83	83	1	78.16	0.94169

```

xxx TABLE:cl_mt_pi_jem_kidseta XXXXXXXXXXXXXXXXXXXX
c1
--
r1    0
    
```

```

xxx TABLE:pi_H_eta XXXXXXXXXXXXXXXXXXXX
    
```

	c1	c2	c3	c79	c80	c81
	-----	-----	-----	-----	-----	-----
r1	0.44008	0.19741	0.16603	0	0	0
r2	0.26004	0.18401	0.1972	0	0	0
r3	0.12804	0.13527	0.18471	0	0	0
r4	0.051745	0.078413	0.13644	0	0	0
r5	0.016976	0.035843	0.079479	0	0	0

r6	0.0044863	0.012918	0.036507	0	0	0
r7	0.00094957	0.0036704	0.013221	0	0	0
r8	0.00016032	0.00082204	0.0037748	0	0	0
r9	2.1522e-05	0.0001451	0.00084955	0	0	0
r10	2.2921e-06	2.0182e-05	0.00015069	0	0	0
r11	1.933e-07	2.2115e-06	2.1061e-05	0	0	0
r12	1.2891e-08	1.9089e-07	2.3192e-06	0	0	0
r13	6.7901e-10	1.2976e-08	2.0116e-07	0	0	0
r14	2.8225e-11	6.9453e-10	1.3741e-08	0	0	0
r15	9.2521e-13	2.9264e-11	7.3906e-10	0	0	0
r16	2.3901e-14	9.7051e-13	3.1293e-11	0	0	0
r17	4.8636e-16	2.5328e-14	1.0429e-12	0	0	0
r18	7.7924e-18	5.2007e-16	2.735e-14	0	0	0
r19	9.8265e-20	8.4004e-18	5.6434e-16	0	0	0
r20	9.7502e-22	1.0672e-19	9.1603e-18	0	0	0
r21	7.6101e-24	1.0662e-21	1.1695e-19	0	0	0
r22	4.6713e-26	8.3759e-24	1.1741e-21	0	0	0
r23	2.2546e-28	5.1729e-26	9.269e-24	0	0	0
r24	8.5548e-31	2.5114e-28	5.7527e-26	0	0	0
r25	2.5514e-33	9.583e-31	2.8066e-28	0	0	0
r26	5.9805e-36	2.8738e-33	1.0762e-30	0	0	0
r27	1.1016e-38	6.7725e-36	3.2434e-33	0	0	0
r28	1.5943e-41	1.2541e-38	7.6811e-36	0	0	0
r29	1.8129e-44	1.8245e-41	1.4293e-38	0	0	0
r30	1.6194e-47	2.0853e-44	2.0897e-41	0	0	0
r31	1.1364e-50	1.8723e-47	2.4002e-44	0	0	0
r32	6.2635e-54	1.3205e-50	2.1657e-47	0	0	0
r33	2.7115e-57	7.3149e-54	1.535e-50	0	0	0
r34	9.2192e-61	3.1826e-57	8.5451e-54	0	0	0
r35	2.4617e-64	1.0875e-60	3.7362e-57	0	0	0
r36	5.1617e-68	2.9183e-64	1.283e-60	0	0	0
r37	8.4992e-72	6.1497e-68	3.4599e-64	0	0	0
r38	1.0989e-75	1.0176e-71	7.327e-68	0	0	0
r39	1.1156e-79	1.3223e-75	1.2185e-71	0	0	0
r40	8.8927e-84	1.3491e-79	1.5911e-75	0	0	0
r41	5.5655e-88	1.0807e-83	1.6313e-79	0	0	0
r42	2.7347e-92	6.7971e-88	1.3133e-83	0	0	0
r43	1.055e-96	3.3564e-92	8.3007e-88	0	0	0
r44	3.1951e-101	1.3012e-96	4.1192e-92	0	0	0
r45	7.5967e-106	3.9605e-101	1.6049e-96	0	0	0
r46	1.418e-110	9.4631e-106	4.9088e-101	0	0	0
r47	2.0777e-115	1.7751e-110	1.1787e-105	0	0	0
r48	2.3898e-120	2.6138e-115	2.2219e-110	0	0	0
r49	2.1579e-125	3.0215e-120	3.2881e-115	0	0	0
r50	1.5294e-130	2.7417e-125	3.8196e-120	0	0	0
r51	8.5093e-136	1.9529e-130	3.4831e-125	0	0	0
r52	3.7162e-141	1.0919e-135	2.4933e-130	0	0	0
r53	1.2739e-146	4.7921e-141	1.401e-135	0	0	0
r54	3.4277e-152	1.6509e-146	6.179e-141	0	0	0
r55	7.2393e-158	4.4641e-152	2.1392e-146	0	0	0
r56	1.2001e-163	9.4748e-158	5.8132e-152	0	0	0
r57	1.5615e-169	1.5784e-163	1.2399e-157	0	0	0
r58	1.5947e-175	2.064e-169	2.0759e-163	0	0	0
r59	1.2782e-181	2.1183e-175	2.7279e-169	0	0	0
r60	8.0416e-188	1.7064e-181	2.8135e-175	0	0	0
r61	3.9708e-194	1.0788e-187	2.2776e-181	0	0	0
r62	1.5389e-200	5.3534e-194	1.4472e-187	0	0	0
r63	4.6807e-207	2.085e-200	7.2168e-194	5.5511e-16	0	0



r64	1.1174e-213	6.3733e-207	2.8246e-200	2.7311e-14	5.5511e-16	0
r65	2.0936e-220	1.529e-213	8.677e-207	1.0428e-12	2.5424e-14	4.4409e-16
r66	3.0785e-227	2.8789e-220	2.092e-213	3.1293e-11	9.7056e-13	2.387e-14
r67	3.5527e-234	4.2543e-227	3.9585e-220	7.3906e-10	2.9264e-11	9.2526e-13
r68	3.2178e-241	4.934e-234	5.8786e-227	1.3741e-08	6.9453e-10	2.8225e-11
r69	2.2873e-248	4.491e-241	6.8517e-234	2.0116e-07	1.2976e-08	6.7901e-10
r70	1.276e-255	3.2082e-248	6.2674e-241	2.3192e-06	1.9089e-07	1.2891e-08
r71	5.5866e-263	1.7986e-255	4.4993e-248	2.1061e-05	2.2115e-06	1.933e-07
r72	1.9196e-270	7.9137e-263	2.535e-255	0.00015069	2.0182e-05	2.2921e-06
r73	5.1762e-278	2.7326e-270	1.1209e-262	0.00084955	0.0001451	2.1522e-05
r74	1.0954e-285	7.4052e-278	3.8897e-270	0.0037748	0.00082204	0.00016032
r75	1.8193e-293	1.5749e-285	1.0593e-277	0.013221	0.0036704	0.00094957
r76	2.3712e-301	2.6286e-293	2.264e-285	0.036507	0.012918	0.0044863
r77	2.4254e-309	3.443e-301	3.7975e-293	0.079479	0.035843	0.016976
r78	1.9469e-317	3.5392e-309	4.9987e-301	0.13644	0.078413	0.051745
r79	0	2.8551e-317	5.1639e-309	0.18471	0.13527	0.12804
r80	0	0	4.1864e-317	0.1972	0.18401	0.26004
r81	0	0	0	0.16603	0.19741	0.44008

```
xxx TABLE:pi_S_eta xxxxxxxxxxxxxxxxxxxxxxx
```

	c1	c2	c3	c4	c5
	-----	-----	-----	-----	-----
r1	0.012224	0.2144	0.54675	0.2144	0.012224
r2	0.012224	0.2144	0.54675	0.2144	0.012224
r3	0.012224	0.2144	0.54675	0.2144	0.012224
r4	0.012224	0.2144	0.54675	0.2144	0.012224
r5	0.012224	0.2144	0.54675	0.2144	0.012224

```
xxx TABLE:pi_eta xxxxxxxxxxxxxxxxxxxxxxx
```

	c1	c2	c3	c403	c404	c405
	-----	-----	-----	-----	-----	-----
r1	...					

### 2.1.3 Parameters Used for Paper Simulations

Full version of parameters used in [Nygaard, Sorensen and Wang \(2020\)](#). This is not printed to save space.

```
% mp_params = snw_mp_param('default_moredense_a65zh266zs5_e2m2', true, 100, 6);
```

## 2.2 Model Controls

This is the example vignette for function: `snw_mp_control` from the [PrjOptiSNW Package](#). This function sets and gets different control parameters.

### 2.2.1 Test SNW\_MP\_CONTROLS Defaults

Call the function with defaults.

```
mp_controls = snw_mp_control('default_base', true);
```

```
pos = 43 ; key = options
```

```
fmincon options:
```

```
Options used by current Algorithm ('interior-point'):
```

```
(Other available algorithms: 'active-set', 'sqp', 'sqp-legacy', 'trust-region-reflective')
```



CONTAINER NAME: mp\_controls Scalars

xx

	i	idx	value
	---	---	-----
A_aux	1	1	NaN
Aeq	2	2	NaN
B_aux	3	3	NaN
Beq	4	4	NaN
bl_compute_drv_stats	5	5	1
bl_print_a4chk	6	6	1
bl_print_a4chk_verbose	7	7	0
bl_print_calibrate_2009	8	8	1
bl_print_calibrate_2009_verbose	9	9	0
bl_print_ds	10	10	1
bl_print_ds_aggregation	11	11	1
bl_print_ds_aggregation_verbose	12	12	0
bl_print_ds_verbose	13	13	0
bl_print_evuvw19_jaeemk	14	14	1
bl_print_evuvw19_jaeemk_verbose	15	15	0
bl_print_evuvw19_jmky	16	16	1
bl_print_evuvw19_jmky_allchecks	17	17	1
bl_print_evuvw19_jmky_allchecks_verbose	18	18	0
bl_print_evuvw19_jmky_mass	19	19	1
bl_print_evuvw19_jmky_mass_verbose	20	20	0
bl_print_evuvw19_jmky_verbose	21	21	0
bl_print_evuvw20_jaeemk	22	22	1
bl_print_evuvw20_jaeemk_verbose	23	23	0
bl_print_find_tax_rate	24	24	1
bl_print_find_tax_rate_verbose	25	25	0
bl_print_precompute	26	26	1
bl_print_precompute_verbose	27	27	0
bl_print_v08_jaeemk	28	28	1
bl_print_v08_jaeemk_verbose	29	29	0
bl_print_v08p08_jaeemk	30	30	1
bl_print_v08p08_jaeemk_verbose	31	31	0
bl_print_v_planner	32	32	1
bl_print_v_planner_verbose	33	33	0
bl_print_vfi	34	34	1
bl_print_vfi_verbose	35	35	0
bl_print_vu_vw	36	36	1
bl_print_vu_vw_verbose	37	37	0
bl_timer	38	38	1
err	39	39	1
fl_max_trchk_perc_increase	40	40	1.5
nonlcon	41	42	NaN
tol	42	45	0.005

-----  
 xxx

CONTAINER NAME: mp\_controls String

xx

	i	idx	string
	---	---	-----
mp_params_name	"1"	"41"	"default_base"



## Chapter 3

# Solving the Dynamic Life Cycle Problem

### 3.1 Life Cycle Dynamic Programming with Marital Status, Children and Savings

This is the example vignette for function: `snw_vfi_main_bisec_vec` from the [PrjOptiSNW Package](#). This function solves for policy function with vectorized bisection. Value function during COVIDless year.

#### 3.1.1 Test SNW\_VFI\_MAIN\_BISECT\_VEC Defaults

Call the function with defaults.

```
mp_param = snw_mp_param('default_docdense');  
[V_VFI,ap_VFI,cons_VFI] = snw_vfi_main_bisec_vec(mp_param);
```

```
SNW_VFI_MAIN_BISEC_VEC: Finished Age Group:83 of 82, time-this-age:9.6616  
SNW_VFI_MAIN_BISEC_VEC: Finished Age Group:82 of 82, time-this-age:6.0665  
SNW_VFI_MAIN_BISEC_VEC: Finished Age Group:81 of 82, time-this-age:6.0938  
SNW_VFI_MAIN_BISEC_VEC: Finished Age Group:80 of 82, time-this-age:6.1322  
SNW_VFI_MAIN_BISEC_VEC: Finished Age Group:79 of 82, time-this-age:5.731  
SNW_VFI_MAIN_BISEC_VEC: Finished Age Group:78 of 82, time-this-age:5.9587  
SNW_VFI_MAIN_BISEC_VEC: Finished Age Group:77 of 82, time-this-age:6.0286  
SNW_VFI_MAIN_BISEC_VEC: Finished Age Group:76 of 82, time-this-age:6.0378  
SNW_VFI_MAIN_BISEC_VEC: Finished Age Group:75 of 82, time-this-age:5.7227  
SNW_VFI_MAIN_BISEC_VEC: Finished Age Group:74 of 82, time-this-age:6.0347  
SNW_VFI_MAIN_BISEC_VEC: Finished Age Group:73 of 82, time-this-age:6.0197  
SNW_VFI_MAIN_BISEC_VEC: Finished Age Group:72 of 82, time-this-age:6.0294  
SNW_VFI_MAIN_BISEC_VEC: Finished Age Group:71 of 82, time-this-age:5.7663  
SNW_VFI_MAIN_BISEC_VEC: Finished Age Group:70 of 82, time-this-age:5.7878  
SNW_VFI_MAIN_BISEC_VEC: Finished Age Group:69 of 82, time-this-age:5.9087  
SNW_VFI_MAIN_BISEC_VEC: Finished Age Group:68 of 82, time-this-age:5.9625  
SNW_VFI_MAIN_BISEC_VEC: Finished Age Group:67 of 82, time-this-age:5.9427  
SNW_VFI_MAIN_BISEC_VEC: Finished Age Group:66 of 82, time-this-age:5.526  
SNW_VFI_MAIN_BISEC_VEC: Finished Age Group:65 of 82, time-this-age:5.9574  
SNW_VFI_MAIN_BISEC_VEC: Finished Age Group:64 of 82, time-this-age:5.9754  
SNW_VFI_MAIN_BISEC_VEC: Finished Age Group:63 of 82, time-this-age:5.9528  
SNW_VFI_MAIN_BISEC_VEC: Finished Age Group:62 of 82, time-this-age:5.7483  
SNW_VFI_MAIN_BISEC_VEC: Finished Age Group:61 of 82, time-this-age:6.0225  
SNW_VFI_MAIN_BISEC_VEC: Finished Age Group:60 of 82, time-this-age:6.091  
SNW_VFI_MAIN_BISEC_VEC: Finished Age Group:59 of 82, time-this-age:6.0448
```

SNW\_VFI\_MAIN\_BISEC\_VEC: Finished Age Group:58 of 82, time-this-age:6.0445  
SNW\_VFI\_MAIN\_BISEC\_VEC: Finished Age Group:57 of 82, time-this-age:5.5331  
SNW\_VFI\_MAIN\_BISEC\_VEC: Finished Age Group:56 of 82, time-this-age:6.0133  
SNW\_VFI\_MAIN\_BISEC\_VEC: Finished Age Group:55 of 82, time-this-age:5.9281  
SNW\_VFI\_MAIN\_BISEC\_VEC: Finished Age Group:54 of 82, time-this-age:5.9348  
SNW\_VFI\_MAIN\_BISEC\_VEC: Finished Age Group:53 of 82, time-this-age:5.576  
SNW\_VFI\_MAIN\_BISEC\_VEC: Finished Age Group:52 of 82, time-this-age:5.9723  
SNW\_VFI\_MAIN\_BISEC\_VEC: Finished Age Group:51 of 82, time-this-age:6.1292  
SNW\_VFI\_MAIN\_BISEC\_VEC: Finished Age Group:50 of 82, time-this-age:5.983  
SNW\_VFI\_MAIN\_BISEC\_VEC: Finished Age Group:49 of 82, time-this-age:5.8518  
SNW\_VFI\_MAIN\_BISEC\_VEC: Finished Age Group:48 of 82, time-this-age:5.6741  
SNW\_VFI\_MAIN\_BISEC\_VEC: Finished Age Group:47 of 82, time-this-age:6.0199  
SNW\_VFI\_MAIN\_BISEC\_VEC: Finished Age Group:46 of 82, time-this-age:6.0128  
SNW\_VFI\_MAIN\_BISEC\_VEC: Finished Age Group:45 of 82, time-this-age:6.2299  
SNW\_VFI\_MAIN\_BISEC\_VEC: Finished Age Group:44 of 82, time-this-age:5.8858  
SNW\_VFI\_MAIN\_BISEC\_VEC: Finished Age Group:43 of 82, time-this-age:6.0074  
SNW\_VFI\_MAIN\_BISEC\_VEC: Finished Age Group:42 of 82, time-this-age:6.1082  
SNW\_VFI\_MAIN\_BISEC\_VEC: Finished Age Group:41 of 82, time-this-age:6.1896  
SNW\_VFI\_MAIN\_BISEC\_VEC: Finished Age Group:40 of 82, time-this-age:5.9484  
SNW\_VFI\_MAIN\_BISEC\_VEC: Finished Age Group:39 of 82, time-this-age:5.7184  
SNW\_VFI\_MAIN\_BISEC\_VEC: Finished Age Group:38 of 82, time-this-age:6.0237  
SNW\_VFI\_MAIN\_BISEC\_VEC: Finished Age Group:37 of 82, time-this-age:6.0886  
SNW\_VFI\_MAIN\_BISEC\_VEC: Finished Age Group:36 of 82, time-this-age:5.9999  
SNW\_VFI\_MAIN\_BISEC\_VEC: Finished Age Group:35 of 82, time-this-age:5.8859  
SNW\_VFI\_MAIN\_BISEC\_VEC: Finished Age Group:34 of 82, time-this-age:6.089  
SNW\_VFI\_MAIN\_BISEC\_VEC: Finished Age Group:33 of 82, time-this-age:6.0487  
SNW\_VFI\_MAIN\_BISEC\_VEC: Finished Age Group:32 of 82, time-this-age:5.972  
SNW\_VFI\_MAIN\_BISEC\_VEC: Finished Age Group:31 of 82, time-this-age:6.0053  
SNW\_VFI\_MAIN\_BISEC\_VEC: Finished Age Group:30 of 82, time-this-age:5.671  
SNW\_VFI\_MAIN\_BISEC\_VEC: Finished Age Group:29 of 82, time-this-age:5.8975  
SNW\_VFI\_MAIN\_BISEC\_VEC: Finished Age Group:28 of 82, time-this-age:6.0471  
SNW\_VFI\_MAIN\_BISEC\_VEC: Finished Age Group:27 of 82, time-this-age:6.0284  
SNW\_VFI\_MAIN\_BISEC\_VEC: Finished Age Group:26 of 82, time-this-age:6.03  
SNW\_VFI\_MAIN\_BISEC\_VEC: Finished Age Group:25 of 82, time-this-age:6.0227  
SNW\_VFI\_MAIN\_BISEC\_VEC: Finished Age Group:24 of 82, time-this-age:5.9344  
SNW\_VFI\_MAIN\_BISEC\_VEC: Finished Age Group:23 of 82, time-this-age:6.0962  
SNW\_VFI\_MAIN\_BISEC\_VEC: Finished Age Group:22 of 82, time-this-age:6.1112  
SNW\_VFI\_MAIN\_BISEC\_VEC: Finished Age Group:21 of 82, time-this-age:5.6128  
SNW\_VFI\_MAIN\_BISEC\_VEC: Finished Age Group:20 of 82, time-this-age:6.0994  
SNW\_VFI\_MAIN\_BISEC\_VEC: Finished Age Group:19 of 82, time-this-age:5.9906  
SNW\_VFI\_MAIN\_BISEC\_VEC: Finished Age Group:18 of 82, time-this-age:5.9374  
SNW\_VFI\_MAIN\_BISEC\_VEC: Finished Age Group:17 of 82, time-this-age:5.9326  
SNW\_VFI\_MAIN\_BISEC\_VEC: Finished Age Group:16 of 82, time-this-age:5.6032  
SNW\_VFI\_MAIN\_BISEC\_VEC: Finished Age Group:15 of 82, time-this-age:6.0086  
SNW\_VFI\_MAIN\_BISEC\_VEC: Finished Age Group:14 of 82, time-this-age:6.0024  
SNW\_VFI\_MAIN\_BISEC\_VEC: Finished Age Group:13 of 82, time-this-age:6.0767  
SNW\_VFI\_MAIN\_BISEC\_VEC: Finished Age Group:12 of 82, time-this-age:5.8031  
SNW\_VFI\_MAIN\_BISEC\_VEC: Finished Age Group:11 of 82, time-this-age:6.012  
SNW\_VFI\_MAIN\_BISEC\_VEC: Finished Age Group:10 of 82, time-this-age:6.0142  
SNW\_VFI\_MAIN\_BISEC\_VEC: Finished Age Group:9 of 82, time-this-age:5.9887  
SNW\_VFI\_MAIN\_BISEC\_VEC: Finished Age Group:8 of 82, time-this-age:6.0433  
SNW\_VFI\_MAIN\_BISEC\_VEC: Finished Age Group:7 of 82, time-this-age:5.5764  
SNW\_VFI\_MAIN\_BISEC\_VEC: Finished Age Group:6 of 82, time-this-age:5.9101  
SNW\_VFI\_MAIN\_BISEC\_VEC: Finished Age Group:5 of 82, time-this-age:5.9695  
SNW\_VFI\_MAIN\_BISEC\_VEC: Finished Age Group:4 of 82, time-this-age:5.9063  
SNW\_VFI\_MAIN\_BISEC\_VEC: Finished Age Group:3 of 82, time-this-age:5.7645  
SNW\_VFI\_MAIN\_BISEC\_VEC: Finished Age Group:2 of 82, time-this-age:5.8967  
SNW\_VFI\_MAIN\_BISEC\_VEC: Finished Age Group:1 of 82, time-this-age:6.0414

Completed SNW\_VFI\_MAIN\_BISEC\_VEC;SNW\_MP\_PARAM=default\_docdense;SNW\_MP\_CONTROL=default\_base;time=497.

### 3.1.2 Define Parameters

Define the matrix dimensions names and dimension vector values. Policy and Value Functions share the same ND dimensional structure.

```
% Grids:
age_grid = 18:100;
agrid = mp_param('agrid');
eta_H_grid = mp_param('eta_H_grid');
eta_S_grid = mp_param('eta_S_grid');
ar_st_eta_HS_grid = string(cellstr([num2str(eta_H_grid', 'hz=%3.2f;'), num2str(eta_S_grid', 'wz=%3.2f;')]);
edu_grid = [0,1];
marry_grid = [0,1];
kids_grid = (1:1:mp_param('n_kidsgrid'))';
% NaN(n_jgrid,n_agrid,n_etagrid,n_educgrid,n_marriedgrid,n_kidsgrid);
cl_mp_datasetdesc = {};
cl_mp_datasetdesc{1} = containers.Map({'name', 'labval'}, {'age', age_grid});
cl_mp_datasetdesc{2} = containers.Map({'name', 'labval'}, {'savings', agrid});
cl_mp_datasetdesc{3} = containers.Map({'name', 'labval'}, {'eta', 1:length(eta_H_grid)});
cl_mp_datasetdesc{4} = containers.Map({'name', 'labval'}, {'edu', edu_grid});
cl_mp_datasetdesc{5} = containers.Map({'name', 'labval'}, {'marry', marry_grid});
cl_mp_datasetdesc{6} = containers.Map({'name', 'labval'}, {'kids', kids_grid});
```

### 3.1.3 Analyze Savings and Shocks

First, analyze Savings Levels and Shocks, Aggregate Over All Others, and do various other calculations.

```
% Generate some Data
mp_support_graph = containers.Map('KeyType', 'char', 'ValueType', 'any');
mp_support_graph('cl_st_xtitle') = {'Savings States, a'};
mp_support_graph('st_legend_loc') = 'eastoutside';
mp_support_graph('bl_graph_logy') = true; % do not log
mp_support_graph('it_legend_select') = 21; % how many shock legends to show
mp_support_graph('cl_colors') = 'jet';

MEAN(VAL(A,Z)), MEAN(AP(A,Z)), MEAN(C(A,Z))

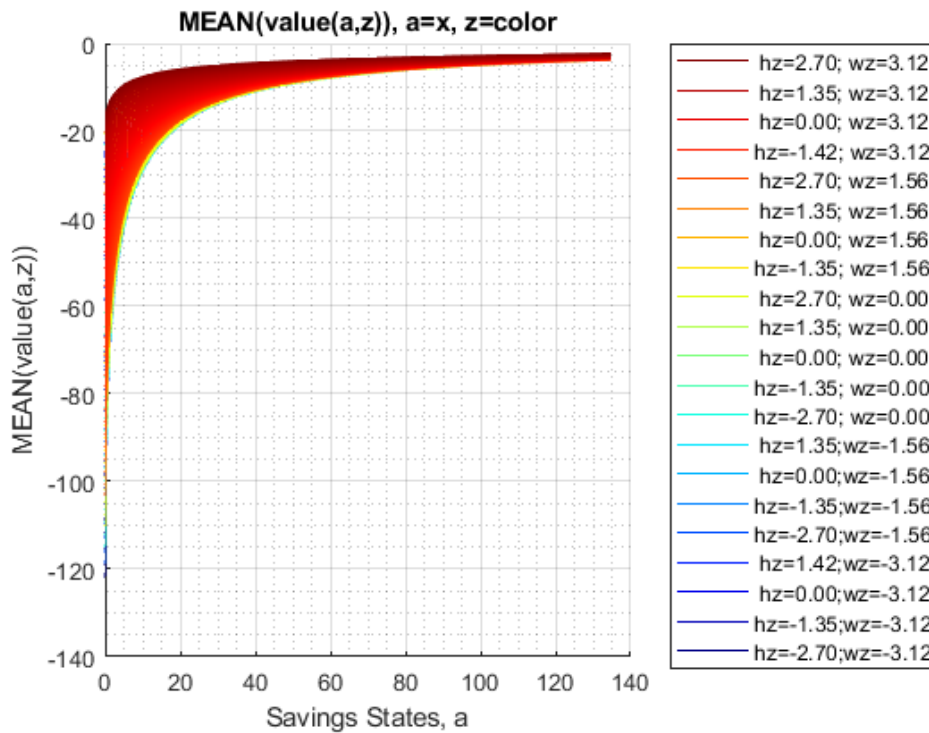
Tabulate value and policies along savings and shocks:

% Set
% NaN(n_jgrid,n_agrid,n_etagrid,n_educgrid,n_marriedgrid,n_kidsgrid);
ar_permute = [1,4,5,6,3,2];
% Value Function
tb_az_v = ff_summ_nd_array("MEAN(VAL(A,Z))", V_VFI, true, ["mean"], 4, 1, cl_mp_datasetdesc, ar_permute);
```

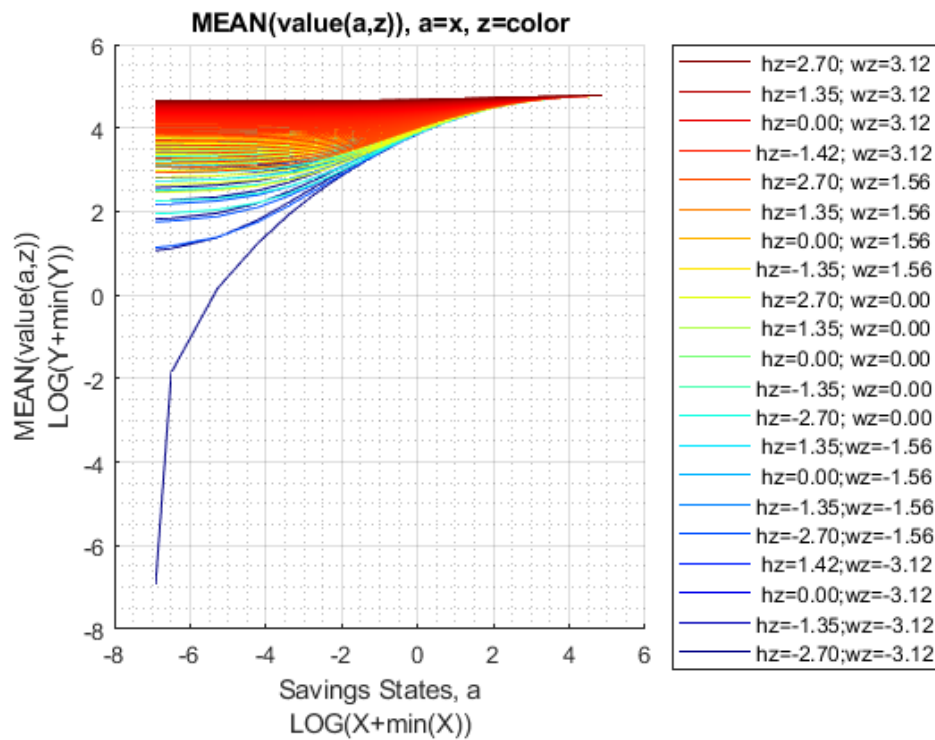
```
xxx MEAN(VAL(A,Z)) xxxxxxxxxxxxxxxxxxxxxxxxxxxxxxxx
  group      savings      mean_eta_1      mean_eta_2      mean_eta_3      mean_eta_4      mean_eta_5      mea
-----
  1          0      -121.95      -119.04      -115.79      -112.34      -108.82      -1
```

```
xxx MEAN(AP(A,Z)) xxxxxxxxxxxxxxxxxxxxxxxxxxxxxxxxxxxx
group      savings      mean_eta_1      mean_eta_2      mean_eta_3      mean_eta_4      mean_eta_5      mea
-----
1          0          0          0          0          0          0
```

```
mp_support_graph('cl_st_graph_title') = {'MEAN(value(a,z)), a=x, z=color'};
mp_support_graph('cl_st_ytitle') = {'MEAN(value(a,z))'};
ff_graph_grid((tb_az_v{1:end, 3:end})', ar_st_eta_HS_grid, agrid, mp_support_graph);
```

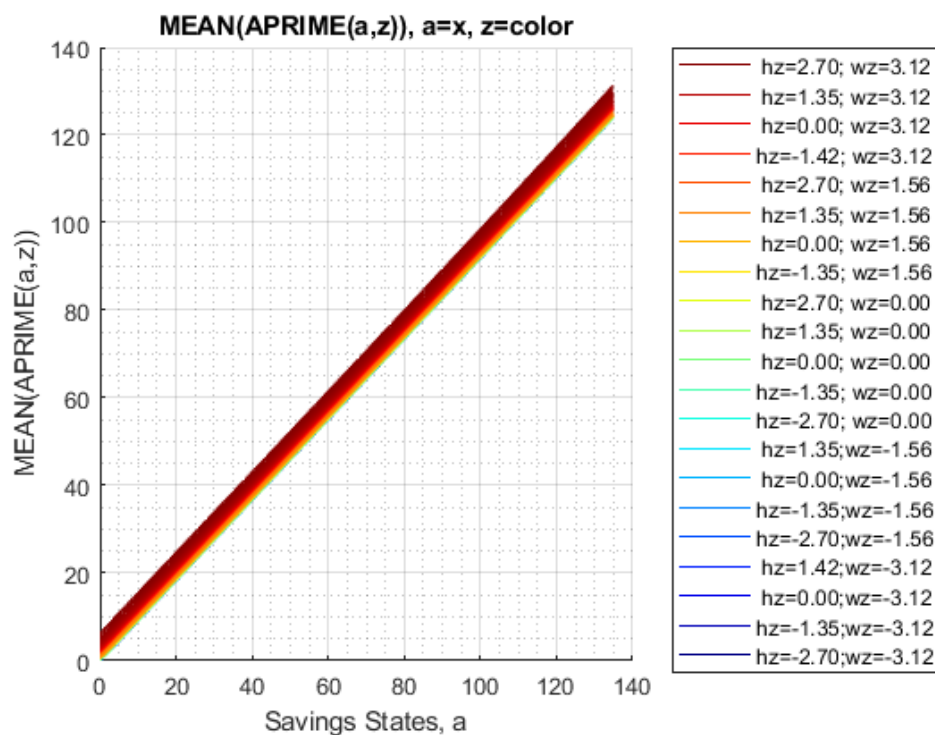


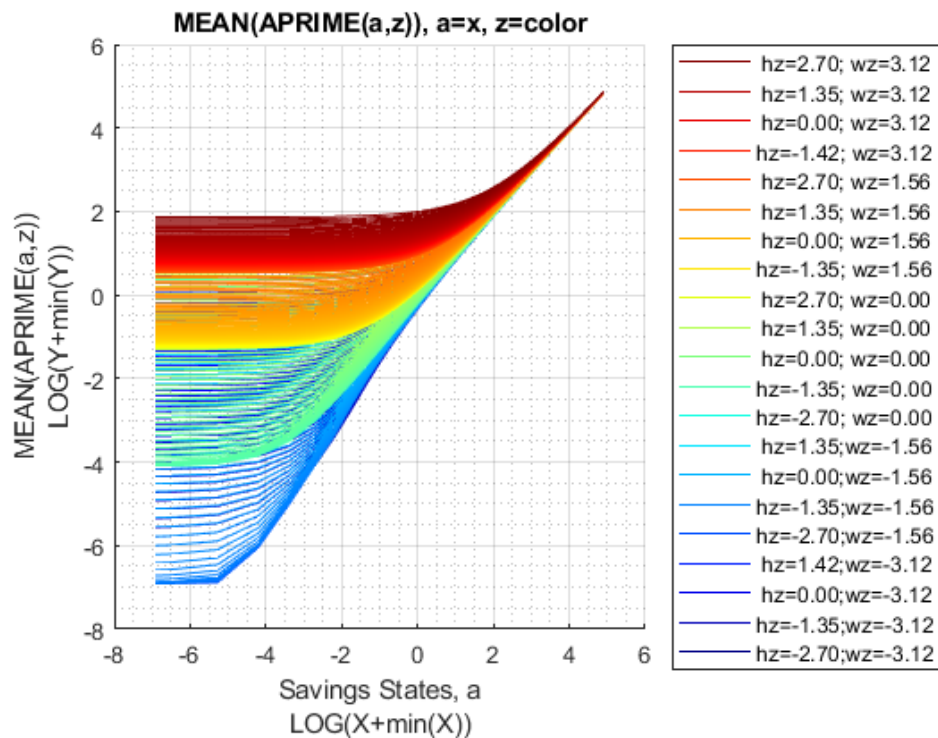




Graph Mean Savings Choices:

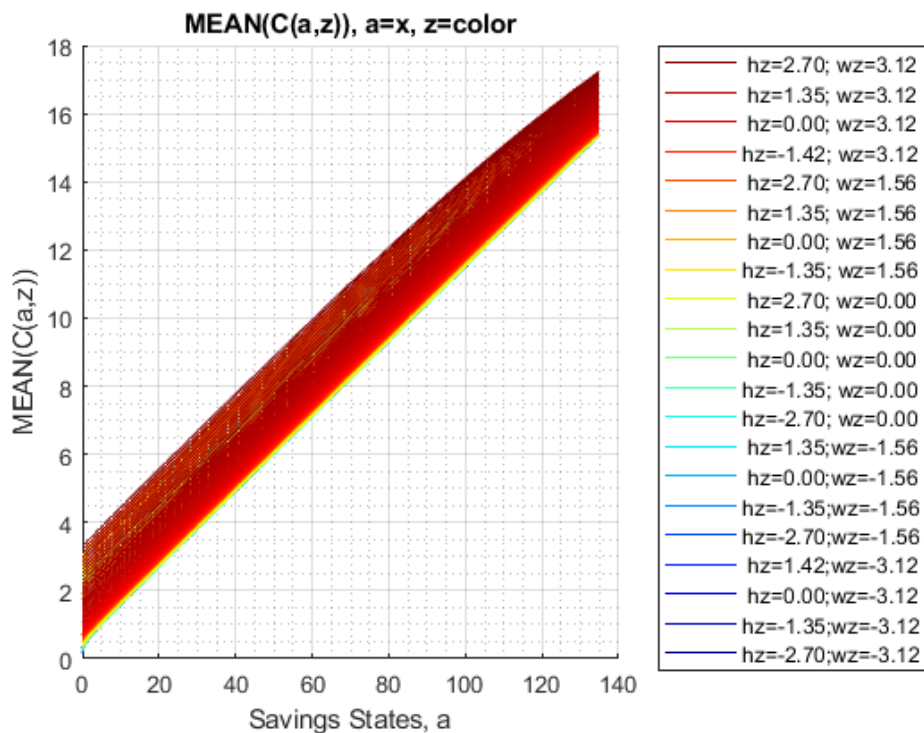
```
mp_support_graph('cl_st_graph_title') = {'MEAN(APRIME(a,z)), a=x, z=color'};
mp_support_graph('cl_st_ytitle') = {'MEAN(APRIME(a,z))'};
ff_graph_grid((tb_az_ap{1:end, 3:end})', ar_st_eta_HS_grid, agrid, mp_support_graph);
```

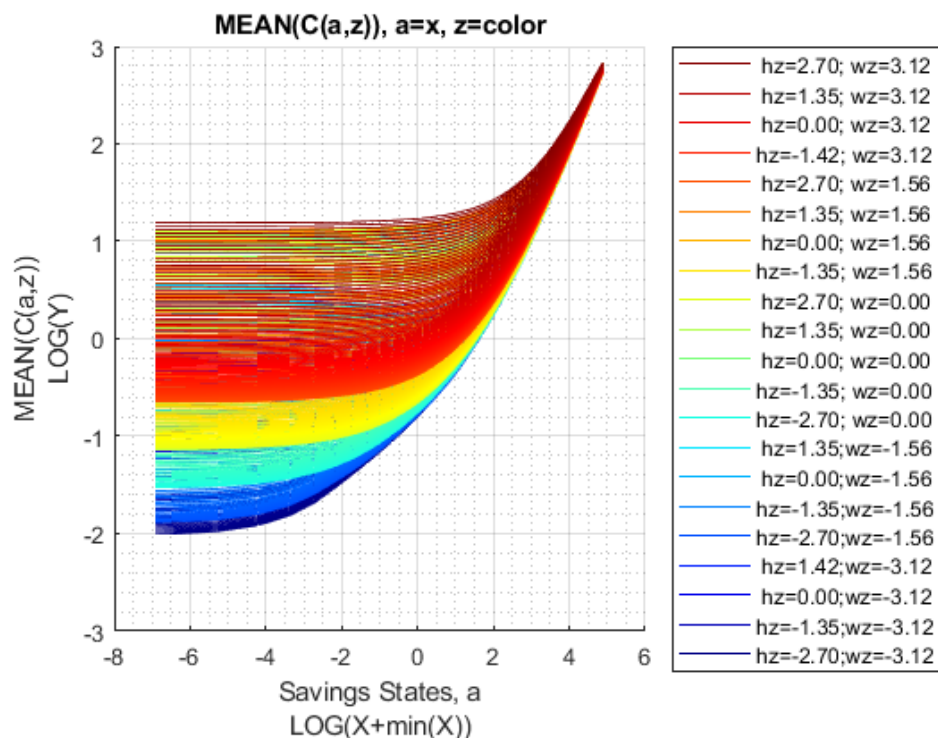




Graph Mean Consumption:

```
mp_support_graph('cl_st_graph_title') = {'MEAN(C(a,z)), a=x, z=color'};
mp_support_graph('cl_st_ytitle') = {'MEAN(C(a,z))'};
ff_graph_grid((tb_az_c{1:end, 3:end})', ar_st_eta_HS_grid, agrid, mp_support_graph);
```





### 3.1.4 Analyze Kids and Marriage and Age

Aggregating over education, savings, and shocks, what are the differential effects of Marriage and Age.

```
% Generate some Data
mp_support_graph = containers.Map('KeyType', 'char', 'ValueType', 'any');
ar_row_grid = [...
    "k0M0", "K1M0", "K2M0", "K3M0", "K4M0", ...
    "k0M1", "K1M1", "K2M1", "K3M1", "K4M1"];
mp_support_graph('cl_st_xtitle') = {'Age'};
mp_support_graph('st_legend_loc') = 'best';
mp_support_graph('bl_graph_logy') = true; % do not log
mp_support_graph('st_rounding') = '6.2f'; % format shock legend
mp_support_graph('cl_scatter_shapes') = {...
    'o', 'd', 's', 'x', '*', ...
    'o', 'd', 's', 'x', '*};
mp_support_graph('cl_colors') = {...
    'red', 'red', 'red', 'red', 'red'...
    'blue', 'blue', 'blue', 'blue', 'blue'};
```

MEAN(VAL(KM,J)), MEAN(AP(KM,J)), MEAN(C(KM,J))

Tabulate value and policies:

```
% Set
% NaN(n_jgrid,n_agrid,n_etagrid,n_educgrid,n_marriedgrid,n_kidsgrid);
ar_permute = [2,3,4,1,6,5];
% Value Function
tb_az_v = ff_summ_nd_array("MEAN(VAL(KM,J))", V_VFI, true, ["mean"], 3, 1, cl_mp_datasetdesc, ar_per
```

xxx	MEAN(VAL(KM,J))	xxxxxx	xxxxxx	xxxxxx	xxxxxx	xxxxxx	xxxxxx	xxxxxx
group	kids	marry	mean_age_18	mean_age_19	mean_age_20	mean_age_21	mean_age_22	mean_age_23
1	1	0	-38.153	-36.95	-35.802	-34.709	-33.718	-32.727
2	2	0	-45.736	-44.24	-42.778	-41.355	-40.041	-38.728

3	3	0	-49.467	-47.957	-46.467	-45.003	-43.644
4	4	0	-53.322	-51.806	-50.292	-48.787	-47.384
5	5	0	-56.129	-54.692	-53.245	-51.795	-50.441
6	1	1	-26.282	-25.268	-24.319	-23.425	-22.612
7	2	1	-30.883	-29.746	-28.66	-27.617	-26.65
8	3	1	-33.096	-31.952	-30.853	-29.79	-28.803
9	4	1	-35.694	-34.564	-33.469	-32.399	-31.401
10	5	1	-37.748	-36.679	-35.641	-34.621	-33.672

% Aprime Choice

```
tb_az_ap = ff_summ_nd_array("MEAN(AP(KM,J))", ap_VFI, true, ["mean"], 3, 1, cl_mp_datasetdesc, ar_pe
```

```
xxx MEAN(AP(KM,J)) xxxxxxxxxxxxxxxxxxxxxxxxxxxxxxxxxxxx
```

group	kids	marry	mean_age_18	mean_age_19	mean_age_20	mean_age_21	mean_age_2
1	1	0	34.497	34.459	34.419	34.455	34.493
2	2	0	34.303	34.259	34.213	34.242	34.272
3	3	0	34.149	34.105	34.058	34.086	34.115
4	4	0	34.057	34.013	33.967	33.996	34.024
5	5	0	33.974	33.933	33.889	33.919	33.95
6	1	1	35.212	35.25	35.288	35.417	35.549
7	2	1	34.954	34.979	35.003	35.113	35.226
8	3	1	34.711	34.728	34.743	34.842	34.943
9	4	1	34.51	34.519	34.527	34.617	34.708
10	5	1	34.225	34.221	34.216	34.29	34.367

% Consumption Choices

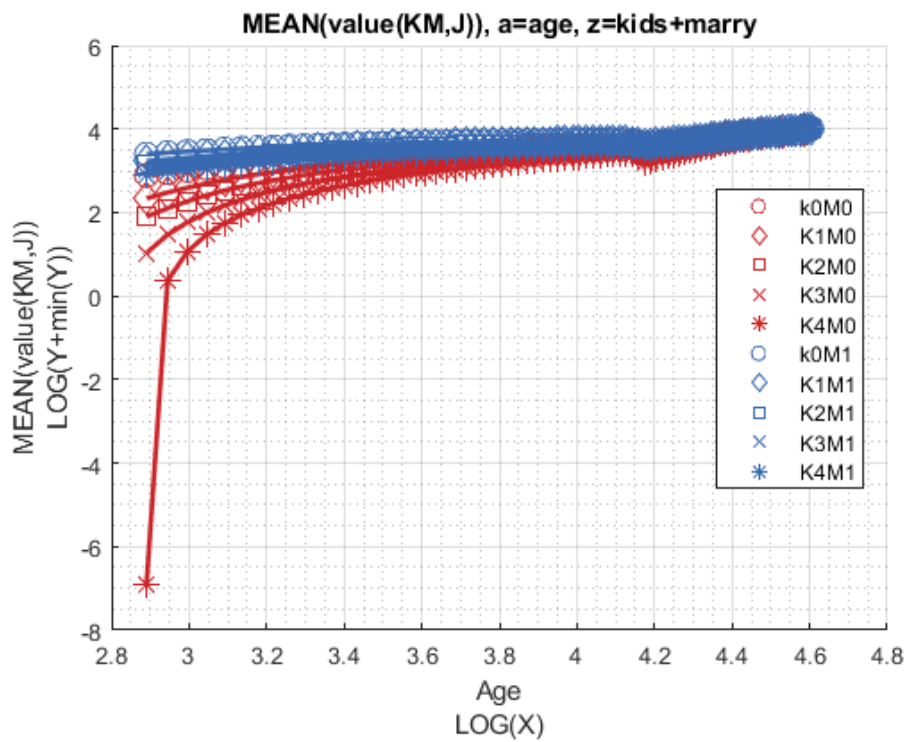
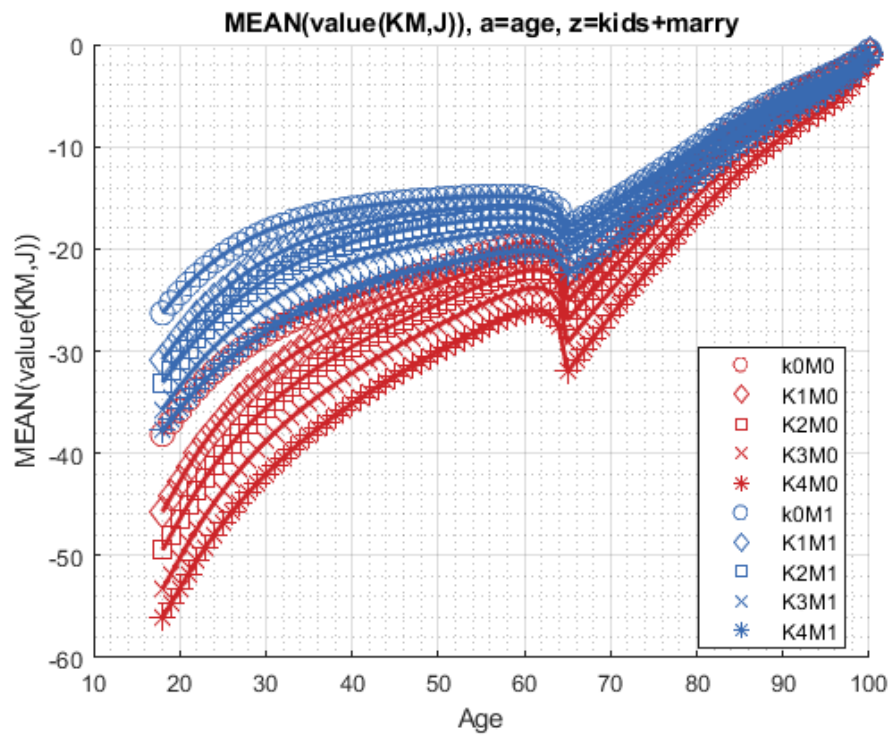
```
tb_az_c = ff_summ_nd_array("MEAN(C(KM,J))", cons_VFI, true, ["mean"], 3, 1, cl_mp_datasetdesc, ar_pe
```

```
xxx MEAN(C(KM,J)) xxxxxxxxxxxxxxxxxxxxxxxxxxxxxxxxxxxx
```

group	kids	marry	mean_age_18	mean_age_19	mean_age_20	mean_age_21	mean_age_2
1	1	0	2.0602	2.0988	2.1385	2.1805	2.2207
2	2	0	2.2548	2.2985	2.3445	2.3938	2.4417
3	3	0	2.4085	2.4527	2.4992	2.5498	2.5989
4	4	0	2.5011	2.5444	2.5902	2.6404	2.6895
5	5	0	2.5841	2.625	2.6684	2.7166	2.7635
6	1	1	2.6152	2.6754	2.7367	2.8014	2.8634
7	2	1	2.678	2.7363	2.7967	2.8619	2.9253
8	3	1	2.7864	2.8428	2.9018	2.966	3.0285
9	4	1	2.8495	2.9021	2.9575	3.0183	3.0775
10	5	1	2.9142	2.9626	3.0136	3.0698	3.124

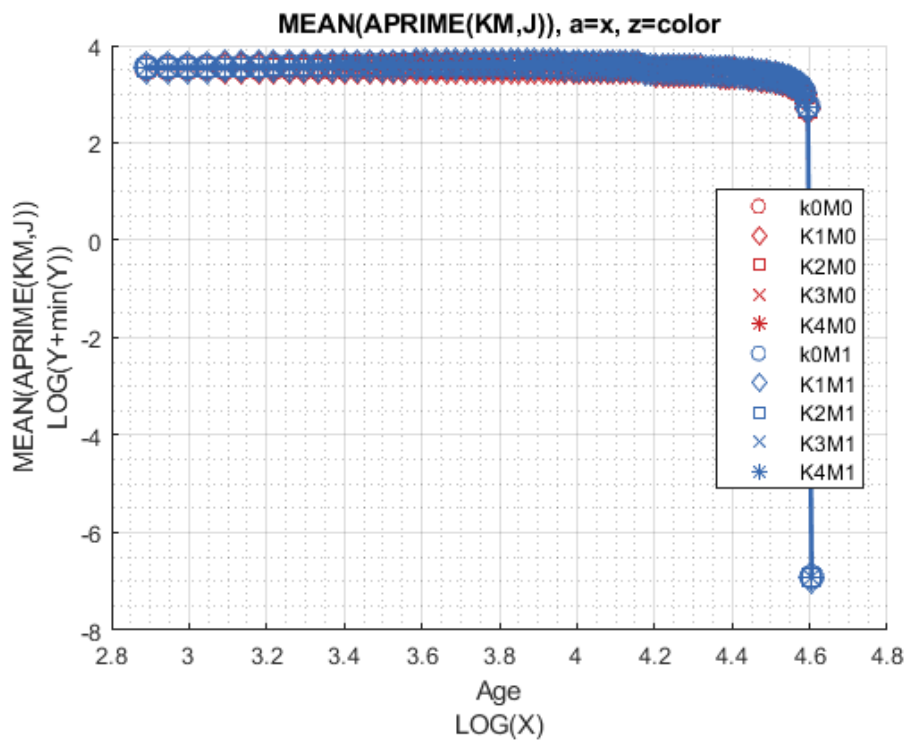
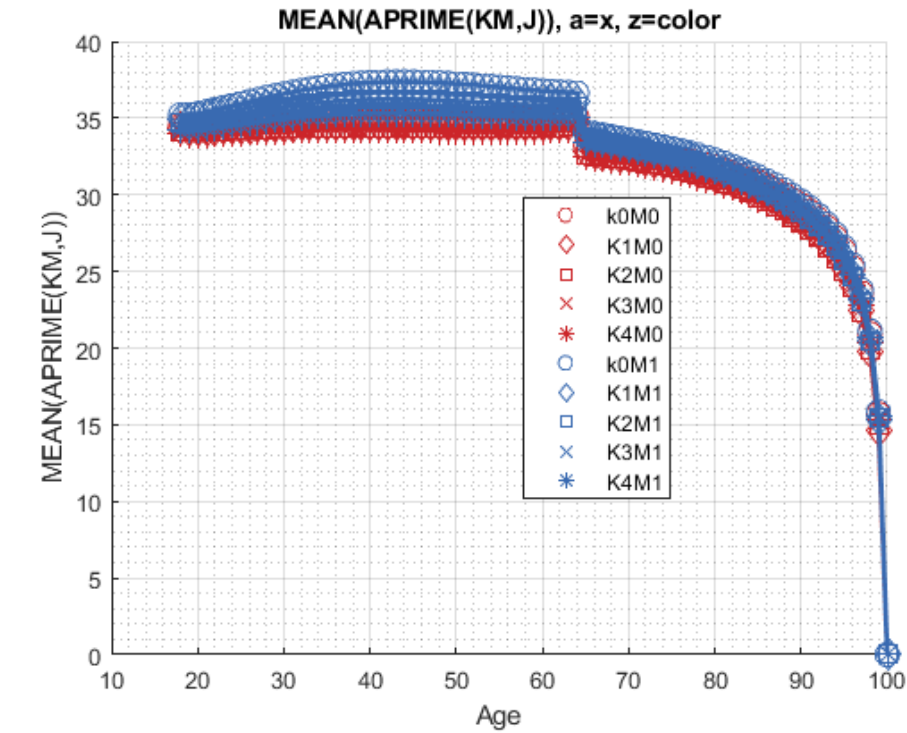
Graph Mean Values:

```
mp_support_graph('cl_st_graph_title') = {'MEAN(value(KM,J)), a=age, z=kids+marry'};
mp_support_graph('cl_st_ytitle') = {'MEAN(value(KM,J))'};
ff_graph_grid((tb_az_v{1:end, 4:end}), ar_row_grid, age_grid, mp_support_graph);
```



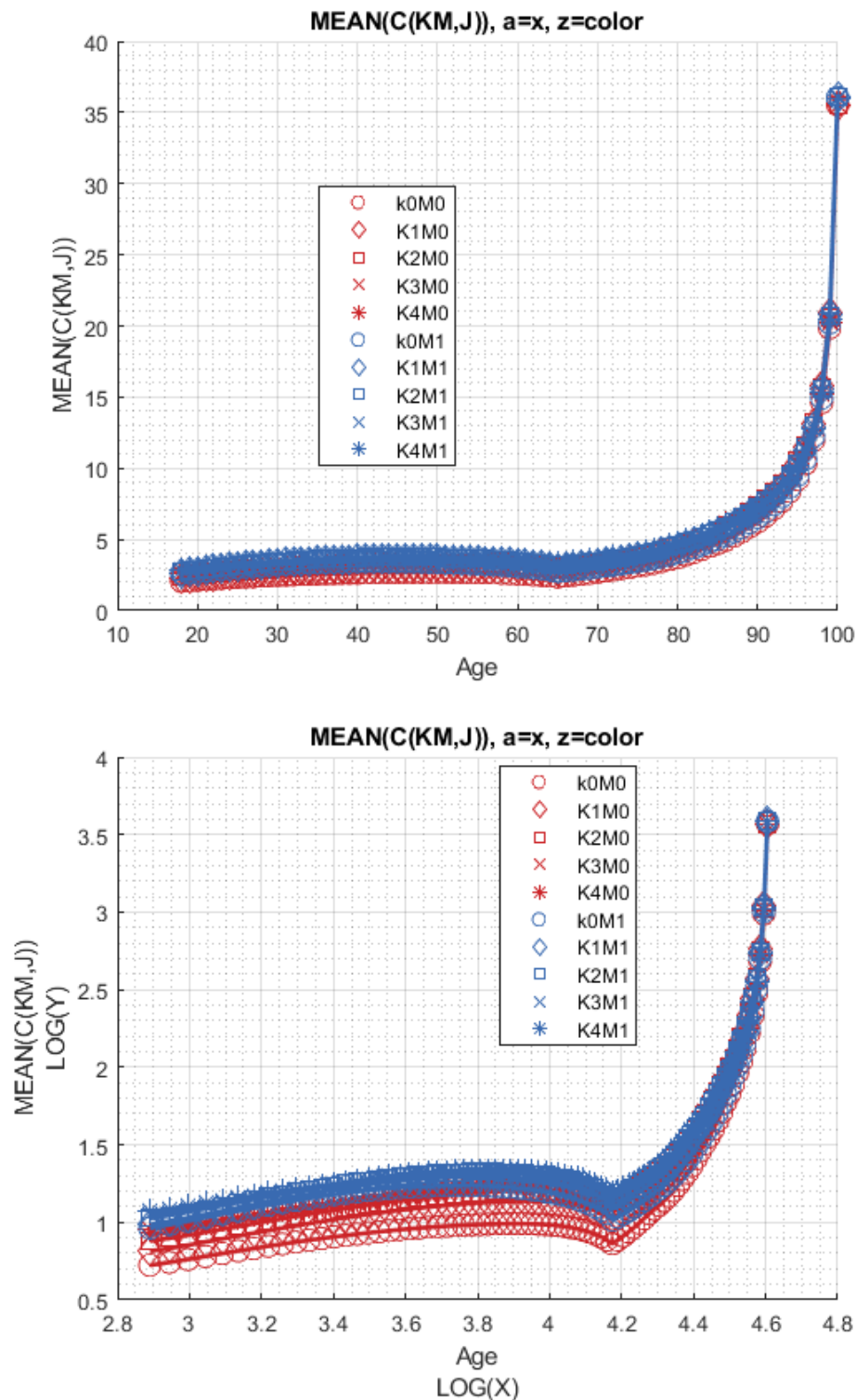
Graph Mean Savings Choices:

```
mp_support_graph('cl_st_graph_title') = {'MEAN(APRIME(KM,J)), a=x, z=color'};
mp_support_graph('cl_st_ytitle') = {'MEAN(APRIME(KM,J))'};
ff_graph_grid((tb_az_ap{1:end, 4:end}), ar_row_grid, age_grid, mp_support_graph);
```



Graph Mean Consumption:

```
mp_support_graph('cl_st_graph_title') = {'MEAN(C(KM,J)), a=x, z=color'};
mp_support_graph('cl_st_ytitle') = {'MEAN(C(KM,J))'};
ff_graph_grid((tb_az_c{1:end, 4:end}), ar_row_grid, age_grid, mp_support_graph);
```



### 3.1.5 Analyze Education and Marriage and Age

Aggregating over education, savings, and shocks, what are the differential effects of Marriage and Age.

```
% Generate some Data
```

```
mp_support_graph = containers.Map('KeyType', 'char', 'ValueType', 'any');
```

```
ar_row_grid = ["E0M0", "E1M0", "E0M1", "E1M1"];
```

```
mp_support_graph('cl_st_xtitle') = {'Age'};
```

```
mp_support_graph('st_legend_loc') = 'best';
```

```
mp_support_graph('bl_graph_logy') = true; % do not log
```

```

mp_support_graph('st_rounding') = '6.2f'; % format shock legend
mp_support_graph('cl_scatter_shapes') = {'*', 'p', '*', 'p' };
mp_support_graph('cl_colors') = {'red', 'red', 'blue', 'blue'};

```

```
MEAN(VAL(EKM,J)), MEAN(AP(EKM,J)), MEAN(C(EKM,J))
```

Tabulate value and policies:

```

% Set
% NaN(n_jgrid,n_agrid,n_etagrid,n_educgrid,n_marriedgrid,n_kidsgrid);
ar_permute = [2,3,6,1,4,5];
% Value Function
tb_az_v = ff_summ_nd_array("MEAN(VAL(EKM,J))", V_VFI, true, ["mean"], 3, 1, cl_mp_datasetdesc, ar_pe

```

```

xxx MEAN(VAL(EKM,J)) xxxxxxxxxxxxxxxxxxxxxxxxxxxxxxxxxxxx
      group   edu   marry   mean_age_18   mean_age_19   mean_age_20   mean_age_21   mean_age_22
      -----   ---   -----   -----
      1         0     0       -51.853     -50.513     -49.192     -47.891     -46.665
      2         1     0       -45.27      -43.745     -42.242     -40.768     -39.426
      3         0     1       -35.075     -33.966     -32.905     -31.884     -30.931
      4         1     1       -30.407     -29.317     -28.272     -27.257     -26.324

```

```

% Aprime Choice
tb_az_ap = ff_summ_nd_array("MEAN(AP(EKM,J))", ap_VFI, true, ["mean"], 3, 1, cl_mp_datasetdesc, ar_p

```

```

xxx MEAN(AP(EKM,J)) xxxxxxxxxxxxxxxxxxxxxxxxxxxxxxxxxxxx
      group   edu   marry   mean_age_18   mean_age_19   mean_age_20   mean_age_21   mean_age_22
      -----   ---   -----   -----
      1         0     0        34.297        34.264        34.23         34.24         34.251
      2         1     0        34.094        34.043        33.989        34.039        34.091
      3         0     1        34.773        34.793        34.812        34.883        34.955
      4         1     1        34.672        34.686        34.698        34.828        34.962

```

```

% Consumption Choices
tb_az_c = ff_summ_nd_array("MEAN(C(EKM,J))", cons_VFI, true, ["mean"], 3, 1, cl_mp_datasetdesc, ar_p

```

```

xxx MEAN(C(EKM,J)) xxxxxxxxxxxxxxxxxxxxxxxxxxxxxxxxxxxx
      group   edu   marry   mean_age_18   mean_age_19   mean_age_20   mean_age_21   mean_age_22
      -----   ---   -----   -----
      1         0     0        2.2603        2.2935        2.3281        2.3646        2.4003
      2         1     0        2.4632        2.5143        2.5682        2.6279        2.6854
      3         0     1        2.623         2.6679        2.714         2.7624        2.8096
      4         1     1        2.9143        2.9798        3.0485        3.1246        3.1978

```

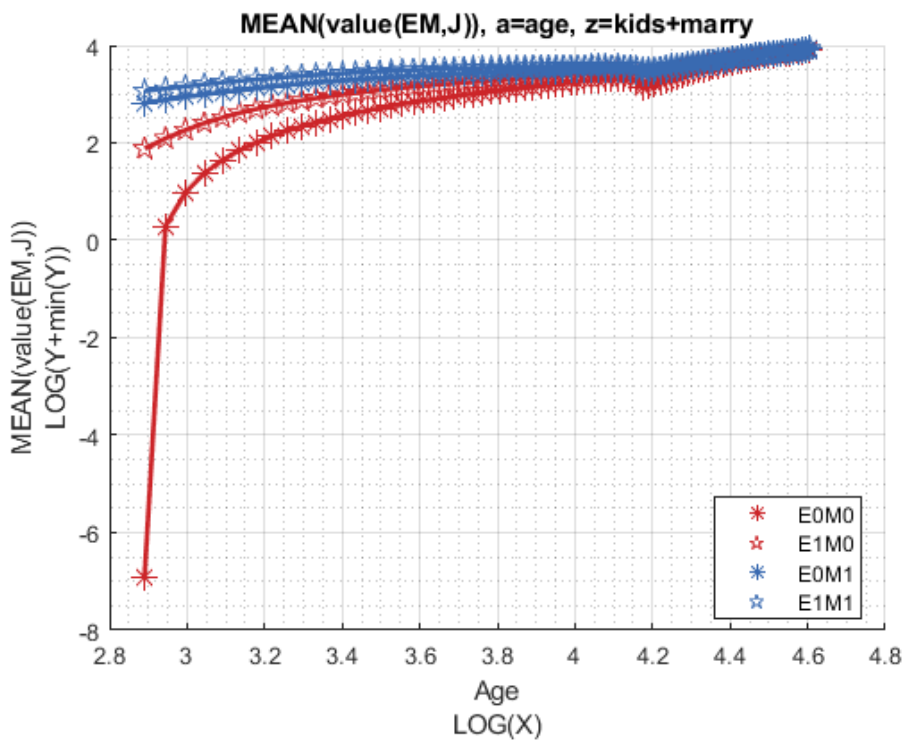
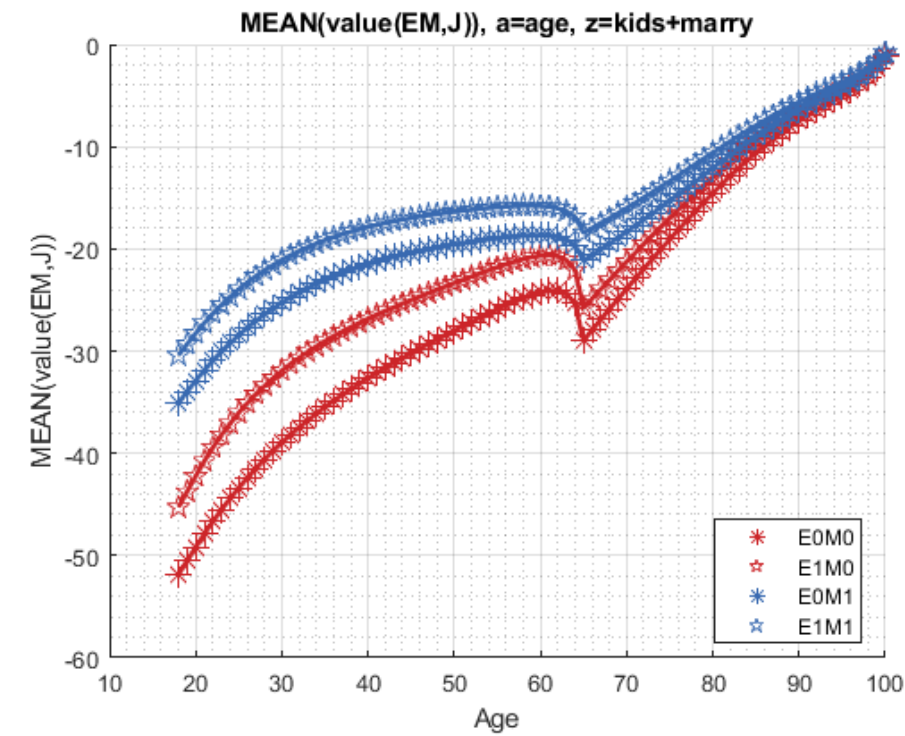
Graph Mean Values:

```

mp_support_graph('cl_st_graph_title') = {'MEAN(value(EM,J)), a=age, z=kids+marry'};
mp_support_graph('cl_st_ytitle') = {'MEAN(value(EM,J))'};
ff_graph_grid((tb_az_v{1:end, 4:end}), ar_row_grid, age_grid, mp_support_graph);

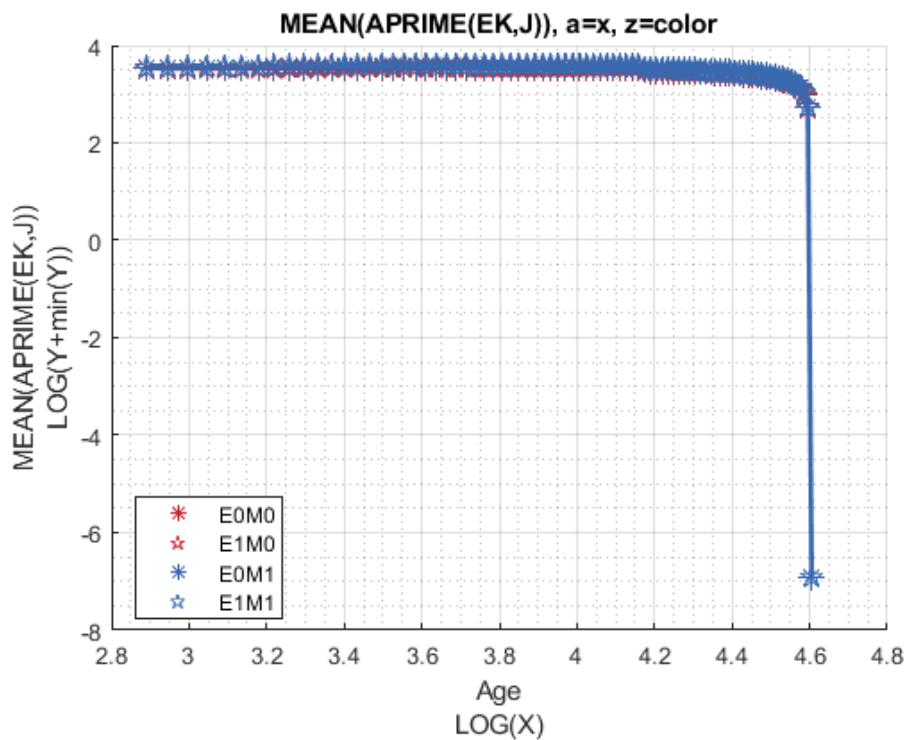
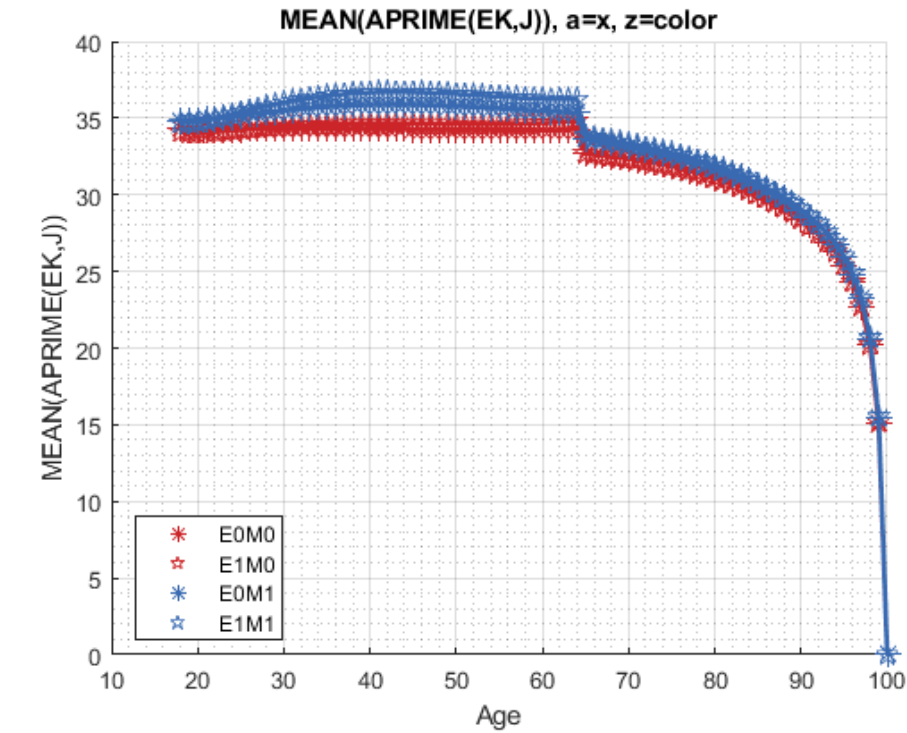
```





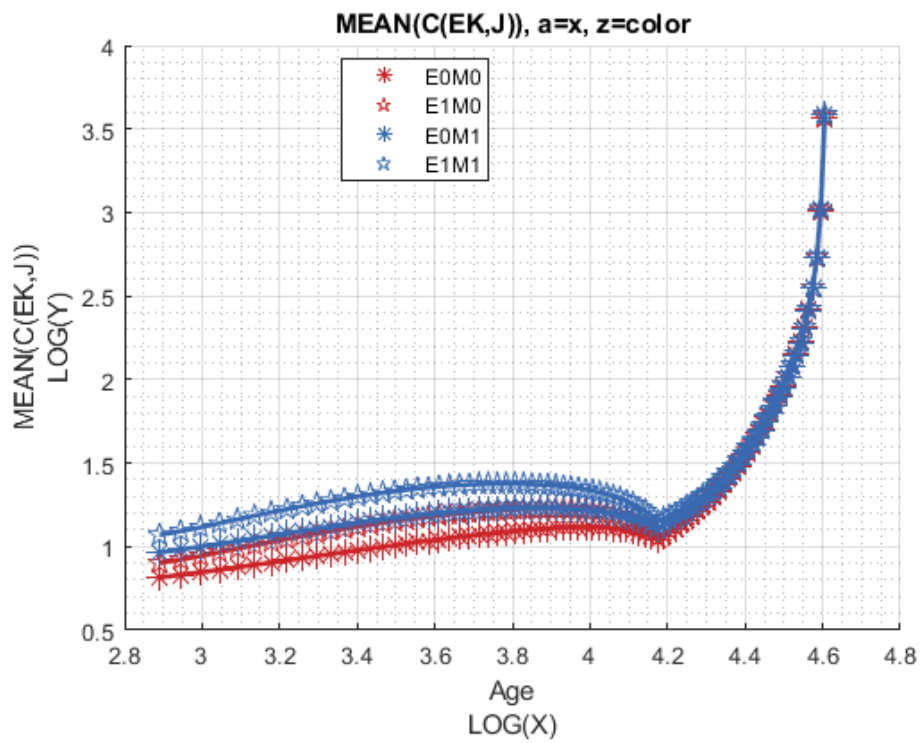
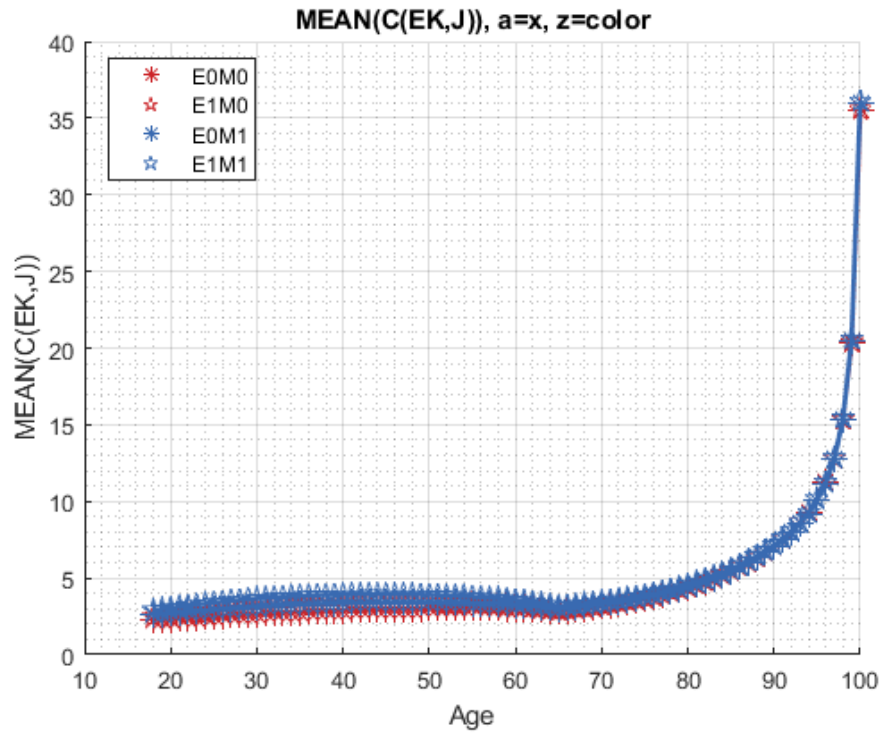
Graph Mean Savings Choices:

```
mp_support_graph('cl_st_graph_title') = {'MEAN(APRIME(EK,J)), a=x, z=color'};
mp_support_graph('cl_st_ytitle') = {'MEAN(APRIME(EK,J))'};
ff_graph_grid((tb_az_ap{1:end, 4:end}), ar_row_grid, age_grid, mp_support_graph);
```



Graph Mean Consumption:

```
mp_support_graph('cl_st_graph_title') = {'MEAN(C(EK,J)), a=x, z=color'};
mp_support_graph('cl_st_ytitle') = {'MEAN(C(EK,J))'};
ff_graph_grid((tb_az_c{1:end, 4:end}), ar_row_grid, age_grid, mp_support_graph);
```





## Chapter 4

# Alternative Value Function Solution Testing

### 4.1 Small Test Exact Solution Looped Minimizer

This is the example vignette for function: [snw\\_vfi\\_main](#) from the [PrjOptiSNW Package](#). This function solves for policy function fully iteratively using matlab minimizer. Small Solution Analysis. This produces the same result as [snw\\_vfi\\_main\\_bisec\\_vec](#), except slower. The purpose of this function is to confirm that the results from [snw\\_vfi\\_main\\_bisec\\_vec](#) is correct.

#### 4.1.1 Test SNW\_VFI\_MAIN Defaults Small

Call the function with defaults parameters.

```
mp_param = snw_mp_param('default_small');  
[V_VFI,ap_VFI,cons_VFI,mp_valpol_more] = snw_vfi_main(mp_param);
```

```
SNW_VFI_MAIN: Finished Age Group:18 of 18  
SNW_VFI_MAIN: Finished Age Group:17 of 18  
SNW_VFI_MAIN: Finished Age Group:16 of 18  
SNW_VFI_MAIN: Finished Age Group:15 of 18  
SNW_VFI_MAIN: Finished Age Group:14 of 18  
SNW_VFI_MAIN: Finished Age Group:13 of 18  
SNW_VFI_MAIN: Finished Age Group:12 of 18  
SNW_VFI_MAIN: Finished Age Group:11 of 18  
SNW_VFI_MAIN: Finished Age Group:10 of 18  
SNW_VFI_MAIN: Finished Age Group:9 of 18  
SNW_VFI_MAIN: Finished Age Group:8 of 18  
SNW_VFI_MAIN: Finished Age Group:7 of 18  
SNW_VFI_MAIN: Finished Age Group:6 of 18  
SNW_VFI_MAIN: Finished Age Group:5 of 18  
SNW_VFI_MAIN: Finished Age Group:4 of 18  
SNW_VFI_MAIN: Finished Age Group:3 of 18  
SNW_VFI_MAIN: Finished Age Group:2 of 18  
SNW_VFI_MAIN: Finished Age Group:1 of 18  
Elapsed time is 515.239525 seconds.  
Completed SNW_VFI_MAIN;SNW_MP_PARAM=default_small;SNW_MP_CONTROL=default_base
```

#### 4.1.2 Small Param Results Define Frames

Define the matrix dimensions names and dimension vector values. Policy and Value Functions share the same ND dimensional structure.

```

% Grids:
age_grid = [19, 22:5:97, 100];
agrid = mp_param('agrid');
eta_H_grid = mp_param('eta_H_grid');
eta_S_grid = mp_param('eta_S_grid');
ar_st_eta_HS_grid = string(cellstr([num2str(eta_H_grid', 'hz=%3.2f;'), num2str(eta_S_grid', 'wz=%3.2
edu_grid = [0,1];
marry_grid = [0,1];
kids_grid = (1:1:mp_param('n_kidsgrid'))';
% NaN(n_jgrid,n_agrid,n_etagrid,n_educgrid,n_marriedgrid,n_kidsgrid);
cl_mp_datasetdesc = {};
cl_mp_datasetdesc{1} = containers.Map({'name', 'labval'}, {'age', age_grid});
cl_mp_datasetdesc{2} = containers.Map({'name', 'labval'}, {'savings', agrid});
cl_mp_datasetdesc{3} = containers.Map({'name', 'labval'}, {'eta', 1:length(eta_H_grid)});
cl_mp_datasetdesc{4} = containers.Map({'name', 'labval'}, {'edu', edu_grid});
cl_mp_datasetdesc{5} = containers.Map({'name', 'labval'}, {'marry', marry_grid});
cl_mp_datasetdesc{6} = containers.Map({'name', 'labval'}, {'kids', kids_grid});

```

### 4.1.3 Analyze Savings and Shocks

First, analyze Savings Levels and Shocks, Aggregate Over All Others, and do various other calculations.

```

% Generate some Data
mp_support_graph = containers.Map('KeyType', 'char', 'ValueType', 'any');
mp_support_graph('cl_st_xtitle') = {'Savings States, a'};
mp_support_graph('st_legend_loc') = 'best';
mp_support_graph('bl_graph_logy') = true; % do not log

MEAN(VAL(A,Z)), MEAN(AP(A,Z)), MEAN(C(A,Z))

Tabulate value and policies along savings and shocks:

% Set
% NaN(n_jgrid,n_agrid,n_etagrid,n_educgrid,n_marriedgrid,n_kidsgrid);
ar_permute = [1,4,5,6,3,2];
% Value Function
tb_az_v = ff_summ_nd_array("MEAN(VAL(A,Z))", V_VFI, true, ["mean"], 4, 1, cl_mp_datasetdesc, ar_perm

```

```

xxx MEAN(VAL(A,Z)) xxxxxxxxxxxxxxxxxxxxxxxxxxxxxxxx
      group      savings      mean_eta_1      mean_eta_2      mean_eta_3      mean_eta_4      mean_eta_5
      -----      -
      1              0      -17.721      -9.4697      -4.6571      -1.7924      -0.23581
      2      0.0097656      -17.284      -9.3219      -4.5706      -1.7215      -0.16909
      3      0.078125      -15.196      -8.4993      -4.1004      -1.3514      0.17326
      4      0.26367      -11.907      -7.0394      -3.3075      -0.78441      0.67194
      5              0.625      -8.4194      -5.2786      -2.3615      -0.19487      1.1461
      6      1.2207      -5.393      -3.5129      -1.3918      0.35026      1.5392
      7      2.1094      -3.0352      -1.9483      -0.50577      0.84352      1.8533
      8      3.3496      -1.2918      -0.66899      0.26902      1.2874      2.1081
      9              5      -0.030416      0.32906      0.92609      1.6707      2.3215
     10      7.1191      0.87699      1.0879      1.4656      1.9934      2.5052
     11      9.7656      1.5329      1.6594      1.8992      2.267      2.6661
     12     12.998      2.0119      2.0896      2.2435      2.4983      2.8056
     13     16.875      2.366      2.4149      2.5152      2.6918      2.9253
     14     21.455      2.6312      2.6629      2.7294      2.8524      3.0281
     15     26.797      2.8329      2.8539      2.8987      2.9852      3.1169
     16     32.959      2.9883      3.0025      3.0334      3.0948      3.1935
     17              40      3.1097      3.1195      3.1411      3.1853      3.2595
     18     47.979      3.2056      3.2125      3.2279      3.2601      3.3161

```

19	56.953	3.2822	3.2872	3.2984	3.322	3.3647
20	66.982	3.3441	3.3478	3.356	3.3736	3.4063
21	78.125	3.3947	3.3974	3.4035	3.4168	3.442
22	90.439	3.4363	3.4383	3.4429	3.4531	3.4727
23	103.98	3.4708	3.4724	3.4759	3.4837	3.4991
24	118.82	3.4997	3.5009	3.5036	3.5097	3.5218
25	135	3.5241	3.525	3.5271	3.5319	3.5415

% Aprime Choice

tb\_az\_ap = ff\_summ\_nd\_array("MEAN(AP(A,Z))", ap\_VFI, true, ["mean"], 4, 1, cl\_mp\_datasetdesc, ar\_per

```
xxx MEAN(AP(A,Z)) xxxxxxxxxxxxxxxxxxxxxxxxxxxxxxxx
```

group	savings	mean_eta_1	mean_eta_2	mean_eta_3	mean_eta_4	mean_eta_5
1	0	3.2168e-05	0.0034996	0.049878	0.24382	0.89299
2	0.0097656	0.00055444	0.0053208	0.053281	0.24787	0.89865
3	0.078125	0.021863	0.029684	0.083029	0.28062	0.93971
4	0.26367	0.13322	0.14773	0.20012	0.3888	1.0591
5	0.625	0.39134	0.41043	0.45332	0.64573	1.3087
6	1.2207	0.84131	0.86393	0.91226	1.0928	1.745
7	2.1094	1.5303	1.5542	1.6156	1.7559	2.3963
8	3.3496	2.4876	2.5118	2.573	2.6876	3.3398
9	5	3.7642	3.7887	3.8498	3.9922	4.592
10	7.1191	5.4275	5.4525	5.5145	5.6929	6.1933
11	9.7656	7.4794	7.5043	7.5679	7.7532	8.1877
12	12.998	9.9124	9.9329	9.9956	10.186	10.627
13	16.875	12.928	12.95	13.005	13.196	13.715
14	21.455	16.529	16.548	16.604	16.783	17.374
15	26.797	20.601	20.618	20.668	20.837	21.462
16	32.959	25.307	25.325	25.37	25.525	26.151
17	40	30.667	30.69	30.742	30.886	31.487
18	47.979	36.761	36.782	36.841	36.999	37.562
19	56.953	43.773	43.795	43.847	44.012	44.56
20	66.982	51.605	51.628	51.688	51.85	52.403
21	78.125	59.955	59.978	60.038	60.211	60.768
22	90.439	69.267	69.29	69.352	69.528	70.097
23	103.98	79.753	79.774	79.834	80.008	80.586
24	118.82	91.116	91.14	91.201	91.367	91.942
25	135	103.47	103.49	103.55	103.72	104.29

% Consumption Choices

tb\_az\_c = ff\_summ\_nd\_array("MEAN(C(A,Z))", cons\_VFI, true, ["mean"], 4, 1, cl\_mp\_datasetdesc, ar\_per

```
xxx MEAN(C(A,Z)) xxxxxxxxxxxxxxxxxxxxxxxxxxxxxxxx
```

group	savings	mean_eta_1	mean_eta_2	mean_eta_3	mean_eta_4	mean_eta_5
1	0	0.30273	0.43104	0.68779	1.2165	2.3367
2	0.0097656	0.31374	0.44069	0.69581	1.2239	2.3424
3	0.078125	0.37308	0.49662	0.74605	1.2709	2.3811
4	0.26367	0.48039	0.59638	0.846	1.3793	2.478
5	0.625	0.64735	0.75736	1.0152	1.5439	2.6496
6	1.2207	0.89648	1.0013	1.2519	1.7913	2.9071
7	2.1094	1.2479	1.3498	1.5854	2.1634	3.2903
8	3.3496	1.7393	1.8394	2.0734	2.6754	3.7896
9	5	2.3872	2.4859	2.7182	3.2909	4.4564
10	7.1191	3.1917	3.289	3.5191	4.0542	5.3181

11	9.7656	4.2188	4.3155	4.543	5.07	6.3986
12	12.998	5.5439	5.6447	5.8722	6.3933	7.7142
13	16.875	7.0334	7.133	7.3676	7.8866	9.1285
14	21.455	8.754	8.8551	9.0887	9.6188	10.789
15	26.797	10.886	10.989	11.228	11.768	12.903
16	32.959	13.336	13.438	13.682	14.235	15.368
17	40	16.151	16.249	16.485	17.049	18.207
18	47.979	19.321	19.42	19.649	20.2	21.394
19	56.953	22.728	22.827	23.062	23.605	24.816
20	66.982	26.539	26.636	26.864	27.41	28.615
21	78.125	31.124	31.221	31.45	31.985	33.186
22	90.439	36.108	36.205	36.431	36.963	38.152
23	103.98	41.345	41.444	41.673	42.206	43.386
24	118.82	47.202	47.298	47.525	48.066	49.248
25	135	53.632	53.731	53.962	54.496	55.685

## 4.2 Small Test Grid Search Solution

This is the example vignette for function: `snw_vfi_main_grid_search` from the [PrjOptiSNW Package](#). This function solves for policy function using grid search. Small Solution Analysis. Small Solution Analysis, husband 5 shocks, wife 1 shocks.

### 4.2.1 Test SNW\_VFI\_MAIN\_GRID\_SEARCH Defaults Small

Call the function with defaults parameters.

```
mp_param = snw_mp_param('default_small');
[V_VFI,ap_VFI,cons_VFI,mp_valpol_more] = snw_vfi_main_grid_search(mp_param);

SNW_VFI_MAIN_GRID_SEARCH: Finished Age Group:18 of 18
SNW_VFI_MAIN_GRID_SEARCH: Finished Age Group:17 of 18
SNW_VFI_MAIN_GRID_SEARCH: Finished Age Group:16 of 18
SNW_VFI_MAIN_GRID_SEARCH: Finished Age Group:15 of 18
SNW_VFI_MAIN_GRID_SEARCH: Finished Age Group:14 of 18
SNW_VFI_MAIN_GRID_SEARCH: Finished Age Group:13 of 18
SNW_VFI_MAIN_GRID_SEARCH: Finished Age Group:12 of 18
SNW_VFI_MAIN_GRID_SEARCH: Finished Age Group:11 of 18
SNW_VFI_MAIN_GRID_SEARCH: Finished Age Group:10 of 18
SNW_VFI_MAIN_GRID_SEARCH: Finished Age Group:9 of 18
SNW_VFI_MAIN_GRID_SEARCH: Finished Age Group:8 of 18
SNW_VFI_MAIN_GRID_SEARCH: Finished Age Group:7 of 18
SNW_VFI_MAIN_GRID_SEARCH: Finished Age Group:6 of 18
SNW_VFI_MAIN_GRID_SEARCH: Finished Age Group:5 of 18
SNW_VFI_MAIN_GRID_SEARCH: Finished Age Group:4 of 18
SNW_VFI_MAIN_GRID_SEARCH: Finished Age Group:3 of 18
SNW_VFI_MAIN_GRID_SEARCH: Finished Age Group:2 of 18
SNW_VFI_MAIN_GRID_SEARCH: Finished Age Group:1 of 18
Elapsed time is 6.771761 seconds.
Completed SNW_VFI_MAIN_GRID_SEARCH;SNW_MP_PARAM=default_small;SNW_MP_CONTROL=default_base
```

### 4.2.2 Small Param Results Define Frames

Define the matrix dimensions names and dimension vector values. Policy and Value Functions share the same ND dimensional structure.

```
% Grids:
age_grid = [19, 22:5:97, 100];
agrid = mp_param('agrid');
eta_H_grid = mp_param('eta_H_grid');
```



```

eta_S_grid = mp_param('eta_S_grid');
ar_st_eta_HS_grid = string(cellstr([num2str(eta_H_grid', 'hz=%3.2f;'), num2str(eta_S_grid', 'wz=%3.2
edu_grid = [0,1];
marry_grid = [0,1];
kids_grid = (1:1:mp_param('n_kidsgrid'))';
% NaN(n_jgrid,n_agrid,n_etagrid,n_educgrid,n_marriedgrid,n_kidsgrid);
cl_mp_datasetdesc = {};
cl_mp_datasetdesc{1} = containers.Map({'name', 'labval'}, {'age', age_grid});
cl_mp_datasetdesc{2} = containers.Map({'name', 'labval'}, {'savings', agrid});
cl_mp_datasetdesc{3} = containers.Map({'name', 'labval'}, {'Hshock', eta_H_grid});
cl_mp_datasetdesc{4} = containers.Map({'name', 'labval'}, {'edu', edu_grid});
cl_mp_datasetdesc{5} = containers.Map({'name', 'labval'}, {'marry', marry_grid});
cl_mp_datasetdesc{6} = containers.Map({'name', 'labval'}, {'kids', kids_grid});

```

### 4.2.3 Analyze Savings and Shocks

First, analyze Savings Levels and Shocks, Aggregate Over All Others, and do various other calculations.

```

% Generate some Data
mp_support_graph = containers.Map('KeyType', 'char', 'ValueType', 'any');
mp_support_graph('cl_st_xtitle') = {'Savings States, a'};
mp_support_graph('st_legend_loc') = 'best';
mp_support_graph('bl_graph_logy') = true; % do not log

MEAN(VAL(A,Z)), MEAN(AP(A,Z)), MEAN(C(A,Z))

Tabulate value and policies along savings and shocks:

% Set
% NaN(n_jgrid,n_agrid,n_etagrid,n_educgrid,n_marriedgrid,n_kidsgrid);
ar_permute = [1,4,5,6,3,2];
% Value Function
tb_az_v = ff_summ_nd_array("MEAN(VAL(A,Z))", V_VFI, true, ["mean"], 4, 1, cl_mp_datasetdesc, ar_perm

```

xxx	MEAN(VAL(A,Z))	xxxxxxxxxxxxxxxxxxxxxxxxxxxxxxxx				
group	savings	mean_Hshock__1_8395	mean_Hshock__0_91976	mean_Hshock_0	mean_Hshoc	
-----	-----	-----	-----	-----	-----	-----
1	0	-17.723	-9.4806	-4.7079	-1.8	
2	0.0097656	-17.287	-9.3335	-4.6223	-1.7	
3	0.078125	-15.289	-8.5102	-4.1607	-1.3	
4	0.26367	-12.169	-7.0906	-3.3823	-0.82	
5	0.625	-8.7667	-5.3975	-2.4071	-0.24	
6	1.2207	-5.7445	-3.6744	-1.4216	0.29	
7	2.1094	-3.3257	-2.112	-0.53821	0.80	
8	3.3496	-1.5195	-0.81731	0.22515	1.2	
9	5	-0.20516	0.20391	0.87016	1.6	
10	7.1191	0.74607	0.98431	1.4069	1.9	
11	9.7656	1.4347	1.5779	1.8454	2.2	
12	12.998	1.9367	2.0246	2.1961	2.4	
13	16.875	2.3099	2.364	2.476	2.6	
14	21.455	2.5887	2.6239	2.6967	2.8	
15	26.797	2.7998	2.8231	2.8727	2.9	
16	32.959	2.963	2.9785	3.0123	3.0	
17	40	3.0902	3.1009	3.1242	3.1	
18	47.979	3.1902	3.1978	3.2144	3.2	
19	56.953	3.27	3.2754	3.2875	3.3	
20	66.982	3.3345	3.3384	3.3471	3.3	
21	78.125	3.3871	3.3899	3.3964	3.4	
22	90.439	3.4301	3.4323	3.4372	3.4	

23	103.98	3.4658	3.4674	3.4712	3.4
24	118.82	3.4957	3.4969	3.4998	3.5
25	135	3.5208	3.5218	3.524	3.5

% Aprime Choice

tb\_az\_ap = ff\_summ\_nd\_array("MEAN(AP(A,Z))", ap\_VFI, true, ["mean"], 4, 1, cl\_mp\_datasetdesc, ar\_per

```
xxx MEAN(AP(A,Z)) xxxxxxxxxxxxxxxxxxxxxxxxxxxxxxxxxxxx
```

group	savings	mean_Hshock__1_8395	mean_Hshock__0_91976	mean_Hshock_0	mean_Hshock
1	0	1	1.1435	1.5972	2.59
2	0.0097656	1.0463	1.213	1.6574	2.61
3	0.078125	1.8009	2.0093	2.1991	2.8
4	0.26367	2.9491	3.0648	3.2454	3.62
5	0.625	4.0602	4.1806	4.2546	4.54
6	1.2207	5.1481	5.2454	5.2731	5.40
7	2.1094	6.1389	6.213	6.25	6.25
8	3.3496	7.0556	7.1019	7.1713	7.1
9	5	7.9537	7.9815	8.0556	8.07
10	7.1191	8.8611	8.8889	8.9398	9.00
11	9.7656	9.7824	9.7963	9.8519	9.92
12	12.998	10.606	10.63	10.648	10.7
13	16.875	11.481	11.491	11.537	11.5
14	21.455	12.407	12.407	12.431	12.4
15	26.797	13.287	13.301	13.306	13.3
16	32.959	14.13	14.13	14.167	14.1
17	40	14.981	14.981	14.991	15.0
18	47.979	15.88	15.88	15.884	15.9
19	56.953	16.75	16.773	16.782	16.7
20	66.982	17.681	17.685	17.699	17.7
21	78.125	18.495	18.5	18.509	18.5
22	90.439	19.338	19.338	19.352	19.
23	103.98	20.25	20.264	20.269	20.2
24	118.82	21.097	21.097	21.13	21.1
25	135	21.963	21.968	21.977	21.9

% Consumption Choices

tb\_az\_c = ff\_summ\_nd\_array("MEAN(C(A,Z))", cons\_VFI, true, ["mean"], 4, 1, cl\_mp\_datasetdesc, ar\_per

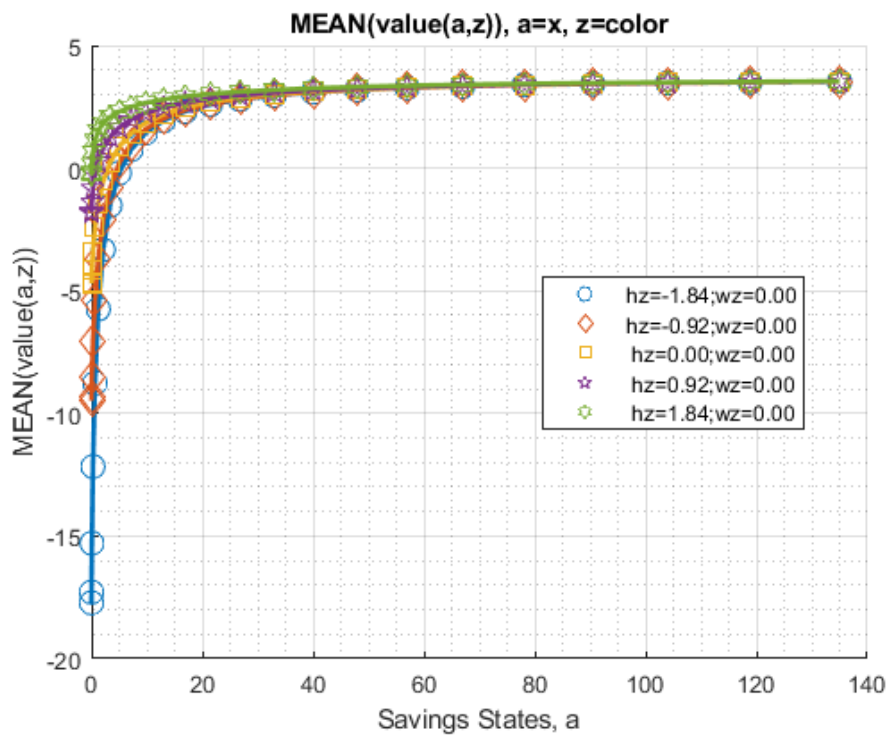
```
xxx MEAN(C(A,Z)) xxxxxxxxxxxxxxxxxxxxxxxxxxxxxxxxxxxx
```

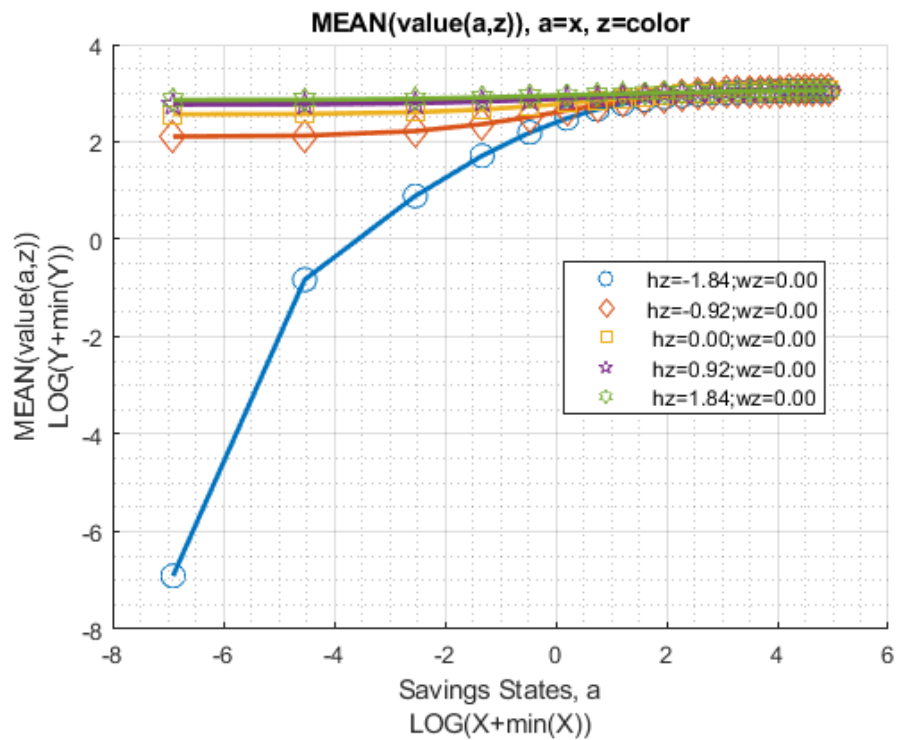
group	savings	mean_Hshock__1_8395	mean_Hshock__0_91976	mean_Hshock_0	mean_Hshock
1	0	0.30277	0.43205	0.70498	1.24
2	0.0097656	0.31384	0.44176	0.71311	1.25
3	0.078125	0.38061	0.49936	0.768	1.31
4	0.26367	0.50208	0.6111	0.86902	1.4
5	0.625	0.67677	0.76238	1.0363	1.58
6	1.2207	0.89732	0.96685	1.2492	1.84
7	2.1094	1.2189	1.2789	1.543	2.24
8	3.3496	1.6892	1.7561	1.9651	2.69
9	5	2.3251	2.4024	2.5736	3.25
10	7.1191	3.1269	3.1903	3.3745	3.94
11	9.7656	4.0839	4.1689	4.3128	4.8
12	12.998	5.4106	5.457	5.6873	6.12
13	16.875	6.9612	7.0462	7.1563	7.63
14	21.455	8.5924	8.7131	8.8962	9.33

15	26.797	10.6	10.647	10.911	11.3
16	32.959	13.149	13.269	13.33	13.8
17	40	16.034	16.154	16.378	16.7
18	47.979	18.971	19.092	19.343	19.7
19	56.953	22.573	22.485	22.69	23.2
20	66.982	26.089	26.168	26.322	26.7
21	78.125	30.843	30.917	31.101	31.1
22	90.439	35.929	36.049	36.177	36.6
23	103.98	40.986	40.918	41.144	41.7
24	118.82	47.072	47.192	47.018	47.5
25	135	53.493	53.538	53.682	54.0

Graph Mean Values:

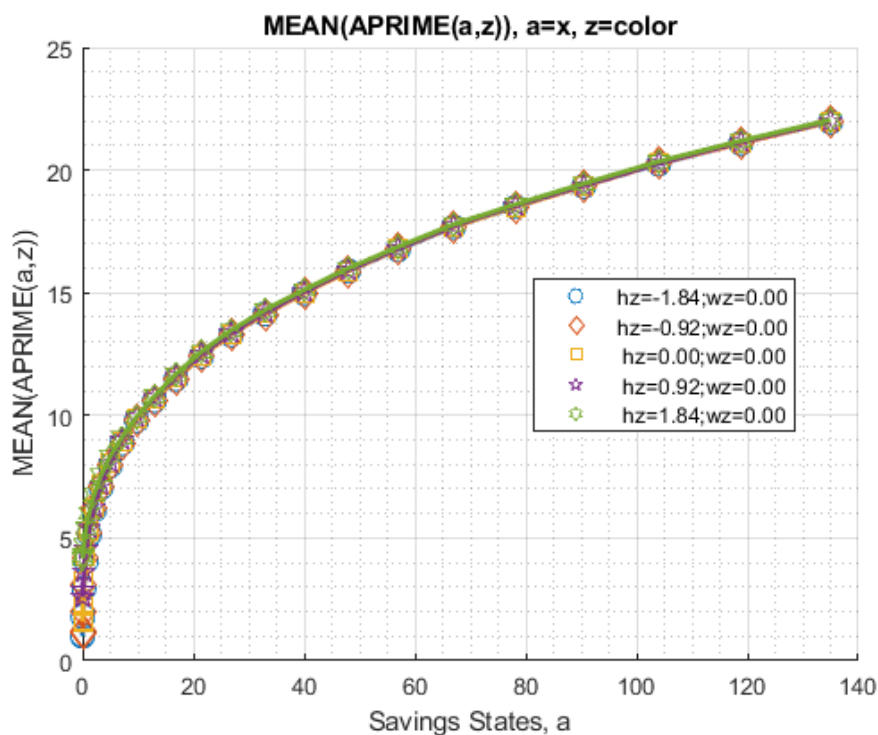
```
mp_support_graph('cl_st_graph_title') = {'MEAN(value(a,z)), a=x, z=color'};
mp_support_graph('cl_st_ytitle') = {'MEAN(value(a,z))'};
ff_graph_grid((tb_az_v{1:end, 3:end})', ar_st_eta_HS_grid, agrid, mp_support_graph);
```

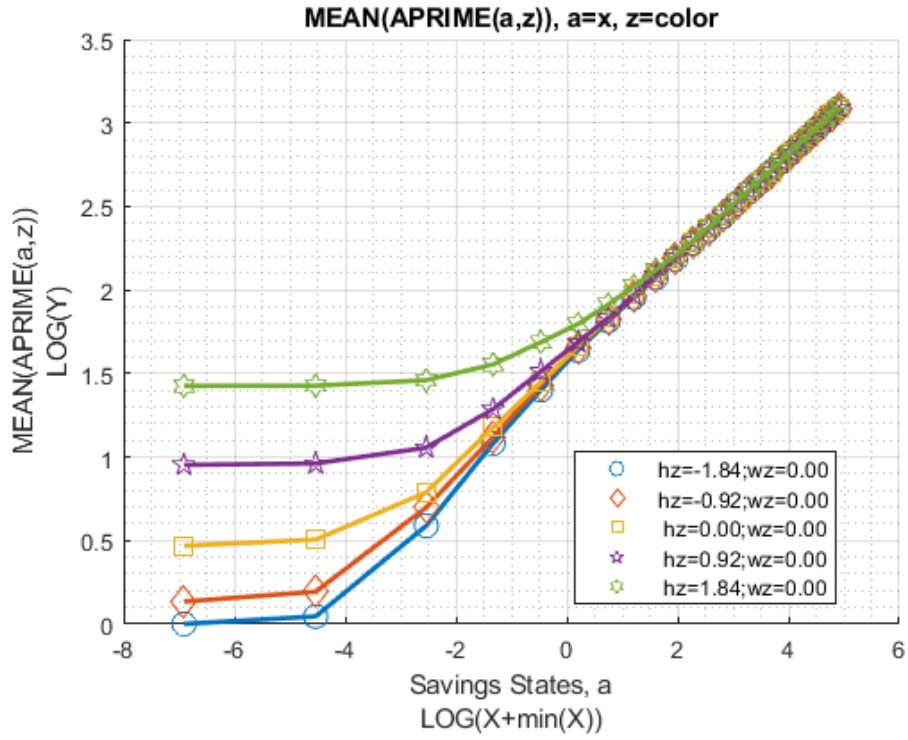




Graph Mean Savings Choices:

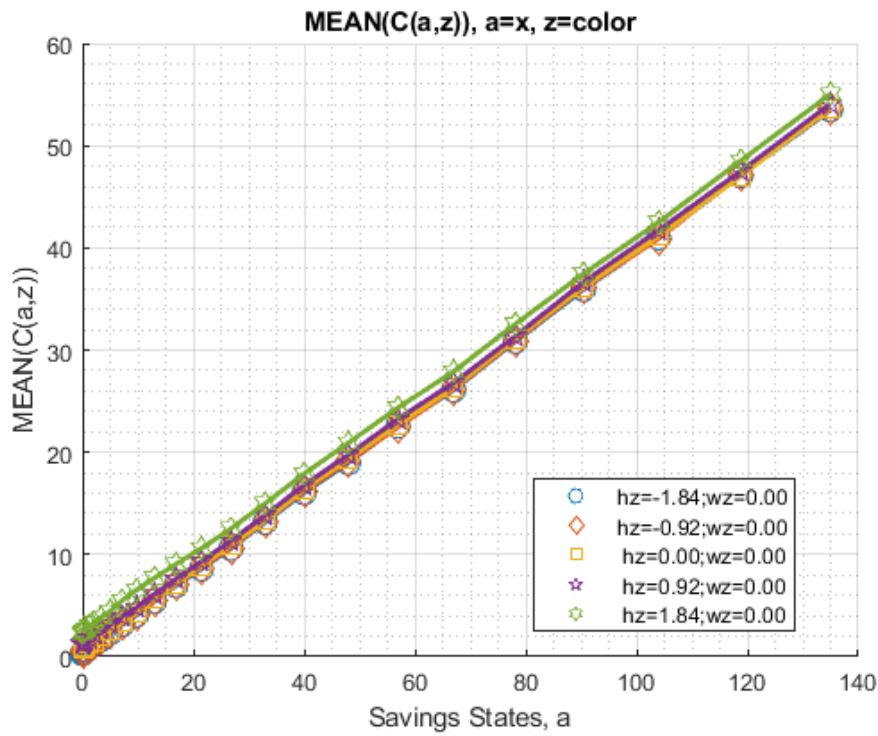
```
mp_support_graph('cl_st_graph_title') = {'MEAN(APRIME(a,z)), a=x, z=color'};
mp_support_graph('cl_st_ytitle') = {'MEAN(APRIME(a,z))'};
ff_graph_grid((tb_az_ap{1:end, 3:end})', ar_st_eta_HS_grid, agrid, mp_support_graph);
```

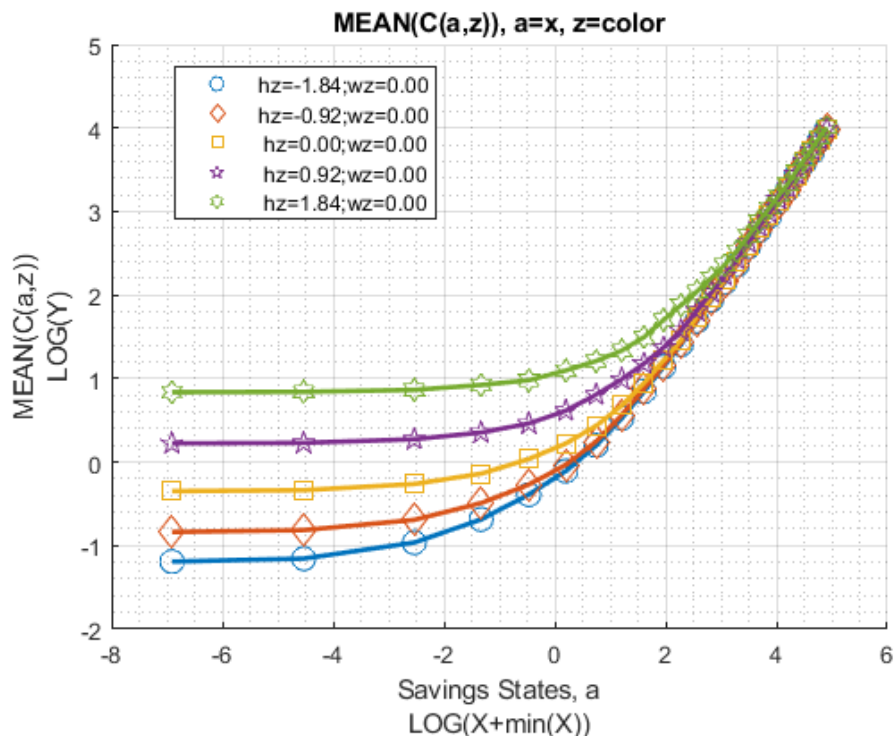




Graph Mean Consumption:

```
mp_support_graph('cl_st_graph_title') = {'MEAN(C(a,z)), a=x, z=color'};
mp_support_graph('cl_st_ytitle') = {'MEAN(C(a,z))'};
ff_graph_grid((tb_az_c{1:end, 3:end})', ar_st_eta_HS_grid, agrid, mp_support_graph);
```





#### 4.2.4 Analyze Kids and Marriage and Age

Aggregating over education, savings, and shocks, what are the differential effects of Marriage and Age.

```
% Generate some Data
mp_support_graph = containers.Map('KeyType', 'char', 'ValueType', 'any');
ar_row_grid = ["k0M0", "K1M0", "K2M0", "k0M1", "K1M1", "K2M1"];
mp_support_graph('cl_st_xtitle') = {'Age'};
mp_support_graph('st_legend_loc') = 'best';
mp_support_graph('bl_graph_logy') = true; % do not log
mp_support_graph('st_rounding') = '6.2f'; % format shock legend
mp_support_graph('cl_scatter_shapes') = {'o', 'd', 's', 'o', 'd', 's'};
mp_support_graph('cl_colors') = {'red', 'red', 'red', 'blue', 'blue', 'blue'};
```

```
MEAN(VAL(KM,J)), MEAN(AP(KM,J)), MEAN(C(KM,J))
```

Tabulate value and policies:

```
% Set
% NaN(n_jgrid,n_agrid,n_etagrid,n_educgrid,n_marriedgrid,n_kidsgrid);
ar_permute = [2,3,4,1,6,5];
% Value Function
tb_az_v = ff_summ_nd_array("MEAN(VAL(KM,J))", V_VFI, true, ["mean"], 3, 1, cl_mp_datasetdesc, ar_per
```

```
xxx MEAN(VAL(KM,J)) xxxxxxxxxxxxxxxxxxxxxxxxxxxxxxxxxxxx
  group  kids  marry  mean_age_19  mean_age_22  mean_age_27  mean_age_32  mean_age_3
-----  ----  -----  -
      1     1     0      1.402      1.6857      1.8728      1.9257      1.894
      2     2     0     -0.12483     0.36646     0.7436     0.9457     1.0402
      3     3     0     -0.89708    -0.41863    -0.032067    0.18508    0.29597
      4     1     1      1.967      2.1822      2.3218      2.3638      2.3393
      5     2     1      0.96762     1.2863     1.5349     1.6741     1.739
      6     3     1      0.51874     0.8123     1.0493     1.1855     1.2514
```

```
% Aprime Choice
```

```
tb_az_ap = ff_summ_nd_array("MEAN(AP(KM,J))", ap_VFI, true, ["mean"], 3, 1, cl_mp_datasetdesc, ar_pe
```

```
xxx MEAN(AP(KM,J)) xxxxxxxxxxxxxxxxxxxxxxxxxxxxxxxxxxxx
```

group	kids	marry	mean_age_19	mean_age_22	mean_age_27	mean_age_32	mean_age_3
1	1	0	12.948	12.924	13.052	13.152	13.224
2	2	0	12.924	12.88	13.008	13.096	13.16
3	3	0	12.86	12.848	12.972	13.084	13.108
4	1	1	12.86	12.856	12.972	13.076	13.14
5	2	1	12.876	12.82	12.956	13.028	13.1
6	3	1	12.804	12.784	12.912	12.984	13.06

% Consumption Choices

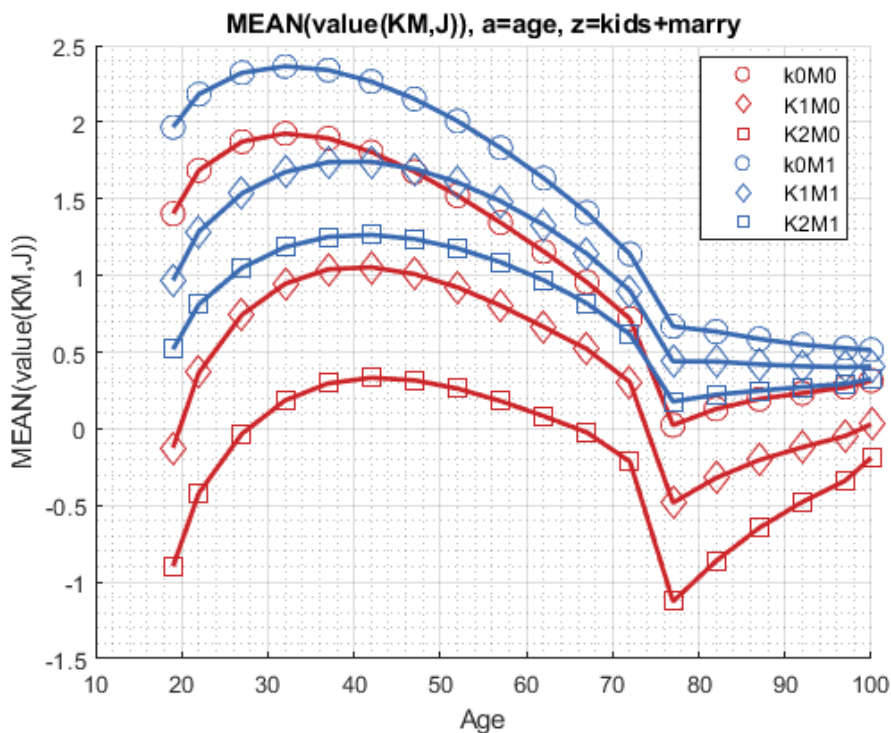
```
tb_az_c = ff_summ_nd_array("MEAN(C(KM,J))", cons_VFI, true, ["mean"], 3, 1, cl_mp_datasetdesc, ar_pe
```

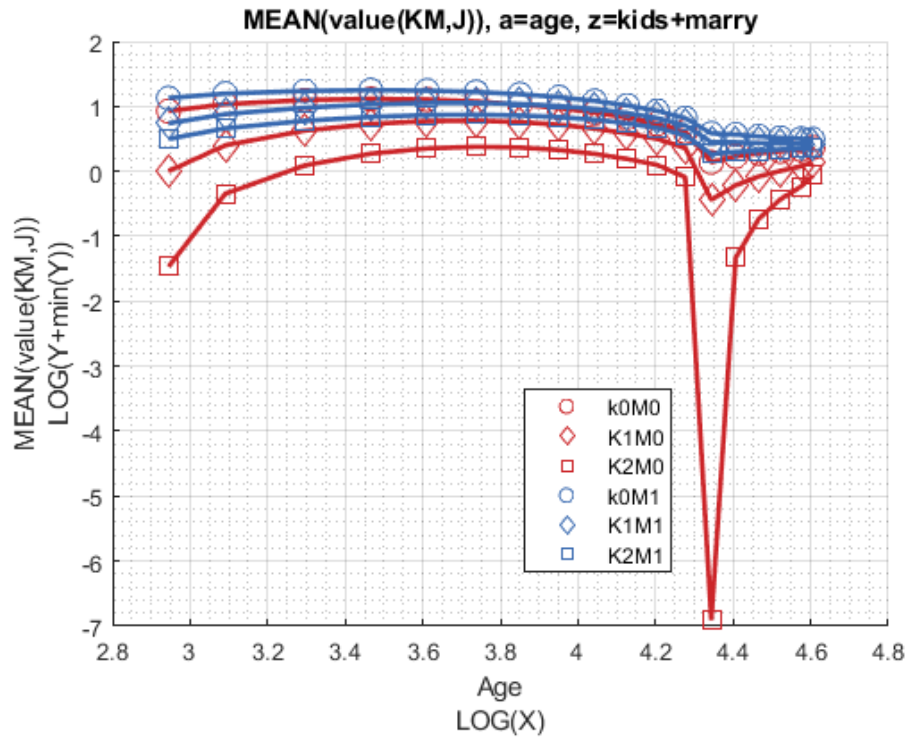
```
xxx MEAN(C(KM,J)) xxxxxxxxxxxxxxxxxxxxxxxxxxxxxxxxxxxx
```

group	kids	marry	mean_age_19	mean_age_22	mean_age_27	mean_age_32	mean_age_3
1	1	0	6.6347	6.7441	6.9773	7.1425	7.2307
2	2	0	6.6476	6.7581	6.9904	7.1656	7.2723
3	3	0	6.6679	6.7696	7.0001	7.1694	7.8468
4	1	1	6.885	7.0096	7.2673	7.4584	7.5792
5	2	1	6.856	6.987	7.2319	7.4245	7.5481
6	3	1	6.8672	6.9855	7.2175	7.4148	7.5346

Graph Mean Values:

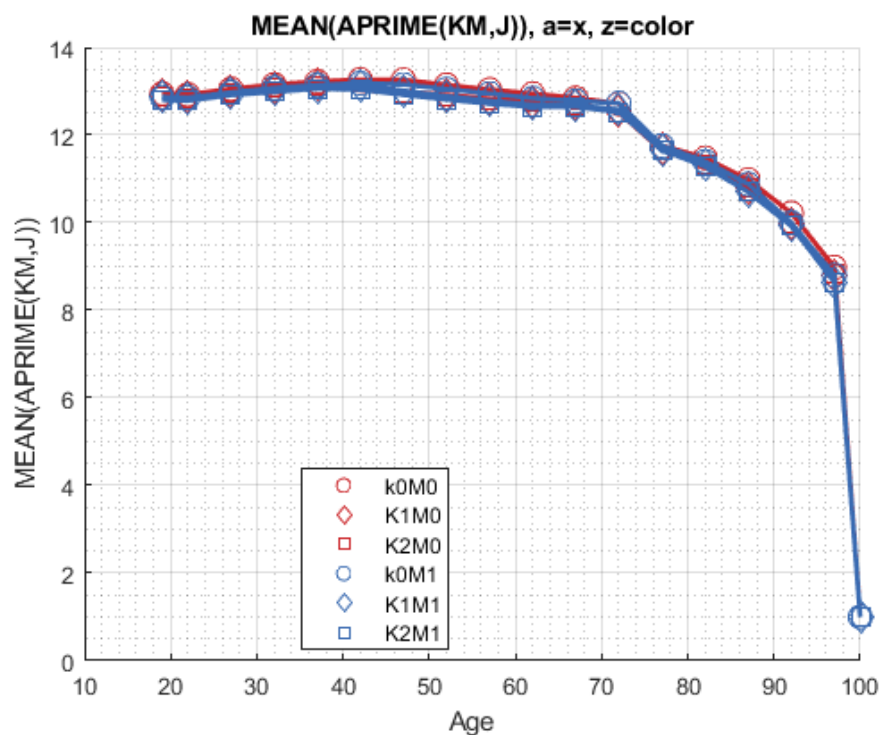
```
mp_support_graph('cl_st_graph_title') = {'MEAN(value(KM,J)), a=age, z=kids+marry'};
mp_support_graph('cl_st_ytitle') = {'MEAN(value(KM,J))'};
ff_graph_grid((tb_az_v{1:end, 4:end}), ar_row_grid, age_grid, mp_support_graph);
```



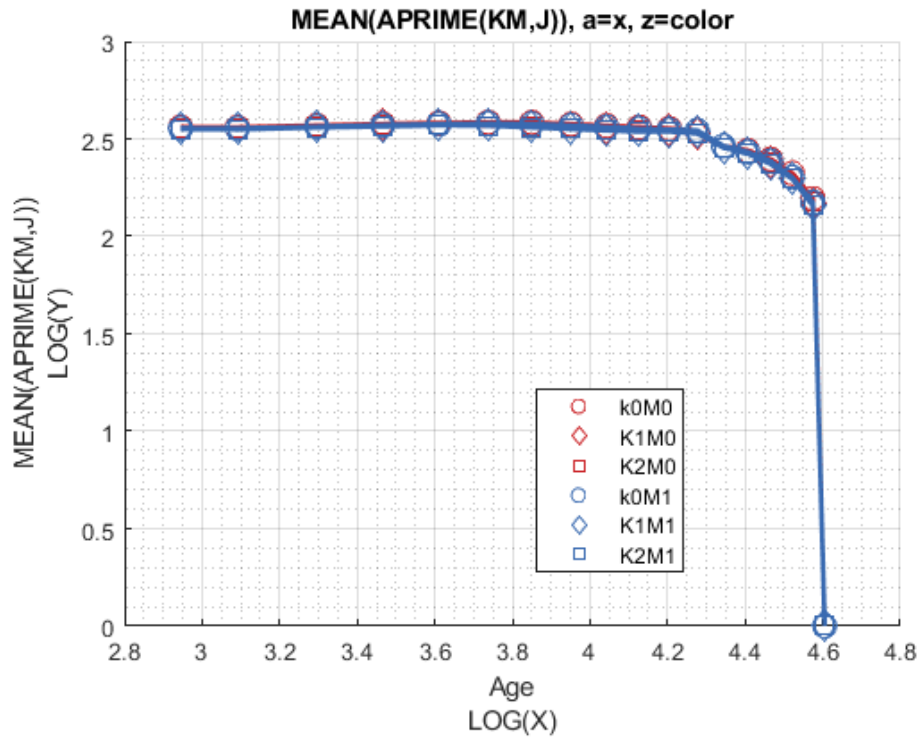


Graph Mean Savings Choices:

```
mp_support_graph('cl_st_graph_title') = {'MEAN(APRIME(KM,J)), a=x, z=color'};
mp_support_graph('cl_st_ytitle') = {'MEAN(APRIME(KM,J))'};
ff_graph_grid((tb_az_ap{1:end, 4:end}), ar_row_grid, age_grid, mp_support_graph);
```

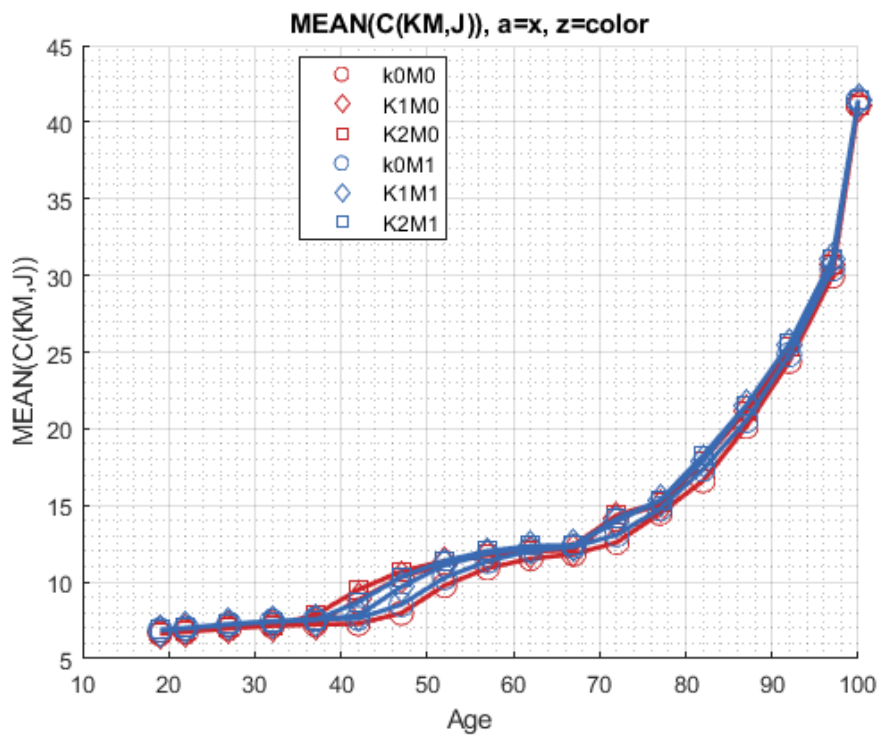


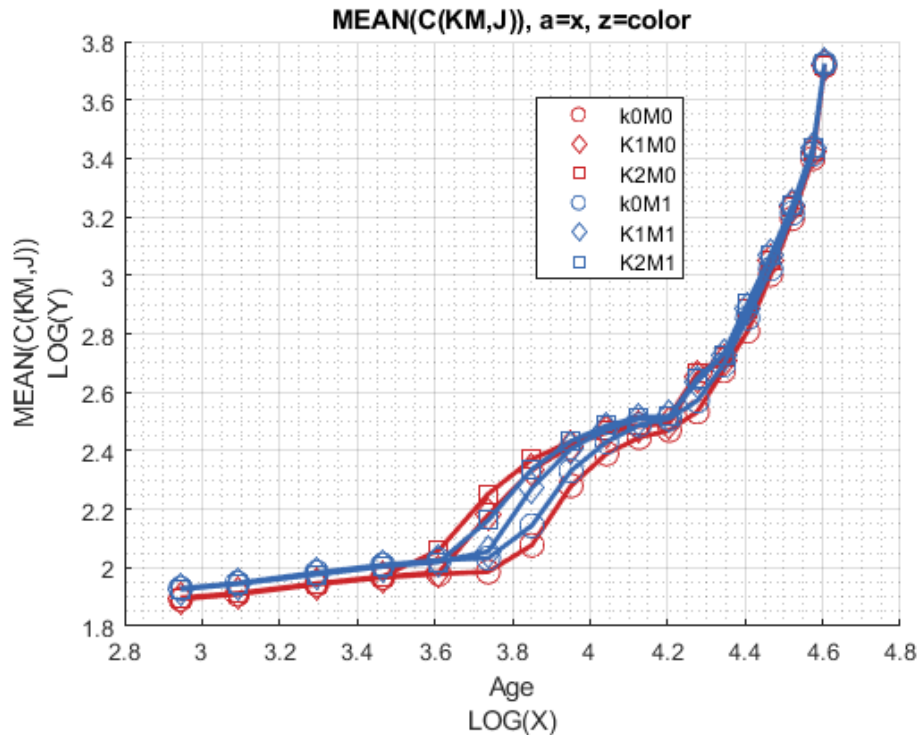




Graph Mean Consumption:

```
mp_support_graph('cl_st_graph_title') = {'MEAN(C(KM,J)), a=x, z=color'};
mp_support_graph('cl_st_ytitle') = {'MEAN(C(KM,J))'};
ff_graph_grid((tb_az_c{1:end, 4:end}), ar_row_grid, age_grid, mp_support_graph);
```





#### 4.2.5 Analyze Education and Marriage and Age

Aggregating over education, savings, and shocks, what are the differential effects of Marriage and Age.

```
% Generate some Data
mp_support_graph = containers.Map('KeyType', 'char', 'ValueType', 'any');
ar_row_grid = ["E0M0", "E1M0", "E0M1", "E1M1"];
mp_support_graph('cl_st_xtitle') = {'Age'};
mp_support_graph('st_legend_loc') = 'best';
mp_support_graph('bl_graph_logy') = true; % do not log
mp_support_graph('st_rounding') = '6.2f'; % format shock legend
mp_support_graph('cl_scatter_shapes') = {'*', 'p', '*', 'p'};
mp_support_graph('cl_colors') = {'red', 'red', 'blue', 'blue'};

MEAN(VAL(EKM,J)), MEAN(AP(EKM,J)), MEAN(C(EKM,J))

Tabulate value and policies:

% Set
% NaN(n_jgrid,n_agrid,n_etagrid,n_educgrid,n_marriedgrid,n_kidsgrid);
ar_permute = [2,3,6,1,4,5];
% Value Function
tb_az_v = ff_summ_nd_array("MEAN(VAL(EKM,J))", V_VFI, true, ["mean"], 3, 1, cl_mp_datasetdesc, ar_per

xxx MEAN(VAL(EKM,J)) xxxxxxxxxxxxxxxxxxxxxxxxxxxxxxxxxxxx
  group   edu   marry   mean_age_19   mean_age_22   mean_age_27   mean_age_32   mean_age_37
  -----   ---   -----   -----
      1      0      0      -0.28978      0.072789      0.36537      0.53629      0.6243
      2      1      0       0.54315      1.0162       1.3575       1.5014       1.5291
      3      0      1       0.77529      1.038        1.2458       1.3693       1.4312
      4      1      1       1.5269       1.8159       2.0249       2.1129       2.1219

% Aprime Choice
tb_az_ap = ff_summ_nd_array("MEAN(AP(EKM,J))", ap_VFI, true, ["mean"], 3, 1, cl_mp_datasetdesc, ar_p
```

```
xxx MEAN(AP(EKM,J)) xxxxxxxxxxxxxxxxxxxxxxxxxxxxxxxxxxxx
```

group	edu	marry	mean_age_19	mean_age_22	mean_age_27	mean_age_32	mean_age_37
1	0	0	12.989	12.979	13.035	13.093	13.131
2	1	0	12.832	12.789	12.987	13.128	13.197
3	0	1	12.933	12.923	12.976	13.021	13.072
4	1	1	12.76	12.717	12.917	13.037	13.128

% Consumption Choices

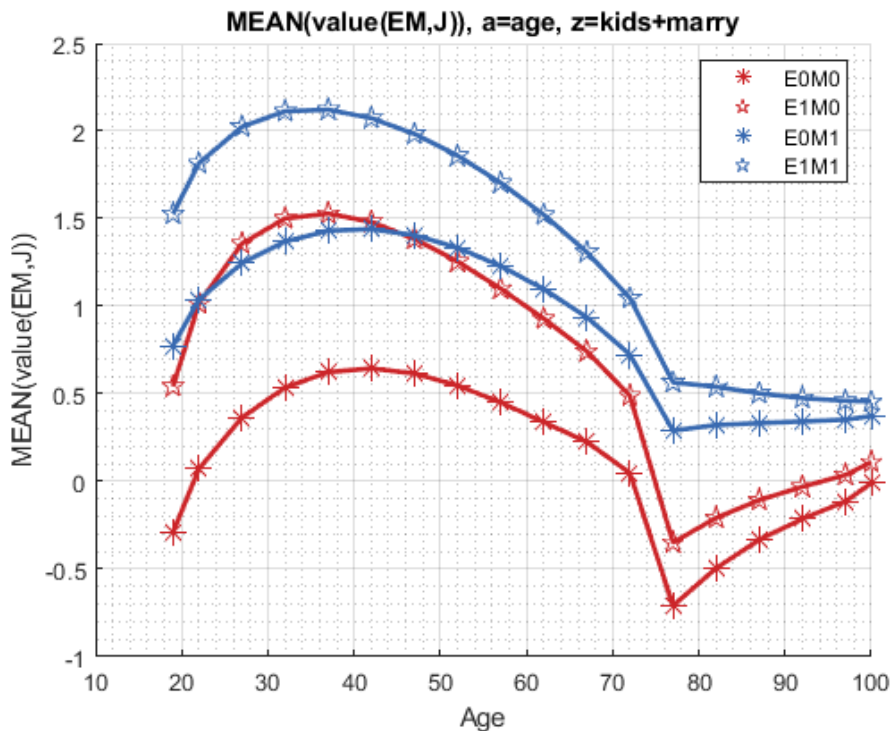
```
tb_az_c = ff_summ_nd_array("MEAN(C(EKM,J))", cons_VFI, true, ["mean"], 3, 1, cl_mp_datasetdesc, ar_p
```

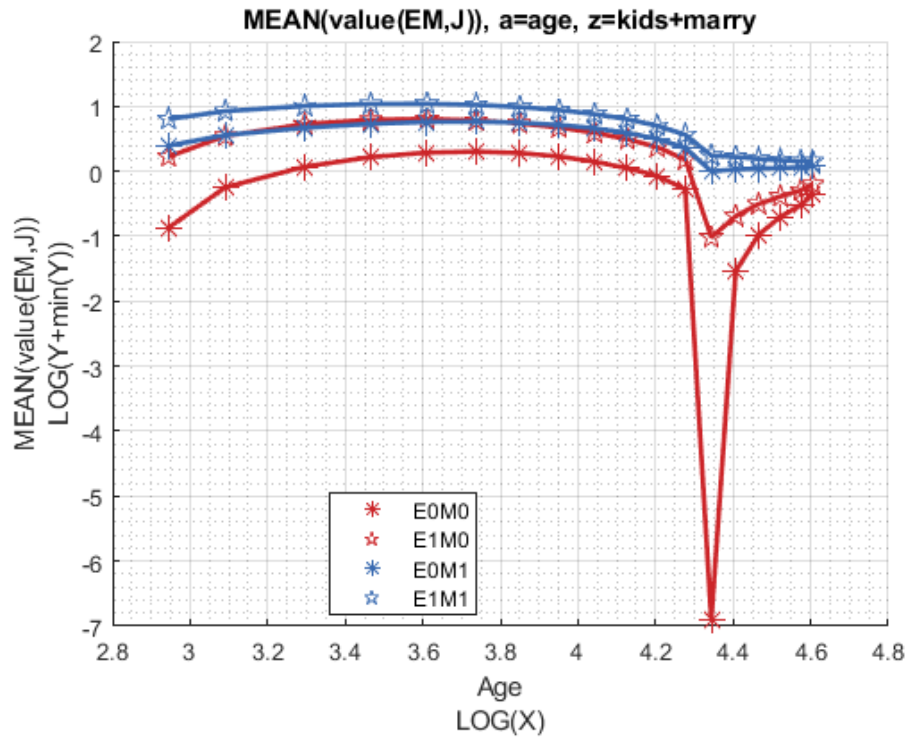
```
xxx MEAN(C(EKM,J)) xxxxxxxxxxxxxxxxxxxxxxxxxxxxxxxxxxxx
```

group	edu	marry	mean_age_19	mean_age_22	mean_age_27	mean_age_32	mean_age_37
1	0	0	6.6262	6.69	6.8285	6.9343	7.2515
2	1	0	6.6738	6.8246	7.1501	7.3841	7.6483
3	0	1	6.8114	6.8929	7.0479	7.1732	7.26
4	1	1	6.9273	7.0952	7.4299	7.692	7.848

Graph Mean Values:

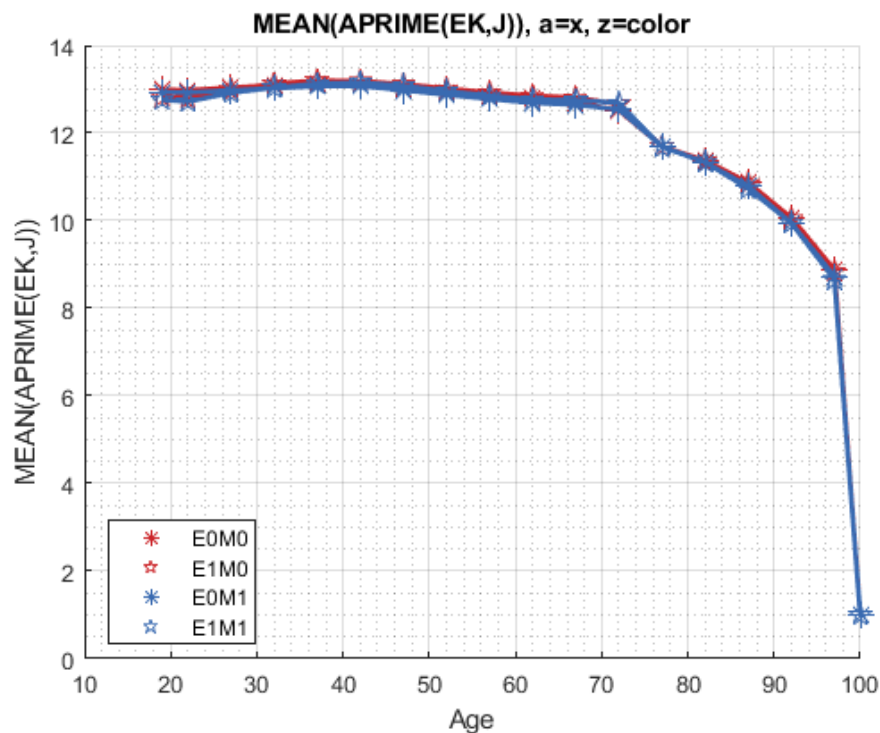
```
mp_support_graph('cl_st_graph_title') = {'MEAN(value(EM,J)), a=age, z=kids+marry'};
mp_support_graph('cl_st_ytitle') = {'MEAN(value(EM,J))'};
ff_graph_grid((tb_az_v{1:end, 4:end}), ar_row_grid, age_grid, mp_support_graph);
```

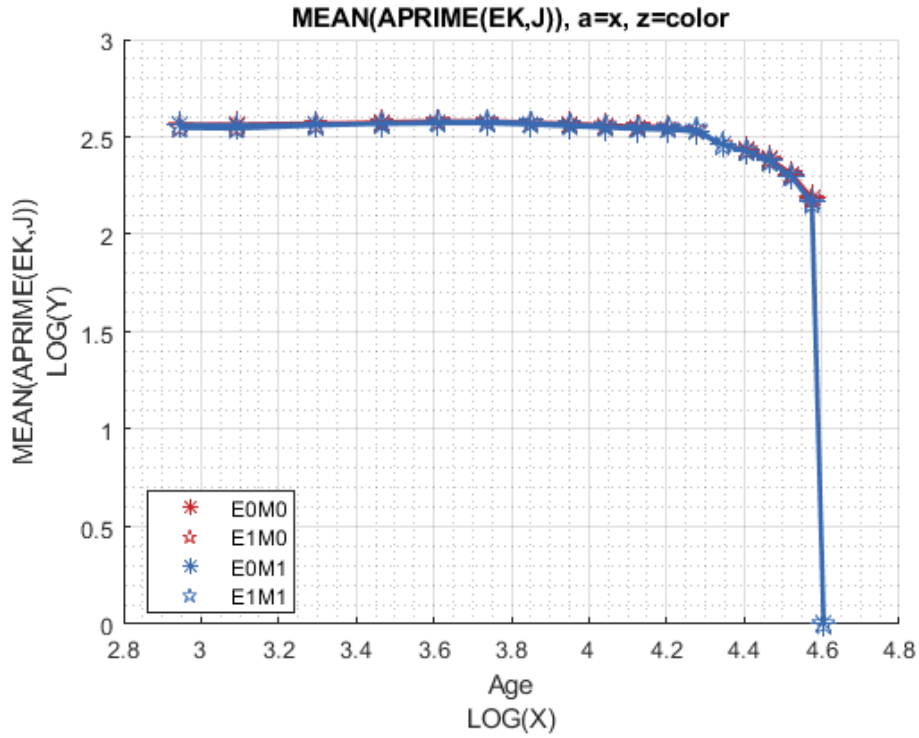




Graph Mean Savings Choices:

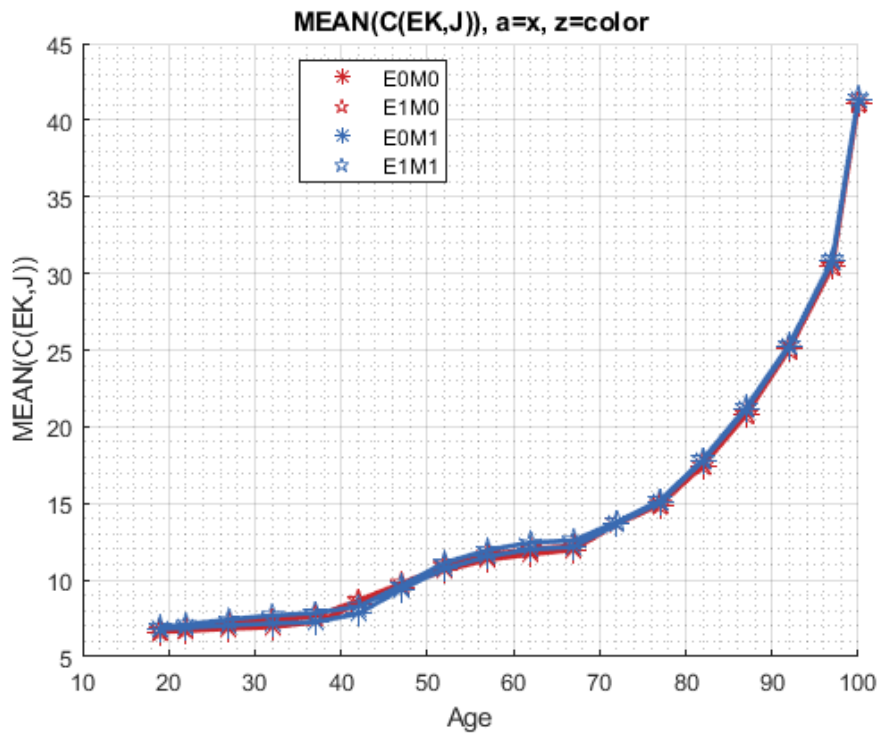
```
mp_support_graph('cl_st_graph_title') = {'MEAN(APRIME(EK,J)), a=x, z=color'};
mp_support_graph('cl_st_ytitle') = {'MEAN(APRIME(EK,J))'};
ff_graph_grid((tb_az_ap{1:end, 4:end}), ar_row_grid, age_grid, mp_support_graph);
```

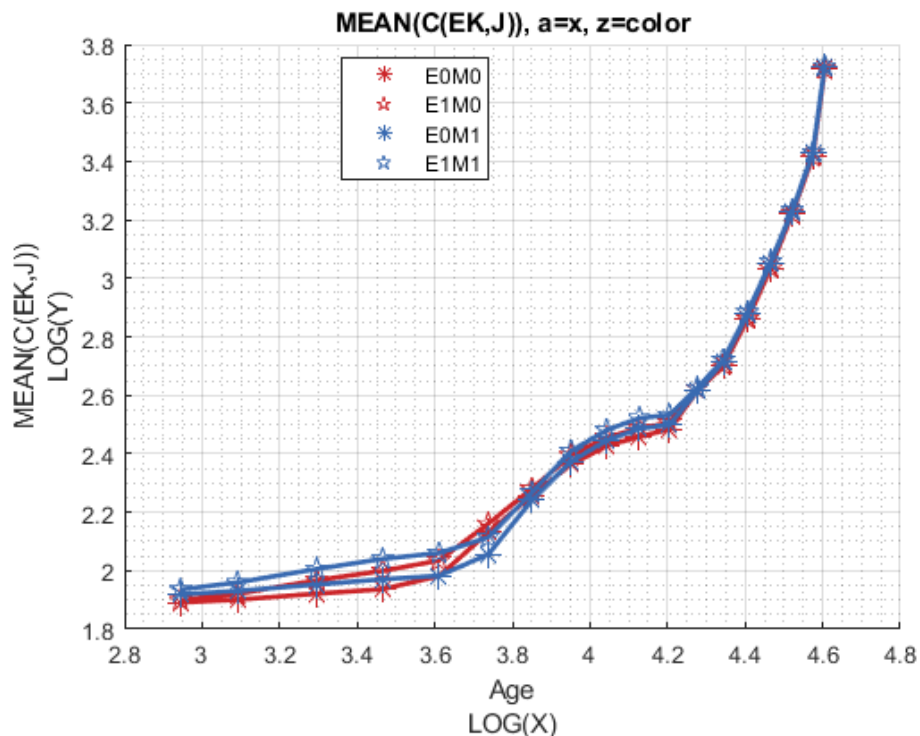




Graph Mean Consumption:

```
mp_support_graph('cl_st_graph_title') = {'MEAN(C(EK,J)), a=x, z=color'};
mp_support_graph('cl_st_ytitle') = {'MEAN(C(EK,J))'};
ff_graph_grid((tb_az_c{1:end, 4:end}), ar_row_grid, age_grid, mp_support_graph);
```





### 4.3 Small Test Exact Solution Vectorized Bisection

This is the example vignette for function: `snw_vfi_main_bisec_vec` from the [PrjOptiSNW Package](#). This function solves for policy function with vectorized bisection. Small Solution Analysis. Small Solution Analysis, husband 5 shocks, wife 1 shocks.

#### 4.3.1 Test SNW\_VFI\_MAIN Defaults Small

Call the function with defaults parameters.

```
mp_param = snw_mp_param('default_small');
[V_VFI,ap_VFI,cons_VFI,mp_valpol_more] = snw_vfi_main_bisec_vec(mp_param);
```

```
SNW_VFI_MAIN_BISEC_VEC: Finished Age Group:18 of 17, time-this-age:0.06059
SNW_VFI_MAIN_BISEC_VEC: Finished Age Group:17 of 17, time-this-age:0.052828
SNW_VFI_MAIN_BISEC_VEC: Finished Age Group:16 of 17, time-this-age:0.032745
SNW_VFI_MAIN_BISEC_VEC: Finished Age Group:15 of 17, time-this-age:0.029085
SNW_VFI_MAIN_BISEC_VEC: Finished Age Group:14 of 17, time-this-age:0.035583
SNW_VFI_MAIN_BISEC_VEC: Finished Age Group:13 of 17, time-this-age:0.034991
SNW_VFI_MAIN_BISEC_VEC: Finished Age Group:12 of 17, time-this-age:0.033648
SNW_VFI_MAIN_BISEC_VEC: Finished Age Group:11 of 17, time-this-age:0.032963
SNW_VFI_MAIN_BISEC_VEC: Finished Age Group:10 of 17, time-this-age:0.033174
SNW_VFI_MAIN_BISEC_VEC: Finished Age Group:9 of 17, time-this-age:0.036843
SNW_VFI_MAIN_BISEC_VEC: Finished Age Group:8 of 17, time-this-age:0.04052
SNW_VFI_MAIN_BISEC_VEC: Finished Age Group:7 of 17, time-this-age:0.028633
SNW_VFI_MAIN_BISEC_VEC: Finished Age Group:6 of 17, time-this-age:0.035108
SNW_VFI_MAIN_BISEC_VEC: Finished Age Group:5 of 17, time-this-age:0.033838
SNW_VFI_MAIN_BISEC_VEC: Finished Age Group:4 of 17, time-this-age:0.033585
SNW_VFI_MAIN_BISEC_VEC: Finished Age Group:3 of 17, time-this-age:0.03214
SNW_VFI_MAIN_BISEC_VEC: Finished Age Group:2 of 17, time-this-age:0.028888
SNW_VFI_MAIN_BISEC_VEC: Finished Age Group:1 of 17, time-this-age:0.031611
Completed SNW_VFI_MAIN_BISEC_VEC;SNW_MP_PARAM=default_small;SNW_MP_CONTROL=default_base;time=0.72345
```

### 4.3.2 Small Param Results Define Frames

Define the matrix dimensions names and dimension vector values. Policy and Value Functions share the same ND dimensional structure.

```
% Grids:
age_grid = [19, 22:5:97, 100];
agrid = mp_param('agrid');
eta_H_grid = mp_param('eta_H_grid');
eta_S_grid = mp_param('eta_S_grid');
ar_st_eta_HS_grid = string(cellstr([num2str(eta_H_grid), 'hz=%3.2f;'], num2str(eta_S_grid), 'wz=%3.2f;'));
edu_grid = [0,1];
marry_grid = [0,1];
kids_grid = (1:1:mp_param('n_kidsgrid'))';
% NaN(n_jgrid,n_agrid,n_etagrid,n_educgrid,n_marriedgrid,n_kidsgrid);
cl_mp_datasetdesc = {};
cl_mp_datasetdesc{1} = containers.Map({'name', 'labval'}, {'age', age_grid});
cl_mp_datasetdesc{2} = containers.Map({'name', 'labval'}, {'savings', agrid});
cl_mp_datasetdesc{3} = containers.Map({'name', 'labval'}, {'Hshock', eta_H_grid});
cl_mp_datasetdesc{4} = containers.Map({'name', 'labval'}, {'edu', edu_grid});
cl_mp_datasetdesc{5} = containers.Map({'name', 'labval'}, {'marry', marry_grid});
cl_mp_datasetdesc{6} = containers.Map({'name', 'labval'}, {'kids', kids_grid});
```

### 4.3.3 Analyze Savings and Shocks

First, analyze Savings Levels and Shocks, Aggregate Over All Others, and do various other calculations.

```
% Generate some Data
mp_support_graph = containers.Map('KeyType', 'char', 'ValueType', 'any');
mp_support_graph('cl_st_xtitle') = {'Savings States, a'};
mp_support_graph('st_legend_loc') = 'best';
mp_support_graph('bl_graph_logy') = true; % do not log

MEAN(VAL(A,Z)), MEAN(AP(A,Z)), MEAN(C(A,Z))

Tabulate value and policies along savings and shocks:

% Set
% NaN(n_jgrid,n_agrid,n_etagrid,n_educgrid,n_marriedgrid,n_kidsgrid);
ar_permute = [1,4,5,6,3,2];
% Value Function
tb_az_v = ff_summ_nd_array("MEAN(VAL(A,Z))", V_VFI, true, ["mean"], 4, 1, cl_mp_datasetdesc, ar_permute);

xxx MEAN(VAL(A,Z)) xxxxxxxxxxxxxxxxxxxxxxxxxxxxxxxxxxxx
      group      savings      mean_Hshock__1_8395      mean_Hshock__0_91976      mean_Hshock_0      mean_Hshock_1
      -----      -
      1              0              -21.426              -13.175              -8.362              -5.4
      2      0.0097656      -20.989              -13.027              -8.2755              -5.4
      3      0.078125      -18.901              -12.204              -7.8053              -5.0
      4      0.26367      -15.612              -10.744              -7.0124              -4.4
      5      0.625      -12.124              -8.9835              -6.0664              -3.8
      6      1.2207      -9.0979              -7.2177              -5.0967              -3.3
      7      2.1094      -6.7401              -5.6532              -4.2107              -2.8
      8      3.3496      -4.9967              -4.3739              -3.4359              -2.4
      9              5      -3.7353              -3.3758              -2.7788              -2.0
     10      7.1191      -2.8279              -2.617              -2.2393              -1.7
     11      9.7656      -2.172              -2.0455              -1.8057              -1.4
     12     12.998      -1.693              -1.6153              -1.4614              -1.2
     13     16.875      -1.3389              -1.2899              -1.1896              -1.0
     14     21.455      -1.0737              -1.042              -0.97552              -0.85
```

15	26.797	-0.872	-0.85104	-0.80614	-0.71
16	32.959	-0.71656	-0.70236	-0.67148	-0.61
17	40	-0.59521	-0.58538	-0.56375	-0.5
18	47.979	-0.49932	-0.49238	-0.47697	-0.44
19	56.953	-0.42266	-0.41768	-0.40651	-0.38
20	66.982	-0.36074	-0.3571	-0.34889	-0.33
21	78.125	-0.31022	-0.30751	-0.30139	-0.28
22	90.439	-0.26861	-0.26658	-0.26196	-0.25
23	103.98	-0.23407	-0.23252	-0.22899	-0.22
24	118.82	-0.20516	-0.20397	-0.20125	-0.19
25	135	-0.1808	-0.17987	-0.17775	-0.17

% Aprime Choice

tb\_az\_ap = ff\_summ\_nd\_array("MEAN(AP(A,Z))", ap\_VFI, true, ["mean"], 4, 1, cl\_mp\_datasetdesc, ar\_per

```
xxx MEAN(AP(A,Z)) xxxxxxxxxxxxxxxxxxxxxxxxxxxxxxxxxxxx
```

group	savings	mean_Hshock__1_8395	mean_Hshock__0_91976	mean_Hshock_0	mean_Hshoc
-----	-----	-----	-----	-----	-----
1	0	3.2159e-05	0.0034995	0.049878	0.24
2	0.0097656	0.00055365	0.0052722	0.053281	0.24
3	0.078125	0.021863	0.029676	0.083029	0.2
4	0.26367	0.13323	0.14751	0.20012	0.38
5	0.625	0.39134	0.41034	0.45315	0.64
6	1.2207	0.84131	0.86393	0.91226	1.0
7	2.1094	1.5303	1.5542	1.6156	1.7
8	3.3496	2.4876	2.5118	2.573	2.6
9	5	3.7642	3.7887	3.8498	3.9
10	7.1191	5.4275	5.4525	5.5145	5.6
11	9.7656	7.4794	7.5043	7.5679	7.7
12	12.998	9.9124	9.9329	9.9956	10.
13	16.875	12.928	12.95	13.005	13.
14	21.455	16.529	16.548	16.604	16.
15	26.797	20.601	20.618	20.668	20.
16	32.959	25.307	25.325	25.37	25.
17	40	30.667	30.689	30.742	30.
18	47.979	36.761	36.782	36.841	36.
19	56.953	43.773	43.795	43.847	44.
20	66.982	51.605	51.628	51.688	51
21	78.125	59.954	59.977	60.037	60.
22	90.439	69.265	69.288	69.35	69.
23	103.98	79.75	79.771	79.831	80
24	118.82	91.112	91.136	91.198	91.
25	135	103.47	103.49	103.54	103

% Consumption Choices

tb\_az\_c = ff\_summ\_nd\_array("MEAN(C(A,Z))", cons\_VFI, true, ["mean"], 4, 1, cl\_mp\_datasetdesc, ar\_per

```
xxx MEAN(C(A,Z)) xxxxxxxxxxxxxxxxxxxxxxxxxxxxxxxxxxxx
```

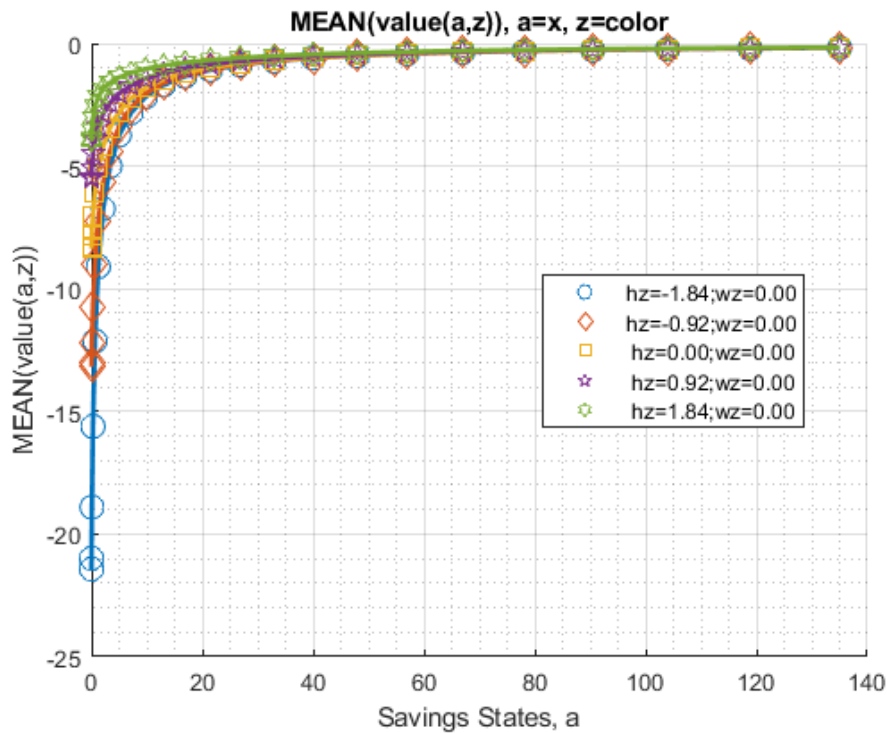
group	savings	mean_Hshock__1_8395	mean_Hshock__0_91976	mean_Hshock_0	mean_Hshoc
-----	-----	-----	-----	-----	-----
1	0	0.30273	0.43104	0.68779	1.21
2	0.0097656	0.31374	0.44074	0.69581	1.22
3	0.078125	0.37308	0.49663	0.74605	1.2
4	0.26367	0.48039	0.59659	0.846	1.37
5	0.625	0.64735	0.75745	1.0153	1.54
6	1.2207	0.89649	1.0013	1.2519	1.79

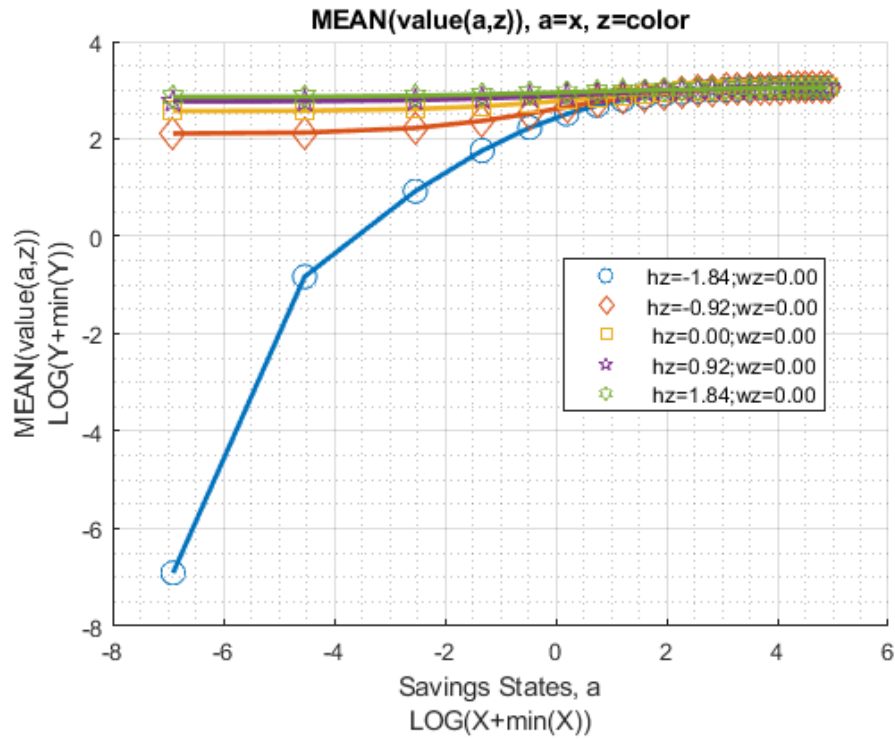


7	2.1094	1.2479	1.3498	1.5854	2.16
8	3.3496	1.7393	1.8394	2.0734	2.67
9	5	2.3872	2.4859	2.7182	3.29
10	7.1191	3.1917	3.289	3.5191	4.05
11	9.7656	4.2188	4.3155	4.543	5.
12	12.998	5.5439	5.6447	5.8722	6.39
13	16.875	7.0334	7.133	7.3676	7.88
14	21.455	8.754	8.8551	9.0887	9.61
15	26.797	10.886	10.989	11.228	11.7
16	32.959	13.336	13.439	13.682	14.2
17	40	16.151	16.249	16.485	17.0
18	47.979	19.321	19.42	19.65	20
19	56.953	22.728	22.827	23.062	23.6
20	66.982	26.539	26.637	26.865	27.
21	78.125	31.125	31.222	31.451	31.9
22	90.439	36.11	36.207	36.433	36.9
23	103.98	41.348	41.447	41.676	42.
24	118.82	47.206	47.302	47.528	48.
25	135	53.636	53.735	53.966	54.5

Graph Mean Values:

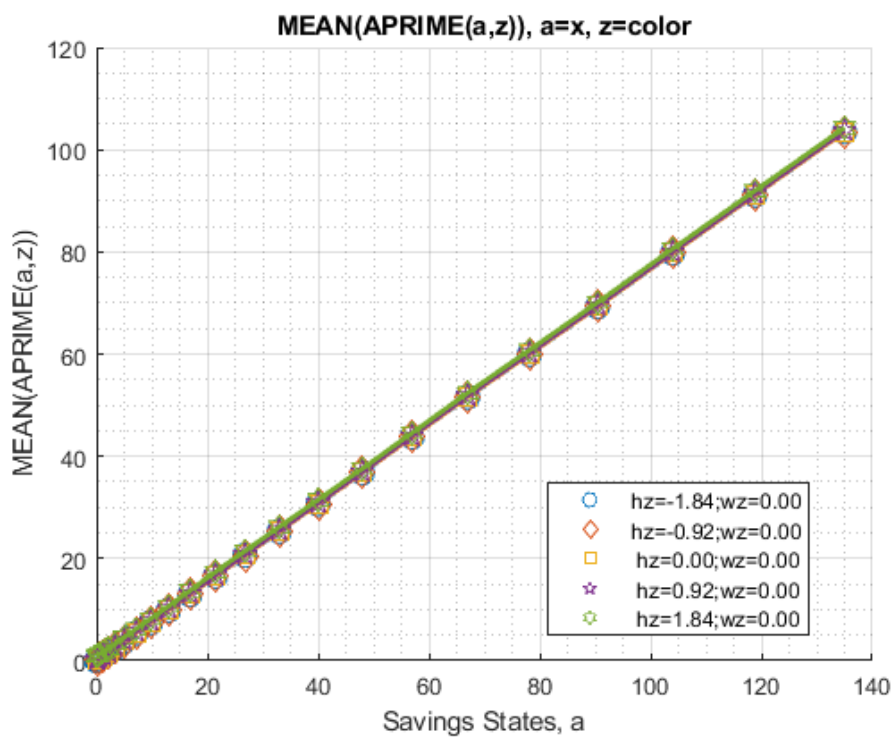
```
mp_support_graph('cl_st_graph_title') = {'MEAN(value(a,z)), a=x, z=color'};
mp_support_graph('cl_st_ytitle') = {'MEAN(value(a,z))'};
ff_graph_grid((tb_az_v{1:end, 3:end})', ar_st_eta_HS_grid, agrid, mp_support_graph);
```

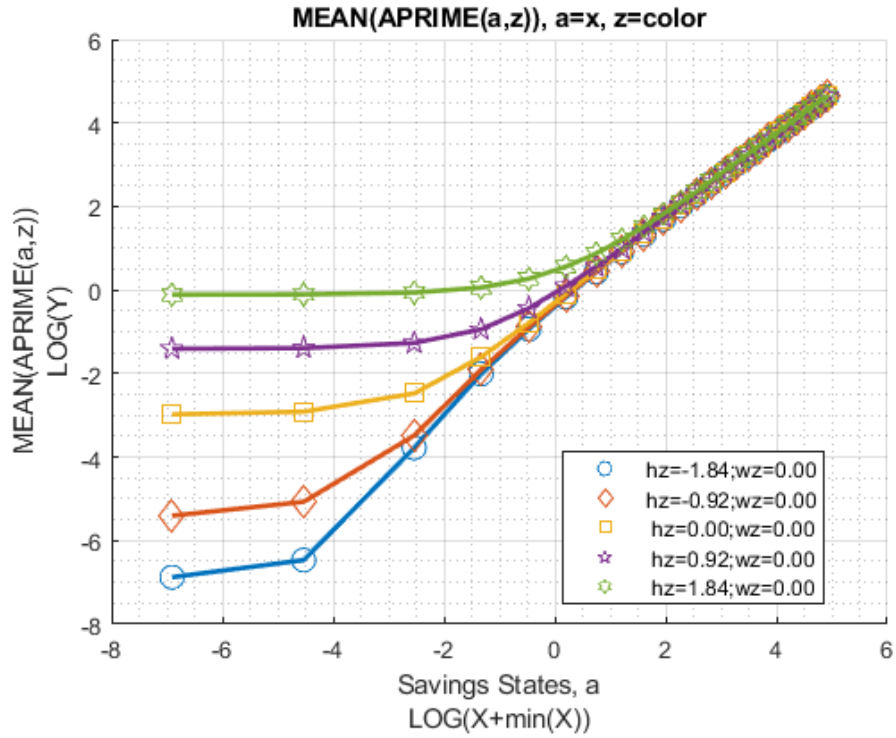




Graph Mean Savings Choices:

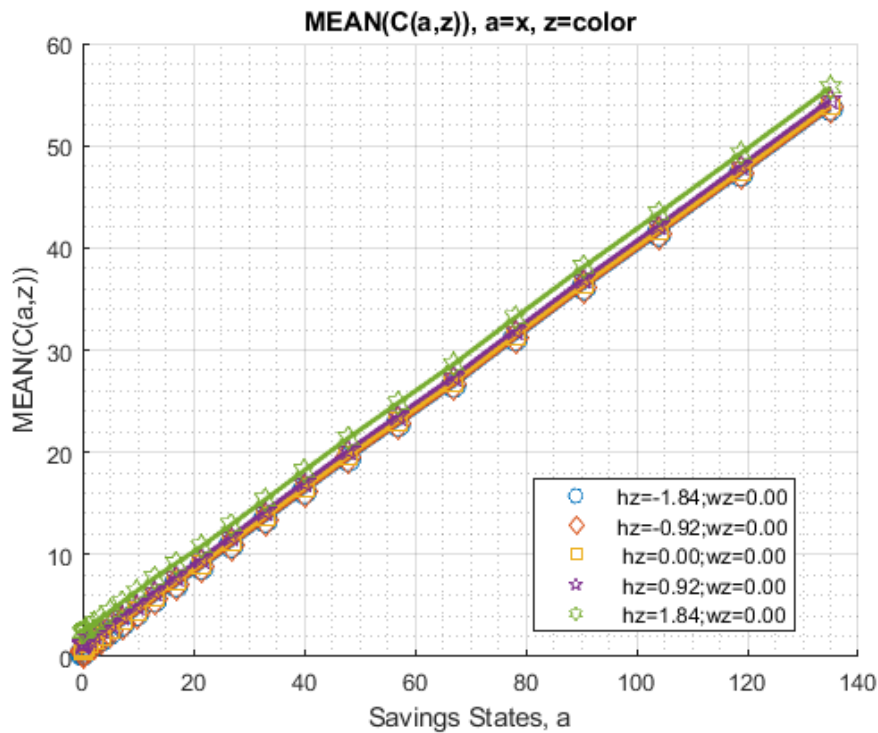
```
mp_support_graph('cl_st_graph_title') = {'MEAN(APRIME(a,z)), a=x, z=color'};
mp_support_graph('cl_st_ytitle') = {'MEAN(APRIME(a,z))'};
ff_graph_grid((tb_az_ap{1:end, 3:end})', ar_st_eta_HS_grid, agrid, mp_support_graph);
```

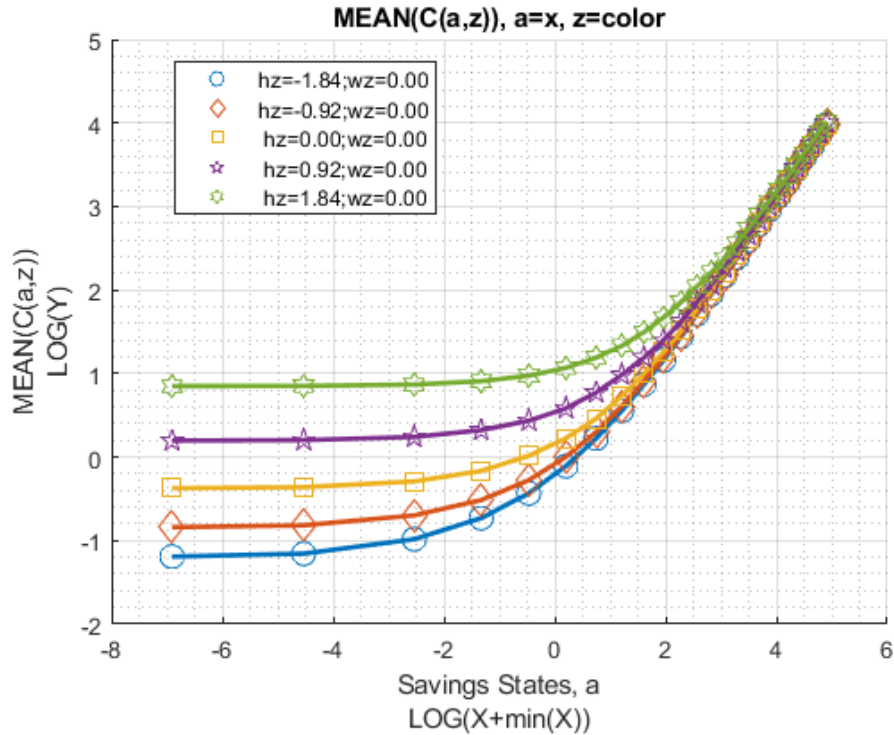




Graph Mean Consumption:

```
mp_support_graph('cl_st_graph_title') = {'MEAN(C(a,z)), a=x, z=color'};
mp_support_graph('cl_st_ytitle') = {'MEAN(C(a,z))'};
ff_graph_grid((tb_az_c{1:end, 3:end})', ar_st_eta_HS_grid, agrid, mp_support_graph);
```





#### 4.3.4 Analyze Kids and Marriage and Age

Aggregating over education, savings, and shocks, what are the differential effects of Marriage and Age.

```
% Generate some Data
mp_support_graph = containers.Map('KeyType', 'char', 'ValueType', 'any');
ar_row_grid = ["k0M0", "K1M0", "K2M0", "k0M1", "K1M1", "K2M1"];
mp_support_graph('cl_st_xtitle') = {'Age'};
mp_support_graph('st_legend_loc') = 'best';
mp_support_graph('bl_graph_logy') = true; % do not log
mp_support_graph('st_rounding') = '6.2f'; % format shock legend
mp_support_graph('cl_scatter_shapes') = {'o', 'd', 's', 'o', 'd', 's'};
mp_support_graph('cl_colors') = {'red', 'red', 'red', 'blue', 'blue', 'blue'};
```

```
MEAN(VAL(KM,J)), MEAN(AP(KM,J)), MEAN(C(KM,J))
```

Tabulate value and policies:

```
% Set
% NaN(n_jgrid,n_agrid,n_etagrid,n_educgrid,n_marriedgrid,n_kidsgrid);
ar_permute = [2,3,4,1,6,5];
% Value Function
tb_az_v = ff_summ_nd_array("MEAN(VAL(KM,J))", V_VFI, true, ["mean"], 3, 1, cl_mp_datasetdesc, ar_per
```

```
xxx MEAN(VAL(KM,J)) xxxxxxxxxxxxxxxxxxxxxxxxxxxxxxxxxxxx
  group  kids  marry  mean_age_19  mean_age_22  mean_age_27  mean_age_32  mean_age_3
-----  ----  -----  -
      1     1     0     -4.7384     -4.2839     -3.9125     -3.6403     -3.4202
      2     2     0     -6.2307     -5.5732     -5.014      -4.5943     -4.2483
      3     3     0     -6.9818     -6.3368     -5.7685     -5.3334     -4.9708
      4     1     1     -4.1822     -3.7934     -3.4691     -3.2086     -2.984
      5     2     1     -5.157      -4.667      -4.2348     -3.8784     -3.5654
      6     3     1     -5.5929     -5.1267     -4.7056     -4.352      -4.0378
```

```
% Aprime Choice
```

```
tb_az_ap = ff_summ_nd_array("MEAN(AP(KM,J))", ap_VFI, true, ["mean"], 3, 1, cl_mp_datasetdesc, ar_pe
```

```
xxx MEAN(AP(KM,J)) xxxxxxxxxxxxxxxxxxxxxxxxxxxxxxxxxxxx
```

group	kids	marry	mean_age_19	mean_age_22	mean_age_27	mean_age_32	mean_age_3
1	1	0	34.931	34.726	34.665	34.554	34.362
2	2	0	34.603	34.334	34.198	33.995	33.692
3	3	0	34.187	33.968	33.877	33.705	33.427
4	1	1	34.821	34.617	34.566	34.458	34.268
5	2	1	34.67	34.45	34.364	34.205	33.951
6	3	1	34.303	34.118	34.065	33.937	33.705

% Consumption Choices

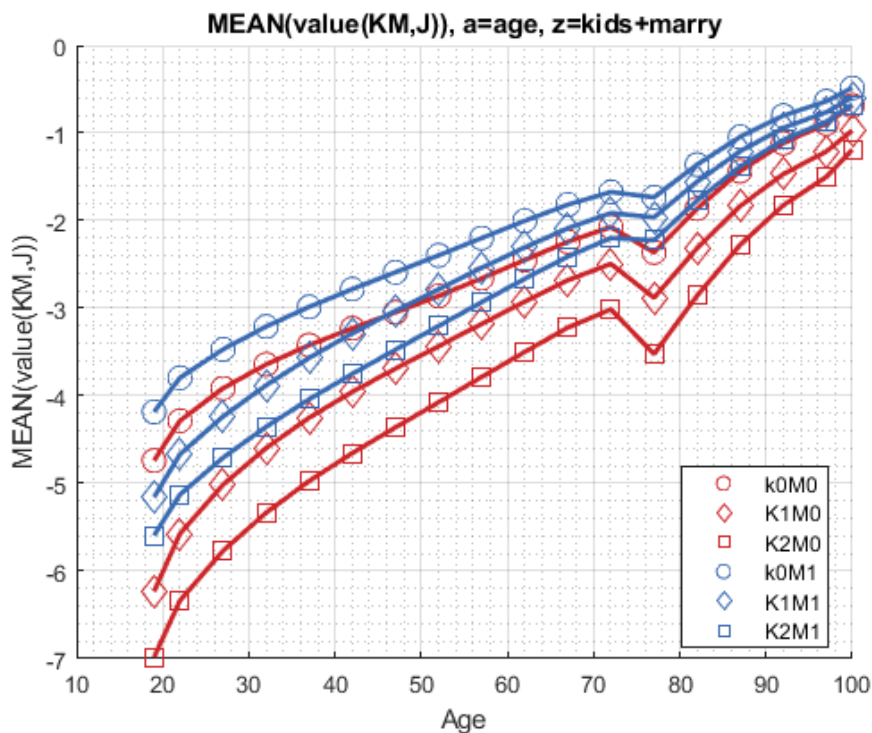
```
tb_az_c = ff_summ_nd_array("MEAN(C(KM,J))", cons_VFI, true, ["mean"], 3, 1, cl_mp_datasetdesc, ar_pe
```

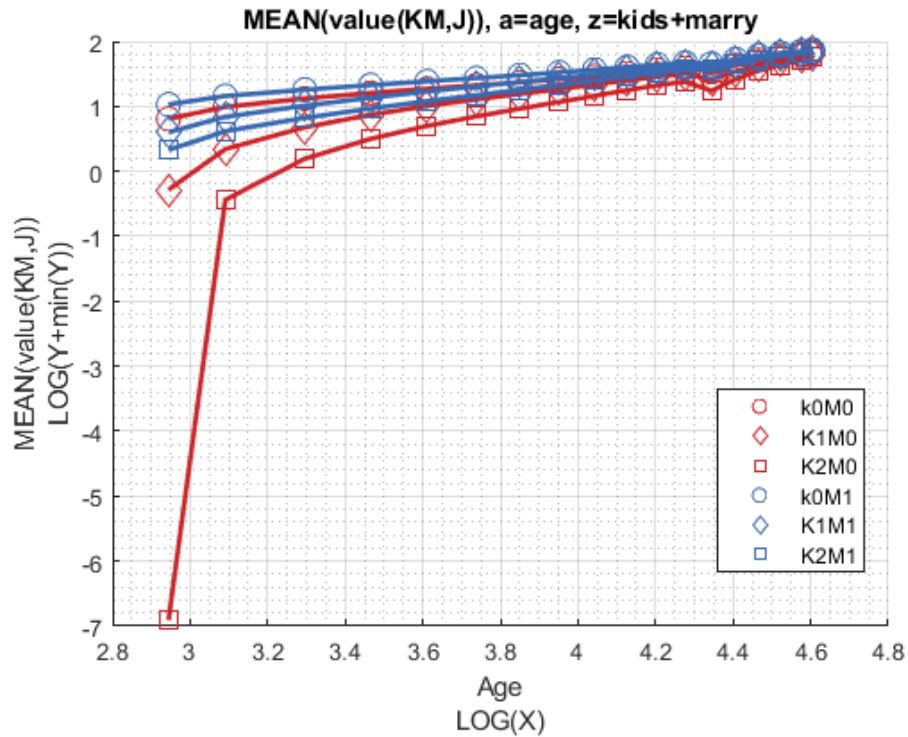
```
xxx MEAN(C(KM,J)) xxxxxxxxxxxxxxxxxxxxxxxxxxxxxxxxxxxx
```

group	kids	marry	mean_age_19	mean_age_22	mean_age_27	mean_age_32	mean_age_3
1	1	0	6.8531	7.1729	7.4988	7.8167	8.1435
2	2	0	7.182	7.5653	7.9659	8.3756	8.813
3	3	0	7.5973	7.931	8.2872	8.6657	9.0783
4	1	1	7.1848	7.5242	7.8662	8.2047	8.552
5	2	1	7.3021	7.6535	8.0269	8.412	8.8205
6	3	1	7.6455	7.9599	8.297	8.6497	9.0324

Graph Mean Values:

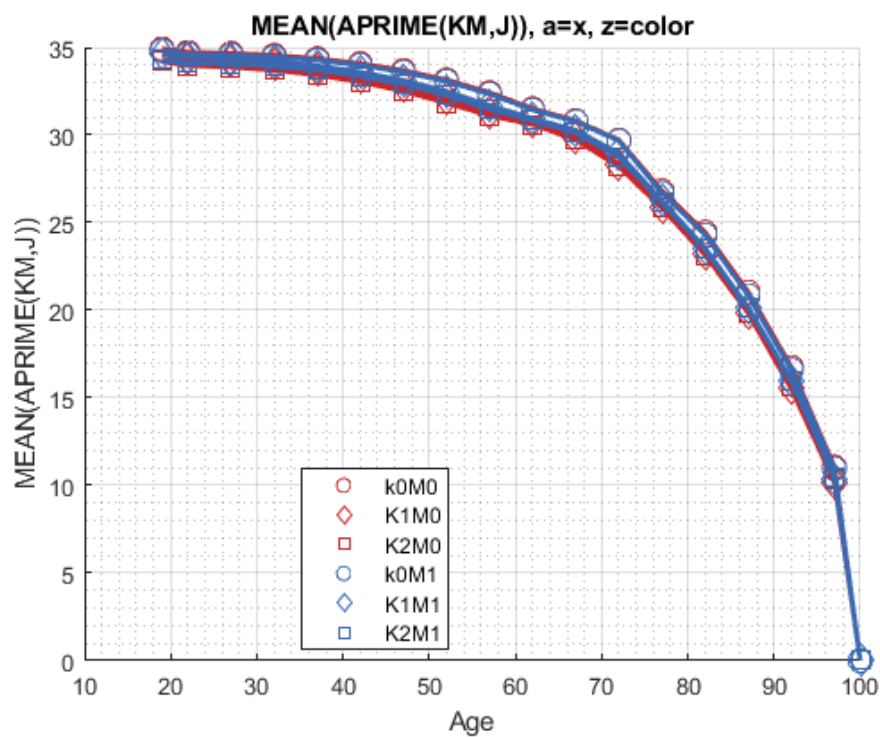
```
mp_support_graph('cl_st_graph_title') = {'MEAN(value(KM,J)), a=age, z=kids+marry'};
mp_support_graph('cl_st_ytitle') = {'MEAN(value(KM,J))'};
ff_graph_grid((tb_az_v{1:end, 4:end}), ar_row_grid, age_grid, mp_support_graph);
```

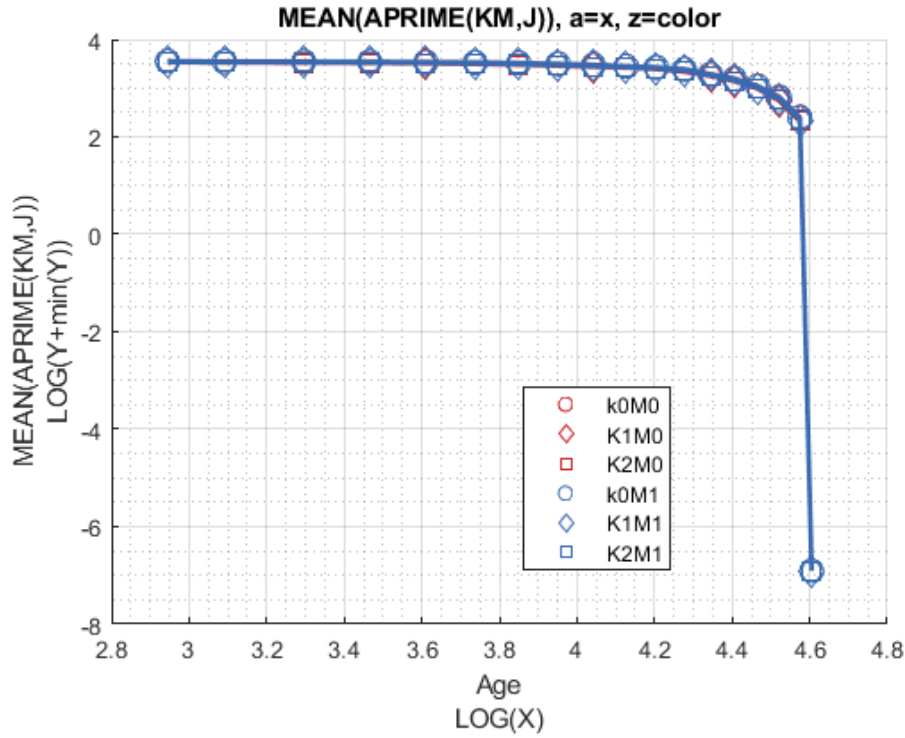




Graph Mean Savings Choices:

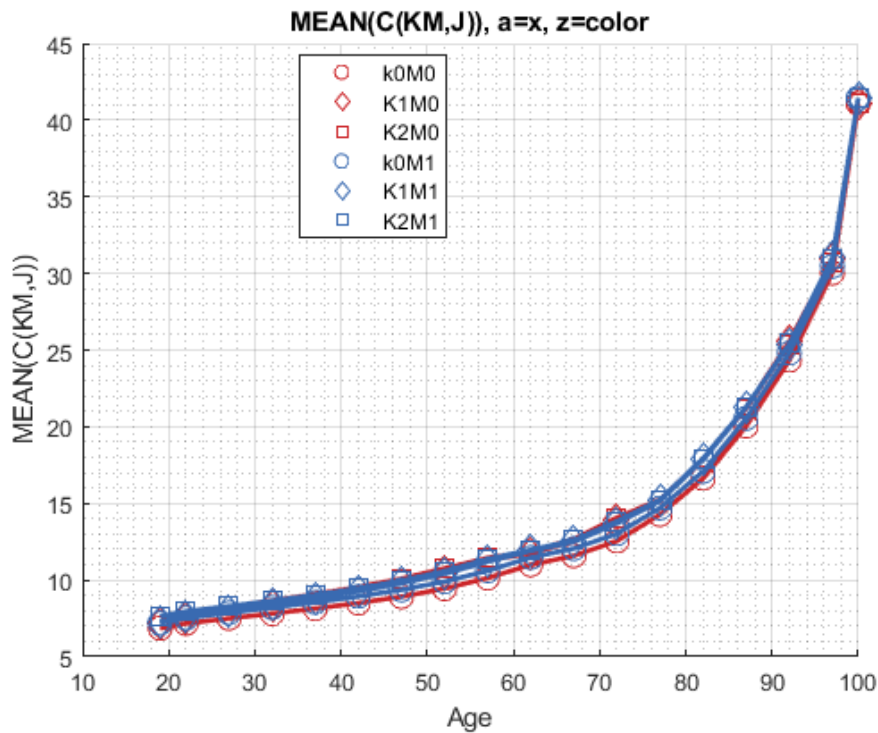
```
mp_support_graph('cl_st_graph_title') = {'MEAN(APRIME(KM,J)), a=x, z=color'};
mp_support_graph('cl_st_ytitle') = {'MEAN(APRIME(KM,J))'};
ff_graph_grid((tb_az_ap{1:end, 4:end}), ar_row_grid, age_grid, mp_support_graph);
```

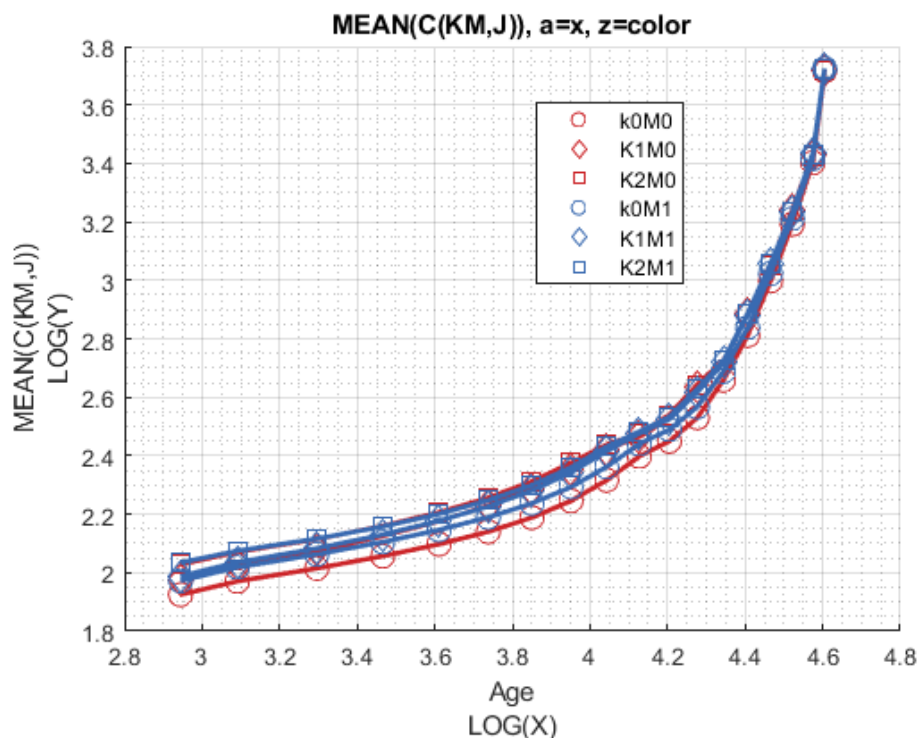




Graph Mean Consumption:

```
mp_support_graph('cl_st_graph_title') = {'MEAN(C(KM,J)), a=x, z=color'};
mp_support_graph('cl_st_ytitle') = {'MEAN(C(KM,J))'};
ff_graph_grid((tb_az_c{1:end, 4:end}), ar_row_grid, age_grid, mp_support_graph);
```





### 4.3.5 Analyze Education and Marriage and Age

Aggregating over education, savings, and shocks, what are the differential effects of Marriage and Age.

```
% Generate some Data
mp_support_graph = containers.Map('KeyType', 'char', 'ValueType', 'any');
ar_row_grid = ["E0M0", "E1M0", "E0M1", "E1M1"];
mp_support_graph('cl_st_xtitle') = {'Age'};
mp_support_graph('st_legend_loc') = 'best';
mp_support_graph('bl_graph_logy') = true; % do not log
mp_support_graph('st_rounding') = '6.2f'; % format shock legend
mp_support_graph('cl_scatter_shapes') = {'*', 'p', '*', 'p'};
mp_support_graph('cl_colors') = {'red', 'red', 'blue', 'blue'};

MEAN(VAL(EKM,J)), MEAN(AP(EKM,J)), MEAN(C(EKM,J))

Tabulate value and policies:

% Set
% NaN(n_jgrid,n_agrid,n_etagrid,n_educgrid,n_marriedgrid,n_kidsgrid);
ar_permute = [2,3,6,1,4,5];
% Value Function
tb_az_v = ff_summ_nd_array("MEAN(VAL(EKM,J))", V_VFI, true, ["mean"], 3, 1, cl_mp_datasetdesc, ar_per

xxx MEAN(VAL(EKM,J)) xxxxxxxxxxxxxxxxxxxxxxxxxxxxxxxxxxxx
  group   edu   marry   mean_age_19   mean_age_22   mean_age_27   mean_age_32   mean_age_37
  -----   ---   -----   -----
      1     0     0       -6.4015      -5.8666      -5.3879      -4.9966      -4.6557
      2     1     0       -5.5658      -4.9294      -4.4088      -4.0487      -3.7705
      3     0     1        -5.35       -4.913       -4.5196      -4.1777      -3.867
      4     1     1       -4.6046      -4.1451      -3.7534      -3.4483      -3.1912

% Aprime Choice
tb_az_ap = ff_summ_nd_array("MEAN(AP(EKM,J))", ap_VFI, true, ["mean"], 3, 1, cl_mp_datasetdesc, ar_p
```



```
xxx MEAN(AP(EKM,J)) xxxxxxxxxxxxxxxxxxxxxxxxxxxxxxxxxxxx
```

group	edu	marry	mean_age_19	mean_age_22	mean_age_27	mean_age_32	mean_age_37
1	0	0	34.682	34.444	34.272	34.048	33.753
2	1	0	34.465	34.241	34.222	34.121	33.901
3	0	1	34.725	34.514	34.372	34.177	33.914
4	1	1	34.47	34.277	34.291	34.223	34.035

% Consumption Choices

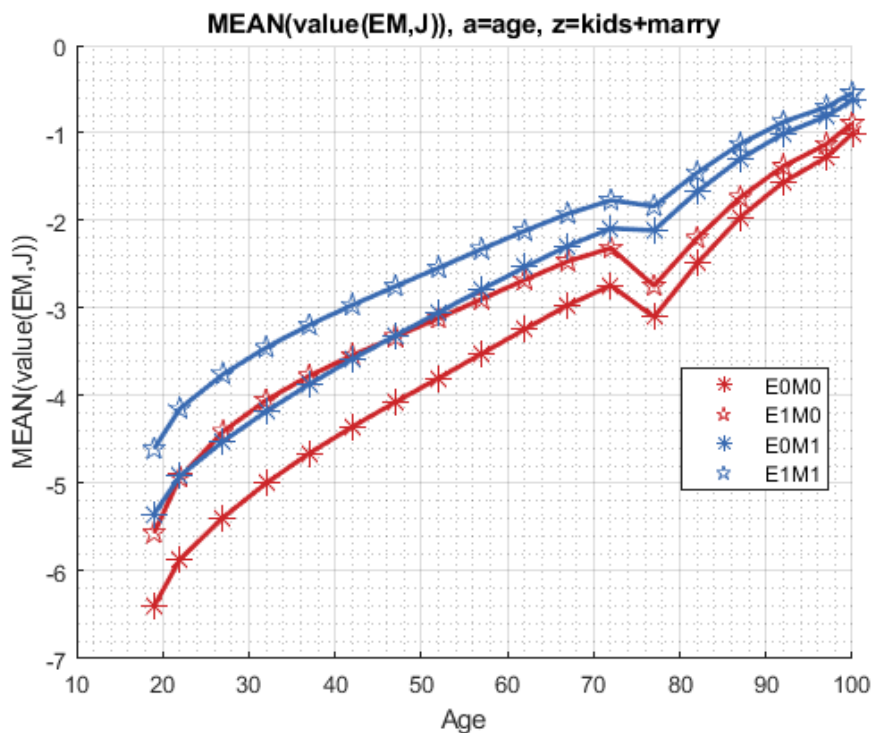
```
tb_az_c = ff_summ_nd_array("MEAN(C(EKM,J))", cons_VFI, true, ["mean"], 3, 1, cl_mp_datasetdesc, ar_p
```

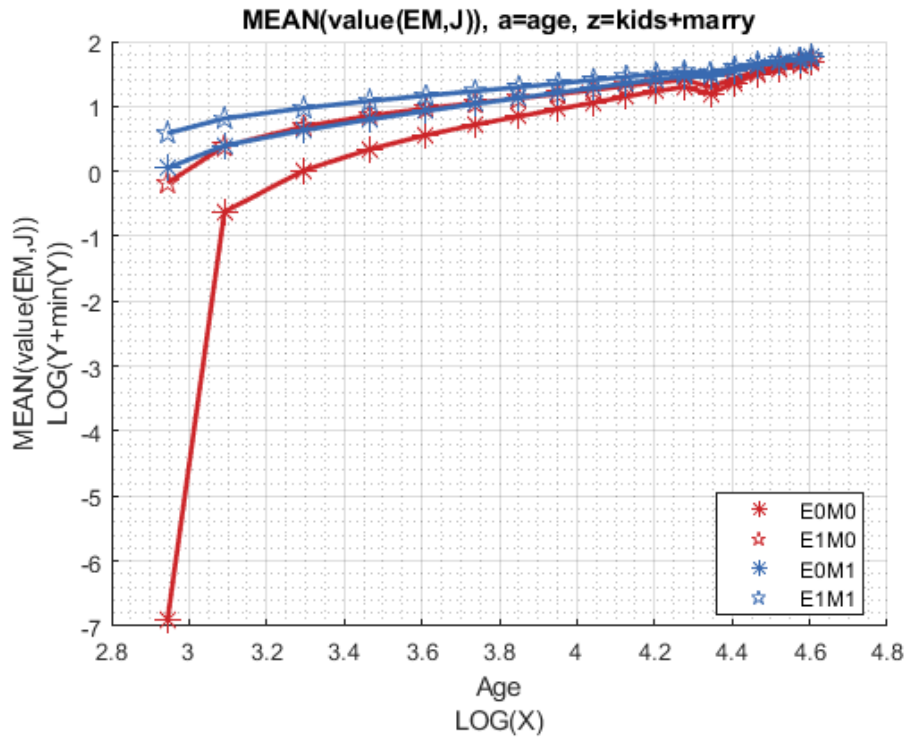
```
xxx MEAN(C(EKM,J)) xxxxxxxxxxxxxxxxxxxxxxxxxxxxxxxxxxxx
```

group	edu	marry	mean_age_19	mean_age_22	mean_age_27	mean_age_32	mean_age_37
1	0	0	7.1022	7.4087	7.7357	8.0845	8.4713
2	1	0	7.3195	7.7041	8.0988	8.4875	8.8852
3	0	1	7.2307	7.5253	7.8393	8.1757	8.5471
4	1	1	7.5242	7.8997	8.2875	8.6685	9.0562

Graph Mean Values:

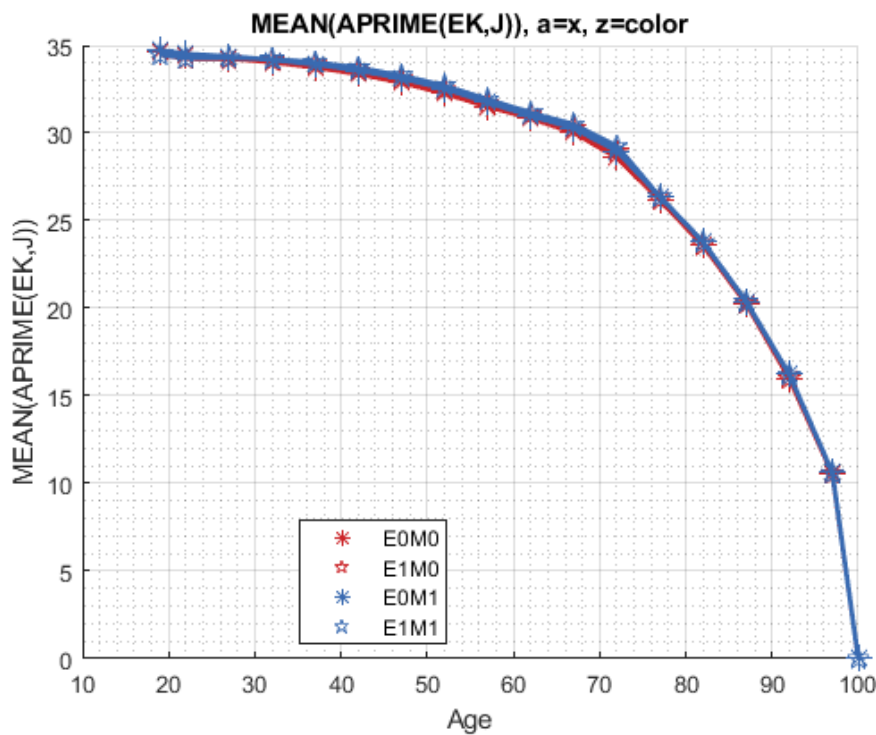
```
mp_support_graph('cl_st_graph_title') = {'MEAN(value(EM,J)), a=age, z=kids+marry'};
mp_support_graph('cl_st_ytitle') = {'MEAN(value(EM,J))'};
ff_graph_grid((tb_az_v{1:end, 4:end}), ar_row_grid, age_grid, mp_support_graph);
```

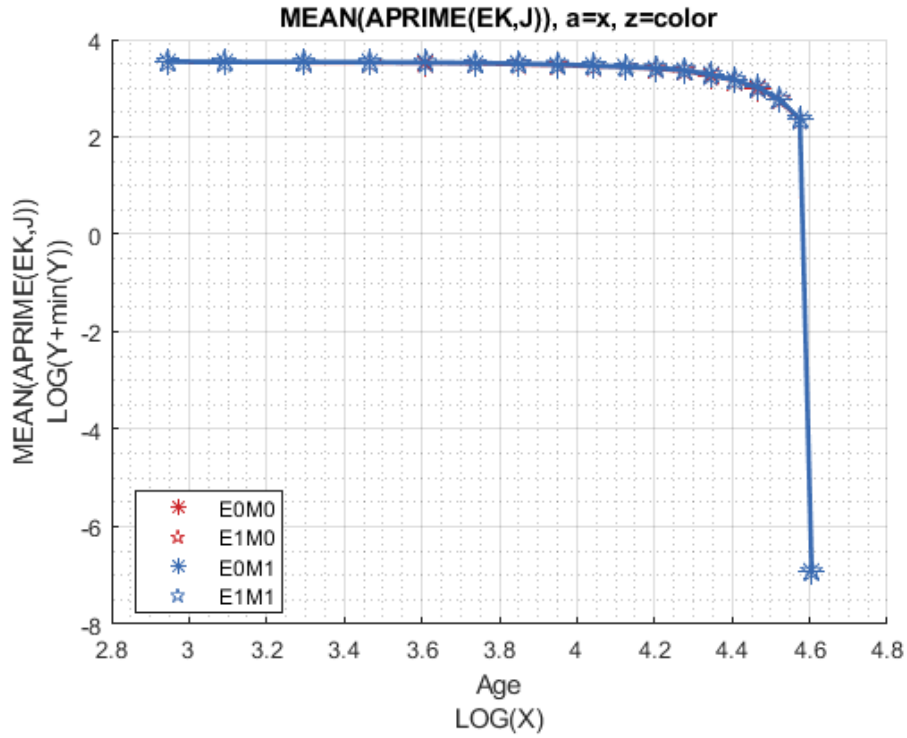




Graph Mean Savings Choices:

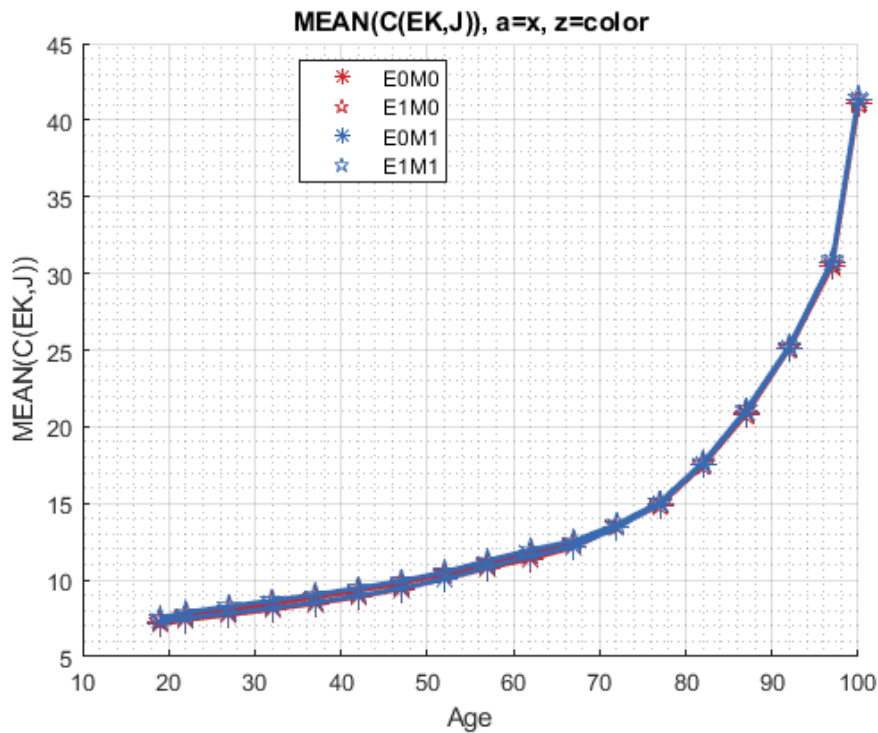
```
mp_support_graph('cl_st_graph_title') = {'MEAN(APRIME(EK,J)), a=x, z=color'};
mp_support_graph('cl_st_ytitle') = {'MEAN(APRIME(EK,J))'};
ff_graph_grid((tb_az_ap{1:end, 4:end}), ar_row_grid, age_grid, mp_support_graph);
```

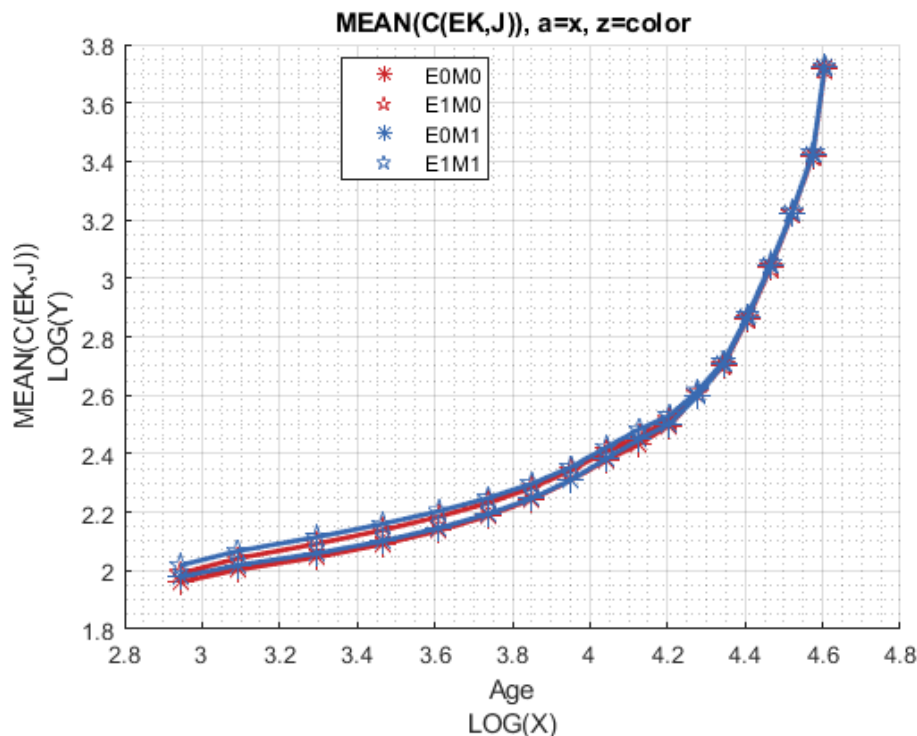




Graph Mean Consumption:

```
mp_support_graph('cl_st_graph_title') = {'MEAN(C(EK,J)), a=x, z=color'};
mp_support_graph('cl_st_ytitle') = {'MEAN(C(EK,J))'};
ff_graph_grid((tb_az_c{1:end, 4:end}), ar_row_grid, age_grid, mp_support_graph);
```





## 4.4 Small Test Exact Solution Spousal Shocks

This is the example vignette for function: `snw_vfi_main_bisec_vec` from the [PrjOptiSNW Package](#). This function solves for policy function with vectorized bisection. Small Solution Analysis, husband 5 shocks, wife 3 shocks.

### 4.4.1 Test SNW\_VFI\_MAIN Defaults Small

Call the function with default parameters.

```
mp_param = snw_mp_param('default_small153');
[V_VFI,ap_VFI,cons_VFI,mp_valpol_more] = snw_vfi_main_bisec_vec(mp_param);
```

```
SNW_VFI_MAIN_BISEC_VEC: Finished Age Group:18 of 17, time-this-age:0.10593
SNW_VFI_MAIN_BISEC_VEC: Finished Age Group:17 of 17, time-this-age:0.086471
SNW_VFI_MAIN_BISEC_VEC: Finished Age Group:16 of 17, time-this-age:0.079532
SNW_VFI_MAIN_BISEC_VEC: Finished Age Group:15 of 17, time-this-age:0.095977
SNW_VFI_MAIN_BISEC_VEC: Finished Age Group:14 of 17, time-this-age:0.081549
SNW_VFI_MAIN_BISEC_VEC: Finished Age Group:13 of 17, time-this-age:0.08703
SNW_VFI_MAIN_BISEC_VEC: Finished Age Group:12 of 17, time-this-age:0.089059
SNW_VFI_MAIN_BISEC_VEC: Finished Age Group:11 of 17, time-this-age:0.094402
SNW_VFI_MAIN_BISEC_VEC: Finished Age Group:10 of 17, time-this-age:0.10011
SNW_VFI_MAIN_BISEC_VEC: Finished Age Group:9 of 17, time-this-age:0.093424
SNW_VFI_MAIN_BISEC_VEC: Finished Age Group:8 of 17, time-this-age:0.095447
SNW_VFI_MAIN_BISEC_VEC: Finished Age Group:7 of 17, time-this-age:0.10832
SNW_VFI_MAIN_BISEC_VEC: Finished Age Group:6 of 17, time-this-age:0.089896
SNW_VFI_MAIN_BISEC_VEC: Finished Age Group:5 of 17, time-this-age:0.09249
SNW_VFI_MAIN_BISEC_VEC: Finished Age Group:4 of 17, time-this-age:0.094699
SNW_VFI_MAIN_BISEC_VEC: Finished Age Group:3 of 17, time-this-age:0.087703
SNW_VFI_MAIN_BISEC_VEC: Finished Age Group:2 of 17, time-this-age:0.0939
SNW_VFI_MAIN_BISEC_VEC: Finished Age Group:1 of 17, time-this-age:0.087152
Completed SNW_VFI_MAIN_BISEC_VEC;SNW_MP_PARAM=default_small153;SNW_MP_CONTROL=default_base;time=1.715
```

### 4.4.2 Small Param Results Define Frames

Define the matrix dimensions names and dimension vector values. Policy and Value Functions share the same ND dimensional structure.

```
% Grids:
age_grid = [19, 22:5:97, 100];
agrid = mp_param('agrid');
eta_H_grid = mp_param('eta_H_grid');
eta_S_grid = mp_param('eta_S_grid');
ar_st_eta_HS_grid = string(cellstr([num2str(eta_H_grid', 'hz=%3.2f;'), num2str(eta_S_grid', 'wz=%3.2f;')]);
edu_grid = [0,1];
marry_grid = [0,1];
kids_grid = (1:1:mp_param('n_kidsgrid'))';
% NaN(n_jgrid,n_agrid,n_etagrid,n_educgrid,n_marriedgrid,n_kidsgrid);
cl_mp_datasetdesc = {};
cl_mp_datasetdesc{1} = containers.Map({'name', 'labval'}, {'age', age_grid});
cl_mp_datasetdesc{2} = containers.Map({'name', 'labval'}, {'savings', agrid});
cl_mp_datasetdesc{3} = containers.Map({'name', 'labval'}, {'eta', 1:length(eta_H_grid)});
cl_mp_datasetdesc{4} = containers.Map({'name', 'labval'}, {'edu', edu_grid});
cl_mp_datasetdesc{5} = containers.Map({'name', 'labval'}, {'marry', marry_grid});
cl_mp_datasetdesc{6} = containers.Map({'name', 'labval'}, {'kids', kids_grid});
```

### 4.4.3 Analyze Savings and Shocks

First, analyze Savings Levels and Shocks, Aggregate Over All Others, and do various other calculations.

```
% Generate some Data
mp_support_graph = containers.Map('KeyType', 'char', 'ValueType', 'any');
mp_support_graph('cl_st_xtitle') = {'Savings States, a'};
mp_support_graph('st_legend_loc') = 'best';
mp_support_graph('bl_graph_logy') = true; % do not log
mp_support_graph('it_legend_select') = 9; % how many shock legends to show
mp_support_graph('cl_colors') = 'jet';
```

MEAN(VAL(A,Z)), MEAN(AP(A,Z)), MEAN(C(A,Z))

Tabulate value and policies along savings and shocks:

```
% Set
% NaN(n_jgrid,n_agrid,n_etagrid,n_educgrid,n_marriedgrid,n_kidsgrid);
ar_permute = [1,4,5,6,3,2];
% Value Function
tb_az_v = ff_summ_nd_array("MEAN(VAL(A,Z))", V_VFI, true, ["mean"], 4, 1, cl_mp_datasetdesc, ar_permute);
```

xxx	MEAN(VAL(A,Z))	xxxxxxxxxxxxxxxxxxxxxxxxxxxx	xxxxxxxxxxxxxxxxxxxxxxxxxxxx	xxxxxxxxxxxxxxxxxxxxxxxxxxxx	xxxxxxxxxxxxxxxxxxxxxxxxxxxx	xxxxxxxxxxxxxxxxxxxxxxxxxxxx	xxxxxxxxxxxxxxxxxxxxxxxxxxxx	xxxxxxxxxxxxxxxxxxxxxxxxxxxx
	group	savings	mean_eta_1	mean_eta_2	mean_eta_3	mean_eta_4	mean_eta_5	mean_eta_6
	-----	-----	-----	-----	-----	-----	-----	-----
	1	0	-24.423	-14.383	-9.0838	-6.1681	-4.6368	-
	2	0.0097656	-23.655	-14.141	-8.9428	-6.0477	-4.521	-2
	3	0.078125	-20.274	-12.864	-8.2087	-5.441	-3.9447	-1
	4	0.26367	-16.052	-10.951	-7.1333	-4.627	-3.2033	-1
	5	0.625	-12.169	-8.9647	-6.0525	-3.918	-2.6128	-1
	6	1.2207	-8.9956	-7.1143	-5.0287	-3.3224	-2.17	-8
	7	2.1094	-6.6026	-5.5315	-4.126	-2.8111	-1.8354	-6
	8	3.3496	-4.8705	-4.2629	-3.3542	-2.3677	-1.5738	-4
	9	5	-3.6341	-3.2853	-2.7087	-1.9911	-1.3595	-3
	10	7.1191	-2.7516	-2.5471	-2.1826	-1.6748	-1.1772	-2
	11	9.7656	-2.1163	-1.9932	-1.7614	-1.4073	-1.0193	-2
	12	12.998	-1.653	-1.5768	-1.4275	-1.1818	-0.88344	-1

13	16.875	-1.3103	-1.2619	-1.1642	-0.99332	-0.76691	-1
14	21.455	-1.0532	-1.0216	-0.95651	-0.83698	-0.66655	-1
15	26.797	-0.85714	-0.83614	-0.79193	-0.7076	-0.57964	-0.
16	32.959	-0.7057	-0.69138	-0.66083	-0.60072	-0.50456	-0.
17	40	-0.58719	-0.57722	-0.55573	-0.51237	-0.43988	-0.
18	47.979	-0.49334	-0.48626	-0.47088	-0.43924	-0.38431	-0.
19	56.953	-0.41818	-0.41306	-0.40187	-0.37849	-0.33661	-0.
20	66.982	-0.35736	-0.35359	-0.34532	-0.32783	-0.29568	-0.
21	78.125	-0.30764	-0.30483	-0.29864	-0.28541	-0.26055	-0.
22	90.439	-0.26663	-0.26451	-0.25982	-0.24971	-0.23034	-0.
23	103.98	-0.23253	-0.23091	-0.22732	-0.21951	-0.20431	-0.
24	118.82	-0.20396	-0.20271	-0.19994	-0.19386	-0.18184	-0
25	135	-0.17985	-0.17888	-0.17671	-0.17193	-0.16238	-0.

% Aprime Choice

tb\_az\_ap = ff\_summ\_nd\_array("MEAN(AP(A,Z))", ap\_VFI, true, ["mean"], 4, 1, cl\_mp\_datasetdesc, ar\_per

xxx	MEAN(AP(A,Z))	xxxxxxxxxxxxxxxxxxxxxxxxxxxxxxxx					
group	savings	mean_eta_1	mean_eta_2	mean_eta_3	mean_eta_4	mean_eta_5	mean
-----	-----	-----	-----	-----	-----	-----	-----
1	0	3.2159e-05	0.0024668	0.032046	0.17185	0.75713	0.00
2	0.0097656	0.00055365	0.0039513	0.034103	0.17524	0.76251	0.00
3	0.078125	0.015815	0.020023	0.052271	0.20181	0.8015	0.0
4	0.26367	0.094638	0.094808	0.12856	0.29193	0.91314	0.
5	0.625	0.31851	0.32442	0.35753	0.52484	1.1543	0.
6	1.2207	0.75143	0.75176	0.79303	0.95962	1.5772	0
7	2.1094	1.4241	1.4284	1.4709	1.6269	2.2293	1
8	3.3496	2.3733	2.3796	2.421	2.5737	3.1535	2
9	5	3.6394	3.6466	3.6884	3.8506	4.3901	3
10	7.1191	5.2875	5.2955	5.3372	5.5015	5.9876	5
11	9.7656	7.3153	7.3234	7.3642	7.5288	8.0042	7
12	12.998	9.7556	9.7616	9.8006	9.967	10.49	9
13	16.875	12.766	12.773	12.807	12.97	13.562	1
14	21.455	16.338	16.342	16.377	16.524	17.139	1
15	26.797	20.401	20.403	20.431	20.57	21.185	2
16	32.959	25.088	25.095	25.124	25.248	25.842	2
17	40	30.463	30.471	30.51	30.633	31.193	
18	47.979	36.558	36.567	36.609	36.754	37.274	3
19	56.953	43.57	43.576	43.612	43.757	44.279	4
20	66.982	51.378	51.387	51.429	51.567	52.101	5
21	78.125	59.666	59.675	59.721	59.878	60.41	
22	90.439	69.02	69.027	69.069	69.228	69.775	
23	103.98	79.509	79.516	79.557	79.706	80.27	7
24	118.82	90.88	90.887	90.929	91.074	91.625	9
25	135	103.23	103.23	103.27	103.42	103.97	1

% Consumption Choices

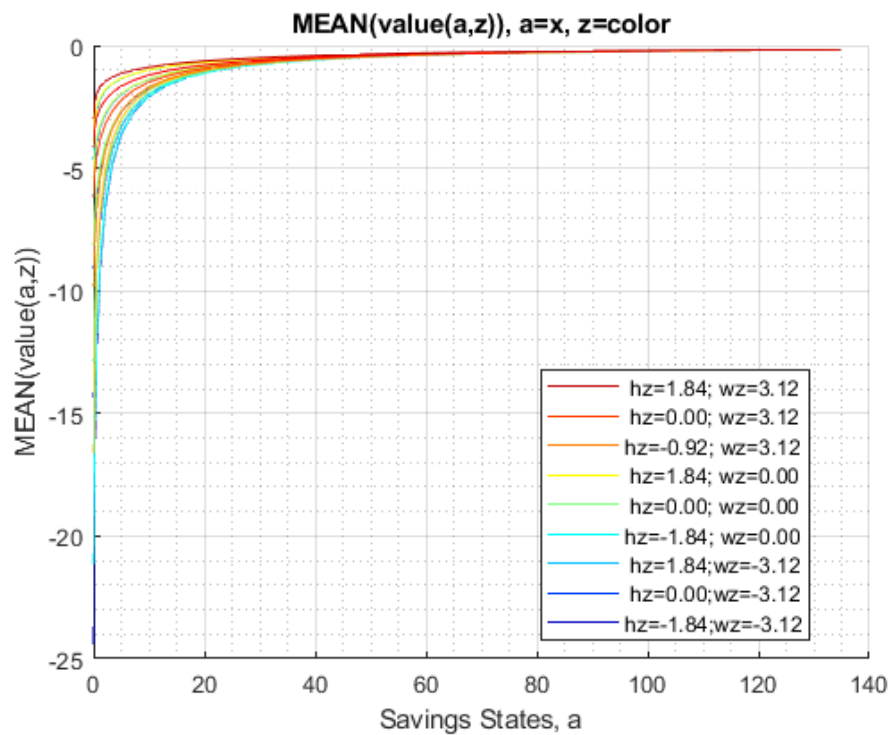
tb\_az\_c = ff\_summ\_nd\_array("MEAN(C(A,Z))", cons\_VFI, true, ["mean"], 4, 1, cl\_mp\_datasetdesc, ar\_per

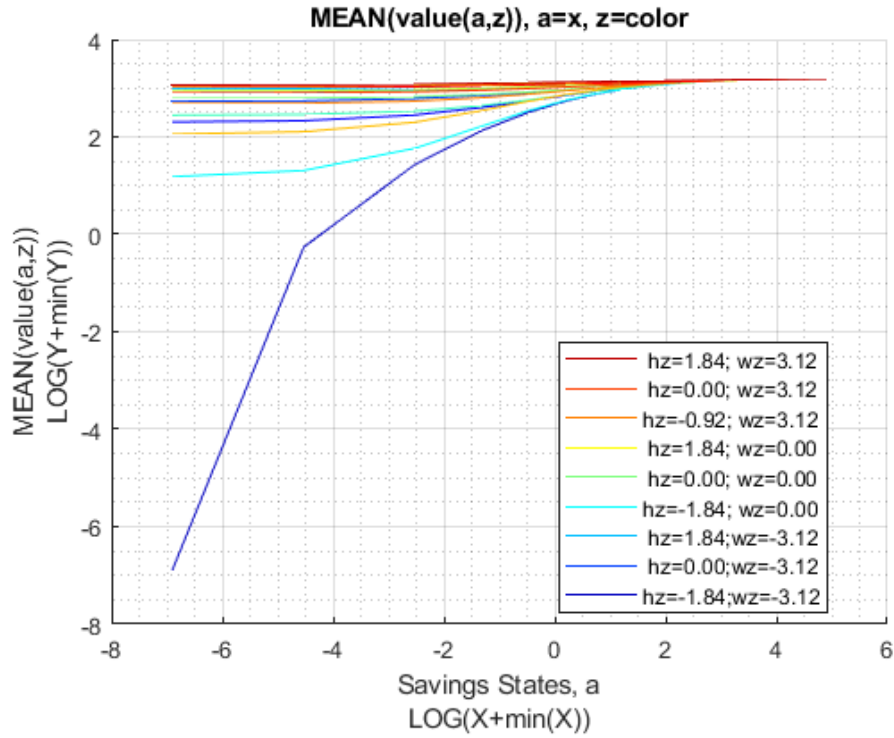
xxx	MEAN(C(A,Z))	xxxxxxxxxxxxxxxxxxxxxxxxxxxxxxxx					
group	savings	mean_eta_1	mean_eta_2	mean_eta_3	mean_eta_4	mean_eta_5	mean
-----	-----	-----	-----	-----	-----	-----	-----
1	0	0.16881	0.29125	0.55695	1.1299	2.3014	0.2
2	0.0097656	0.17988	0.30127	0.56634	1.1379	2.3074	0.3
3	0.078125	0.24566	0.36575	0.62833	1.1912	2.3483	0.3
4	0.26367	0.38648	0.50942	0.76949	1.318	2.4533	0.

5	0.625	0.58919	0.70456	0.96359	1.5071	2.6337	0.6
6	1.2207	0.85722	0.97603	1.2247	1.7675	2.9054	0.
7	2.1094	1.2268	1.3395	1.5846	2.1362	3.2884	1.
8	3.3496	1.7279	1.837	2.0808	2.6338	3.8076	1.
9	5	2.3875	2.4944	2.7359	3.2775	4.4904	2.
10	7.1191	3.2081	3.3133	3.5534	4.0911	5.3563	3.
11	9.7656	4.2601	4.3643	4.6042	5.1402	6.4149	4.
12	12.998	5.5783	5.6843	5.9251	6.4581	7.684	5.
13	16.875	7.0733	7.1787	7.4234	7.9594	9.1154	7.
14	21.455	8.823	8.9302	9.1737	9.7243	10.857	8.
15	26.797	10.964	11.073	11.324	11.882	13.013	10
16	32.959	13.433	13.538	13.787	14.36	15.511	13
17	40	16.233	16.337	16.576	17.149	18.335	16
18	47.979	19.402	19.505	19.741	20.291	21.516	19
19	56.953	22.81	22.914	23.156	23.707	24.93	22
20	66.982	26.645	26.747	26.982	27.54	28.75	26
21	78.125	31.292	31.394	31.626	32.165	33.377	31
22	90.439	36.234	36.338	36.573	37.11	38.307	36
23	103.98	41.468	41.572	41.808	42.355	43.535	41
24	118.82	47.317	47.421	47.656	48.207	49.4	47
25	135	53.752	53.857	54.095	54.642	55.842	53

Graph Mean Values:

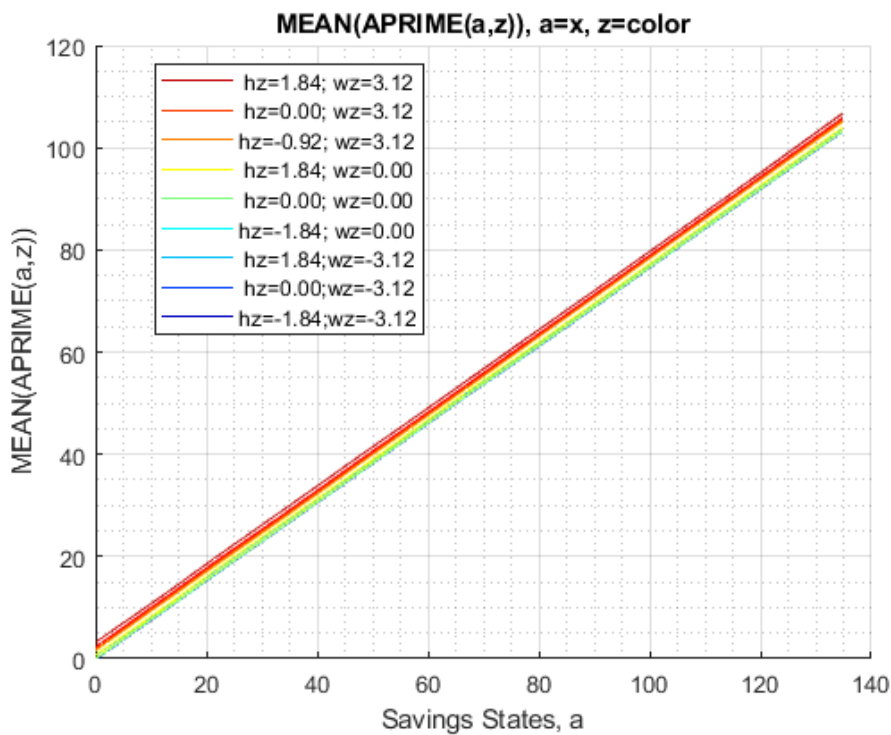
```
mp_support_graph('cl_st_graph_title') = {'MEAN(value(a,z)), a=x, z=color'};
mp_support_graph('cl_st_ytitle') = {'MEAN(value(a,z))'};
ff_graph_grid((tb_az_v{1:end, 3:end})', ar_st_eta_HS_grid, agrid, mp_support_graph);
```



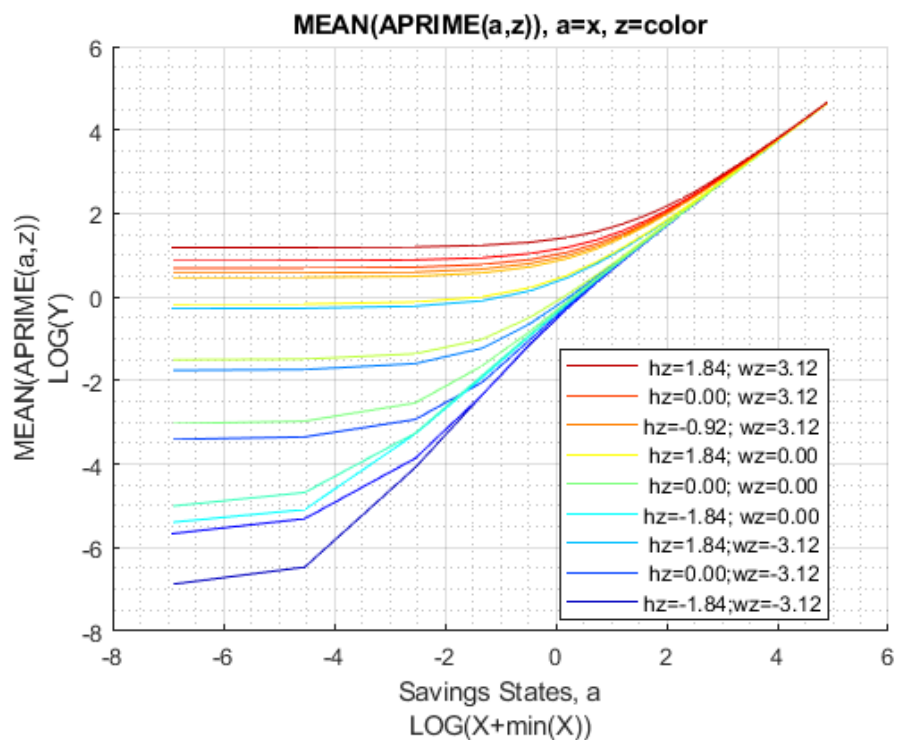


Graph Mean Savings Choices:

```
mp_support_graph('cl_st_graph_title') = {'MEAN(APRIME(a,z)), a=x, z=color'};
mp_support_graph('cl_st_ytitle') = {'MEAN(APRIME(a,z))'};
ff_graph_grid((tb_az_ap{1:end, 3:end})', ar_st_eta_HS_grid, agrid, mp_support_graph);
```

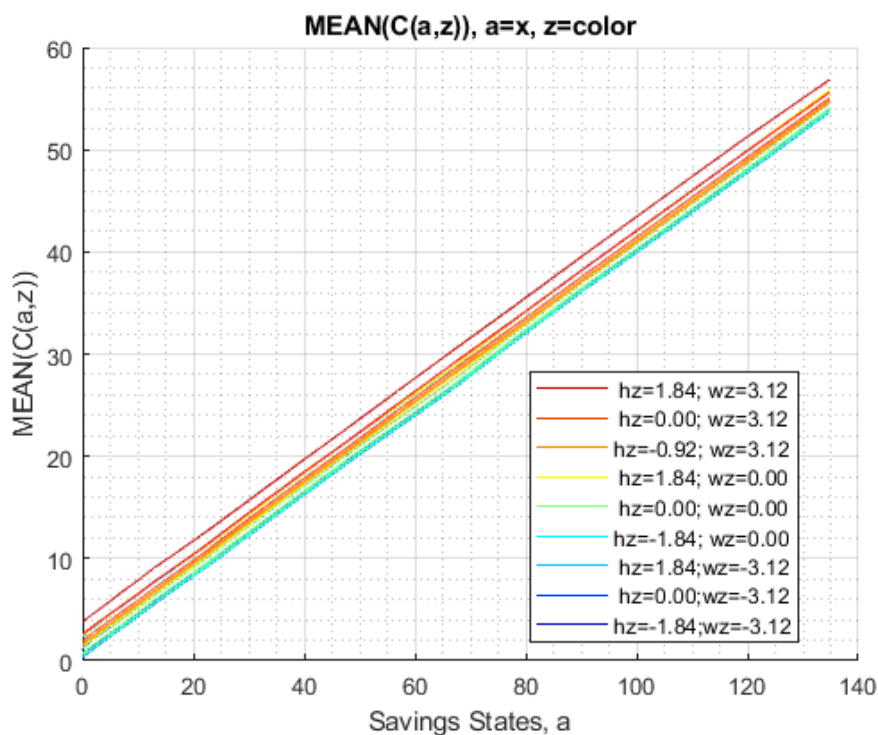


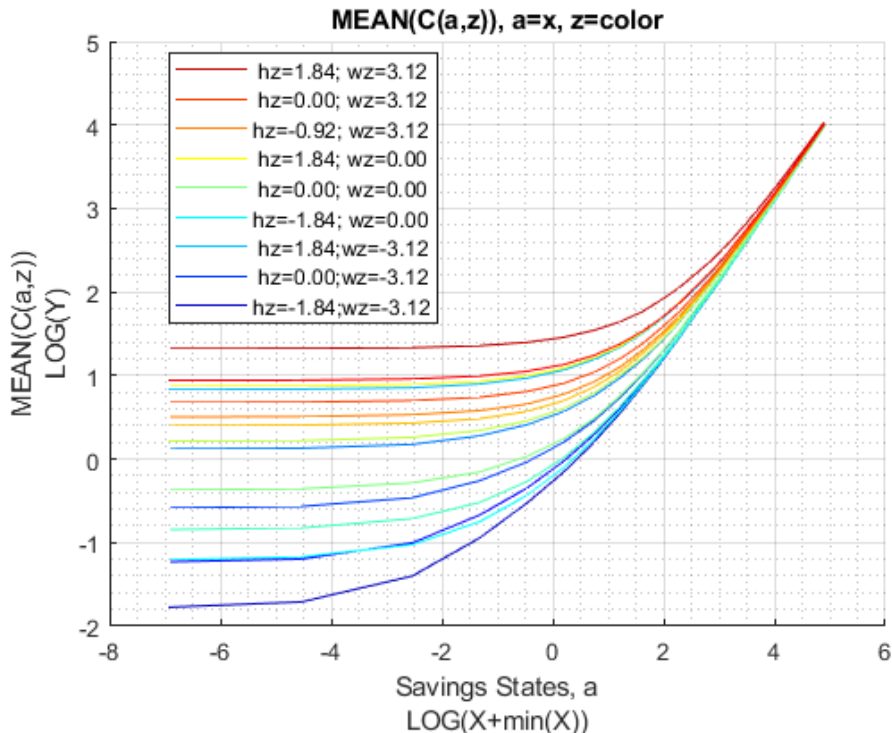




Graph Mean Consumption:

```
mp_support_graph('cl_st_graph_title') = {'MEAN(C(a,z)), a=x, z=color'};
mp_support_graph('cl_st_ytitle') = {'MEAN(C(a,z))'};
ff_graph_grid((tb_az_c{1:end, 3:end})', ar_st_eta_HS_grid, agrid, mp_support_graph);
```





#### 4.4.4 Analyze Kids and Marriage and Age

Aggregating over education, savings, and shocks, what are the differential effects of Marriage and Age.

```
% Generate some Data
mp_support_graph = containers.Map('KeyType', 'char', 'ValueType', 'any');
ar_row_grid = ["k0M0", "K1M0", "K2M0", "k0M1", "K1M1", "K2M1"];
mp_support_graph('cl_st_xtitle') = {'Age'};
mp_support_graph('st_legend_loc') = 'best';
mp_support_graph('bl_graph_logy') = true; % do not log
mp_support_graph('st_rounding') = '6.2f'; % format shock legend
mp_support_graph('cl_scatter_shapes') = { 'o', 'd', 's', 'o', 'd', 's' };
mp_support_graph('cl_colors') = {'red', 'red', 'red', 'blue', 'blue', 'blue'};

MEAN(VAL(KM,J)), MEAN(AP(KM,J)), MEAN(C(KM,J))

Tabulate value and policies:

% Set
% NaN(n_jgrid,n_agrid,n_etagrid,n_educgrid,n_marriedgrid,n_kidsgrid);
ar_permute = [2,3,4,1,6,5];
% Value Function
tb_az_v = ff_summ_nd_array("MEAN(VAL(KM,J))", V_VFI, true, ["mean"], 3, 1, cl_mp_datasetdesc, ar_per

xxx MEAN(VAL(KM,J)) xxxxxxxxxxxxxxxxxxxxxxxxxxxxxxxxxxxx
  group  kids  marry  mean_age_19  mean_age_22  mean_age_27  mean_age_32  mean_age_3
-----  ----  -----  -----  -----  -----  -----  -----
      1     1     0     -4.7384     -4.2839     -3.9125     -3.6403     -3.4202
      2     2     0     -6.2307     -5.5732     -5.014      -4.5943     -4.2483
      3     3     0     -6.9818     -6.3368     -5.7685     -5.3334     -4.9708
      4     1     1     -3.4759     -3.1424     -2.8538     -2.6272     -2.4359
      5     2     1     -4.325      -3.9032     -3.5196     -3.2101     -2.9428
      6     3     1     -4.7282     -4.3225     -3.9432     -3.6317     -3.3597

% Aprime Choice
```

```
tb_az_ap = ff_summ_nd_array("MEAN(AP(KM,J))", ap_VFI, true, ["mean"], 3, 1, cl_mp_datasetdesc, ar_pe
```

```
xxx MEAN(AP(KM,J)) xxxxxxxxxxxxxxxxxxxxxxxxxxxxxxxxxxxx
```

group	kids	marry	mean_age_19	mean_age_22	mean_age_27	mean_age_32	mean_age_3
1	1	0	34.931	34.726	34.665	34.554	34.362
2	2	0	34.603	34.334	34.198	33.995	33.692
3	3	0	34.187	33.968	33.877	33.705	33.427
4	1	1	35.713	35.611	35.7	35.727	35.66
5	2	1	35.368	35.246	35.284	35.242	35.101
6	3	1	34.903	34.81	34.86	34.834	34.7

% Consumption Choices

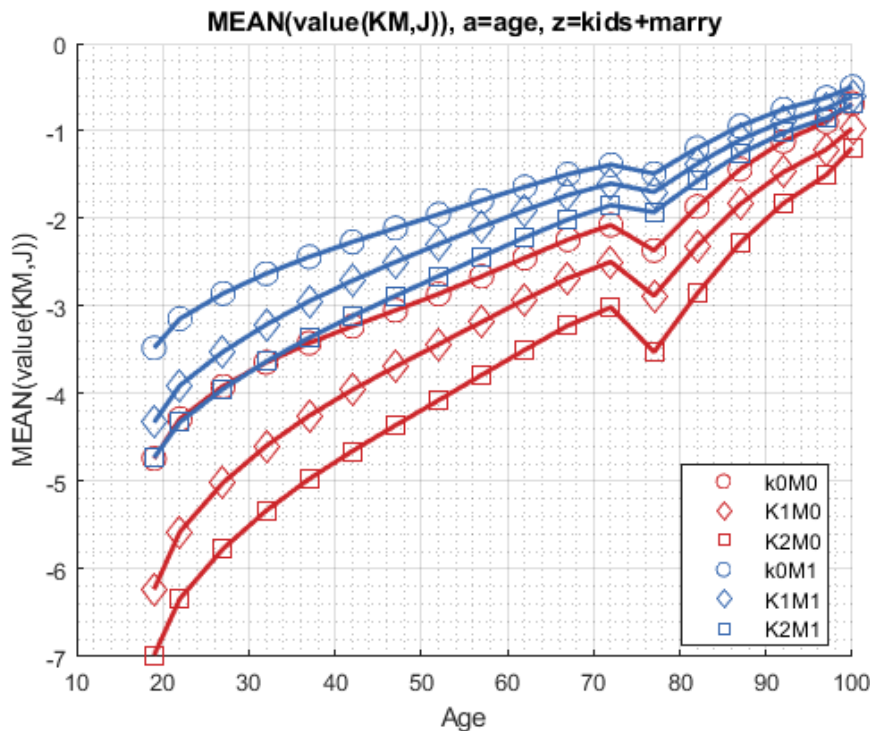
```
tb_az_c = ff_summ_nd_array("MEAN(C(KM,J))", cons_VFI, true, ["mean"], 3, 1, cl_mp_datasetdesc, ar_pe
```

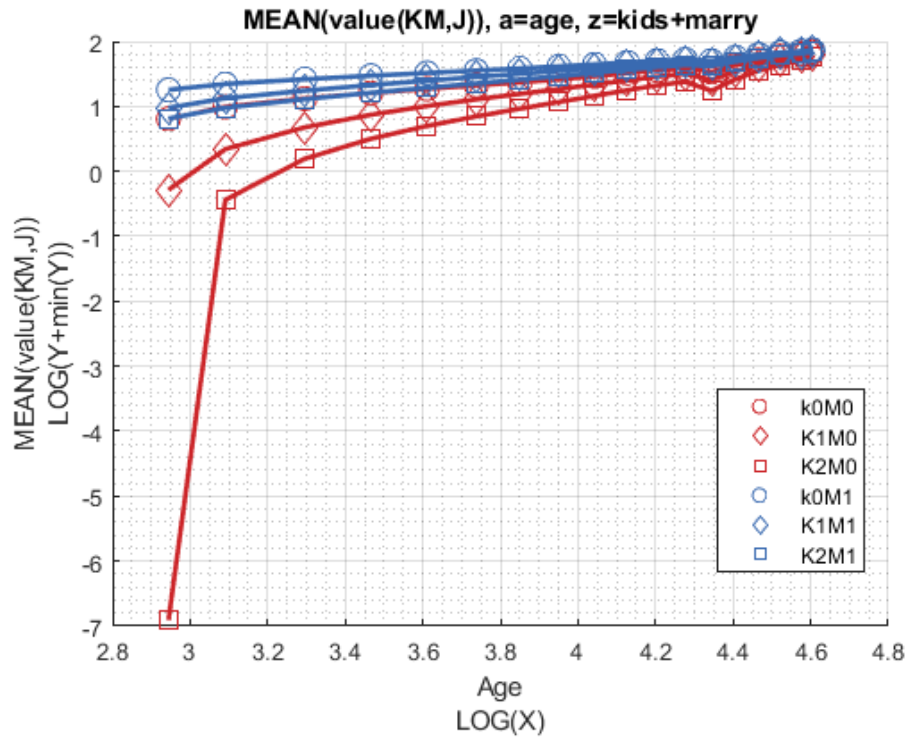
```
xxx MEAN(C(KM,J)) xxxxxxxxxxxxxxxxxxxxxxxxxxxxxxxxxxxx
```

group	kids	marry	mean_age_19	mean_age_22	mean_age_27	mean_age_32	mean_age_3
1	1	0	6.8531	7.1729	7.4988	7.8167	8.1435
2	2	0	7.182	7.5653	7.9659	8.3756	8.813
3	3	0	7.5973	7.931	8.2872	8.6657	9.0783
4	1	1	7.7992	8.182	8.5624	8.9321	9.311
5	2	1	7.879	8.2553	8.6555	9.0645	9.4908
6	3	1	8.1608	8.4911	8.8566	9.2297	9.6299

Graph Mean Values:

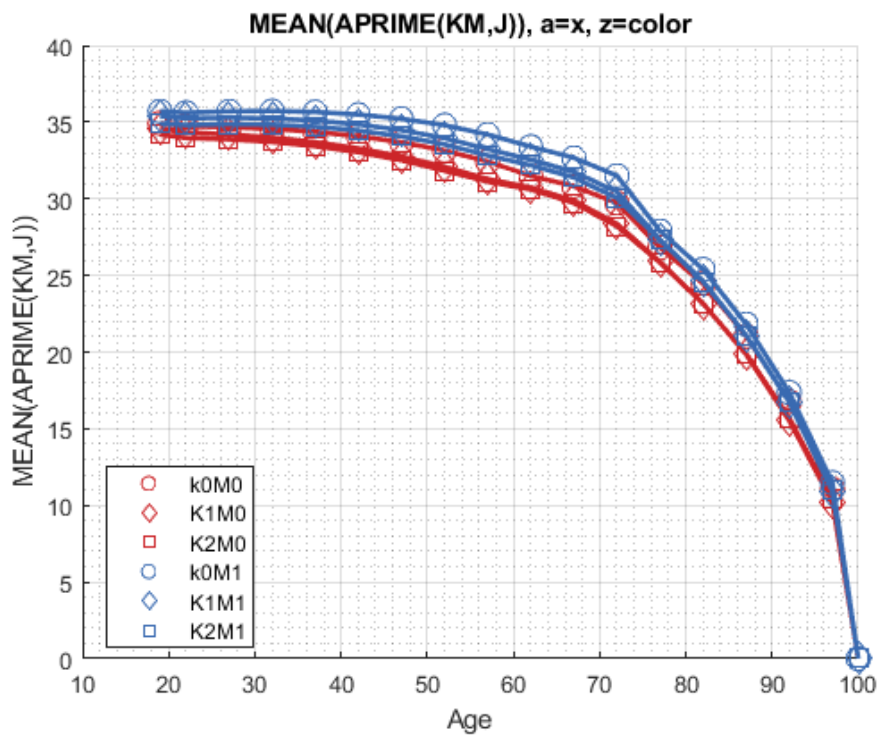
```
mp_support_graph('cl_st_graph_title') = {'MEAN(value(KM,J)), a=age, z=kids+marry'};
mp_support_graph('cl_st_ytitle') = {'MEAN(value(KM,J))'};
ff_graph_grid((tb_az_v{1:end, 4:end}), ar_row_grid, age_grid, mp_support_graph);
```

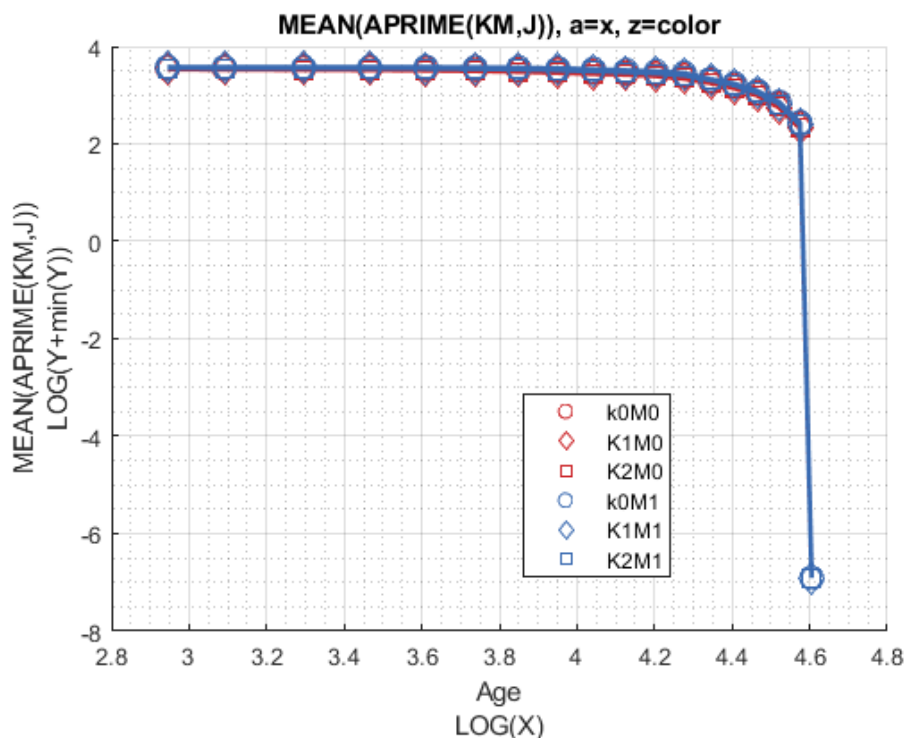




Graph Mean Savings Choices:

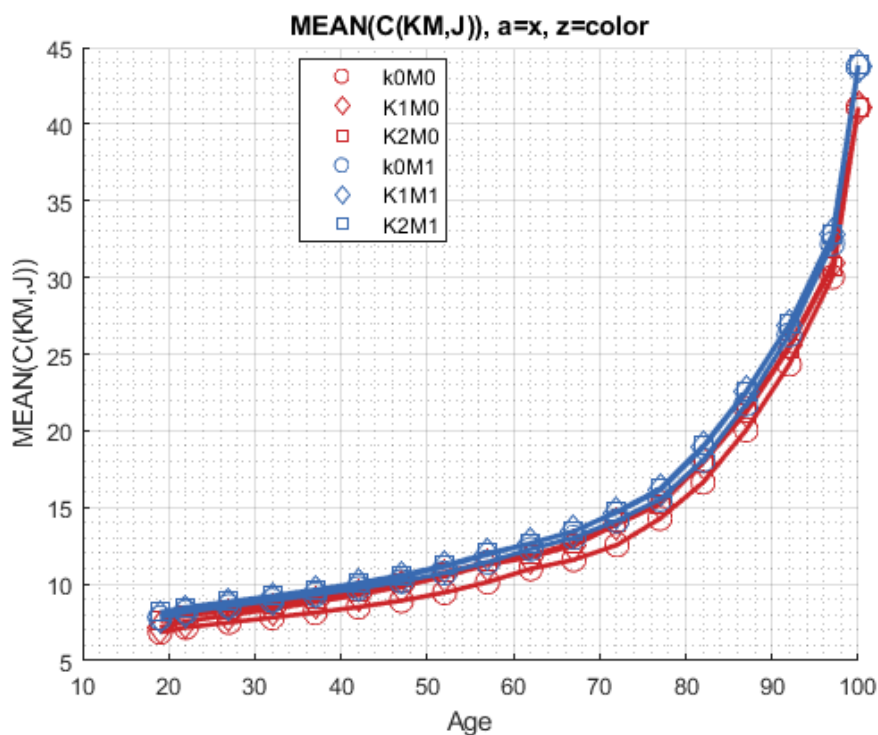
```
mp_support_graph('cl_st_graph_title') = {'MEAN(APRIME(KM,J)), a=x, z=color'};
mp_support_graph('cl_st_ytitle') = {'MEAN(APRIME(KM,J))'};
ff_graph_grid((tb_az_ap{1:end, 4:end}), ar_row_grid, age_grid, mp_support_graph);
```

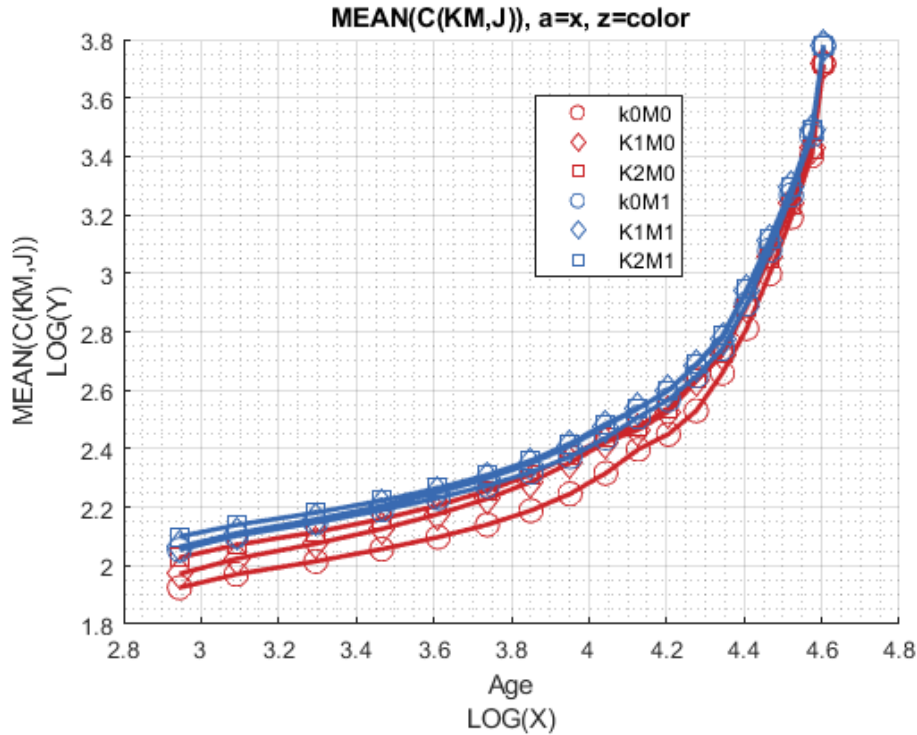




Graph Mean Consumption:

```
mp_support_graph('cl_st_graph_title') = {'MEAN(C(KM,J)), a=x, z=color'};
mp_support_graph('cl_st_ytitle') = {'MEAN(C(KM,J))'};
ff_graph_grid((tb_az_c{1:end, 4:end}), ar_row_grid, age_grid, mp_support_graph);
```





#### 4.4.5 Analyze Education and Marriage and Age

Aggregating over education, savings, and shocks, what are the differential effects of Marriage and Age.

```
% Generate some Data
mp_support_graph = containers.Map('KeyType', 'char', 'ValueType', 'any');
ar_row_grid = ["E0M0", "E1M0", "E0M1", "E1M1"];
mp_support_graph('cl_st_xtitle') = {'Age'};
mp_support_graph('st_legend_loc') = 'best';
mp_support_graph('bl_graph_logy') = true; % do not log
mp_support_graph('st_rounding') = '6.2f'; % format shock legend
mp_support_graph('cl_scatter_shapes') = {'*', 'p', '*', 'p'};
mp_support_graph('cl_colors') = {'red', 'red', 'blue', 'blue'};

MEAN(VAL(EKM,J)), MEAN(AP(EKM,J)), MEAN(C(EKM,J))

Tabulate value and policies:

% Set
% NaN(n_jgrid,n_agrid,n_etagrid,n_educgrid,n_marriedgrid,n_kidsgrid);
ar_permute = [2,3,6,1,4,5];
% Value Function
tb_az_v = ff_summ_nd_array("MEAN(VAL(EKM,J))", V_VFI, true, ["mean"], 3, 1, cl_mp_datasetdesc, ar_per

xxx MEAN(VAL(EKM,J)) xxxxxxxxxxxxxxxxxxxxxxxxxxxxxxxxxxxx
      group      edu      marry      mean_age_19      mean_age_22      mean_age_27      mean_age_32      mean_age_37
      -----      ---      -----      -----      -----      -----      -----      -----
          1          0          0          -6.4015          -5.8666          -5.3879          -4.9966          -4.6557
          2          1          0          -5.5658          -4.9294          -4.4088          -4.0487          -3.7705
          3          0          1          -4.4764          -4.1029          -3.7581          -3.4622          -3.1968
          4          1          1          -3.8764          -3.4759          -3.1196          -2.8504          -2.6288

% Aprime Choice
tb_az_ap = ff_summ_nd_array("MEAN(AP(EKM,J))", ap_VFI, true, ["mean"], 3, 1, cl_mp_datasetdesc, ar_p
```

```
xxx MEAN(AP(EKM,J)) xxxxxxxxxxxxxxxxxxxxxxxxxxxxxxxxxxxx
```

group	edu	marry	mean_age_19	mean_age_22	mean_age_27	mean_age_32	mean_age_37
1	0	0	34.682	34.444	34.272	34.048	33.753
2	1	0	34.465	34.241	34.222	34.121	33.901
3	0	1	35.363	35.234	35.193	35.099	34.934
4	1	1	35.293	35.21	35.37	35.437	35.374

% Consumption Choices

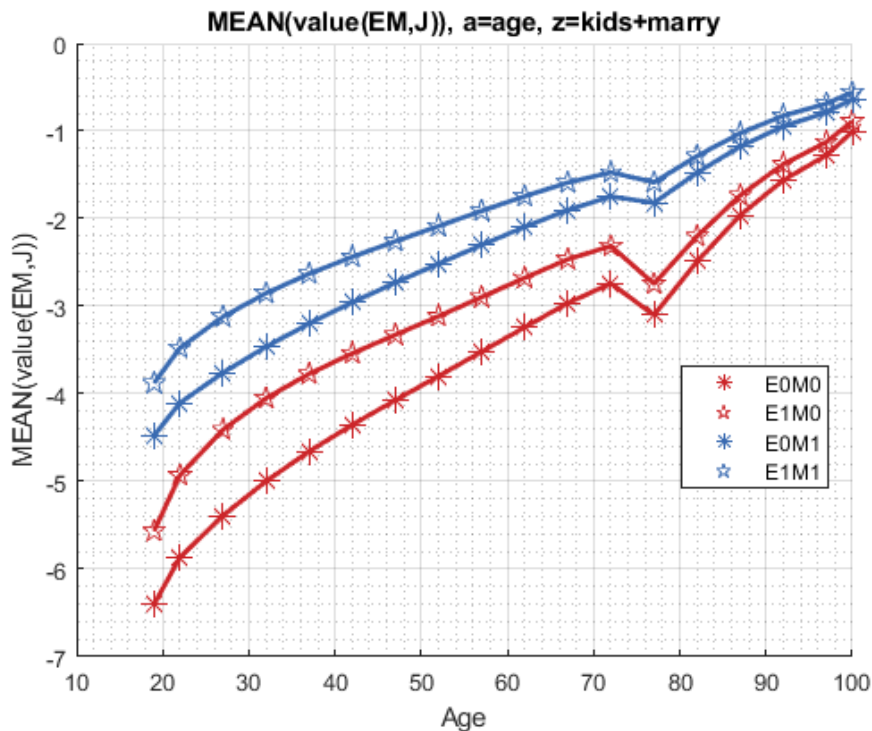
```
tb_az_c = ff_summ_nd_array("MEAN(C(EKM,J))", cons_VFI, true, ["mean"], 3, 1, cl_mp_datasetdesc, ar_p
```

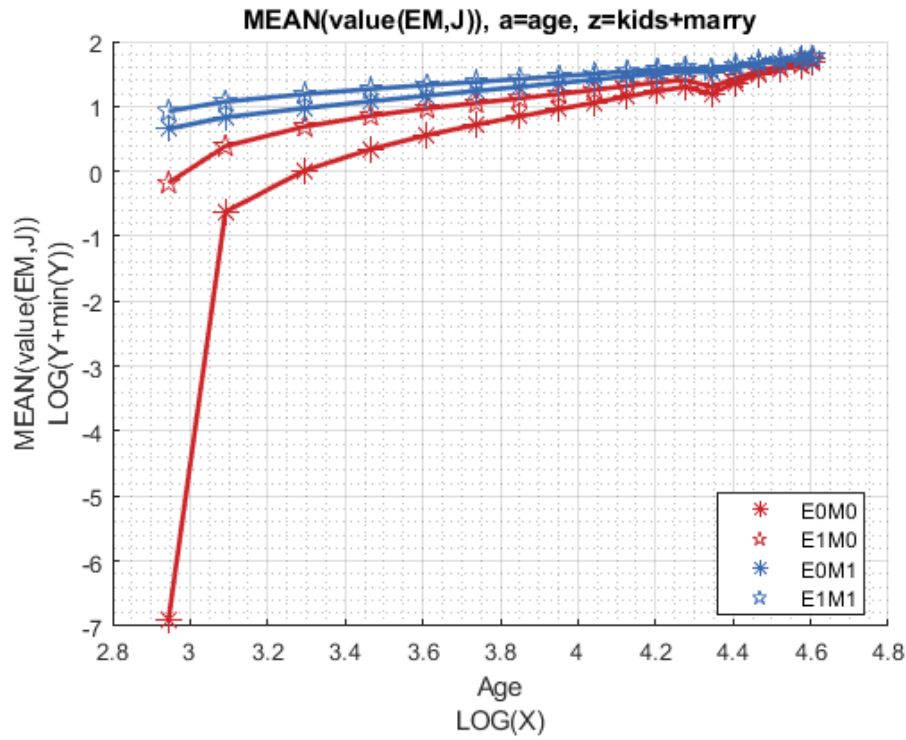
```
xxx MEAN(C(EKM,J)) xxxxxxxxxxxxxxxxxxxxxxxxxxxxxxxxxxxx
```

group	edu	marry	mean_age_19	mean_age_22	mean_age_27	mean_age_32	mean_age_37
1	0	0	7.1022	7.4087	7.7357	8.0845	8.4713
2	1	0	7.3195	7.7041	8.0988	8.4875	8.8852
3	0	1	7.7587	8.0743	8.4083	8.7618	9.1489
4	1	1	8.134	8.5446	8.9747	9.3891	9.8055

Graph Mean Values:

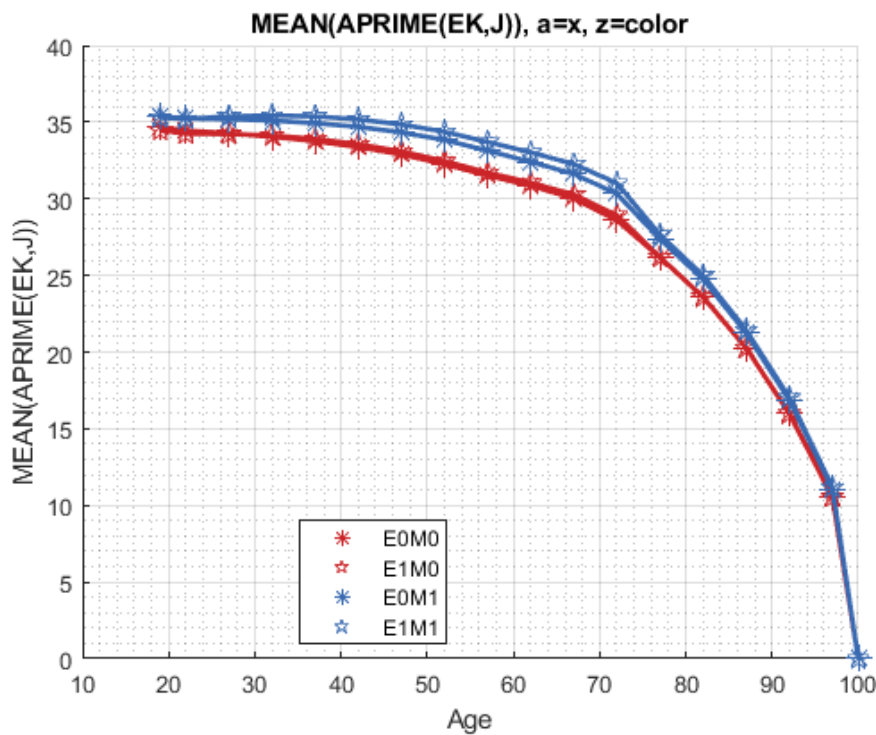
```
mp_support_graph('cl_st_graph_title') = {'MEAN(value(EM,J)), a=age, z=kids+marry'};
mp_support_graph('cl_st_ytitle') = {'MEAN(value(EM,J))'};
ff_graph_grid((tb_az_v{1:end, 4:end}), ar_row_grid, age_grid, mp_support_graph);
```



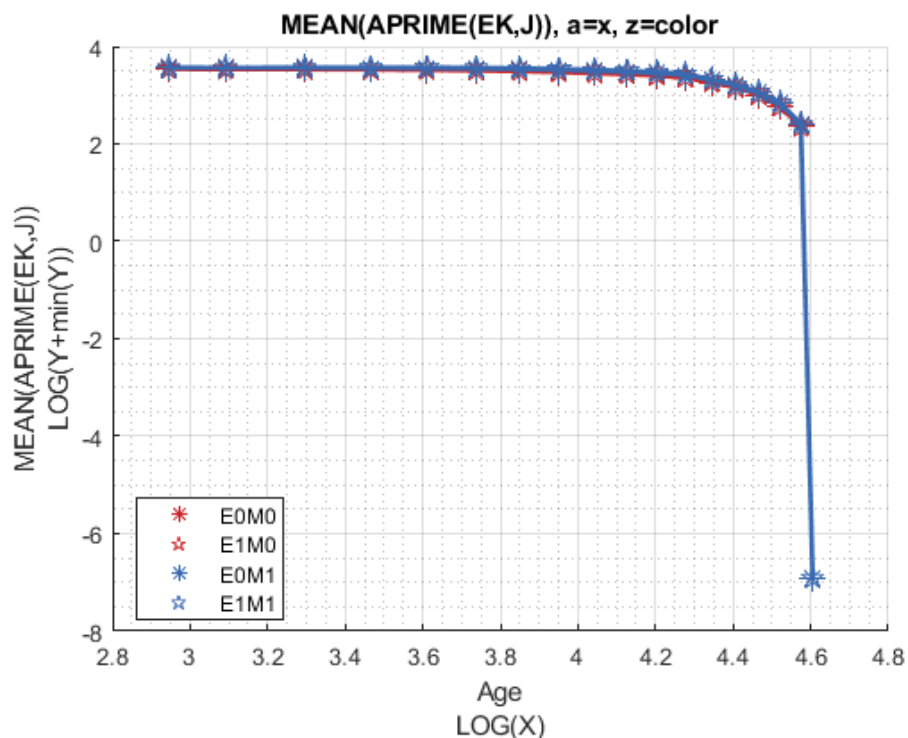


Graph Mean Savings Choices:

```
mp_support_graph('cl_st_graph_title') = {'MEAN(APRIME(EK,J)), a=x, z=color'};
mp_support_graph('cl_st_ytitle') = {'MEAN(APRIME(EK,J))'};
ff_graph_grid((tb_az_ap{1:end, 4:end}), ar_row_grid, age_grid, mp_support_graph);
```

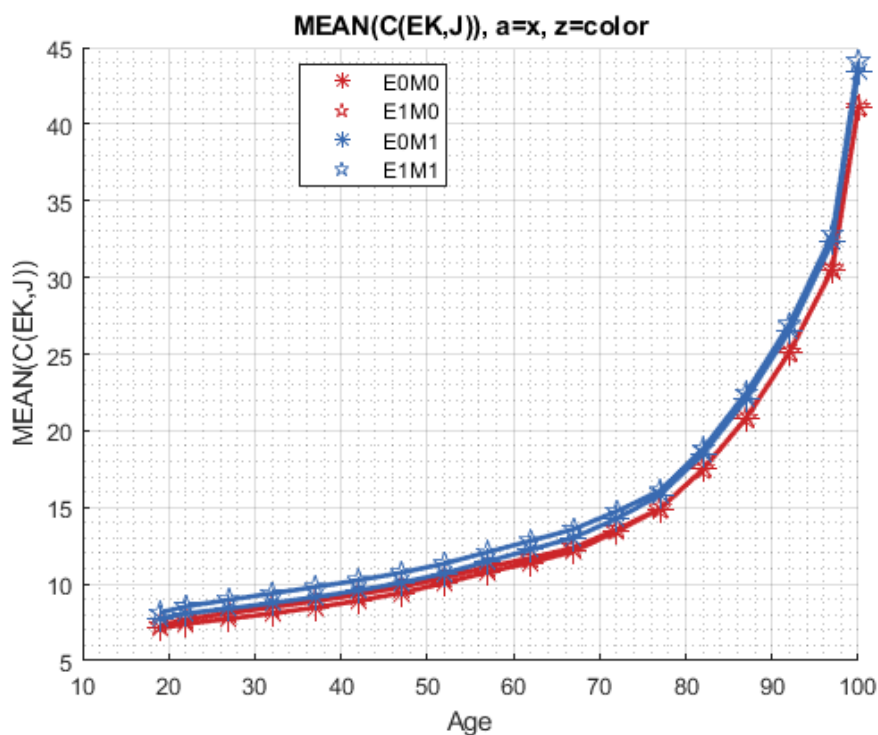


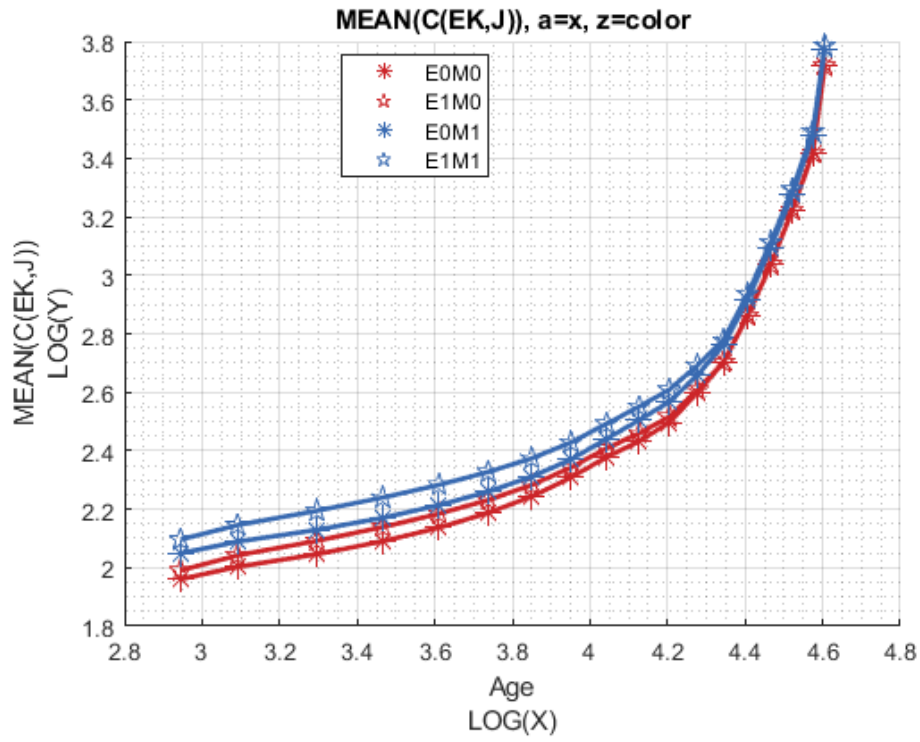




Graph Mean Consumption:

```
mp_support_graph('cl_st_graph_title') = {'MEAN(C(EK,J)), a=x, z=color'};
mp_support_graph('cl_st_ytitle') = {'MEAN(C(EK,J))'};
ff_graph_grid((tb_az_c{1:end}, 4:end}), ar_row_grid, age_grid, mp_support_graph);
```





## Chapter 5

# Solution with Unemployment

### 5.1 Life Cycle Dynamic Programming under Unemployment Shock

This is the example vignette for function: `snw_vfi_main_bisec_vec` from the [PrjOptiSNW Package](#). This function solves for policy function using Exact Vectorized Solution. Value in 2020 with surprise COVID unemployment Shock, with non-covid year Value as the continuation function. The file focuses on the change in value function, asset choice, and consumption choice given a one period unemployment shock (that does not reappear in the future again).

#### 5.1.1 Test SNW\_VFI\_UNEMP

Solve the Regular Value and Also the Unemployment Value.

First, solve for value without unemployment issue (use the vectorized code that was previously tested):

```
mp_params = snw_mp_param('default_docdense');
mp_controls = snw_mp_control('default_test');
[V_VFI_ss,ap_VFI_ss,cons_VFI_ss,mp_valpol_more_ss] = ...
    snw_vfi_main_bisec_vec(mp_params, mp_controls);
```

```
SNW_VFI_MAIN_BISEC_VEC: Finished Age Group:83 of 82, time-this-age:7.9376
SNW_VFI_MAIN_BISEC_VEC: Finished Age Group:82 of 82, time-this-age:6.2356
SNW_VFI_MAIN_BISEC_VEC: Finished Age Group:81 of 82, time-this-age:6.2155
SNW_VFI_MAIN_BISEC_VEC: Finished Age Group:80 of 82, time-this-age:6.3254
SNW_VFI_MAIN_BISEC_VEC: Finished Age Group:79 of 82, time-this-age:6.3074
SNW_VFI_MAIN_BISEC_VEC: Finished Age Group:78 of 82, time-this-age:6.2427
SNW_VFI_MAIN_BISEC_VEC: Finished Age Group:77 of 82, time-this-age:6.1961
SNW_VFI_MAIN_BISEC_VEC: Finished Age Group:76 of 82, time-this-age:6.4401
SNW_VFI_MAIN_BISEC_VEC: Finished Age Group:75 of 82, time-this-age:6.0576
SNW_VFI_MAIN_BISEC_VEC: Finished Age Group:74 of 82, time-this-age:6.3188
SNW_VFI_MAIN_BISEC_VEC: Finished Age Group:73 of 82, time-this-age:6.1781
SNW_VFI_MAIN_BISEC_VEC: Finished Age Group:72 of 82, time-this-age:6.3078
SNW_VFI_MAIN_BISEC_VEC: Finished Age Group:71 of 82, time-this-age:6.4338
SNW_VFI_MAIN_BISEC_VEC: Finished Age Group:70 of 82, time-this-age:6.33
SNW_VFI_MAIN_BISEC_VEC: Finished Age Group:69 of 82, time-this-age:6.4742
SNW_VFI_MAIN_BISEC_VEC: Finished Age Group:68 of 82, time-this-age:6.2434
SNW_VFI_MAIN_BISEC_VEC: Finished Age Group:67 of 82, time-this-age:6.196
SNW_VFI_MAIN_BISEC_VEC: Finished Age Group:66 of 82, time-this-age:6.3067
SNW_VFI_MAIN_BISEC_VEC: Finished Age Group:65 of 82, time-this-age:6.381
SNW_VFI_MAIN_BISEC_VEC: Finished Age Group:64 of 82, time-this-age:6.3403
SNW_VFI_MAIN_BISEC_VEC: Finished Age Group:63 of 82, time-this-age:6.4496
SNW_VFI_MAIN_BISEC_VEC: Finished Age Group:62 of 82, time-this-age:6.1753
```

SNW\_VFI\_MAIN\_BISEC\_VEC: Finished Age Group:61 of 82, time-this-age:6.3953  
SNW\_VFI\_MAIN\_BISEC\_VEC: Finished Age Group:60 of 82, time-this-age:6.2145  
SNW\_VFI\_MAIN\_BISEC\_VEC: Finished Age Group:59 of 82, time-this-age:6.3754  
SNW\_VFI\_MAIN\_BISEC\_VEC: Finished Age Group:58 of 82, time-this-age:6.1826  
SNW\_VFI\_MAIN\_BISEC\_VEC: Finished Age Group:57 of 82, time-this-age:6.4472  
SNW\_VFI\_MAIN\_BISEC\_VEC: Finished Age Group:56 of 82, time-this-age:6.3577  
SNW\_VFI\_MAIN\_BISEC\_VEC: Finished Age Group:55 of 82, time-this-age:6.3632  
SNW\_VFI\_MAIN\_BISEC\_VEC: Finished Age Group:54 of 82, time-this-age:6.3623  
SNW\_VFI\_MAIN\_BISEC\_VEC: Finished Age Group:53 of 82, time-this-age:6.477  
SNW\_VFI\_MAIN\_BISEC\_VEC: Finished Age Group:52 of 82, time-this-age:6.4007  
SNW\_VFI\_MAIN\_BISEC\_VEC: Finished Age Group:51 of 82, time-this-age:6.1299  
SNW\_VFI\_MAIN\_BISEC\_VEC: Finished Age Group:50 of 82, time-this-age:6.0888  
SNW\_VFI\_MAIN\_BISEC\_VEC: Finished Age Group:49 of 82, time-this-age:6.0058  
SNW\_VFI\_MAIN\_BISEC\_VEC: Finished Age Group:48 of 82, time-this-age:6.4668  
SNW\_VFI\_MAIN\_BISEC\_VEC: Finished Age Group:47 of 82, time-this-age:6.7856  
SNW\_VFI\_MAIN\_BISEC\_VEC: Finished Age Group:46 of 82, time-this-age:6.6894  
SNW\_VFI\_MAIN\_BISEC\_VEC: Finished Age Group:45 of 82, time-this-age:6.5303  
SNW\_VFI\_MAIN\_BISEC\_VEC: Finished Age Group:44 of 82, time-this-age:6.5652  
SNW\_VFI\_MAIN\_BISEC\_VEC: Finished Age Group:43 of 82, time-this-age:6.4601  
SNW\_VFI\_MAIN\_BISEC\_VEC: Finished Age Group:42 of 82, time-this-age:6.5478  
SNW\_VFI\_MAIN\_BISEC\_VEC: Finished Age Group:41 of 82, time-this-age:6.5693  
SNW\_VFI\_MAIN\_BISEC\_VEC: Finished Age Group:40 of 82, time-this-age:6.4817  
SNW\_VFI\_MAIN\_BISEC\_VEC: Finished Age Group:39 of 82, time-this-age:6.1035  
SNW\_VFI\_MAIN\_BISEC\_VEC: Finished Age Group:38 of 82, time-this-age:6.3312  
SNW\_VFI\_MAIN\_BISEC\_VEC: Finished Age Group:37 of 82, time-this-age:6.652  
SNW\_VFI\_MAIN\_BISEC\_VEC: Finished Age Group:36 of 82, time-this-age:6.5706  
SNW\_VFI\_MAIN\_BISEC\_VEC: Finished Age Group:35 of 82, time-this-age:6.3328  
SNW\_VFI\_MAIN\_BISEC\_VEC: Finished Age Group:34 of 82, time-this-age:6.3866  
SNW\_VFI\_MAIN\_BISEC\_VEC: Finished Age Group:33 of 82, time-this-age:6.3876  
SNW\_VFI\_MAIN\_BISEC\_VEC: Finished Age Group:32 of 82, time-this-age:6.5786  
SNW\_VFI\_MAIN\_BISEC\_VEC: Finished Age Group:31 of 82, time-this-age:6.4579  
SNW\_VFI\_MAIN\_BISEC\_VEC: Finished Age Group:30 of 82, time-this-age:6.4423  
SNW\_VFI\_MAIN\_BISEC\_VEC: Finished Age Group:29 of 82, time-this-age:6.5074  
SNW\_VFI\_MAIN\_BISEC\_VEC: Finished Age Group:28 of 82, time-this-age:6.6582  
SNW\_VFI\_MAIN\_BISEC\_VEC: Finished Age Group:27 of 82, time-this-age:6.6605  
SNW\_VFI\_MAIN\_BISEC\_VEC: Finished Age Group:26 of 82, time-this-age:6.7467  
SNW\_VFI\_MAIN\_BISEC\_VEC: Finished Age Group:25 of 82, time-this-age:6.567  
SNW\_VFI\_MAIN\_BISEC\_VEC: Finished Age Group:24 of 82, time-this-age:6.6851  
SNW\_VFI\_MAIN\_BISEC\_VEC: Finished Age Group:23 of 82, time-this-age:6.7011  
SNW\_VFI\_MAIN\_BISEC\_VEC: Finished Age Group:22 of 82, time-this-age:6.3939  
SNW\_VFI\_MAIN\_BISEC\_VEC: Finished Age Group:21 of 82, time-this-age:6.5634  
SNW\_VFI\_MAIN\_BISEC\_VEC: Finished Age Group:20 of 82, time-this-age:6.4832  
SNW\_VFI\_MAIN\_BISEC\_VEC: Finished Age Group:19 of 82, time-this-age:6.4651  
SNW\_VFI\_MAIN\_BISEC\_VEC: Finished Age Group:18 of 82, time-this-age:6.5353  
SNW\_VFI\_MAIN\_BISEC\_VEC: Finished Age Group:17 of 82, time-this-age:6.4967  
SNW\_VFI\_MAIN\_BISEC\_VEC: Finished Age Group:16 of 82, time-this-age:6.387  
SNW\_VFI\_MAIN\_BISEC\_VEC: Finished Age Group:15 of 82, time-this-age:6.345  
SNW\_VFI\_MAIN\_BISEC\_VEC: Finished Age Group:14 of 82, time-this-age:6.577  
SNW\_VFI\_MAIN\_BISEC\_VEC: Finished Age Group:13 of 82, time-this-age:6.7646  
SNW\_VFI\_MAIN\_BISEC\_VEC: Finished Age Group:12 of 82, time-this-age:6.8183  
SNW\_VFI\_MAIN\_BISEC\_VEC: Finished Age Group:11 of 82, time-this-age:6.4142  
SNW\_VFI\_MAIN\_BISEC\_VEC: Finished Age Group:10 of 82, time-this-age:6.342  
SNW\_VFI\_MAIN\_BISEC\_VEC: Finished Age Group:9 of 82, time-this-age:6.4692  
SNW\_VFI\_MAIN\_BISEC\_VEC: Finished Age Group:8 of 82, time-this-age:6.5127  
SNW\_VFI\_MAIN\_BISEC\_VEC: Finished Age Group:7 of 82, time-this-age:6.5417  
SNW\_VFI\_MAIN\_BISEC\_VEC: Finished Age Group:6 of 82, time-this-age:6.5962  
SNW\_VFI\_MAIN\_BISEC\_VEC: Finished Age Group:5 of 82, time-this-age:6.4304  
SNW\_VFI\_MAIN\_BISEC\_VEC: Finished Age Group:4 of 82, time-this-age:6.3748

SNW\_VFI\_MAIN\_BISEC\_VEC: Finished Age Group:3 of 82, time-this-age:6.2745

SNW\_VFI\_MAIN\_BISEC\_VEC: Finished Age Group:2 of 82, time-this-age:6.5175

SNW\_VFI\_MAIN\_BISEC\_VEC: Finished Age Group:1 of 82, time-this-age:6.3803

Completed SNW\_VFI\_MAIN\_BISEC\_VEC;SNW\_MP\_PARAM=default\_docdense;SNW\_MP\_CONTROL=default\_test;time=535.

CONTAINER NAME: mp\_outcomes ND Array (Matrix etc)

	i	idx	ndim	numel	rowN	colN	sum	mean	std
V_VFI	1	1	6	4.37e+07	83	5.265e+05	-8.6673e+08	-19.834	28.17
ap_VFI	2	2	6	4.37e+07	83	5.265e+05	1.4164e+09	32.412	36.
cons_VFI	3	3	6	4.37e+07	83	5.265e+05	2.131e+08	4.8764	8.326

xxx TABLE:V\_VFI xxxxxxxxxxxxxxxxxxxxxxx

	c1	c2	c3	c4	c5	c526496	c526497	c526498
r1	-376.05	-375.66	-373.17	-367.4	-358.05	-6.68	-6.5297	-6.379
r2	-363.8	-363.41	-360.93	-355.25	-346.25	-6.4892	-6.3437	-6.197
r3	-351.75	-351.36	-348.9	-343.44	-334.9	-6.2948	-6.1538	-6.011
r4	-339.81	-339.45	-337.16	-332.06	-324.04	-6.095	-5.9584	-5.8
r5	-328.99	-328.65	-326.51	-321.72	-314.17	-5.9054	-5.7725	-5.637
r79	-14.033	-14.02	-13.926	-13.689	-13.287	-0.22848	-0.21775	-0.2076
r80	-12.564	-12.55	-12.457	-12.22	-11.818	-0.17427	-0.16611	-0.1584
r81	-10.778	-10.764	-10.671	-10.434	-10.032	-0.11927	-0.11368	-0.1084
r82	-8.4226	-8.4089	-8.3155	-8.0786	-7.6766	-0.06597	-0.06284	-0.05992
r83	-5.0665	-5.0529	-4.9595	-4.7226	-4.3206	-0.020968	-0.019972	-0.01903

xxx TABLE:ap\_VFI xxxxxxxxxxxxxxxxxxxxxxx

	c1	c2	c3	c4	c5	c526496	c526497	c526498	c526499
r1	0	0	0.0005656	0.0075134	0.022901	114.76	120.42	126.29	132
r2	0	0	0.00051498	0.0065334	0.021549	114.87	120.54	126.42	132
r3	0	0	0.00051498	0.0049294	0.019875	114.98	120.67	126.57	132
r4	0	0	0.00051498	0.0047937	0.019672	115.74	121.44	127.36	133
r5	0	0	0.00048517	0.0046683	0.019484	116.51	122.22	128.16	134
r79	0	0	0	0	0.00051498	81.091	85.68	90.325	94.
r80	0	0	0	0	0	76.669	80.55	84.292	88.
r81	0	0	0	0	0	68.313	71.52	74.459	77
r82	0	0	0	0	0	50.126	53.467	56.953	58.
r83	0	0	0	0	0	0	0	0	0

xxx TABLE:cons\_VFI xxxxxxxxxxxxxxxxxxxxxxx

	c1	c2	c3	c4	c5	c526496	c526497	c526498
r1	0.036717	0.037251	0.040426	0.04363	0.048012	9.6396	9.8066	9.9533
r2	0.036717	0.037251	0.040477	0.04461	0.049364	9.8014	9.9571	10.088
r3	0.036717	0.037251	0.040477	0.046214	0.051039	9.9664	10.108	10.22
r4	0.038144	0.038678	0.041903	0.047776	0.052666	10.118	10.244	10.339
r5	0.039534	0.040068	0.043323	0.04929	0.054241	10.258	10.369	10.446
r79	0.19737	0.19791	0.20163	0.21175	0.23093	35.811	37.046	38.418
r80	0.19737	0.19791	0.20163	0.21175	0.23145	40.207	42.15	44.426
r81	0.19737	0.19791	0.20163	0.21175	0.23145	48.541	51.158	54.236
r82	0.19737	0.19791	0.20163	0.21175	0.23145	66.71	69.193	71.724

r83      0.19737      0.19791      0.20163      0.21175      0.23145      116.82      122.65      128.66

Second, solve for the unemployment value, use the exact-bisec result code, call the `snw_vfi_main_bisec_vec.m` function with a third input of existing value. `xi` is the share of income lost during covid year given surprise covid shock, `b` is the share of income loss that is covered by unemployment insurance. `xi=0.5` and `b=0` means will lose 50 percent of income given COVID shocks, and the loss will not be covered at all by unemployment insurance.

```
mp_params('xi') = 0.5;
mp_params('b') = 0;
mp_params('a2_covidyr') = mp_params('a2_covidyr_manna_heaven');
[V_VFI_unemp,ap_VFI_unemp,cons_VFI_unemp,mp_valpol_more_unemp] = ...
    snw_vfi_main_bisec_vec(mp_params, mp_controls, V_VFI_ss);
```

```
SNW_VFI_MAIN_BISEC_VEC 1 Period Unemp Shock: Age 1 of 82, time-this-age:6.2923
SNW_VFI_MAIN_BISEC_VEC 1 Period Unemp Shock: Age 2 of 82, time-this-age:6.5203
SNW_VFI_MAIN_BISEC_VEC 1 Period Unemp Shock: Age 3 of 82, time-this-age:6.0245
SNW_VFI_MAIN_BISEC_VEC 1 Period Unemp Shock: Age 4 of 82, time-this-age:6.5906
SNW_VFI_MAIN_BISEC_VEC 1 Period Unemp Shock: Age 5 of 82, time-this-age:6.4748
SNW_VFI_MAIN_BISEC_VEC 1 Period Unemp Shock: Age 6 of 82, time-this-age:6.515
SNW_VFI_MAIN_BISEC_VEC 1 Period Unemp Shock: Age 7 of 82, time-this-age:6.1144
SNW_VFI_MAIN_BISEC_VEC 1 Period Unemp Shock: Age 8 of 82, time-this-age:6.2132
SNW_VFI_MAIN_BISEC_VEC 1 Period Unemp Shock: Age 9 of 82, time-this-age:6.5055
SNW_VFI_MAIN_BISEC_VEC 1 Period Unemp Shock: Age 10 of 82, time-this-age:6.4562
SNW_VFI_MAIN_BISEC_VEC 1 Period Unemp Shock: Age 11 of 82, time-this-age:6.0604
SNW_VFI_MAIN_BISEC_VEC 1 Period Unemp Shock: Age 12 of 82, time-this-age:6.641
SNW_VFI_MAIN_BISEC_VEC 1 Period Unemp Shock: Age 13 of 82, time-this-age:6.5864
SNW_VFI_MAIN_BISEC_VEC 1 Period Unemp Shock: Age 14 of 82, time-this-age:6.3514
SNW_VFI_MAIN_BISEC_VEC 1 Period Unemp Shock: Age 15 of 82, time-this-age:6.3017
SNW_VFI_MAIN_BISEC_VEC 1 Period Unemp Shock: Age 16 of 82, time-this-age:6.2902
SNW_VFI_MAIN_BISEC_VEC 1 Period Unemp Shock: Age 17 of 82, time-this-age:6.5771
SNW_VFI_MAIN_BISEC_VEC 1 Period Unemp Shock: Age 18 of 82, time-this-age:6.163
SNW_VFI_MAIN_BISEC_VEC 1 Period Unemp Shock: Age 19 of 82, time-this-age:6.2954
SNW_VFI_MAIN_BISEC_VEC 1 Period Unemp Shock: Age 20 of 82, time-this-age:6.162
SNW_VFI_MAIN_BISEC_VEC 1 Period Unemp Shock: Age 21 of 82, time-this-age:6.0779
SNW_VFI_MAIN_BISEC_VEC 1 Period Unemp Shock: Age 22 of 82, time-this-age:6.1283
SNW_VFI_MAIN_BISEC_VEC 1 Period Unemp Shock: Age 23 of 82, time-this-age:6.3978
SNW_VFI_MAIN_BISEC_VEC 1 Period Unemp Shock: Age 24 of 82, time-this-age:6.4584
SNW_VFI_MAIN_BISEC_VEC 1 Period Unemp Shock: Age 25 of 82, time-this-age:5.9292
SNW_VFI_MAIN_BISEC_VEC 1 Period Unemp Shock: Age 26 of 82, time-this-age:6.1225
SNW_VFI_MAIN_BISEC_VEC 1 Period Unemp Shock: Age 27 of 82, time-this-age:6.4045
SNW_VFI_MAIN_BISEC_VEC 1 Period Unemp Shock: Age 28 of 82, time-this-age:6.4834
SNW_VFI_MAIN_BISEC_VEC 1 Period Unemp Shock: Age 29 of 82, time-this-age:6.2843
SNW_VFI_MAIN_BISEC_VEC 1 Period Unemp Shock: Age 30 of 82, time-this-age:6.2094
SNW_VFI_MAIN_BISEC_VEC 1 Period Unemp Shock: Age 31 of 82, time-this-age:6.4612
SNW_VFI_MAIN_BISEC_VEC 1 Period Unemp Shock: Age 32 of 82, time-this-age:6.1629
SNW_VFI_MAIN_BISEC_VEC 1 Period Unemp Shock: Age 33 of 82, time-this-age:6.4799
SNW_VFI_MAIN_BISEC_VEC 1 Period Unemp Shock: Age 34 of 82, time-this-age:6.4272
SNW_VFI_MAIN_BISEC_VEC 1 Period Unemp Shock: Age 35 of 82, time-this-age:6.5508
SNW_VFI_MAIN_BISEC_VEC 1 Period Unemp Shock: Age 36 of 82, time-this-age:6.1381
SNW_VFI_MAIN_BISEC_VEC 1 Period Unemp Shock: Age 37 of 82, time-this-age:6.0588
SNW_VFI_MAIN_BISEC_VEC 1 Period Unemp Shock: Age 38 of 82, time-this-age:6.1133
SNW_VFI_MAIN_BISEC_VEC 1 Period Unemp Shock: Age 39 of 82, time-this-age:5.9731
SNW_VFI_MAIN_BISEC_VEC 1 Period Unemp Shock: Age 40 of 82, time-this-age:6.2753
SNW_VFI_MAIN_BISEC_VEC 1 Period Unemp Shock: Age 41 of 82, time-this-age:6.4228
SNW_VFI_MAIN_BISEC_VEC 1 Period Unemp Shock: Age 42 of 82, time-this-age:6.0784
SNW_VFI_MAIN_BISEC_VEC 1 Period Unemp Shock: Age 43 of 82, time-this-age:5.8926
SNW_VFI_MAIN_BISEC_VEC 1 Period Unemp Shock: Age 44 of 82, time-this-age:6.1351
SNW_VFI_MAIN_BISEC_VEC 1 Period Unemp Shock: Age 45 of 82, time-this-age:5.9147
```

```

SNW_VFI_MAIN_BISEC_VEC 1 Period Unemp Shock: Age 46 of 82, time-this-age:6.4062
SNW_VFI_MAIN_BISEC_VEC 1 Period Unemp Shock: Age 47 of 82, time-this-age:6.7344
SNW_VFI_MAIN_BISEC_VEC 1 Period Unemp Shock: Age 48 of 82, time-this-age:6.278
SNW_VFI_MAIN_BISEC_VEC 1 Period Unemp Shock: Age 49 of 82, time-this-age:6.2085
SNW_VFI_MAIN_BISEC_VEC 1 Period Unemp Shock: Age 50 of 82, time-this-age:6.0966
SNW_VFI_MAIN_BISEC_VEC 1 Period Unemp Shock: Age 51 of 82, time-this-age:6.3449
SNW_VFI_MAIN_BISEC_VEC 1 Period Unemp Shock: Age 52 of 82, time-this-age:6.2717
SNW_VFI_MAIN_BISEC_VEC 1 Period Unemp Shock: Age 53 of 82, time-this-age:6.4826
SNW_VFI_MAIN_BISEC_VEC 1 Period Unemp Shock: Age 54 of 82, time-this-age:6.3431
SNW_VFI_MAIN_BISEC_VEC 1 Period Unemp Shock: Age 55 of 82, time-this-age:5.9453
SNW_VFI_MAIN_BISEC_VEC 1 Period Unemp Shock: Age 56 of 82, time-this-age:6.2613
SNW_VFI_MAIN_BISEC_VEC 1 Period Unemp Shock: Age 57 of 82, time-this-age:6.2364
SNW_VFI_MAIN_BISEC_VEC 1 Period Unemp Shock: Age 58 of 82, time-this-age:6.0578
SNW_VFI_MAIN_BISEC_VEC 1 Period Unemp Shock: Age 59 of 82, time-this-age:6.1279
SNW_VFI_MAIN_BISEC_VEC 1 Period Unemp Shock: Age 60 of 82, time-this-age:6.1238
SNW_VFI_MAIN_BISEC_VEC 1 Period Unemp Shock: Age 61 of 82, time-this-age:6.2806
SNW_VFI_MAIN_BISEC_VEC 1 Period Unemp Shock: Age 62 of 82, time-this-age:5.9344
SNW_VFI_MAIN_BISEC_VEC 1 Period Unemp Shock: Age 63 of 82, time-this-age:6.0212
SNW_VFI_MAIN_BISEC_VEC 1 Period Unemp Shock: Age 64 of 82, time-this-age:6.3424
SNW_VFI_MAIN_BISEC_VEC 1 Period Unemp Shock: Age 65 of 82, time-this-age:5.863
SNW_VFI_MAIN_BISEC_VEC 1 Period Unemp Shock: Age 66 of 82, time-this-age:6.1349
SNW_VFI_MAIN_BISEC_VEC 1 Period Unemp Shock: Age 67 of 82, time-this-age:5.9904
SNW_VFI_MAIN_BISEC_VEC 1 Period Unemp Shock: Age 68 of 82, time-this-age:5.9675
SNW_VFI_MAIN_BISEC_VEC 1 Period Unemp Shock: Age 69 of 82, time-this-age:5.7964
SNW_VFI_MAIN_BISEC_VEC 1 Period Unemp Shock: Age 70 of 82, time-this-age:6.0091
SNW_VFI_MAIN_BISEC_VEC 1 Period Unemp Shock: Age 71 of 82, time-this-age:6.0331
SNW_VFI_MAIN_BISEC_VEC 1 Period Unemp Shock: Age 72 of 82, time-this-age:5.8808
SNW_VFI_MAIN_BISEC_VEC 1 Period Unemp Shock: Age 73 of 82, time-this-age:6.0943
SNW_VFI_MAIN_BISEC_VEC 1 Period Unemp Shock: Age 74 of 82, time-this-age:6.0279
SNW_VFI_MAIN_BISEC_VEC 1 Period Unemp Shock: Age 75 of 82, time-this-age:6.1533
SNW_VFI_MAIN_BISEC_VEC 1 Period Unemp Shock: Age 76 of 82, time-this-age:6.0662
SNW_VFI_MAIN_BISEC_VEC 1 Period Unemp Shock: Age 77 of 82, time-this-age:5.7827
SNW_VFI_MAIN_BISEC_VEC 1 Period Unemp Shock: Age 78 of 82, time-this-age:6.1473
SNW_VFI_MAIN_BISEC_VEC 1 Period Unemp Shock: Age 79 of 82, time-this-age:6.071
SNW_VFI_MAIN_BISEC_VEC 1 Period Unemp Shock: Age 80 of 82, time-this-age:6.1187
SNW_VFI_MAIN_BISEC_VEC 1 Period Unemp Shock: Age 81 of 82, time-this-age:5.9865
SNW_VFI_MAIN_BISEC_VEC 1 Period Unemp Shock: Age 82 of 82, time-this-age:6.1363
SNW_VFI_MAIN_BISEC_VEC 1 Period Unemp Shock: Age 83 of 82, time-this-age:7.7853
Completed SNW_VFI_MAIN_BISEC_VEC 1 Period Unemp Shock;SNW_MP_PARAM=default_docdense;SNW_MP_CONTROL=d

```

```

-----
XXXXXXXXXXXXXXXXXXXXXXXXXXXXXXXXXXXXXXXXXXXXXXXXXXXX
CONTAINER NAME: mp_outcomes ND Array (Matrix etc)
XXXXXXXXXXXXXXXXXXXXXXXXXXXXXXXXXXXXXXXXXXXXXXXXXXXX
      i   idx   ndim   numel   rowN   colN   sum   mean   std
      -   ---   ----   -
V_VFI   1     1     6     4.37e+07   83     5.265e+05   -8.9196e+08   -20.411   29.20
ap_VFI  2     2     6     4.37e+07   83     5.265e+05    1.3793e+09    31.564   36.67
cons_VFI 3     3     6     4.37e+07   83     5.265e+05    2.1007e+08    4.807   8.326

```

```

xxx TABLE:V_VFI XXXXXXXXXXXXXXXXXXXXXXX
      c1      c2      c3      c4      c5      c526496      c526497      c526498
      -----
r1    -402.51   -401.01   -392.48   -379.06   -366.5    -6.8096    -6.6548    -6.500
r2    -390.26   -388.76   -380.23   -366.81   -354.4    -6.618     -6.4683    -6.318
r3    -378.21   -376.71   -368.18   -354.76   -342.64   -6.4227    -6.278     -6.132
r4    -365.26   -363.87   -355.91   -343.19   -331.62   -6.2297    -6.0896    -5.948

```

r5	-353.53	-352.23	-344.77	-332.67	-321.59	-6.0467	-5.9107	-5.773
r79	-14.033	-14.02	-13.926	-13.689	-13.287	-0.2305	-0.21962	-0.2093
r80	-12.564	-12.55	-12.457	-12.22	-11.818	-0.17582	-0.16751	-0.1596
r81	-10.778	-10.764	-10.671	-10.434	-10.032	-0.12032	-0.11462	-0.1092
r82	-8.4226	-8.4089	-8.3155	-8.0786	-7.6766	-0.066524	-0.063355	-0.06039
r83	-5.0665	-5.0529	-4.9595	-4.7226	-4.3206	-0.021146	-0.020134	-0.01918

```
xxx TABLE:ap_VFI xxxxxxxxxxxxxxxxxxxxxx
```

	c1	c2	c3	c4	c5	c526496	c526497	c526498	c526499	c526500
	--	--	--	--	-----	-----	-----	-----	-----	-----
r1	0	0	0	0	0.0092181	110.07	115.71	121.57	127.63	133.94
r2	0	0	0	0	0.008238	110.04	115.69	121.55	127.63	133.96
r3	0	0	0	0	0.0066341	110	115.66	121.54	127.64	133.99
r4	0	0	0	0	0.0058019	110.29	115.97	121.86	127.98	134.34
r5	0	0	0	0	0.004998	110.59	116.28	122.19	128.33	134.7
r79	0	0	0	0	0.00051498	81.091	85.231	89.301	93.347	97.387
r80	0	0	0	0	0	75.865	79.539	83.281	87.018	90.672
r81	0	0	0	0	0	67.78	70.52	73.459	76.816	81.091
r82	0	0	0	0	0	50.126	53.467	56.104	57.737	60.587
r83	0	0	0	0	0	0	0	0	0	0

```
xxx TABLE:cons_VFI xxxxxxxxxxxxxxxxxxxxxx
```

	c1	c2	c3	c4	c5	c526496	c526497	c526498
	-----	-----	-----	-----	-----	-----	-----	-----
r1	0.018623	0.019158	0.022901	0.033062	0.04363	9.4621	9.6396	9.8066
r2	0.018623	0.019158	0.022901	0.033062	0.04461	9.6318	9.8014	9.9571
r3	0.018623	0.019158	0.022901	0.033062	0.046214	9.8074	9.9664	10.108
r4	0.019354	0.019888	0.023632	0.033792	0.047776	9.971	10.118	10.244
r5	0.020066	0.020601	0.024344	0.034504	0.04929	10.123	10.258	10.369
r79	0.19737	0.19791	0.20163	0.21175	0.23093	34.787	36.471	38.418
r80	0.19737	0.19791	0.20163	0.21175	0.23145	40.001	42.15	44.426
r81	0.19737	0.19791	0.20163	0.21175	0.23145	48.074	51.158	54.236
r82	0.19737	0.19791	0.20163	0.21175	0.23145	65.719	68.202	71.583
r83	0.19737	0.19791	0.20163	0.21175	0.23145	115.84	121.66	127.68

Difference Between Value and Choices In Unemployment and Future Periods

```
V_VFI_unemp_drop = V_VFI_ss - V_VFI_unemp;
ap_VFI_unemp_drop = ap_VFI_ss - ap_VFI_unemp;
cons_VFI_unemp_drop = cons_VFI_ss - cons_VFI_unemp;
```

## 5.1.2 Define Parameter Frames

Define the matrix dimensions names and dimension vector values. Policy and Value Functions share the same ND dimensional structure.

```
% Grids:
age_grid = 18:100;
agrid = mp_params('agrid');
eta_H_grid = mp_params('eta_H_grid');
eta_S_grid = mp_params('eta_S_grid');
ar_st_eta_HS_grid = string(cellstr([num2str(eta_H_grid', 'hz=%3.2f;'), num2str(eta_S_grid', 'wz=%3.2f;')], 'wz=%3.2f;');
edu_grid = [0,1];
marry_grid = [0,1];
kids_grid = (1:1:mp_params('n_kidsgrid'))';
% NaN(n_jgrid,n_agrid,n_etagrid,n_educgrid,n_marriedgrid,n_kidsgrid);
cl_mp_datasetdesc = {};
cl_mp_datasetdesc{1} = containers.Map({'name', 'labval'}, {'age', age_grid});
```



```

cl_mp_datasetdesc{2} = containers.Map({'name', 'labval'}, {'savings', agrid});
cl_mp_datasetdesc{3} = containers.Map({'name', 'labval'}, {'eta', 1:length(eta_H_grid)});
cl_mp_datasetdesc{4} = containers.Map({'name', 'labval'}, {'edu', edu_grid});
cl_mp_datasetdesc{5} = containers.Map({'name', 'labval'}, {'marry', marry_grid});
cl_mp_datasetdesc{6} = containers.Map({'name', 'labval'}, {'kids', kids_grid});

```

### 5.1.3 Analyze Savings and Shocks

First, analyze Savings Levels and Shocks, Aggregate Over All Others, and do various other calculations.

```
% Generate some Data
```

```

mp_support_graph = containers.Map('KeyType', 'char', 'ValueType', 'any');
mp_support_graph('cl_st_xtitle') = {'Savings States, a'};
mp_support_graph('st_legend_loc') = 'eastoutside';
mp_support_graph('bl_graph_logy') = true; % do not log
mp_support_graph('it_legend_select') = 15; % how many shock legends to show
mp_support_graph('cl_colors') = 'jet';

```

```

MEAN(VAL(A,Z) - VAL(A,Z|unemp)), MEAN(AP(A,Z) - AP(A,Z|unemp)), MEAN(C(A,Z) -
C(A,Z|unemp))

```

Tabulate value and policies along savings and shocks:

```
% Set
```

```

% NaN(n_jgrid,n_agrid,n_etagrid,n_educgrid,n_marriedgrid,n_kidsgrid);
ar_permute = [1,4,5,6,3,2];

```

```
% Value Function
```

```
tb_az_v = ff_summ_nd_array("MEAN(v(A,Z) - v(A,Z|unemp))", V_VFI_unemp_drop, true, ["mean"], 4, 1, cl
```

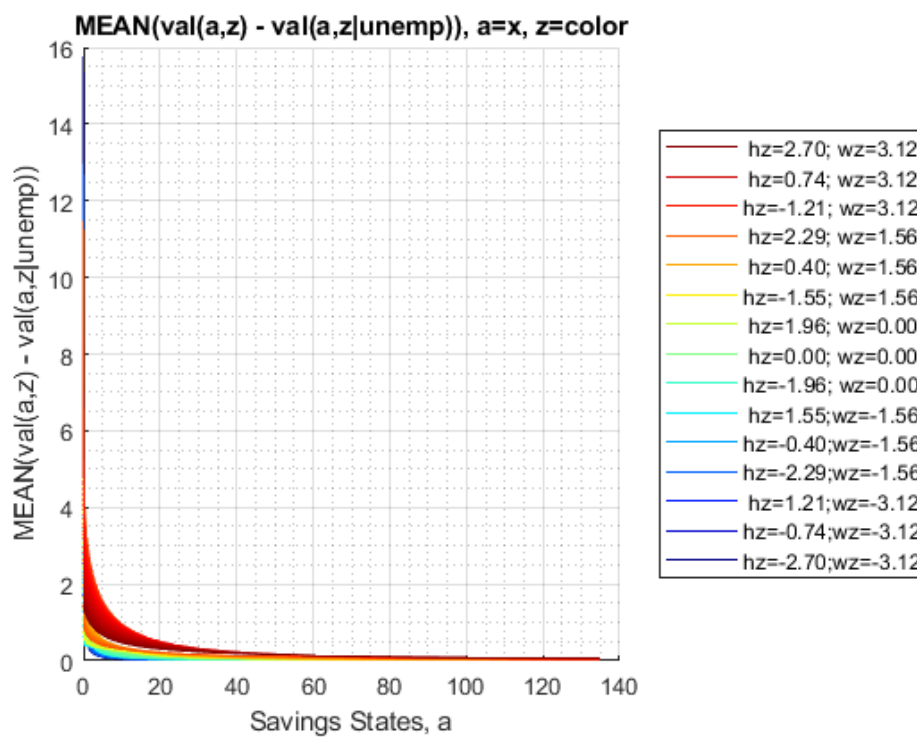
```

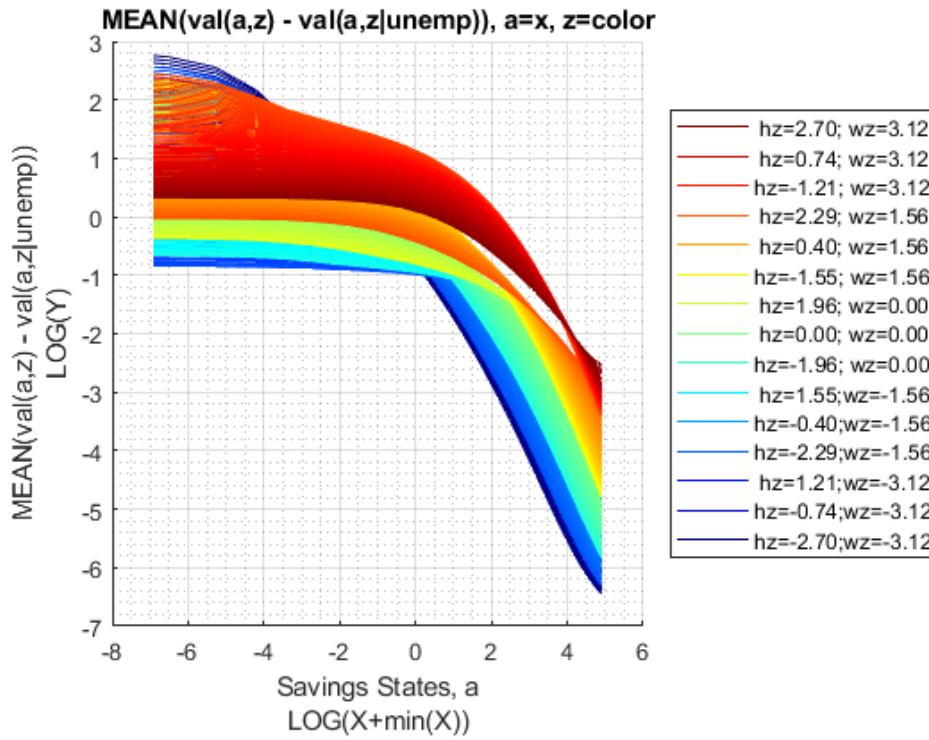
xxx MEAN(v(A,Z) - v(A,Z|unemp)) xxxxxxxxxxxxxxxxxxxxxxxxxxxxxxxxxxxx
  group      savings      mean_eta_1      mean_eta_2      mean_eta_3      mean_eta_4      mean_eta_5      mea
-----
  1          0          15.757          14.81          13.917          13.077          12.285

```

1                    0            0.019312            0.020444            0.021649            0.02293            0.024294            0

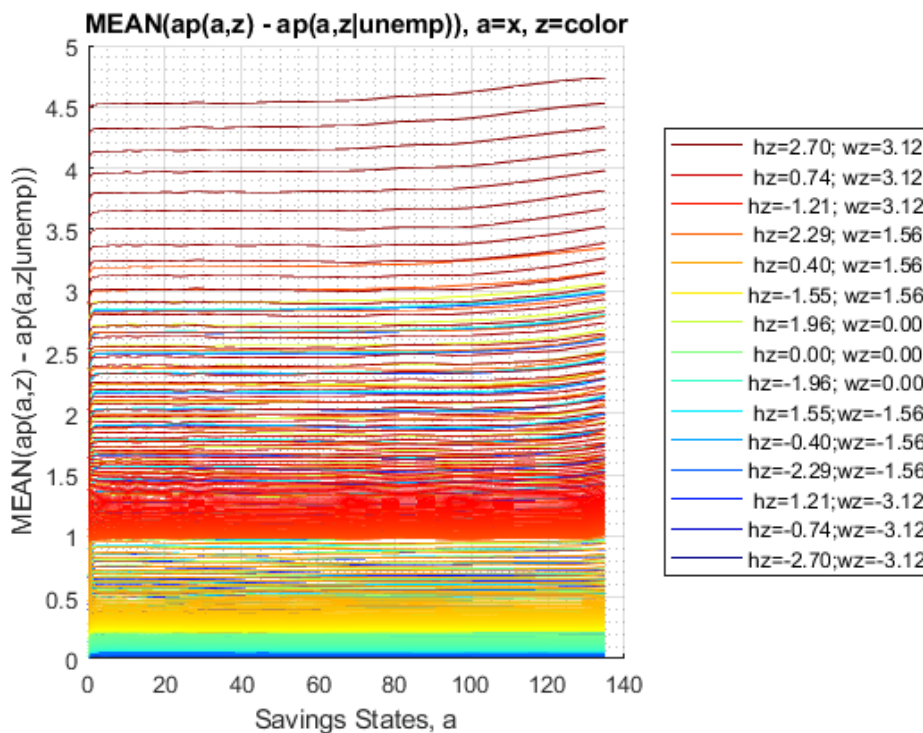
```
mp_support_graph('cl_st_graph_title') = {'MEAN(val(a,z) - val(a,z|unemp)), a=x, z=color'};
mp_support_graph('cl_st_ytitle') = {'MEAN(val(a,z) - val(a,z|unemp))'};
ff_graph_grid((tb_az_v{1:end, 3:end})', ar_st_eta_HS_grid, agrid, mp_support_graph);
```

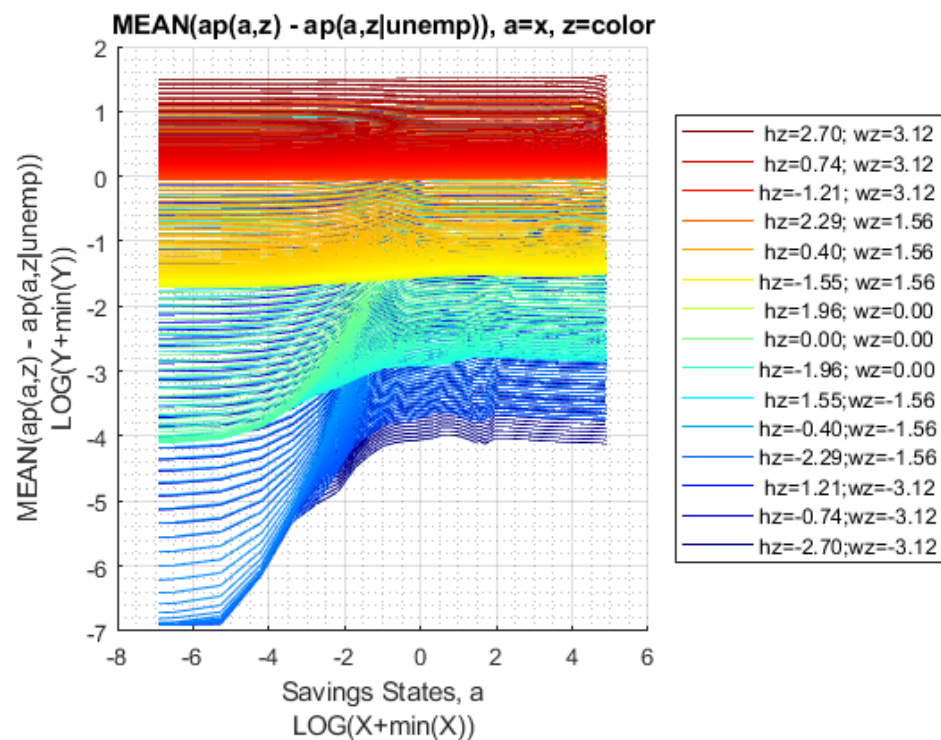




Graph Mean Savings Choices Change:

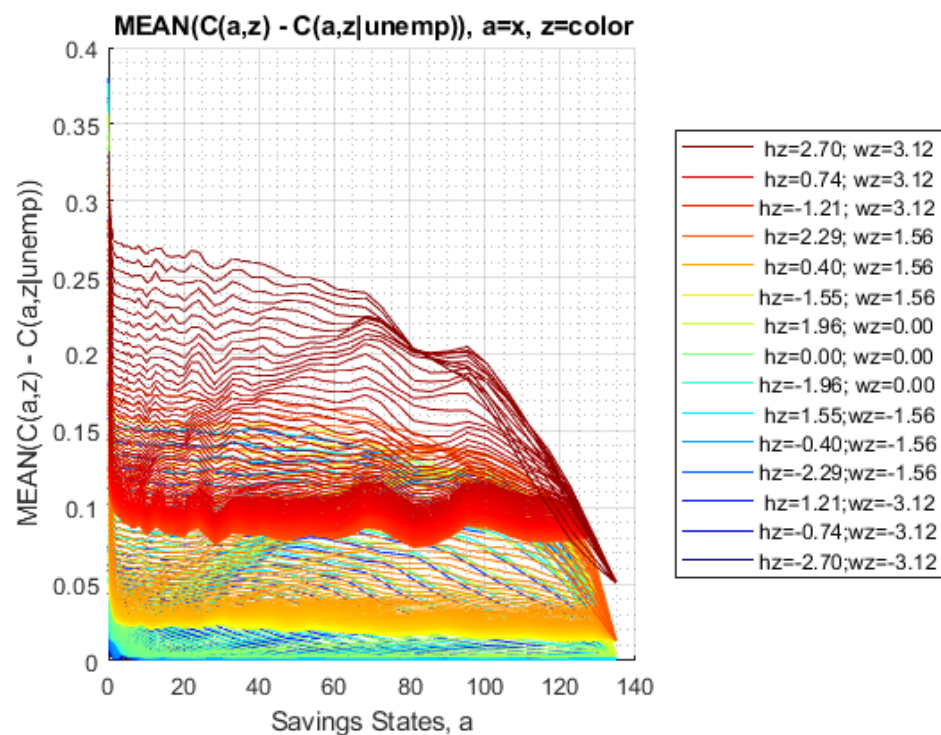
```
mp_support_graph('cl_st_graph_title') = {'MEAN(ap(a,z) - ap(a,z|unemp)), a=x, z=color'};
mp_support_graph('cl_st_ytitle') = {'MEAN(ap(a,z) - ap(a,z|unemp))'};
ff_graph_grid((tb_az_ap{1:end, 3:end})', ar_st_eta_HS_grid, agrid, mp_support_graph);
```

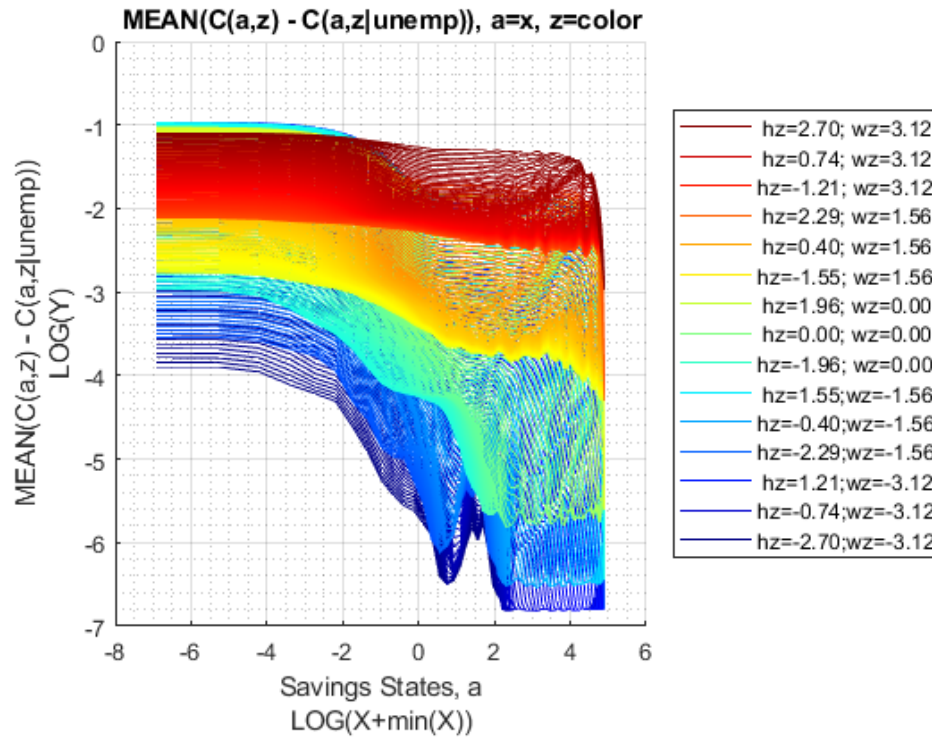




Graph Mean Consumption Change:

```
mp_support_graph('cl_st_graph_title') = {'MEAN(C(a,z) - C(a,z|unemp))', a=x, z=color};
mp_support_graph('cl_st_ytitle') = {'MEAN(C(a,z) - C(a,z|unemp))'};
ff_graph_grid((tb_az_c{1:end, 3:end})', ar_st_eta_HS_grid, agrid, mp_support_graph);
```





### 5.1.4 Analyze Kids and Marriage and Age

Aggregating over education, savings, and shocks, what are the differential effects of Marriage and Age.

```
% Generate some Data
mp_support_graph = containers.Map('KeyType', 'char', 'ValueType', 'any');
ar_row_grid = [...
    "k0M0", "K1M0", "K2M0", "K3M0", "K4M0", ...
    "k0M1", "K1M1", "K2M1", "K3M1", "K4M1"];
mp_support_graph('cl_st_xtitle') = {'Age'};
mp_support_graph('st_legend_loc') = 'best';
mp_support_graph('bl_graph_logy') = true; % do not log
mp_support_graph('st_rounding') = '6.2f'; % format shock legend
mp_support_graph('cl_scatter_shapes') = {...
    'o', 'd', 's', 'x', '*', ...
    'o', 'd', 's', 'x', '*'};
mp_support_graph('cl_colors') = {...
    'red', 'red', 'red', 'red', 'red'...
    'blue', 'blue', 'blue', 'blue', 'blue'};
```

MEAN(V(KM,J) - V(KM,J | unemp)), MEAN(ap(KM,J) - ap(KM,J | unemp)), MEAN(c(KM,J) - c(KM,J | unemp))

Tabulate value and policies:

```
% Set
% NaN(n_jgrid,n_agrid,n_etagrid,n_educgrid,n_marriedgrid,n_kidsgrid);
ar_permute = [2,3,4,1,6,5];
% Value Function
tb_az_v = ff_summ_nd_array("MEAN(V(KM,J) - V(KM,J | unemp))", V_VFI_unemp_drop, true, ["mean"], 3, 1
```

group	kids	marry	mean_age_18	mean_age_19	mean_age_20	mean_age_21	mean_age_2
1	1	0	0.61725	0.59976	0.58199	0.56601	0.55229

2	2	0	0.8282	0.80576	0.78226	0.75802	0.73679
3	3	0	0.96839	0.94588	0.92133	0.89232	0.86693
4	4	0	1.0956	1.0721	1.0458	1.0127	0.98375
5	5	0	1.2019	1.1787	1.1519	1.1158	1.0843
6	1	1	0.76869	0.75018	0.73196	0.71662	0.70371
7	2	1	0.93097	0.90782	0.88415	0.86307	0.84465
8	3	1	1.0192	0.99485	0.96959	0.94589	0.92513
9	4	1	1.1177	1.0921	1.0652	1.039	1.016
10	5	1	1.1589	1.1352	1.1089	1.0814	1.0577

% Aprime Choice

```
tb_az_ap = ff_summ_nd_array("MEAN(ap(KM,J) - ap(KM,J | unemp))", ap_VFI_unemp_drop, true, ["mean"],
```

```
xxx MEAN(ap(KM,J) - ap(KM,J | unemp)) xxxxxxxxxxxxxxxxxxxxxxxxxxxxxxxx
```

group	kids	marry	mean_age_18	mean_age_19	mean_age_20	mean_age_21	mean_age_2
1	1	0	0.54442	0.54173	0.53857	0.57709	0.6155
2	2	0	0.53845	0.53471	0.53034	0.56817	0.60591
3	3	0	0.53193	0.52758	0.5228	0.56021	0.59766
4	4	0	0.52782	0.52325	0.51825	0.55544	0.59269
5	5	0	0.52378	0.51921	0.5141	0.55117	0.58841
6	1	1	1.1324	1.1758	1.22	1.3121	1.4051
7	2	1	1.0397	1.0754	1.1117	1.1944	1.2779
8	3	1	0.97116	1.0022	1.0333	1.1099	1.1873
9	4	1	0.89614	0.92283	0.94936	1.0215	1.094
10	5	1	0.78037	0.79821	0.81602	0.87841	0.94111

% Consumption Choices

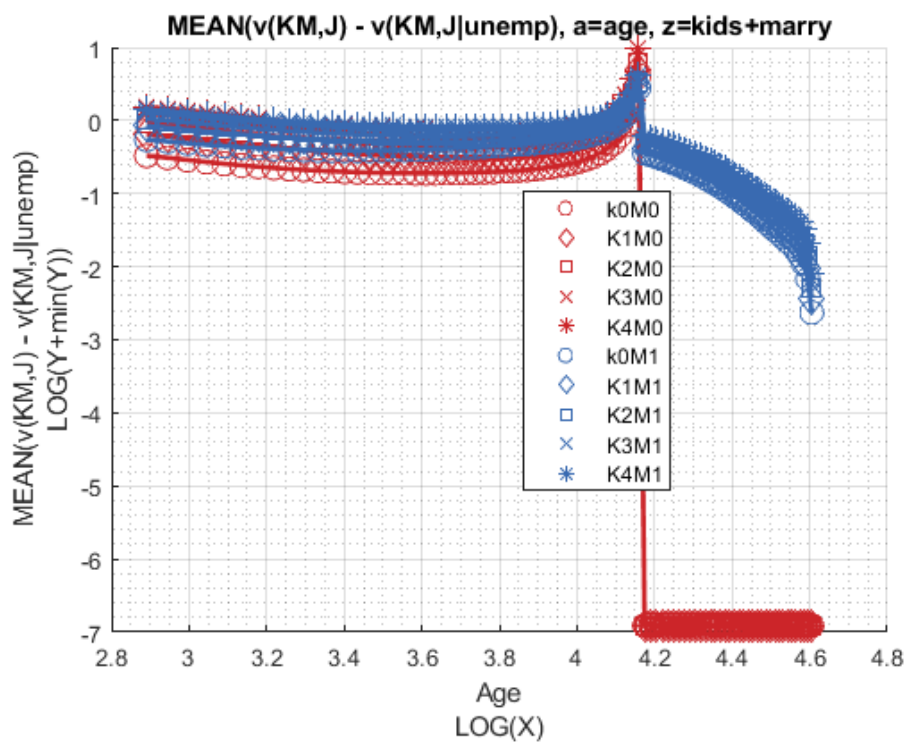
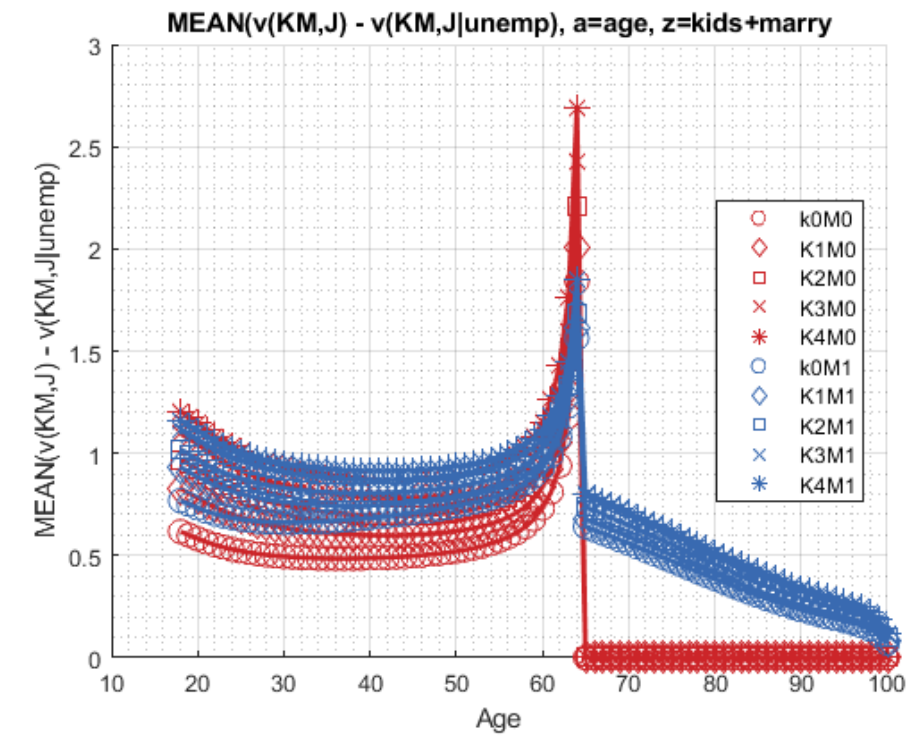
```
tb_az_c = ff_summ_nd_array("MEAN(c(KM,J) - c(KM,J | unemp))", cons_VFI_unemp_drop, true, ["mean"], 3
```

```
xxx MEAN(c(KM,J) - c(KM,J | unemp)) xxxxxxxxxxxxxxxxxxxxxxxxxxxxxxxx
```

group	kids	marry	mean_age_18	mean_age_19	mean_age_20	mean_age_21	mean_age_2
1	1	0	0.049956	0.052643	0.055802	0.056135	0.05627
2	2	0	0.05592	0.059662	0.064032	0.065053	0.065864
3	3	0	0.062441	0.066796	0.071572	0.073013	0.074107
4	4	0	0.066548	0.071126	0.076127	0.077784	0.07908
5	5	0	0.070592	0.075167	0.080271	0.082051	0.083363
6	1	1	0.091533	0.09707	0.10273	0.10671	0.11016
7	2	1	0.087319	0.093037	0.098883	0.10344	0.10744
8	3	1	0.089145	0.09428	0.10003	0.10457	0.1086
9	4	1	0.095251	0.099402	0.10424	0.10703	0.1095
10	5	1	0.1016	0.10608	0.11098	0.11351	0.11573

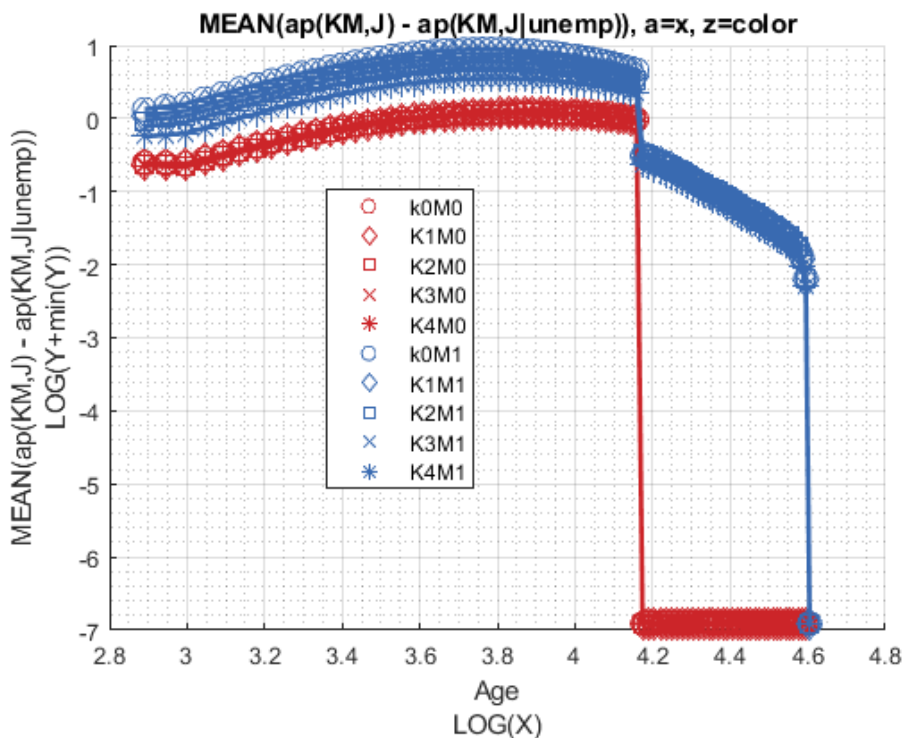
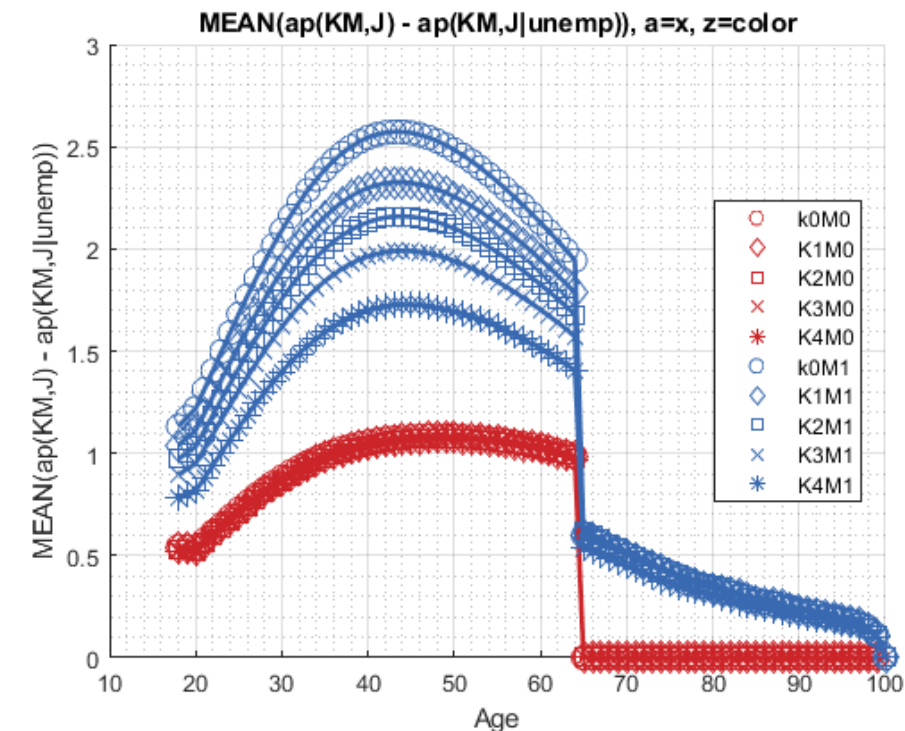
Graph Mean Values Change:

```
mp_support_graph('cl_st_graph_title') = {'MEAN(v(KM,J) - v(KM,J|unemp), a=age, z=kids+marry}';
mp_support_graph('cl_st_ytitle') = {'MEAN(v(KM,J) - v(KM,J|unemp)}';
ff_graph_grid((tb_az_v{1:end, 4:end}), ar_row_grid, age_grid, mp_support_graph);
```



Graph Mean Savings Choices Change:

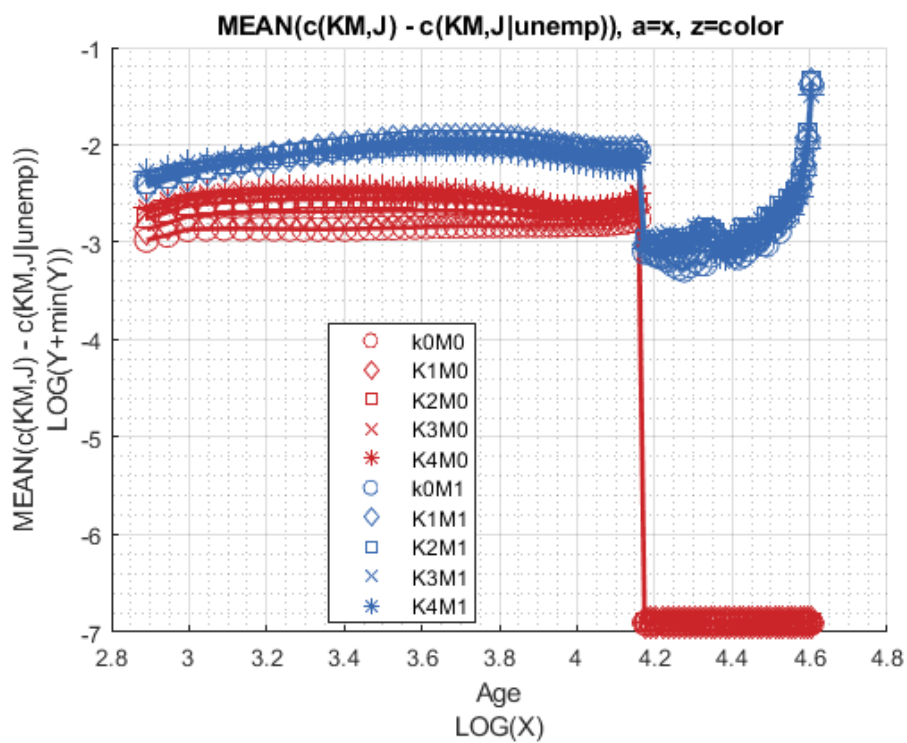
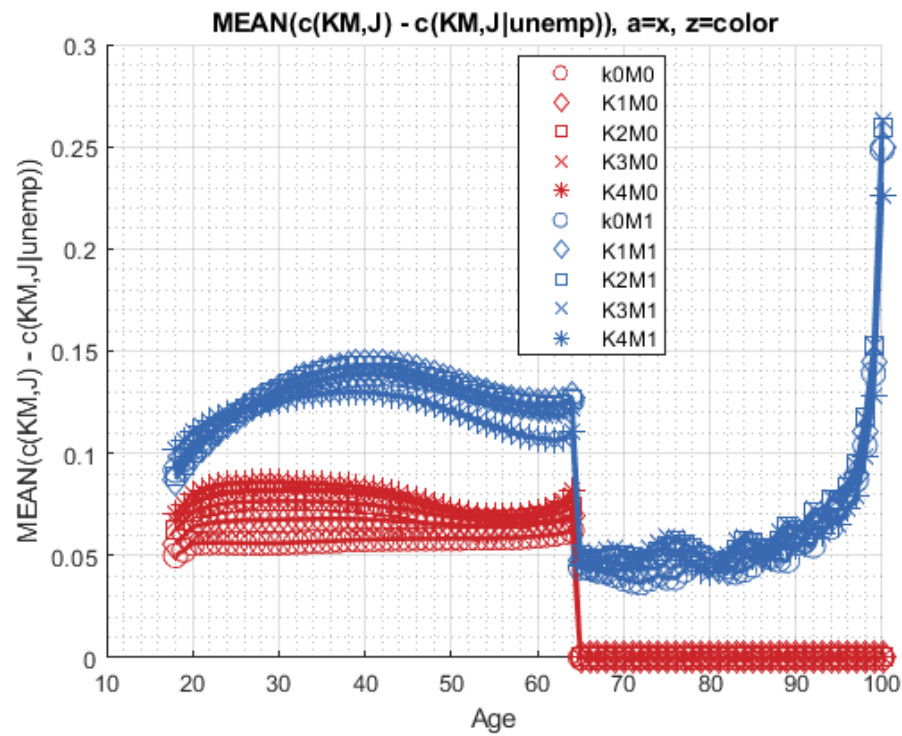
```
mp_support_graph('cl_st_graph_title') = {'MEAN(ap(KM,J) - ap(KM,J|unemp))', a=x, z=color};
mp_support_graph('cl_st_ytitle') = {'MEAN(ap(KM,J) - ap(KM,J|unemp))'};
ff_graph_grid((tb_az_ap{1:end, 4:end}), ar_row_grid, age_grid, mp_support_graph);
```



Graph Mean Consumption Change:

```
mp_support_graph('cl_st_graph_title') = {'MEAN(c(KM,J) - c(KM,J|unemp))', a=x, z=color};
mp_support_graph('cl_st_ytitle') = {'MEAN(c(KM,J) - c(KM,J|unemp))'};
ff_graph_grid((tb_az_c{1:end, 4:end}), ar_row_grid, age_grid, mp_support_graph);
```





### 5.1.5 Analyze Education and Marriage and Age

Aggregating over education, savings, and shocks, what are the differential effects of Marriage and Age.

% Generate some Data

```
mp_support_graph = containers.Map('KeyType', 'char', 'ValueType', 'any');
ar_row_grid = ["E0M0", "E1M0", "E0M1", "E1M1"];
mp_support_graph('cl_st_xtitle') = {'Age'};
mp_support_graph('st_legend_loc') = 'best';
mp_support_graph('bl_graph_logy') = true; % do not log
```

```
mp_support_graph('st_rounding') = '6.2f'; % format shock legend
mp_support_graph('cl_scatter_shapes') = {'*', 'p', '*', 'p' };
mp_support_graph('cl_colors') = {'red', 'red', 'blue', 'blue'};
```

```
MEAN(v(EKM,J) - v(EKM,J|unemp)), MEAN(ap(EM,J) - ap(EM,J|unemp)), MEAN(c(EM,J) -
c(EM,J|unemp))
```

Tabulate value and policies:

```
% Set
% NaN(n_jgrid,n_agrid,n_etagrid,n_educgrid,n_marriedgrid,n_kidsgrid);
ar_permute = [2,3,6,1,4,5];
% Value Function
tb_az_v = ff_summ_nd_array("MEAN(v(EM,J) - v(EM,J|unemp))", V_VFI_unemp_drop, true, ["mean"], 3, 1,
```

```
xxx MEAN(v(EM,J) - v(EM,J|unemp)) xxxxxxxxxxxxxxxxxxxxxxxxxxxxxxxx
  group   edu   marry   mean_age_18   mean_age_19   mean_age_20   mean_age_21   mean_age_22
  -----   ---   -----   -----
      1     0     0       0.98417     0.96522     0.94504     0.92586     0.90827
      2     1     0       0.90037     0.87569     0.84826     0.8121      0.78137
      3     0     1       1.0511      1.0316      1.0114      0.99333     0.97709
      4     1     1       0.9471      0.92052     0.89256     0.86506     0.84177
```

```
% Aprime Choice
tb_az_ap = ff_summ_nd_array("MEAN(ap(EM,J) - ap(EM,J|unemp))", ap_VFI_unemp_drop, true, ["mean"], 3,
```

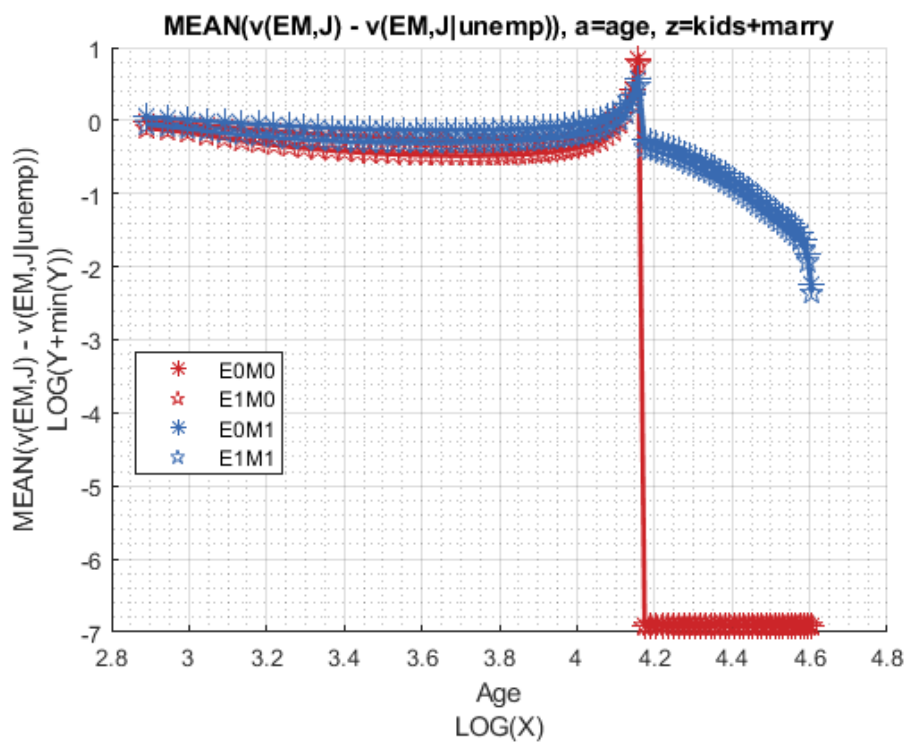
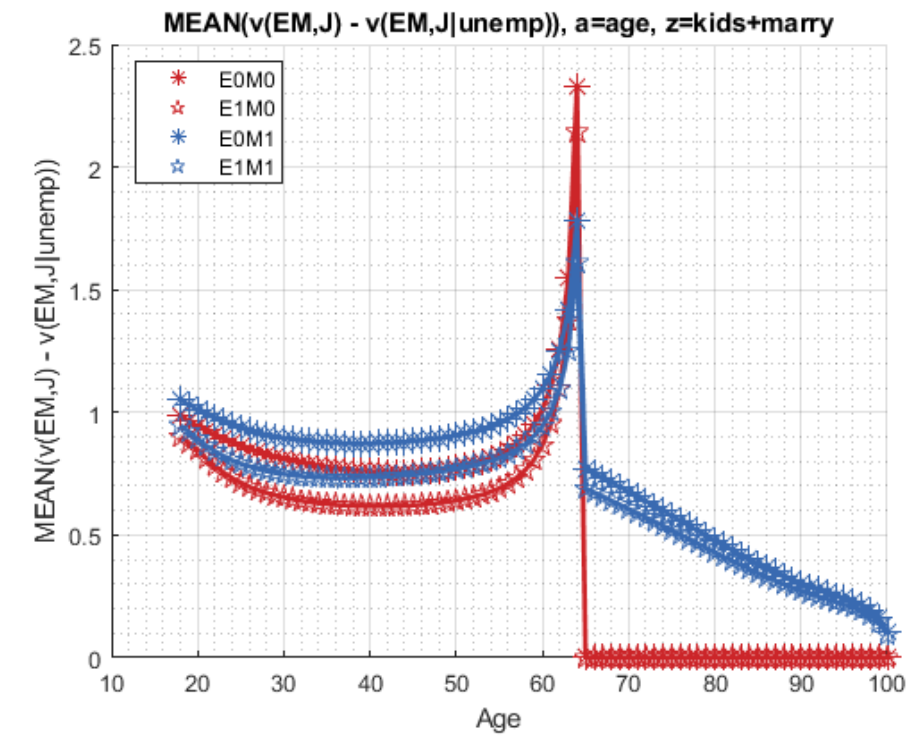
```
xxx MEAN(ap(EM,J) - ap(EM,J|unemp)) xxxxxxxxxxxxxxxxxxxxxxxxxxxxxxxx
  group   edu   marry   mean_age_18   mean_age_19   mean_age_20   mean_age_21   mean_age_22
  -----   ---   -----   -----
      1     0     0       0.54413     0.54211     0.53973     0.56238     0.58448
      2     1     0       0.52244     0.51648     0.50989     0.56245     0.61559
      3     0     1       0.93049     0.95921     0.9882      1.0448      1.1013
      4     1     1       0.99745     1.0306      1.0639      1.1617      1.2608
```

```
% Consumption Choices
tb_az_c = ff_summ_nd_array("MEAN(c(EM,J) - c(EM,J|unemp))", cons_VFI_unemp_drop, true, ["mean"], 3,
```

```
xxx MEAN(c(EM,J) - c(EM,J|unemp)) xxxxxxxxxxxxxxxxxxxxxxxxxxxxxxxx
  group   edu   marry   mean_age_18   mean_age_19   mean_age_20   mean_age_21   mean_age_22
  -----   ---   -----   -----
      1     0     0       0.050247    0.052266    0.054642    0.055442    0.05623
      2     1     0       0.071936    0.077892    0.08448     0.086172    0.087244
      3     0     1       0.079086    0.082612    0.086438    0.089119    0.091706
      4     1     1       0.10685     0.11333     0.12031     0.12499     0.12887
```

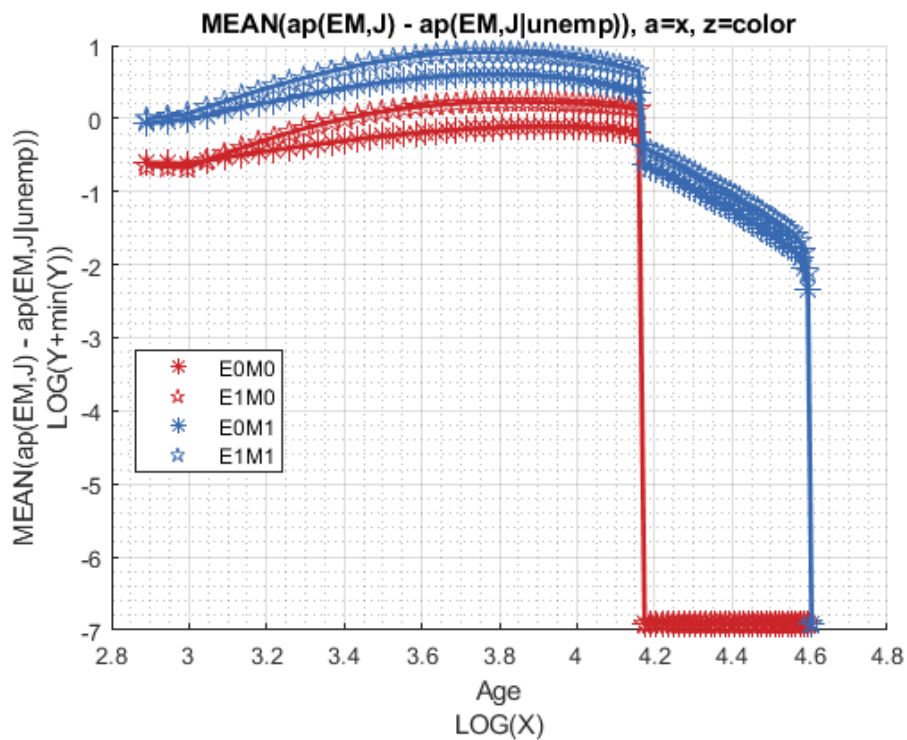
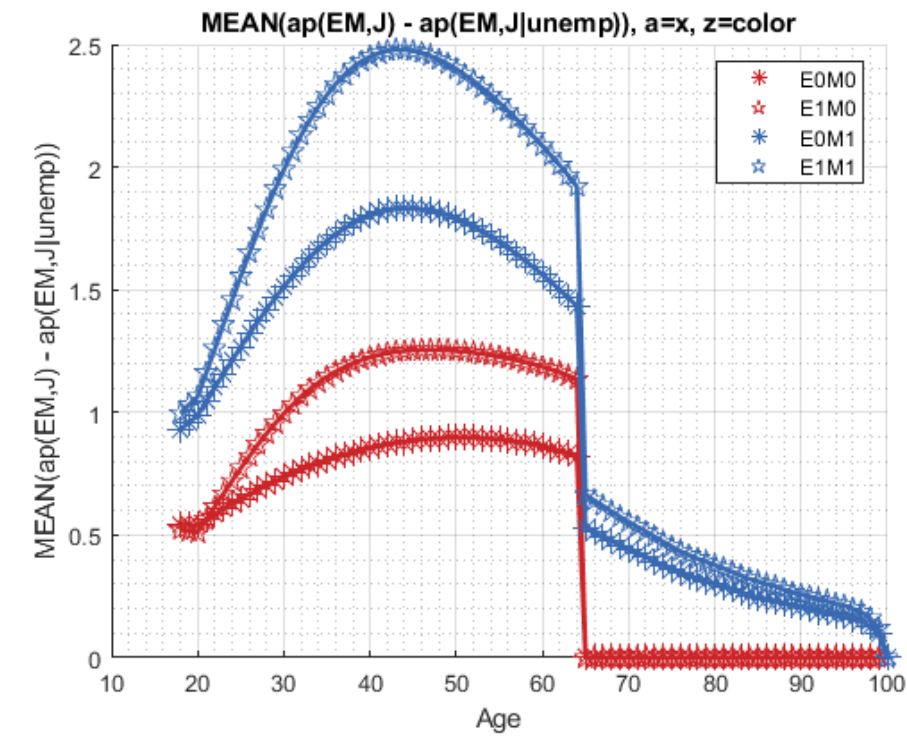
Graph Mean Values Change:

```
mp_support_graph('cl_st_graph_title') = {'MEAN(v(EM,J) - v(EM,J|unemp))', a=age, z=kids+marry'};
mp_support_graph('cl_st_ytitle') = {'MEAN(v(EM,J) - v(EM,J|unemp))'};
ff_graph_grid((tb_az_v{1:end, 4:end}), ar_row_grid, age_grid, mp_support_graph);
```



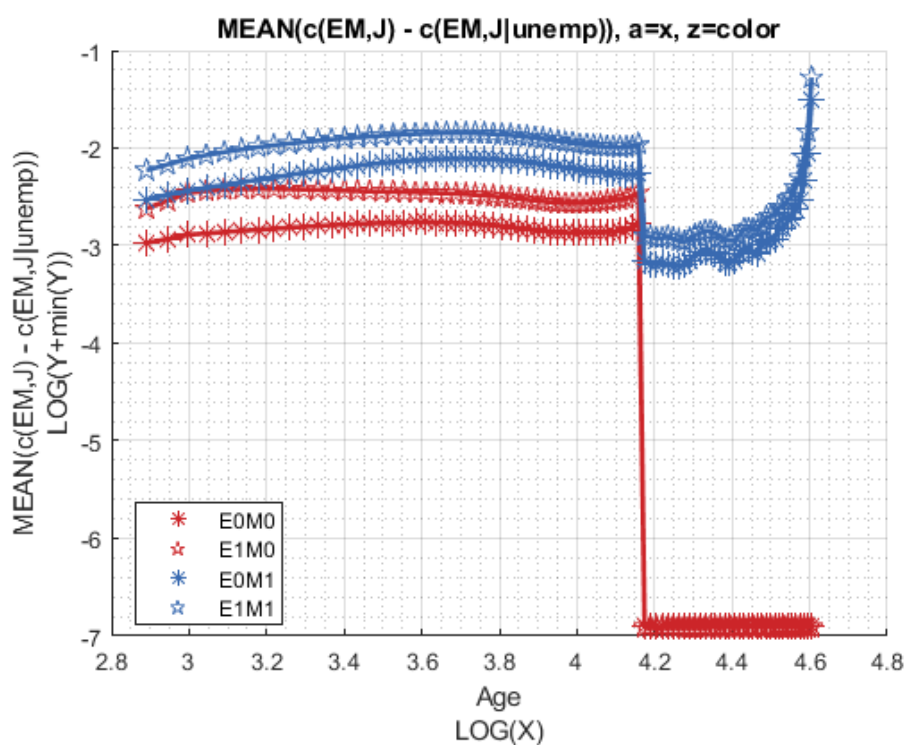
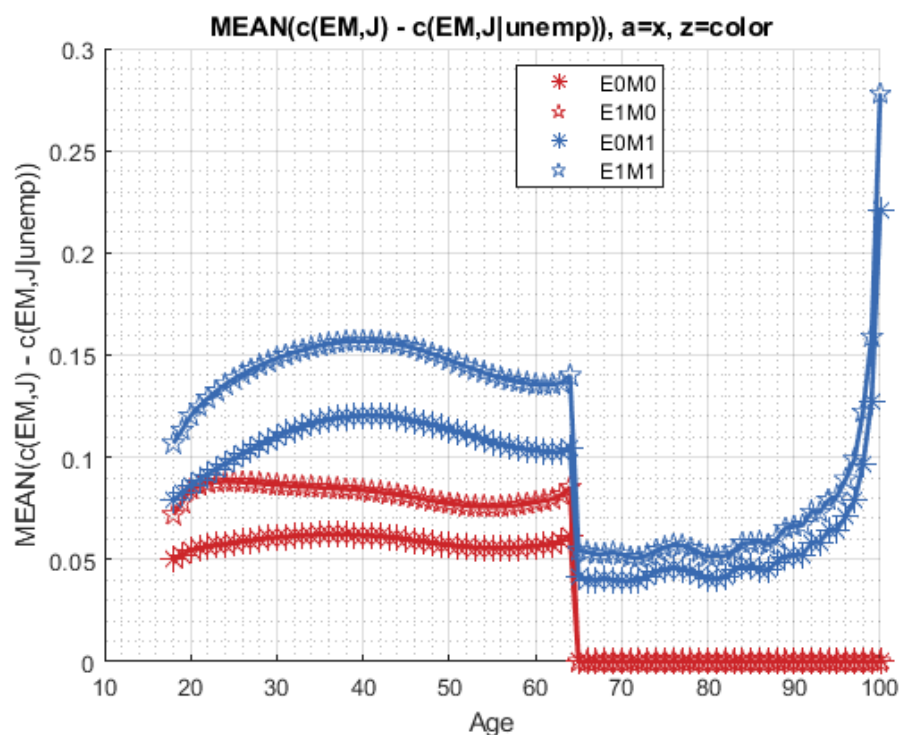
Graph Mean Savings Choices Change:

```
mp_support_graph('cl_st_graph_title') = {'MEAN(ap(EM,J) - ap(EM,J|unemp))', a=x, z=color'};
mp_support_graph('cl_st_ytitle') = {'MEAN(ap(EM,J) - ap(EM,J|unemp))'};
ff_graph_grid((tb_az_ap{1:end, 4:end}), ar_row_grid, age_grid, mp_support_graph);
```



Graph Mean Consumption Change:

```
mp_support_graph('cl_st_graph_title') = {'MEAN(c(EM,J) - c(EM,J|unemp))', a=x, z=color};
mp_support_graph('cl_st_ytitle') = {'MEAN(c(EM,J) - c(EM,J|unemp))'};
ff_graph_grid((tb_az_c{1:end, 4:end}), ar_row_grid, age_grid, mp_support_graph);
```



## 5.2 Life Cycle Dynamic Programming under Great Recession Unemployment Shock

This is the example vignette for function: [snw\\_v08p08\\_jaeemk](#) from the [PrjOptiSNW Package](#). Solving the dynamic programming problem conditional on having an one period unemployment shock that is expected with known unemployment probability. Unemployment probability is a function of the realized state-space next year, specifically, it is determined by age and education. Bush 2008 checks were received by households in expectation of forth-coming unemployment shocks, ex-ante the realization

of shocks. During COVID, the shocks were received ex-post the realization of shocks. In both cases, stimulus checks were determined based on ex-ante information.

Due to expected shock, households consume less and save more in 2008 than under steady-state, as shown below. Value/welfare overall is lower in 2008 than under steady-state.

### 5.2.1 Test SNW\_V08P08\_JAEEMK

First, solve for value without unemployment issue (use the vectorized code that was previously tested). This is the steady state results, but also the results in 2009 without unemployment.

```
mp_more_inputs = containers.Map('KeyType','char', 'ValueType','any');
mp_more_inputs('fl_ss_non_college') = 0.225;
mp_more_inputs('fl_ss_college') = 0.271;
mp_more_inputs('fl_scaleconvertor') = 54831;
% st_param_group = 'default_small';
% st_param_group = 'default_dense';
st_param_group = 'default_docdense';
mp_params = snw_mp_param(st_param_group, false, 'tauchen', false, 8, 8, mp_more_inputs);
mp_controls = snw_mp_control('default_test');
mp_controls('bl_print_vfi') = false;
mp_controls('bl_print_vfi_verbose') = false;
mp_controls('bl_print_ds') = false;
mp_controls('bl_print_ds_verbose') = false;
[V_VFI_ss, ap_VFI_ss, cons_VFI_ss] = snw_vfi_main_bisec_vec(mp_params, mp_controls);
```

Completed SNW\_VFI\_MAIN\_BISEC\_VEC;SNW\_MP\_PARAM=default\_docdense;SNW\_MP\_CONTROL=default\_test;time=526.

```
V_emp_2009 = V_VFI_ss;
```

Second, solve for the unemployment value, use the exact-bisec result code, call the `snw_vfi_main_bisec_vec.m` function with a third input of existing value.  $\xi$  is the share of income lost during covid year given surprise covid shock,  $b$  is the share of income loss that is covered by unemployment insurance. If  $\xi=0.5$  and  $b=0$  means will lose 50 percent of income given 2009 great recession shocks, and the loss will not be covered at all by unemployment insurance.

```
mp_params('xi') = 0.532;
mp_params('b') = 0.37992;
mp_params('a2_covidyr') = mp_params('a2_greatrecession_2009');
[V_unemp_2009] = snw_vfi_main_bisec_vec(mp_params, mp_controls, V_VFI_ss);
```

Completed SNW\_VFI\_MAIN\_BISEC\_VEC 1 Period Unemp Shock;SNW\_MP\_PARAM=default\_docdense;SNW\_MP\_CONTROL=d

Third, solve for 2008 policy and value function given employed and unemployed value function in 2009,

```
[V_2008, ap_2008, cons_2008, ev_empshk_2009] = ...
    snw_v08p08_jaeemk(mp_params, mp_controls, V_emp_2009, V_unemp_2009);
```

Completed SNW\_VFI\_MAIN\_BISEC\_VEC 1 Period Unemp Shock;SNW\_MP\_PARAM=default\_docdense;SNW\_MP\_CONTROL=d

Completed SNW\_V08P08\_JAEEMK;SNW\_MP\_PARAM=default\_docdense;SNW\_MP\_CONTROL=default\_test;time=534.4681

```
-----
XXXXXXXXXXXXXXXXXXXXXXXXXXXXXXXXXXXXXXXXXXXXXXXXXXXX
```

```
CONTAINER NAME: mp_outcomes ND Array (Matrix etc)
```

```
XXXXXXXXXXXXXXXXXXXXXXXXXXXXXXXXXXXXXXXXXXXXXXXXXXXX
```

	i	idx	ndim	numel	rowN	colN	sum	mean	std
V_2008	1	1	6	4.37e+07	83	5.265e+05	-8.6418e+08	-19.775	28.
ap_2008	2	2	6	4.37e+07	83	5.265e+05	1.4164e+09	32.413	36.7
cons_2008	3	3	6	4.37e+07	83	5.265e+05	2.1314e+08	4.8774	8.32

## 5.2. LIFE CYCLE DYNAMIC PROGRAMMING UNDER GREAT RECESSION UNEMPLOYMENT SHOCK127

xxx TABLE:V\_2008 xxxxxxxxxxxxxxxxxxxxxxxx

	c1	c2	c3	c4	c5	c526496	c526497	c526498
r1	-377.6	-377.2	-374.55	-368.41	-358.7	-6.6852	-6.5348	-6.384
r2	-365.34	-364.94	-362.31	-356.26	-346.87	-6.4943	-6.3486	-6.202
r3	-353.22	-352.83	-350.3	-344.47	-335.51	-6.3002	-6.1591	-6.016
r4	-341.2	-340.84	-338.49	-333.04	-324.62	-6.1007	-5.964	-5.825
r5	-330.3	-329.97	-327.77	-322.66	-314.72	-5.9113	-5.7784	-5.643
r79	-13.739	-13.726	-13.636	-13.409	-13.022	-0.22845	-0.21772	-0.2076
r80	-12.3	-12.287	-12.198	-11.97	-11.583	-0.17425	-0.16609	-0.158
r81	-10.552	-10.538	-10.449	-10.221	-9.8344	-0.11926	-0.11367	-0.1084
r82	-8.2458	-8.2327	-8.1431	-7.9156	-7.5286	-0.065967	-0.062837	-0.05992
r83	-4.9602	-4.9471	-4.8576	-4.6301	-4.2431	-0.020966	-0.019971	-0.01903

xxx TABLE:ap\_2008 xxxxxxxxxxxxxxxxxxxxxxxx

	c1	c2	c3	c4	c5	c526496	c526497
r1	0.00051498	0.00051498	0.0032921	0.0091501	0.023607	114.76	120.42
r2	0.00051498	0.00051498	0.0030624	0.0084089	0.022296	114.88	120.54
r3	0	0	0.0016162	0.0069216	0.020659	114.99	120.67
r4	0	0	0.0016317	0.0069002	0.020494	115.74	121.44
r5	0	0	0.0016507	0.0068855	0.020347	116.52	122.23
r79	0	0	0	0	0.00051498	81.091	85.68
r80	0	0	0	0	0	76.669	80.556
r81	0	0	0	0	0	68.313	71.526
r82	0	0	0	0	0	50.126	53.467
r83	0	0	0	0	0	0	0

xxx TABLE:cons\_2008 xxxxxxxxxxxxxxxxxxxxxxxx

	c1	c2	c3	c4	c5	c526496	c526497	c526498
r1	0.036202	0.036736	0.0377	0.041994	0.047306	9.6346	9.8024	9.9503
r2	0.036202	0.036736	0.037929	0.042735	0.048617	9.7969	9.9535	10.086
r3	0.036717	0.037251	0.039375	0.044222	0.050255	9.962	10.105	10.219
r4	0.038144	0.038678	0.040786	0.045669	0.051843	10.114	10.242	10.338
r5	0.039534	0.040068	0.042157	0.047073	0.053379	10.254	10.367	10.447
r79	0.2016	0.20214	0.20586	0.21598	0.23516	35.82	37.055	38.423
r80	0.2016	0.20214	0.20586	0.21598	0.23568	40.216	42.153	44.428
r81	0.2016	0.20214	0.20586	0.21598	0.23568	48.55	51.16	54.237
r82	0.2016	0.20214	0.20586	0.21598	0.23568	66.719	69.201	71.733
r83	0.2016	0.20214	0.20586	0.21598	0.23568	116.83	122.65	128.67

Difference Between Value and Choices In steady state and in 2008, given expected unemployment (one-period) shock due to the great recession, [snw\\_v08p08\\_jaeemk](#).

V\_VFI\_unemp\_drop = V\_VFI\_ss - V\_2008;

ap\_VFI\_unemp\_drop = ap\_VFI\_ss - ap\_2008;

cons\_VFI\_unemp\_drop = cons\_VFI\_ss - cons\_2008;

### 5.2.2 Define Parameter Frames

Define the matrix dimensions names and dimension vector values. Policy and Value Functions share the same ND dimensional structure.

% Grids:

age\_grid = 18:100;

agrid = mp\_params('agrid');

```

eta_H_grid = mp_params('eta_H_grid');
eta_S_grid = mp_params('eta_S_grid');
ar_st_eta_HS_grid = string(cellstr([num2str(eta_H_grid), 'hz=%3.2f;'], num2str(eta_S_grid), 'wz=%3.2
edu_grid = [0,1];
marry_grid = [0,1];
kids_grid = (1:1:mp_params('n_kidsgrid'))';
% NaN(n_jgrid,n_agrid,n_etagrid,n_educgrid,n_marriedgrid,n_kidsgrid);
cl_mp_datasetdesc = {};
cl_mp_datasetdesc{1} = containers.Map({'name', 'labval'}, {'age', age_grid});
cl_mp_datasetdesc{2} = containers.Map({'name', 'labval'}, {'savings', agrid});
cl_mp_datasetdesc{3} = containers.Map({'name', 'labval'}, {'eta', 1:length(eta_H_grid)});
cl_mp_datasetdesc{4} = containers.Map({'name', 'labval'}, {'edu', edu_grid});
cl_mp_datasetdesc{5} = containers.Map({'name', 'labval'}, {'marry', marry_grid});
cl_mp_datasetdesc{6} = containers.Map({'name', 'labval'}, {'kids', kids_grid});

```

### 5.2.3 Analyze Savings and Shocks

First, analyze Savings Levels and Shocks, Aggregate Over All Others, and do various other calculations.

```

% Generate some Data
mp_support_graph = containers.Map('KeyType', 'char', 'ValueType', 'any');
mp_support_graph('cl_st_xtitle') = {'Savings States, a'};
mp_support_graph('st_legend_loc') = 'eastoutside';
mp_support_graph('bl_graph_logy') = true; % do not log
mp_support_graph('it_legend_select') = 15; % how many shock legends to show
mp_support_graph('cl_colors') = 'jet';

MEAN(VAL(A,Z) - VAL(A,Z, 08wthEV09unemshk)), MEAN(AP(A,Z) - AP(A,Z, 08wthEV09unemshk)),
MEAN(C(A,Z) - C(A,Z, 08wthEV09unemshk))

Tabulate value and policies along savings and shocks:

% Set
% NaN(n_jgrid,n_agrid,n_etagrid,n_educgrid,n_marriedgrid,n_kidsgrid);
ar_permute = [1,4,5,6,3,2];
% Value Function
tb_az_v = ff_summ_nd_array("MEAN(v(A,Z) - v(A,Z, 08wthEV09unemshk))", V_VFI_unemp_drop, true, ["mean

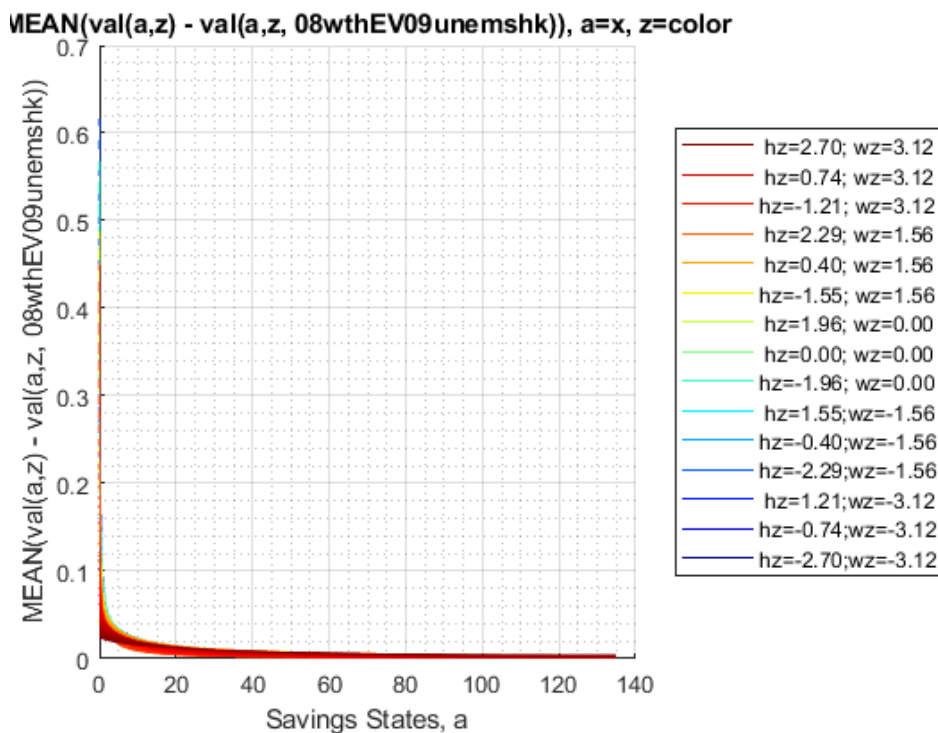
xxx MEAN(v(A,Z) - v(A,Z, 08wthEV09unemshk)) xxxxxxxxxxxxxxxxxxxxxxxxxxxxxxxx
  group      savings      mean_eta_1      mean_eta_2      mean_eta_3      mean_eta_4      mean_eta_5      mea
  -----      -
  1              0          0.61601          0.59253          0.56551          0.53755          0.5101

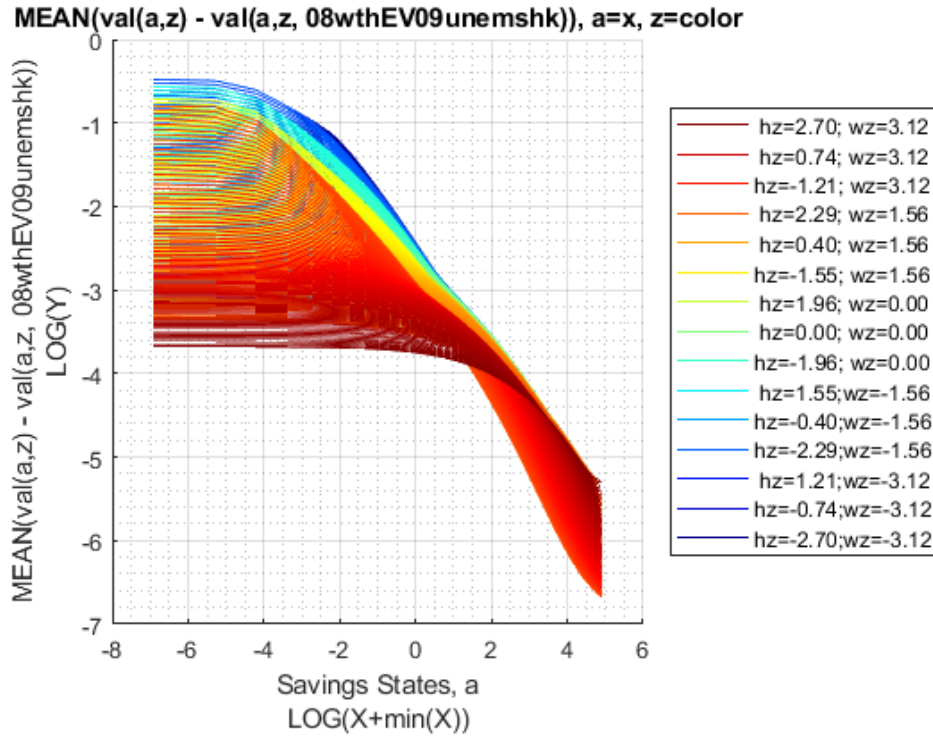
```



5            0.032959       -0.00025565       -0.00039576       -0.00048282       -0.00053831       -0.00059111

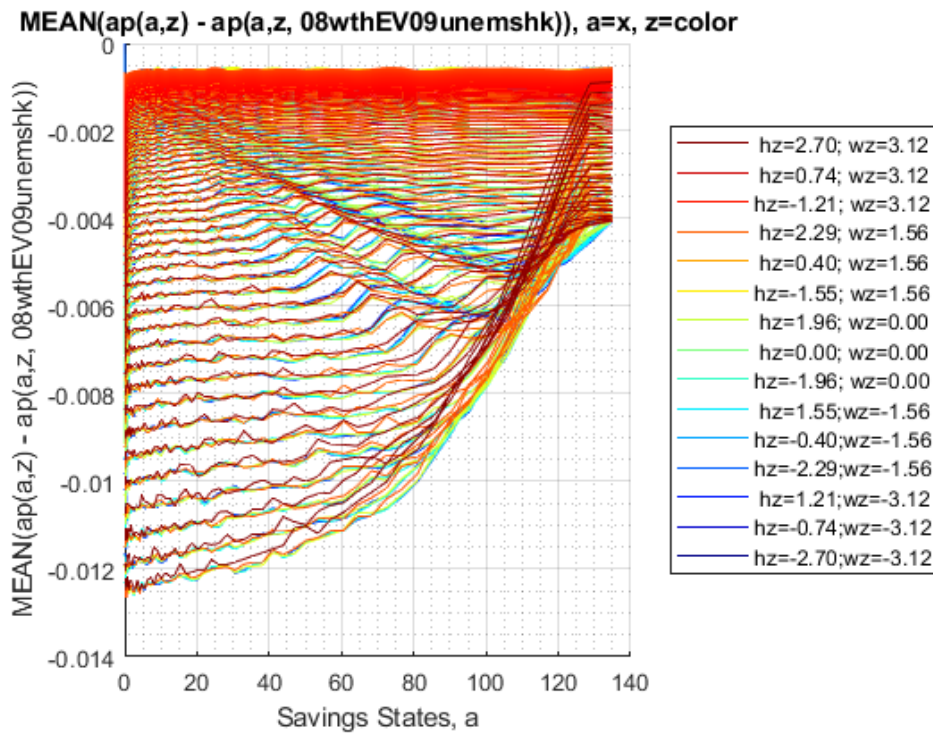
```
mp_support_graph('cl_st_graph_title') = {'MEAN(val(a,z) - val(a,z, 08wthEV09unemshk)), a=x, z=color'}
mp_support_graph('cl_st_ytitle') = {'MEAN(val(a,z) - val(a,z, 08wthEV09unemshk))'};
ff_graph_grid((tb_az_v{1:end, 3:end})', ar_st_eta_HS_grid, agrid, mp_support_graph);
```

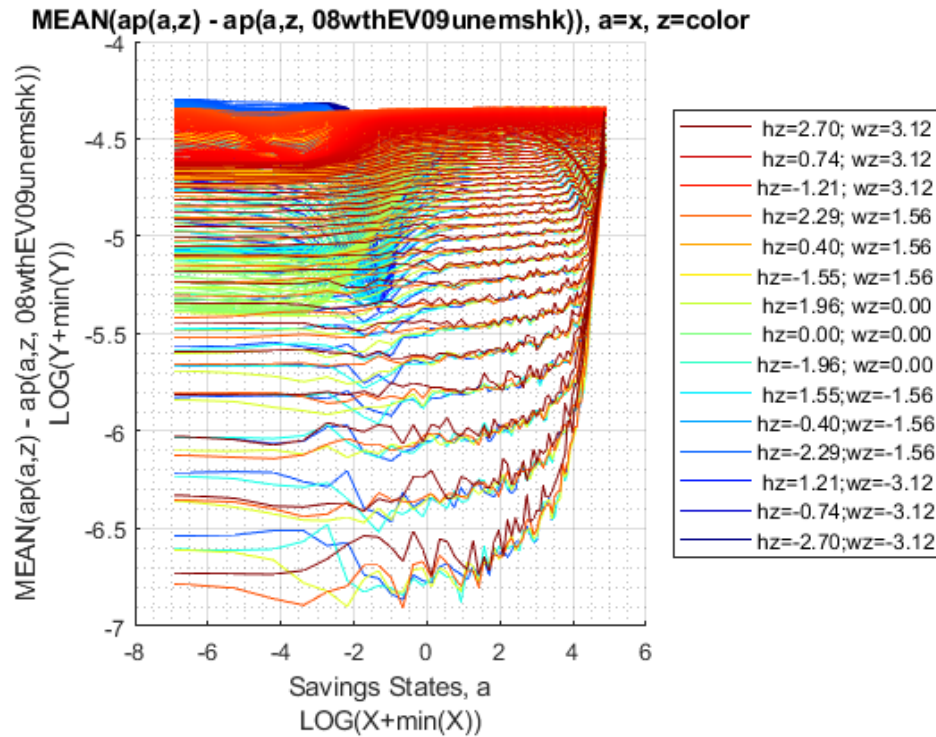




Graph Mean Savings Choices Change:

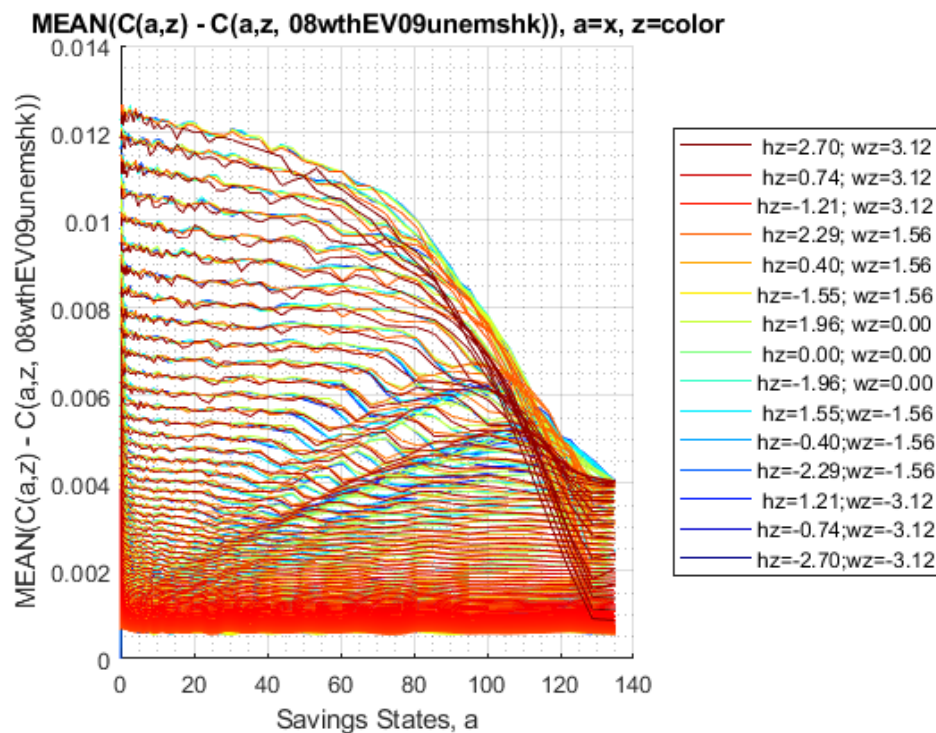
```
mp_support_graph('cl_st_graph_title') = {'MEAN(ap(a,z) - ap(a,z, 08wthEV09unemshk)), a=x, z=color'};
mp_support_graph('cl_st_ytitle') = {'MEAN(ap(a,z) - ap(a,z, 08wthEV09unemshk))'};
ff_graph_grid((tb_az_ap{1:end, 3:end})', ar_st_eta_HS_grid, agrid, mp_support_graph);
```

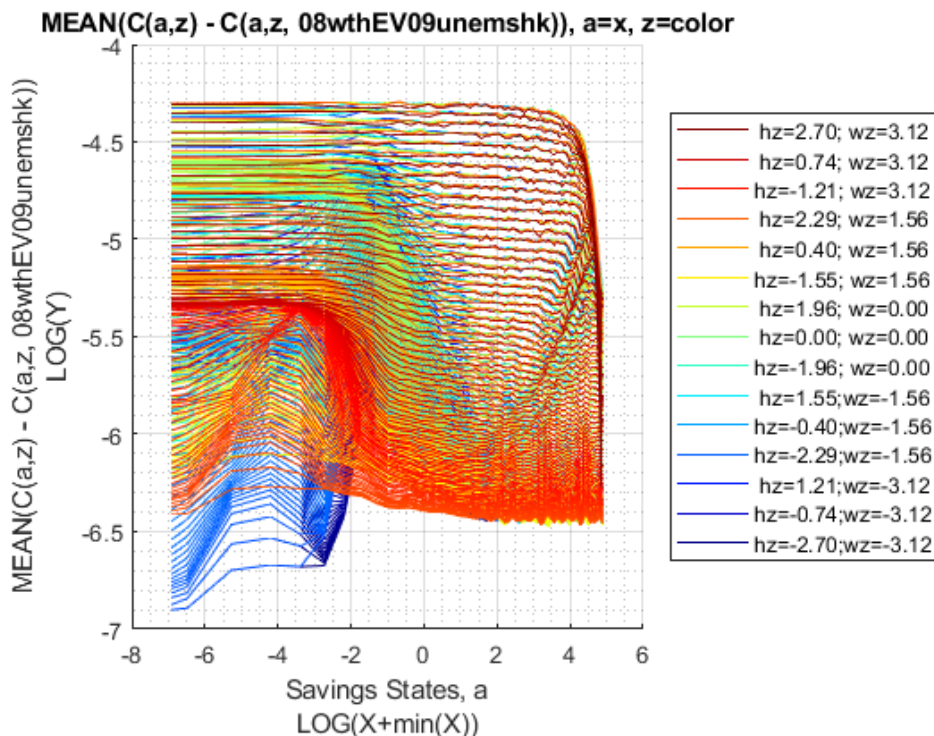




Graph Mean Consumption Change:

```
mp_support_graph('cl_st_graph_title') = {'MEAN(C(a,z) - C(a,z, 08wthEV09unemshk)), a=x, z=color'};
mp_support_graph('cl_st_ytitle') = {'MEAN(C(a,z) - C(a,z, 08wthEV09unemshk))'};
ff_graph_grid((tb_az_c{1:end, 3:end})', ar_st_eta_HS_grid, agrid, mp_support_graph);
```





### 5.2.4 Analyze Kids and Marriage and Age

Aggregating over education, savings, and shocks, what are the differential effects of Marriage and Age.

```
% Generate some Data
mp_support_graph = containers.Map('KeyType', 'char', 'ValueType', 'any');
ar_row_grid = [...
    "k0M0", "K1M0", "K2M0", "K3M0", "K4M0", ...
    "k0M1", "K1M1", "K2M1", "K3M1", "K4M1"];
mp_support_graph('cl_st_xtitle') = {'Age'};
mp_support_graph('st_legend_loc') = 'best';
mp_support_graph('bl_graph_logy') = true; % do not log
mp_support_graph('st_rounding') = '6.2f'; % format shock legend
mp_support_graph('cl_scatter_shapes') = {...
    'o', 'd', 's', 'x', '*'}, ...
    'o', 'd', 's', 'x', '*'};
mp_support_graph('cl_colors') = {...
    'red', 'red', 'red', 'red', 'red'...
    'blue', 'blue', 'blue', 'blue', 'blue'};
```

MEAN(V(KM,J) - V(KM,J | unemp)), MEAN(ap(KM,J) - ap(KM,J | unemp)), MEAN(c(KM,J) - c(KM,J | unemp))

Tabulate value and policies:

```
% Set
% NaN(n_jgrid,n_agrid,n_etagrid,n_educgrid,n_marriedgrid,n_kidsgrid);
ar_permute = [2,3,4,1,6,5];
% Value Function
tb_az_v = ff_summ_nd_array("MEAN(V(KM,J) - V(KM,J | unemp))", V_VFI_unemp_drop, true, ["mean"], 3, 1
```

group	kids	marry	mean_age_18	mean_age_19	mean_age_20	mean_age_21	mean_age_22
1	1	0	0.046286	0.045154	0.045206	0.044045	0.043041

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2	2	0	0.061509	0.060105	0.060105	0.058309	0.05672
3	3	0	0.071135	0.069801	0.06956	0.06751	0.065702
4	4	0	0.080137	0.0788	0.078496	0.076191	0.074156
5	5	0	0.087487	0.086234	0.085827	0.083393	0.081251
6	1	1	0.035539	0.034243	0.033548	0.032741	0.032045
7	2	1	0.043811	0.042205	0.041298	0.040208	0.039233
8	3	1	0.048496	0.046783	0.045815	0.044615	0.043554
9	4	1	0.053774	0.051966	0.05096	0.049624	0.048442
10	5	1	0.058404	0.056626	0.055602	0.05418	0.052931

% Aprime Choice

```
tb_az_ap = ff_summ_nd_array("MEAN(ap(KM,J) - ap(KM,J | unemp))", ap_VFI_unemp_drop, true, ["mean"],
```

```
xxx MEAN(ap(KM,J) - ap(KM,J | unemp)) xxxxxxxxxxxxxxxxxxxxxxxxxxxxxxxx
```

group	kids	marry	mean_age_18	mean_age_19	mean_age_20	mean_age_21	mean_age_2
1	1	0	-0.0020954	-0.0022922	-0.0023124	-0.0023781	-0.002452
2	2	0	-0.0025384	-0.0028561	-0.0028769	-0.002923	-0.0029984
3	3	0	-0.0029997	-0.0034133	-0.003403	-0.0033945	-0.0033908
4	4	0	-0.0033272	-0.0037849	-0.0037592	-0.0037304	-0.003723
5	5	0	-0.0036714	-0.0040673	-0.0040589	-0.0040155	-0.0039849
6	1	1	-0.0033041	-0.003509	-0.0035692	-0.0036765	-0.0037787
7	2	1	-0.0035178	-0.0037456	-0.003797	-0.0038875	-0.0039924
8	3	1	-0.0038496	-0.0040777	-0.00411	-0.0041767	-0.0042559
9	4	1	-0.004079	-0.0043493	-0.0043317	-0.0043657	-0.0044326
10	5	1	-0.0043828	-0.0047223	-0.0045492	-0.0045848	-0.0046013

% Consumption Choices

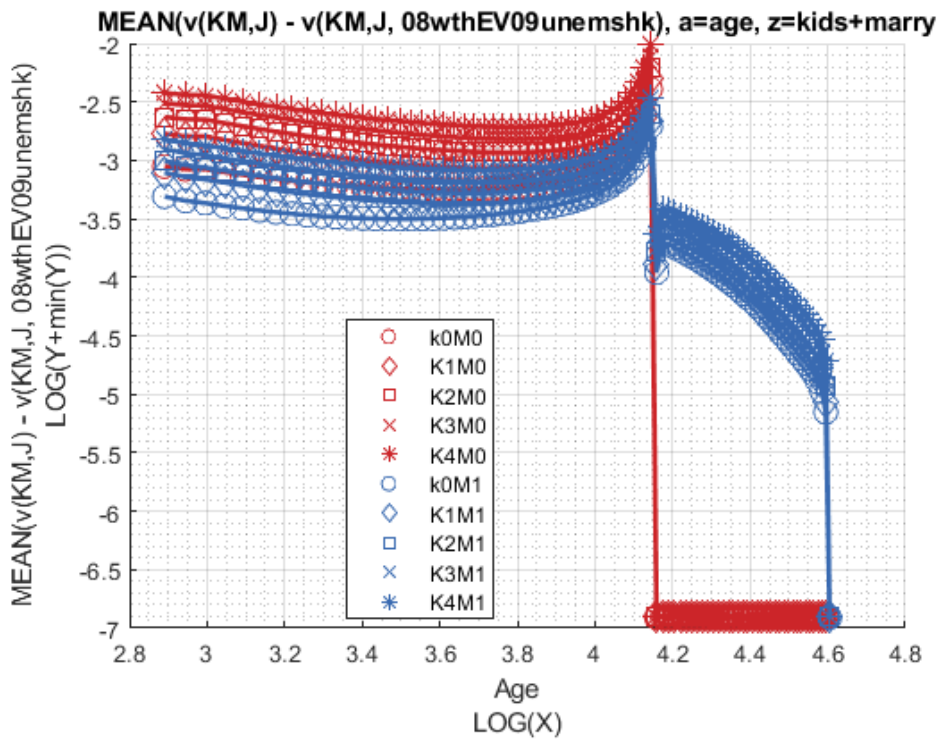
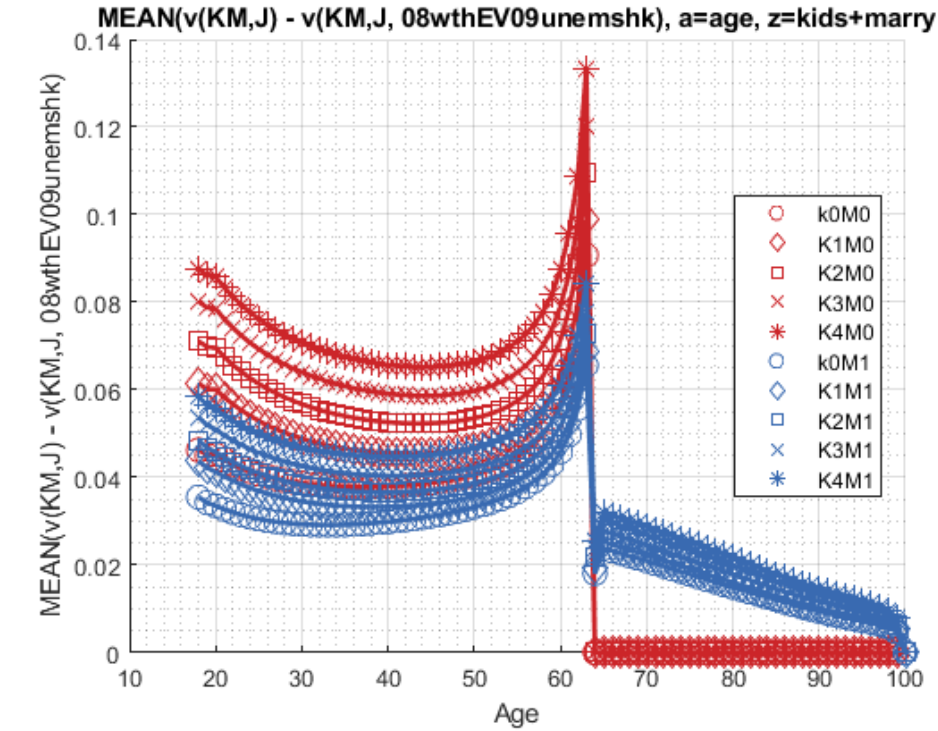
```
tb_az_c = ff_summ_nd_array("MEAN(c(KM,J) - c(KM,J | unemp))", cons_VFI_unemp_drop, true, ["mean"], 3
```

```
xxx MEAN(c(KM,J) - c(KM,J | unemp)) xxxxxxxxxxxxxxxxxxxxxxxxxxxxxxxx
```

group	kids	marry	mean_age_18	mean_age_19	mean_age_20	mean_age_21	mean_age_2
1	1	0	0.0020954	0.0022922	0.0023124	0.0023781	0.002452
2	2	0	0.0025384	0.0028561	0.0028769	0.002923	0.0029984
3	3	0	0.0029997	0.0034133	0.003403	0.0033945	0.0033908
4	4	0	0.0033272	0.0037849	0.0037592	0.0037304	0.003723
5	5	0	0.0036714	0.0040673	0.0040589	0.0040155	0.0039849
6	1	1	0.0033041	0.003509	0.0035692	0.0036765	0.0037787
7	2	1	0.0035178	0.0037456	0.003797	0.0038875	0.0039924
8	3	1	0.0038496	0.0040777	0.00411	0.0041767	0.0042559
9	4	1	0.004079	0.0043493	0.0043317	0.0043657	0.0044326
10	5	1	0.0043828	0.0047223	0.0045492	0.0045848	0.0046013

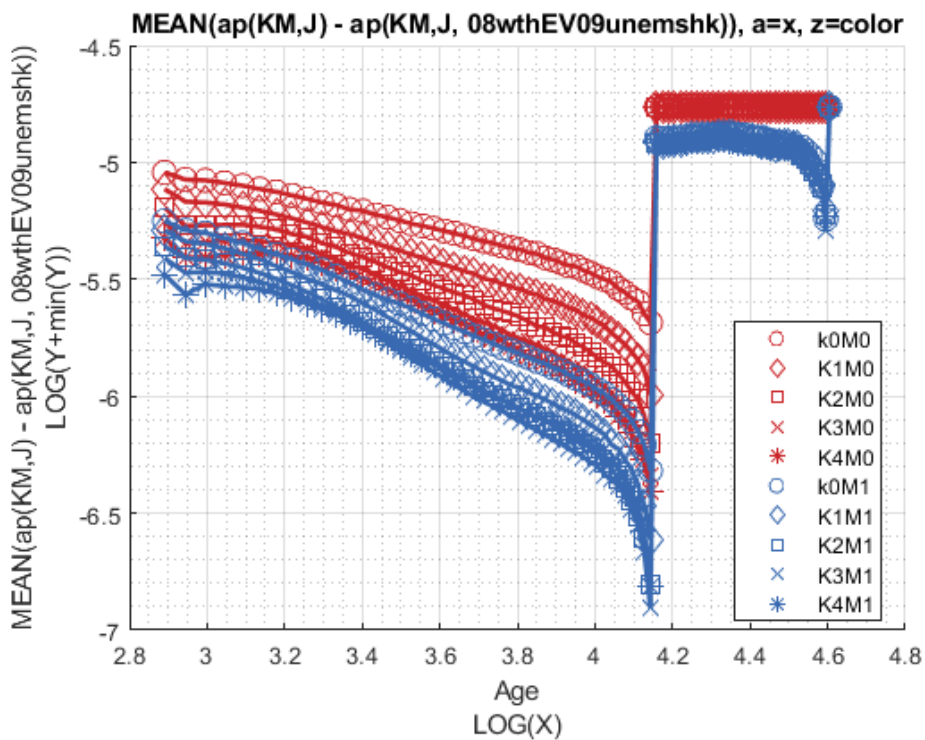
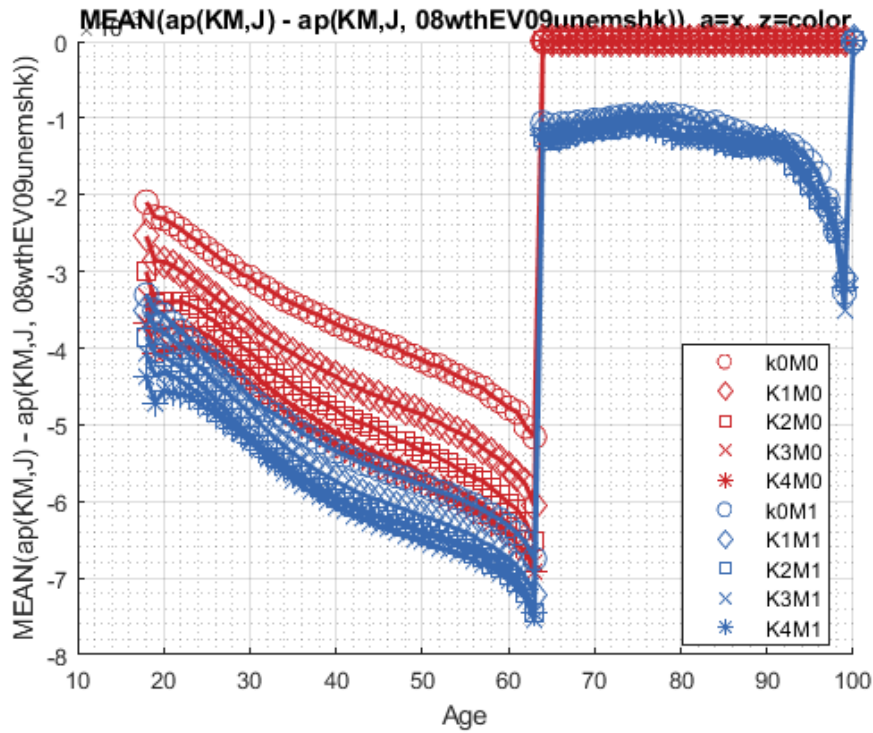
Graph Mean Values Change:

```
mp_support_graph('cl_st_graph_title') = {'MEAN(v(KM,J) - v(KM,J, 08wthEV09unemshk), a=age, z=kids+ma
mp_support_graph('cl_st_ytitle') = {'MEAN(v(KM,J) - v(KM,J, 08wthEV09unemshk)'};
ff_graph_grid((tb_az_v{1:end, 4:end}), ar_row_grid, age_grid, mp_support_graph);
```



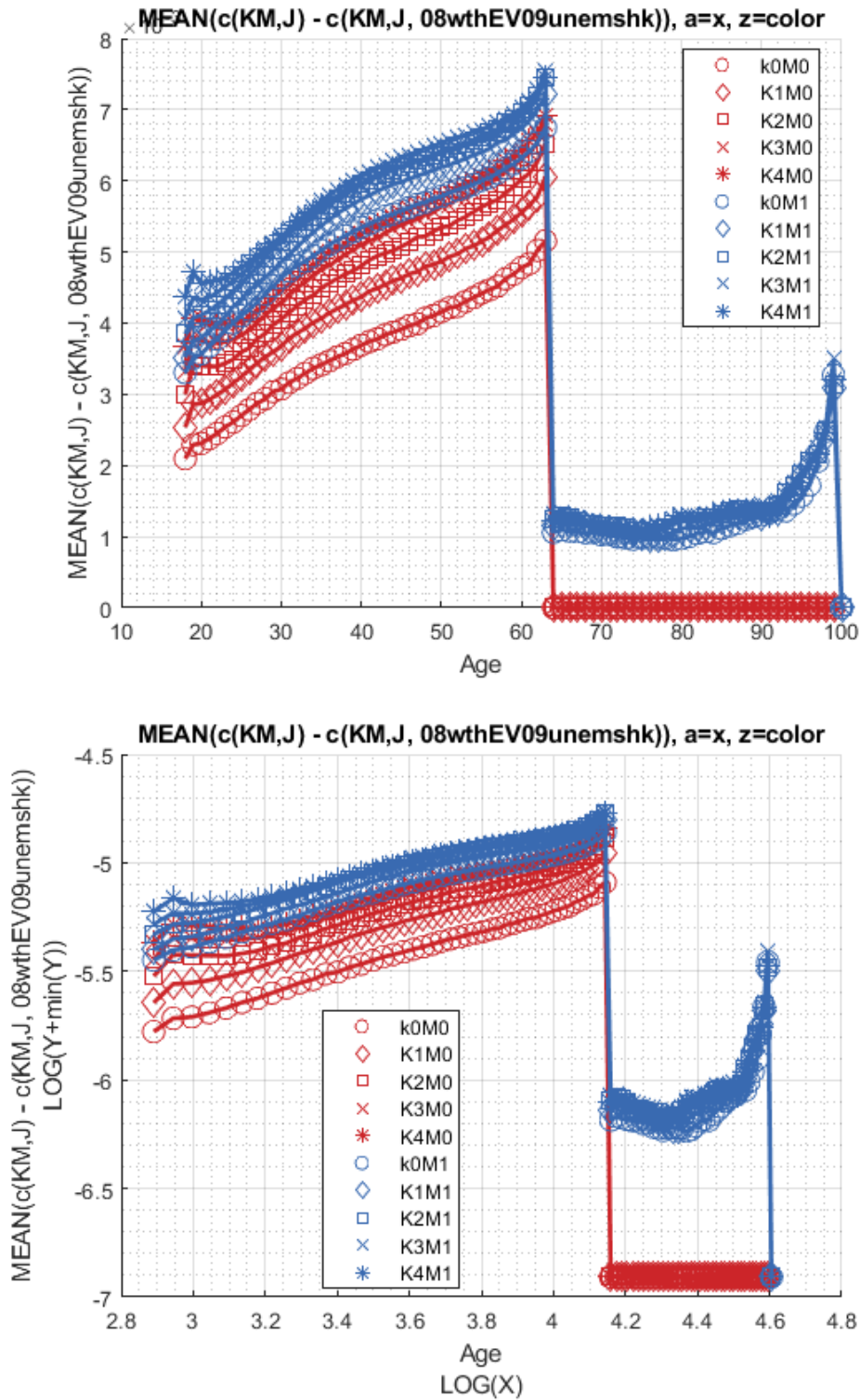
Graph Mean Savings Choices Change:

```
mp_support_graph('cl_st_graph_title') = {'MEAN(ap(KM,J) - ap(KM,J, 08wthEV09unemshk))', a=x, z=color'}
mp_support_graph('cl_st_ytitle') = {'MEAN(ap(KM,J) - ap(KM,J, 08wthEV09unemshk))'};
ff_graph_grid((tb_az_ap{1:end, 4:end}), ar_row_grid, age_grid, mp_support_graph);
```



Graph Mean Consumption Change:

```
mp_support_graph('cl_st_graph_title') = {'MEAN(c(KM,J) - c(KM,J, 08wthEV09unemshk))', a=x, z=color'};
mp_support_graph('cl_st_ytitle') = {'MEAN(c(KM,J) - c(KM,J, 08wthEV09unemshk))'};
ff_graph_grid((tb_az_c{1:end, 4:end}), ar_row_grid, age_grid, mp_support_graph);
```



### 5.2.5 Analyze Education and Marriage and Age

Aggregating over education, savings, and shocks, what are the differential effects of Marriage and Age.

```
% Generate some Data
```

```
mp_support_graph = containers.Map('KeyType', 'char', 'ValueType', 'any');
```

```
ar_row_grid = ["E0M0", "E1M0", "E0M1", "E1M1"];
```

```
mp_support_graph('cl_st_xtitle') = {'Age'};
```

```
mp_support_graph('st_legend_loc') = 'best';
```

```
mp_support_graph('bl_graph_logy') = true; % do not log
```



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```
mp_support_graph('st_rounding') = '6.2f'; % format shock legend
mp_support_graph('cl_scatter_shapes') = {'*', 'p', '*', 'p' };
mp_support_graph('cl_colors') = {'red', 'red', 'blue', 'blue'};
```

```
MEAN(v(EKM,J) - v(EKM,J, 08wthEV09unemshk)), MEAN(ap(EM,J, steady) - ap(EM,J,
08wthEV09unemshk)), MEAN(c(EM,J, steady) - c(EM,J, 08wthEV09unemshk))
```

Tabulate value and policies:

```
% Set
% NaN(n_jgrid,n_agrid,n_etagrid,n_educgrid,n_marriedgrid,n_kidsgrid);
ar_permute = [2,3,6,1,4,5];
% Value Function
tb_az_v = ff_summ_nd_array("MEAN(v(EM,J, steady) - v(EM,J, 08wthEV09unemshk))", V_VFI_unemp_drop, tr
```

```
xxx MEAN(v(EM,J, steady) - v(EM,J, 08wthEV09unemshk)) xxxxxxxxxxxxxxxxxxxxxxxxxxxxxxxx
```

group	edu	marry	mean_age_18	mean_age_19	mean_age_20	mean_age_21	mean_age_22
1	0	0	0.084881	0.083361	0.083388	0.08165	0.080055
2	1	0	0.05374	0.052677	0.052289	0.050129	0.048293
3	0	1	0.059454	0.057684	0.056623	0.055357	0.05421
4	1	1	0.036556	0.035045	0.034267	0.03319	0.032272

```
% Aprime Choice
tb_az_ap = ff_summ_nd_array("MEAN(ap(EM,J, steady) - ap(EM,J, 08wthEV09unemshk))", ap_VFI_unemp_drop
```

```
xxx MEAN(ap(EM,J, steady) - ap(EM,J, 08wthEV09unemshk)) xxxxxxxxxxxxxxxxxxxxxxxxxxxxxxxx
```

group	edu	marry	mean_age_18	mean_age_19	mean_age_20	mean_age_21	mean_age_22
1	0	0	-0.0028826	-0.003052	-0.0031902	-0.0032817	-0.0033667
2	1	0	-0.0029702	-0.0035135	-0.003374	-0.0032948	-0.003253
3	0	1	-0.003801	-0.0039575	-0.0040645	-0.0041885	-0.0043137
4	1	1	-0.0038523	-0.004204	-0.0040784	-0.004088	-0.0041106

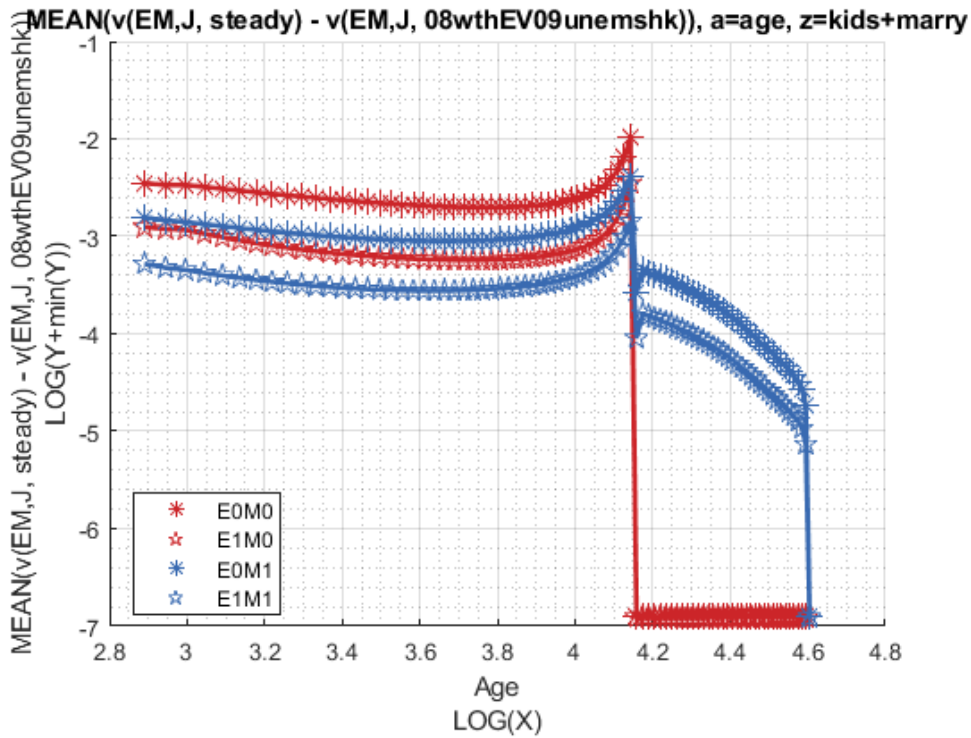
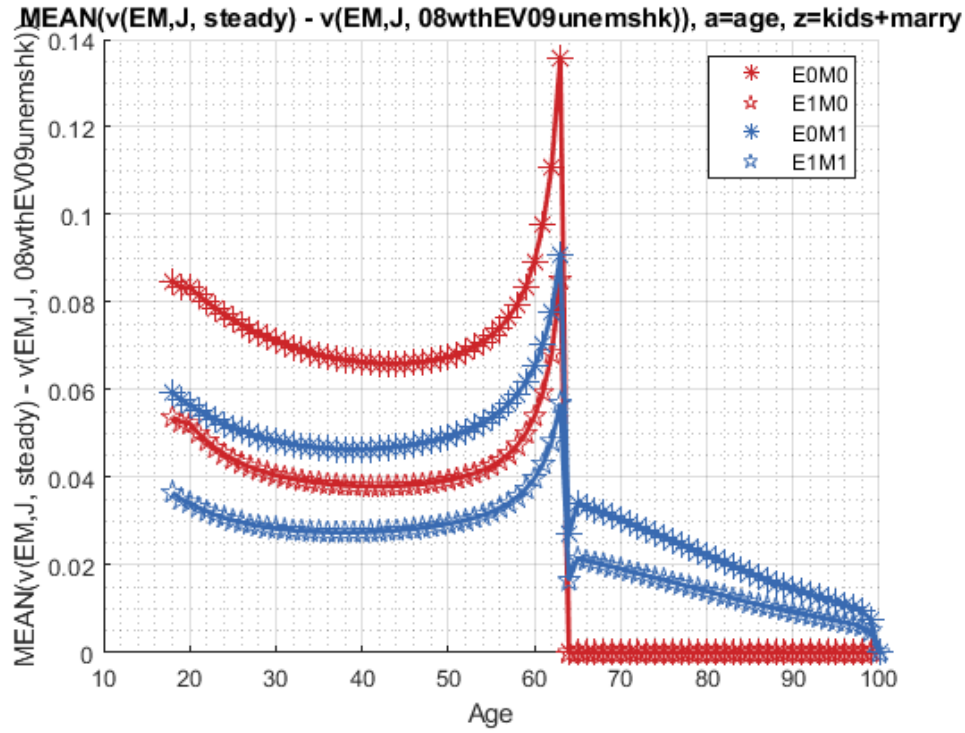
```
% Consumption Choices
tb_az_c = ff_summ_nd_array("MEAN(c(EM,J, steady) - c(EM,J, 08wthEV09unemshk))", cons_VFI_unemp_drop,
```

```
xxx MEAN(c(EM,J, steady) - c(EM,J, 08wthEV09unemshk)) xxxxxxxxxxxxxxxxxxxxxxxxxxxxxxxx
```

group	edu	marry	mean_age_18	mean_age_19	mean_age_20	mean_age_21	mean_age_22
1	0	0	0.0028826	0.003052	0.0031902	0.0032817	0.0033667
2	1	0	0.0029702	0.0035135	0.003374	0.0032948	0.003253
3	0	1	0.003801	0.0039575	0.0040645	0.0041885	0.0043137
4	1	1	0.0038523	0.004204	0.0040784	0.004088	0.0041106

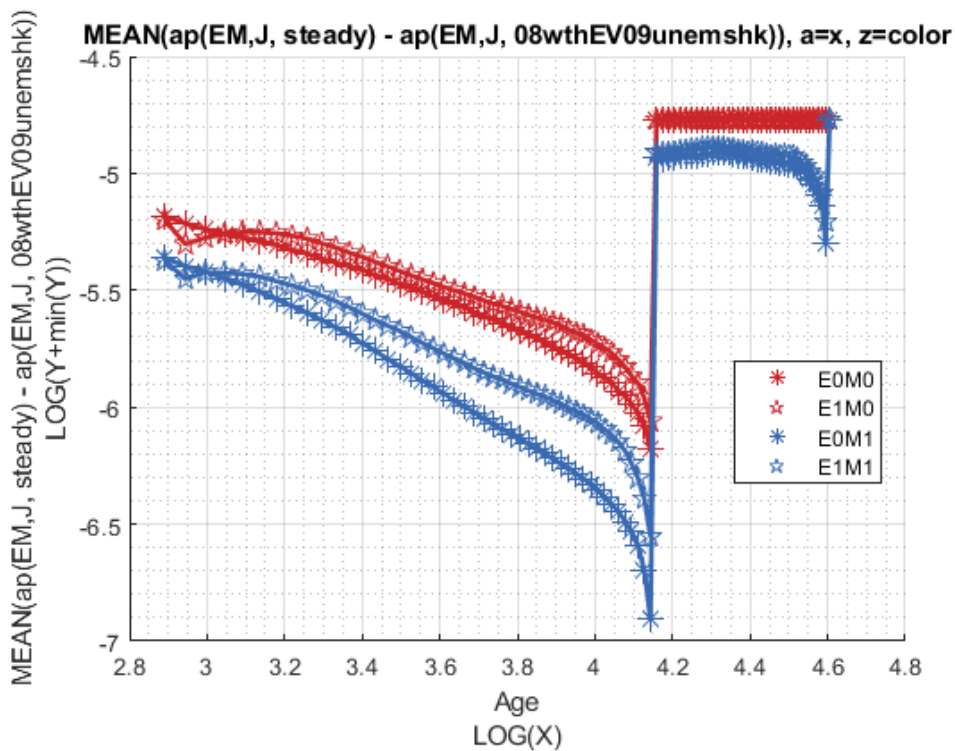
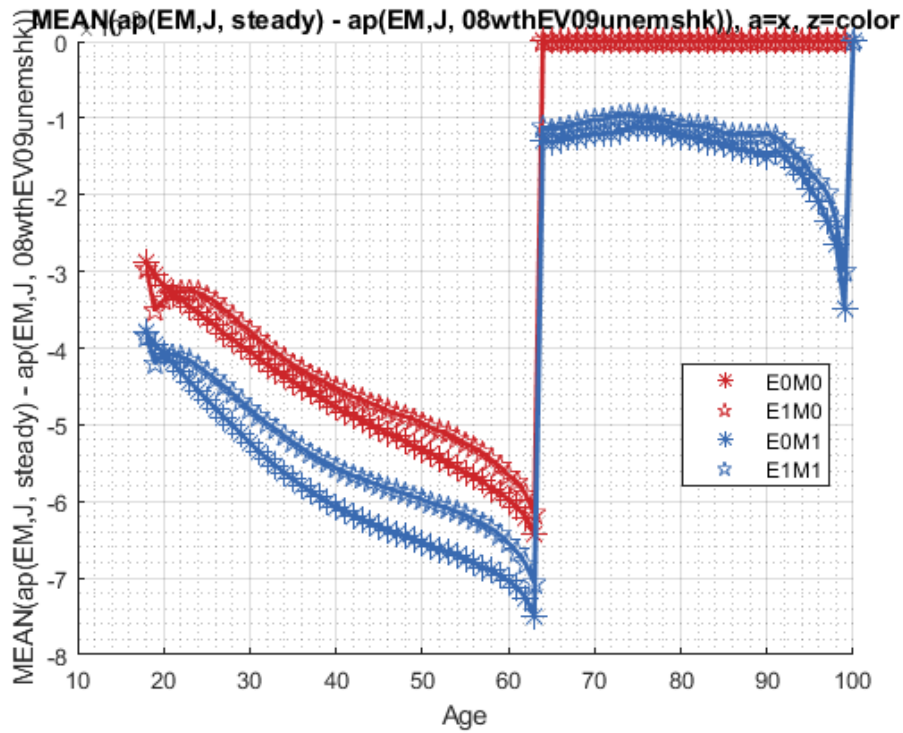
Graph Mean Values Change:

```
mp_support_graph('cl_st_graph_title') = {'MEAN(v(EM,J, steady) - v(EM,J, 08wthEV09unemshk))', a=age,
mp_support_graph('cl_st_ytitle') = {'MEAN(v(EM,J, steady) - v(EM,J, 08wthEV09unemshk))'};
ff_graph_grid((tb_az_v{1:end, 4:end}), ar_row_grid, age_grid, mp_support_graph);
```



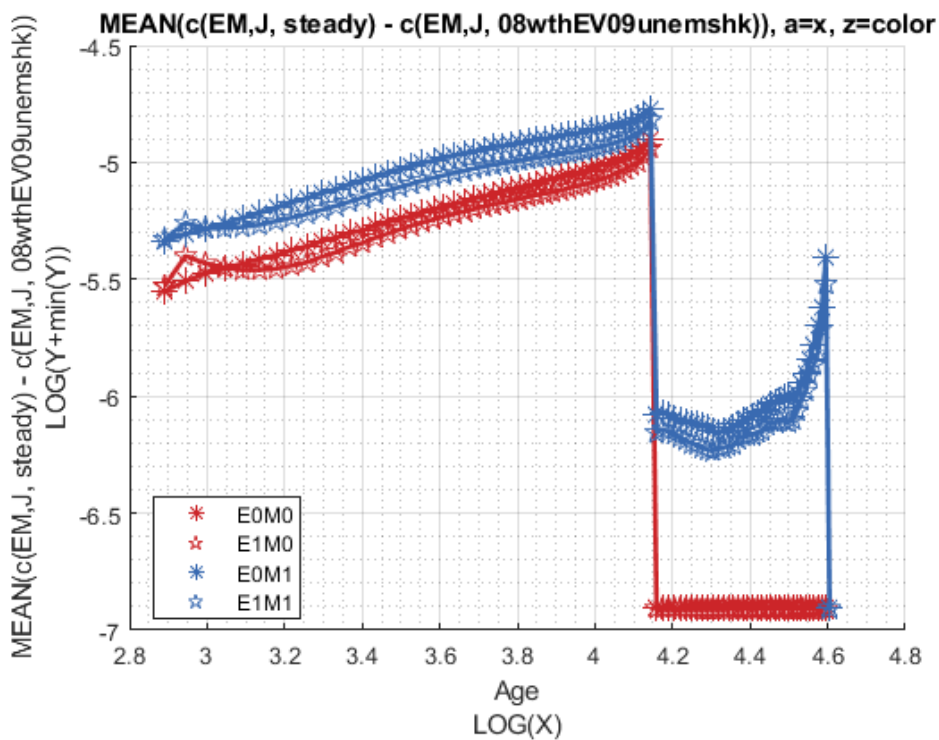
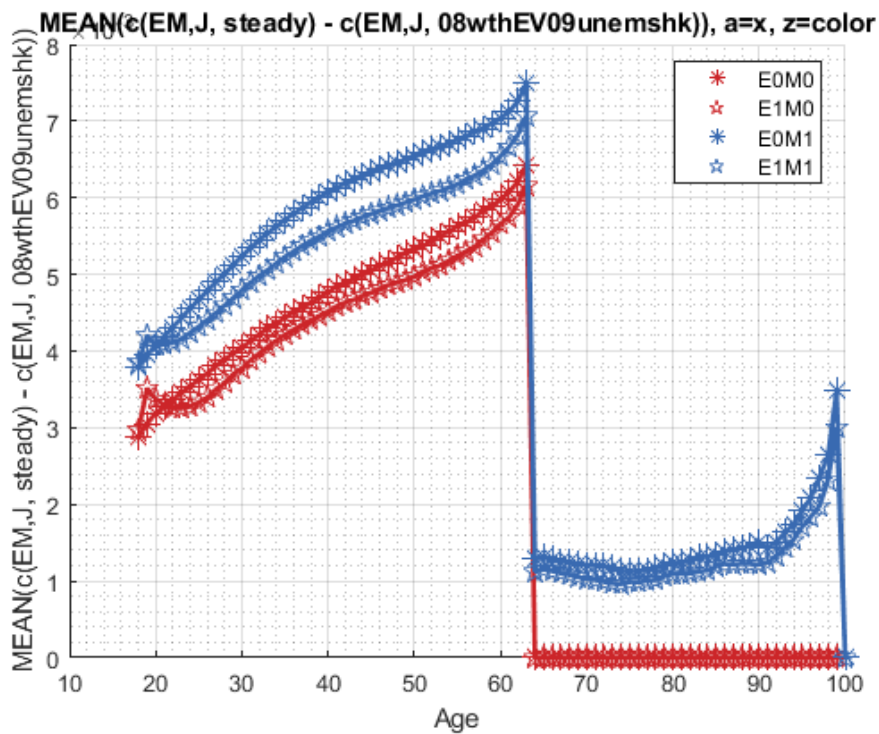
Graph Mean Savings Choices Change:

```
mp_support_graph('cl_st_graph_title') = {'MEAN(ap(EM,J, steady) - ap(EM,J, 08wthEV09unemshk))', a=x,
mp_support_graph('cl_st_ytitle') = {'MEAN(ap(EM,J, steady) - ap(EM,J, 08wthEV09unemshk))'};
ff_graph_grid((tb_az_ap{1:end, 4:end}), ar_row_grid, age_grid, mp_support_graph);
```



Graph Mean Consumption Change:

```
mp_support_graph('cl_st_graph_title') = {'MEAN(c(EM,J, steady) - c(EM,J, 08wthEV09unemshk))', a=x, z=
mp_support_graph('cl_st_ytitle') = {'MEAN(c(EM,J, steady) - c(EM,J, 08wthEV09unemshk))'};
ff_graph_grid((tb_az_c{1:end, 4:end}), ar_row_grid, age_grid, mp_support_graph);
```



## Chapter 6

# Solution with First and Second Rounds CARES Stimulus

### 6.1 Life Cycle Dynamic Programming under with CARES Act Stimulus Checks

This is the example vignette for function: [snw\\_vfi\\_main\\_bisec\\_vec\\_stimulus](#) from the [PrjOptiSNW Package](#). This function solves for policy function using Exact Vectorized Solution. Value in 2020 with surprise COVID unemployment Shock, with non-covid year Value as the continuation function, and provides households with stimulus checks specified in the 1st and 2nd round under actual Trump admin policies. The file focuses on the change in value function, asset choice, and consumption choice given a one period unemployment shock (that does not reappear in the future again). Solving this provides the distribution needed for the Biden checks, American Rescue Plan, problem.

#### 6.1.1 Test SNW\_VFI\_MAIN\_BISEC\_VEC\_STIMULUS

Solve the Regular Value and Also the Unemployment Value.

First, solve for value without unemployment issue (use the vectorized code that was previously tested):

```
mp_params = snw_mp_param('default_dodense');
mp_controls = snw_mp_control('default_test');
[V_VFI_ss,ap_VFI_ss,cons_VFI_ss,mp_valpol_more_ss] = ...
    snw_vfi_main_bisec_vec(mp_params, mp_controls);
```

```
SNW_VFI_MAIN_BISEC_VEC: Finished Age Group:83 of 82, time-this-age:8.1976
SNW_VFI_MAIN_BISEC_VEC: Finished Age Group:82 of 82, time-this-age:6.3715
SNW_VFI_MAIN_BISEC_VEC: Finished Age Group:81 of 82, time-this-age:6.1286
SNW_VFI_MAIN_BISEC_VEC: Finished Age Group:80 of 82, time-this-age:6.0961
SNW_VFI_MAIN_BISEC_VEC: Finished Age Group:79 of 82, time-this-age:6.1788
SNW_VFI_MAIN_BISEC_VEC: Finished Age Group:78 of 82, time-this-age:6.2505
SNW_VFI_MAIN_BISEC_VEC: Finished Age Group:77 of 82, time-this-age:6.1271
SNW_VFI_MAIN_BISEC_VEC: Finished Age Group:76 of 82, time-this-age:6.1446
SNW_VFI_MAIN_BISEC_VEC: Finished Age Group:75 of 82, time-this-age:5.8643
SNW_VFI_MAIN_BISEC_VEC: Finished Age Group:74 of 82, time-this-age:6.3012
SNW_VFI_MAIN_BISEC_VEC: Finished Age Group:73 of 82, time-this-age:5.9394
SNW_VFI_MAIN_BISEC_VEC: Finished Age Group:72 of 82, time-this-age:6.142
SNW_VFI_MAIN_BISEC_VEC: Finished Age Group:71 of 82, time-this-age:5.978
SNW_VFI_MAIN_BISEC_VEC: Finished Age Group:70 of 82, time-this-age:6.107
SNW_VFI_MAIN_BISEC_VEC: Finished Age Group:69 of 82, time-this-age:6.0351
SNW_VFI_MAIN_BISEC_VEC: Finished Age Group:68 of 82, time-this-age:6.1776
SNW_VFI_MAIN_BISEC_VEC: Finished Age Group:67 of 82, time-this-age:6.0961
SNW_VFI_MAIN_BISEC_VEC: Finished Age Group:66 of 82, time-this-age:6.0576
```

SNW\_VFI\_MAIN\_BISEC\_VEC: Finished Age Group:65 of 82, time-this-age:5.9533  
SNW\_VFI\_MAIN\_BISEC\_VEC: Finished Age Group:64 of 82, time-this-age:6.2248  
SNW\_VFI\_MAIN\_BISEC\_VEC: Finished Age Group:63 of 82, time-this-age:5.965  
SNW\_VFI\_MAIN\_BISEC\_VEC: Finished Age Group:62 of 82, time-this-age:6.8146  
SNW\_VFI\_MAIN\_BISEC\_VEC: Finished Age Group:61 of 82, time-this-age:7.1769  
SNW\_VFI\_MAIN\_BISEC\_VEC: Finished Age Group:60 of 82, time-this-age:6.3121  
SNW\_VFI\_MAIN\_BISEC\_VEC: Finished Age Group:59 of 82, time-this-age:6.3631  
SNW\_VFI\_MAIN\_BISEC\_VEC: Finished Age Group:58 of 82, time-this-age:6.1827  
SNW\_VFI\_MAIN\_BISEC\_VEC: Finished Age Group:57 of 82, time-this-age:6.0925  
SNW\_VFI\_MAIN\_BISEC\_VEC: Finished Age Group:56 of 82, time-this-age:6.3425  
SNW\_VFI\_MAIN\_BISEC\_VEC: Finished Age Group:55 of 82, time-this-age:6.3273  
SNW\_VFI\_MAIN\_BISEC\_VEC: Finished Age Group:54 of 82, time-this-age:6.3841  
SNW\_VFI\_MAIN\_BISEC\_VEC: Finished Age Group:53 of 82, time-this-age:6.6004  
SNW\_VFI\_MAIN\_BISEC\_VEC: Finished Age Group:52 of 82, time-this-age:6.2408  
SNW\_VFI\_MAIN\_BISEC\_VEC: Finished Age Group:51 of 82, time-this-age:6.2591  
SNW\_VFI\_MAIN\_BISEC\_VEC: Finished Age Group:50 of 82, time-this-age:6.2645  
SNW\_VFI\_MAIN\_BISEC\_VEC: Finished Age Group:49 of 82, time-this-age:6.3071  
SNW\_VFI\_MAIN\_BISEC\_VEC: Finished Age Group:48 of 82, time-this-age:6.373  
SNW\_VFI\_MAIN\_BISEC\_VEC: Finished Age Group:47 of 82, time-this-age:6.706  
SNW\_VFI\_MAIN\_BISEC\_VEC: Finished Age Group:46 of 82, time-this-age:6.6956  
SNW\_VFI\_MAIN\_BISEC\_VEC: Finished Age Group:45 of 82, time-this-age:6.4754  
SNW\_VFI\_MAIN\_BISEC\_VEC: Finished Age Group:44 of 82, time-this-age:6.4592  
SNW\_VFI\_MAIN\_BISEC\_VEC: Finished Age Group:43 of 82, time-this-age:6.5326  
SNW\_VFI\_MAIN\_BISEC\_VEC: Finished Age Group:42 of 82, time-this-age:6.6336  
SNW\_VFI\_MAIN\_BISEC\_VEC: Finished Age Group:41 of 82, time-this-age:6.485  
SNW\_VFI\_MAIN\_BISEC\_VEC: Finished Age Group:40 of 82, time-this-age:7.2556  
SNW\_VFI\_MAIN\_BISEC\_VEC: Finished Age Group:39 of 82, time-this-age:6.4432  
SNW\_VFI\_MAIN\_BISEC\_VEC: Finished Age Group:38 of 82, time-this-age:6.3289  
SNW\_VFI\_MAIN\_BISEC\_VEC: Finished Age Group:37 of 82, time-this-age:6.8039  
SNW\_VFI\_MAIN\_BISEC\_VEC: Finished Age Group:36 of 82, time-this-age:6.5217  
SNW\_VFI\_MAIN\_BISEC\_VEC: Finished Age Group:35 of 82, time-this-age:6.3529  
SNW\_VFI\_MAIN\_BISEC\_VEC: Finished Age Group:34 of 82, time-this-age:6.8033  
SNW\_VFI\_MAIN\_BISEC\_VEC: Finished Age Group:33 of 82, time-this-age:6.5971  
SNW\_VFI\_MAIN\_BISEC\_VEC: Finished Age Group:32 of 82, time-this-age:6.3756  
SNW\_VFI\_MAIN\_BISEC\_VEC: Finished Age Group:31 of 82, time-this-age:6.4397  
SNW\_VFI\_MAIN\_BISEC\_VEC: Finished Age Group:30 of 82, time-this-age:6.534  
SNW\_VFI\_MAIN\_BISEC\_VEC: Finished Age Group:29 of 82, time-this-age:6.5172  
SNW\_VFI\_MAIN\_BISEC\_VEC: Finished Age Group:28 of 82, time-this-age:6.6958  
SNW\_VFI\_MAIN\_BISEC\_VEC: Finished Age Group:27 of 82, time-this-age:7.0906  
SNW\_VFI\_MAIN\_BISEC\_VEC: Finished Age Group:26 of 82, time-this-age:6.3312  
SNW\_VFI\_MAIN\_BISEC\_VEC: Finished Age Group:25 of 82, time-this-age:6.6834  
SNW\_VFI\_MAIN\_BISEC\_VEC: Finished Age Group:24 of 82, time-this-age:6.5892  
SNW\_VFI\_MAIN\_BISEC\_VEC: Finished Age Group:23 of 82, time-this-age:6.7868  
SNW\_VFI\_MAIN\_BISEC\_VEC: Finished Age Group:22 of 82, time-this-age:6.5247  
SNW\_VFI\_MAIN\_BISEC\_VEC: Finished Age Group:21 of 82, time-this-age:6.5358  
SNW\_VFI\_MAIN\_BISEC\_VEC: Finished Age Group:20 of 82, time-this-age:6.7883  
SNW\_VFI\_MAIN\_BISEC\_VEC: Finished Age Group:19 of 82, time-this-age:6.3319  
SNW\_VFI\_MAIN\_BISEC\_VEC: Finished Age Group:18 of 82, time-this-age:6.4524  
SNW\_VFI\_MAIN\_BISEC\_VEC: Finished Age Group:17 of 82, time-this-age:6.4512  
SNW\_VFI\_MAIN\_BISEC\_VEC: Finished Age Group:16 of 82, time-this-age:6.4475  
SNW\_VFI\_MAIN\_BISEC\_VEC: Finished Age Group:15 of 82, time-this-age:6.4821  
SNW\_VFI\_MAIN\_BISEC\_VEC: Finished Age Group:14 of 82, time-this-age:6.9806  
SNW\_VFI\_MAIN\_BISEC\_VEC: Finished Age Group:13 of 82, time-this-age:6.744  
SNW\_VFI\_MAIN\_BISEC\_VEC: Finished Age Group:12 of 82, time-this-age:6.353  
SNW\_VFI\_MAIN\_BISEC\_VEC: Finished Age Group:11 of 82, time-this-age:6.3679  
SNW\_VFI\_MAIN\_BISEC\_VEC: Finished Age Group:10 of 82, time-this-age:6.5458  
SNW\_VFI\_MAIN\_BISEC\_VEC: Finished Age Group:9 of 82, time-this-age:6.3679  
SNW\_VFI\_MAIN\_BISEC\_VEC: Finished Age Group:8 of 82, time-this-age:6.5428

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SNW\_VFI\_MAIN\_BISEC\_VEC: Finished Age Group:7 of 82, time-this-age:6.8776  
 SNW\_VFI\_MAIN\_BISEC\_VEC: Finished Age Group:6 of 82, time-this-age:6.3248  
 SNW\_VFI\_MAIN\_BISEC\_VEC: Finished Age Group:5 of 82, time-this-age:6.2553  
 SNW\_VFI\_MAIN\_BISEC\_VEC: Finished Age Group:4 of 82, time-this-age:6.66  
 SNW\_VFI\_MAIN\_BISEC\_VEC: Finished Age Group:3 of 82, time-this-age:6.4982  
 SNW\_VFI\_MAIN\_BISEC\_VEC: Finished Age Group:2 of 82, time-this-age:6.3466  
 SNW\_VFI\_MAIN\_BISEC\_VEC: Finished Age Group:1 of 82, time-this-age:6.3944  
 Completed SNW\_VFI\_MAIN\_BISEC\_VEC;SNW\_MP\_PARAM=default\_docdense;SNW\_MP\_CONTROL=default\_test;time=535.

CONTAINER NAME: mp\_outcomes ND Array (Matrix etc)

	i	idx	ndim	numel	rowN	colN	sum	mean	std
V_VFI	1	1	6	4.37e+07	83	5.265e+05	-8.6673e+08	-19.834	28.17
ap_VFI	2	2	6	4.37e+07	83	5.265e+05	1.4164e+09	32.412	36.
cons_VFI	3	3	6	4.37e+07	83	5.265e+05	2.131e+08	4.8764	8.326

xxx TABLE:V\_VFI

	c1	c2	c3	c4	c5	c526496	c526497	c526498
r1	-376.05	-375.66	-373.17	-367.4	-358.05	-6.68	-6.5297	-6.379
r2	-363.8	-363.41	-360.93	-355.25	-346.25	-6.4892	-6.3437	-6.197
r3	-351.75	-351.36	-348.9	-343.44	-334.9	-6.2948	-6.1538	-6.011
r4	-339.81	-339.45	-337.16	-332.06	-324.04	-6.095	-5.9584	-5.8
r5	-328.99	-328.65	-326.51	-321.72	-314.17	-5.9054	-5.7725	-5.637
r79	-14.033	-14.02	-13.926	-13.689	-13.287	-0.22848	-0.21775	-0.2076
r80	-12.564	-12.55	-12.457	-12.22	-11.818	-0.17427	-0.16611	-0.1584
r81	-10.778	-10.764	-10.671	-10.434	-10.032	-0.11927	-0.11368	-0.1084
r82	-8.4226	-8.4089	-8.3155	-8.0786	-7.6766	-0.06597	-0.06284	-0.05992
r83	-5.0665	-5.0529	-4.9595	-4.7226	-4.3206	-0.020968	-0.019972	-0.01903

xxx TABLE:ap\_VFI

	c1	c2	c3	c4	c5	c526496	c526497	c526498	c52
r1	0	0	0.0005656	0.0075134	0.022901	114.76	120.42	126.29	132
r2	0	0	0.00051498	0.0065334	0.021549	114.87	120.54	126.42	132
r3	0	0	0.00051498	0.0049294	0.019875	114.98	120.67	126.57	132
r4	0	0	0.00051498	0.0047937	0.019672	115.74	121.44	127.36	133
r5	0	0	0.00048517	0.0046683	0.019484	116.51	122.22	128.16	134
r79	0	0	0	0	0.00051498	81.091	85.68	90.325	94.
r80	0	0	0	0	0	76.669	80.55	84.292	88.
r81	0	0	0	0	0	68.313	71.52	74.459	77.
r82	0	0	0	0	0	50.126	53.467	56.953	58.
r83	0	0	0	0	0	0	0	0	0

xxx TABLE:cons\_VFI

	c1	c2	c3	c4	c5	c526496	c526497	c526498
r1	0.036717	0.037251	0.040426	0.04363	0.048012	9.6396	9.8066	9.9533
r2	0.036717	0.037251	0.040477	0.04461	0.049364	9.8014	9.9571	10.088
r3	0.036717	0.037251	0.040477	0.046214	0.051039	9.9664	10.108	10.22
r4	0.038144	0.038678	0.041903	0.047776	0.052666	10.118	10.244	10.339
r5	0.039534	0.040068	0.043323	0.04929	0.054241	10.258	10.369	10.446

r79	0.19737	0.19791	0.20163	0.21175	0.23093	35.811	37.046	38.418
r80	0.19737	0.19791	0.20163	0.21175	0.23145	40.207	42.15	44.426
r81	0.19737	0.19791	0.20163	0.21175	0.23145	48.541	51.158	54.236
r82	0.19737	0.19791	0.20163	0.21175	0.23145	66.71	69.193	71.724
r83	0.19737	0.19791	0.20163	0.21175	0.23145	116.82	122.65	128.66

Second, solve for the unemployment value, use the exact-bisec result code, call the `snw_vfi_main_bisec_vec.m` function with a third input of existing value. `xi` is the share of income lost during covid year given surprise covid shock, `b` is the share of income loss that is covered by unemployment insurance. `xi=0.5` and `b=0` means will lose 50 percent of income given COVID shocks, and the loss will not be covered at all by unemployment insurance. Calling the `snw_vfi_main_bisec_vec_stimulus` means households will receive positive amounts of stimulus given household structure (marital status and children count), as well as their total household income level.

```
mp_params('xi') = 0.5;
mp_params('b') = 0;
mp_params('a2_covidyr') = mp_params('a2_covidyr_manna_heaven');
[V_VFI_wthtrumpchk, ap_VFI_wthtrumpchecks, cons_VFI_wthtrumpchk, mp_valpol_more_wthtrumpchk] = ...
    snw_vfi_main_bisec_vec_stimulus(mp_params, mp_controls, V_VFI_ss);
```

```
SNW_VFI_MAIN_BISEC_VEC 1 Period Unemp Shock: Age 1 of 82, time-this-age:6.62
SNW_VFI_MAIN_BISEC_VEC 1 Period Unemp Shock: Age 2 of 82, time-this-age:6.6881
SNW_VFI_MAIN_BISEC_VEC 1 Period Unemp Shock: Age 3 of 82, time-this-age:6.8137
SNW_VFI_MAIN_BISEC_VEC 1 Period Unemp Shock: Age 4 of 82, time-this-age:6.5643
SNW_VFI_MAIN_BISEC_VEC 1 Period Unemp Shock: Age 5 of 82, time-this-age:6.6084
SNW_VFI_MAIN_BISEC_VEC 1 Period Unemp Shock: Age 6 of 82, time-this-age:6.658
SNW_VFI_MAIN_BISEC_VEC 1 Period Unemp Shock: Age 7 of 82, time-this-age:6.8349
SNW_VFI_MAIN_BISEC_VEC 1 Period Unemp Shock: Age 8 of 82, time-this-age:6.5825
SNW_VFI_MAIN_BISEC_VEC 1 Period Unemp Shock: Age 9 of 82, time-this-age:6.5439
SNW_VFI_MAIN_BISEC_VEC 1 Period Unemp Shock: Age 10 of 82, time-this-age:6.6846
SNW_VFI_MAIN_BISEC_VEC 1 Period Unemp Shock: Age 11 of 82, time-this-age:6.5489
SNW_VFI_MAIN_BISEC_VEC 1 Period Unemp Shock: Age 12 of 82, time-this-age:6.6835
SNW_VFI_MAIN_BISEC_VEC 1 Period Unemp Shock: Age 13 of 82, time-this-age:7.0851
SNW_VFI_MAIN_BISEC_VEC 1 Period Unemp Shock: Age 14 of 82, time-this-age:6.7157
SNW_VFI_MAIN_BISEC_VEC 1 Period Unemp Shock: Age 15 of 82, time-this-age:6.6425
SNW_VFI_MAIN_BISEC_VEC 1 Period Unemp Shock: Age 16 of 82, time-this-age:6.8711
SNW_VFI_MAIN_BISEC_VEC 1 Period Unemp Shock: Age 17 of 82, time-this-age:6.746
SNW_VFI_MAIN_BISEC_VEC 1 Period Unemp Shock: Age 18 of 82, time-this-age:6.6717
SNW_VFI_MAIN_BISEC_VEC 1 Period Unemp Shock: Age 19 of 82, time-this-age:6.9565
SNW_VFI_MAIN_BISEC_VEC 1 Period Unemp Shock: Age 20 of 82, time-this-age:7.0231
SNW_VFI_MAIN_BISEC_VEC 1 Period Unemp Shock: Age 21 of 82, time-this-age:6.6252
SNW_VFI_MAIN_BISEC_VEC 1 Period Unemp Shock: Age 22 of 82, time-this-age:6.5266
SNW_VFI_MAIN_BISEC_VEC 1 Period Unemp Shock: Age 23 of 82, time-this-age:6.6398
SNW_VFI_MAIN_BISEC_VEC 1 Period Unemp Shock: Age 24 of 82, time-this-age:6.6428
SNW_VFI_MAIN_BISEC_VEC 1 Period Unemp Shock: Age 25 of 82, time-this-age:6.5884
SNW_VFI_MAIN_BISEC_VEC 1 Period Unemp Shock: Age 26 of 82, time-this-age:6.9986
SNW_VFI_MAIN_BISEC_VEC 1 Period Unemp Shock: Age 27 of 82, time-this-age:6.58
SNW_VFI_MAIN_BISEC_VEC 1 Period Unemp Shock: Age 28 of 82, time-this-age:6.3892
SNW_VFI_MAIN_BISEC_VEC 1 Period Unemp Shock: Age 29 of 82, time-this-age:6.8717
SNW_VFI_MAIN_BISEC_VEC 1 Period Unemp Shock: Age 30 of 82, time-this-age:6.5103
SNW_VFI_MAIN_BISEC_VEC 1 Period Unemp Shock: Age 31 of 82, time-this-age:6.7253
SNW_VFI_MAIN_BISEC_VEC 1 Period Unemp Shock: Age 32 of 82, time-this-age:7.0548
SNW_VFI_MAIN_BISEC_VEC 1 Period Unemp Shock: Age 33 of 82, time-this-age:6.7513
SNW_VFI_MAIN_BISEC_VEC 1 Period Unemp Shock: Age 34 of 82, time-this-age:6.7784
SNW_VFI_MAIN_BISEC_VEC 1 Period Unemp Shock: Age 35 of 82, time-this-age:6.6639
SNW_VFI_MAIN_BISEC_VEC 1 Period Unemp Shock: Age 36 of 82, time-this-age:6.8596
SNW_VFI_MAIN_BISEC_VEC 1 Period Unemp Shock: Age 37 of 82, time-this-age:6.6734
SNW_VFI_MAIN_BISEC_VEC 1 Period Unemp Shock: Age 38 of 82, time-this-age:6.5029
SNW_VFI_MAIN_BISEC_VEC 1 Period Unemp Shock: Age 39 of 82, time-this-age:7.02
```



6.1. LIFE CYCLE DYNAMIC PROGRAMMING UNDER WITH CARES ACT STIMULUS CHECKS145

```

SNW_VFI_MAIN_BISEC_VEC 1 Period Unemp Shock: Age 40 of 82, time-this-age:6.6714
SNW_VFI_MAIN_BISEC_VEC 1 Period Unemp Shock: Age 41 of 82, time-this-age:6.5598
SNW_VFI_MAIN_BISEC_VEC 1 Period Unemp Shock: Age 42 of 82, time-this-age:6.7617
SNW_VFI_MAIN_BISEC_VEC 1 Period Unemp Shock: Age 43 of 82, time-this-age:6.5979
SNW_VFI_MAIN_BISEC_VEC 1 Period Unemp Shock: Age 44 of 82, time-this-age:6.7787
SNW_VFI_MAIN_BISEC_VEC 1 Period Unemp Shock: Age 45 of 82, time-this-age:7.1311
SNW_VFI_MAIN_BISEC_VEC 1 Period Unemp Shock: Age 46 of 82, time-this-age:6.6511
SNW_VFI_MAIN_BISEC_VEC 1 Period Unemp Shock: Age 47 of 82, time-this-age:6.826
SNW_VFI_MAIN_BISEC_VEC 1 Period Unemp Shock: Age 48 of 82, time-this-age:6.6529
SNW_VFI_MAIN_BISEC_VEC 1 Period Unemp Shock: Age 49 of 82, time-this-age:6.447
SNW_VFI_MAIN_BISEC_VEC 1 Period Unemp Shock: Age 50 of 82, time-this-age:6.5167
SNW_VFI_MAIN_BISEC_VEC 1 Period Unemp Shock: Age 51 of 82, time-this-age:6.5401
SNW_VFI_MAIN_BISEC_VEC 1 Period Unemp Shock: Age 52 of 82, time-this-age:6.722
SNW_VFI_MAIN_BISEC_VEC 1 Period Unemp Shock: Age 53 of 82, time-this-age:6.5741
SNW_VFI_MAIN_BISEC_VEC 1 Period Unemp Shock: Age 54 of 82, time-this-age:6.9319
SNW_VFI_MAIN_BISEC_VEC 1 Period Unemp Shock: Age 55 of 82, time-this-age:7.182
SNW_VFI_MAIN_BISEC_VEC 1 Period Unemp Shock: Age 56 of 82, time-this-age:7.6984
SNW_VFI_MAIN_BISEC_VEC 1 Period Unemp Shock: Age 57 of 82, time-this-age:6.4441
SNW_VFI_MAIN_BISEC_VEC 1 Period Unemp Shock: Age 58 of 82, time-this-age:6.891
SNW_VFI_MAIN_BISEC_VEC 1 Period Unemp Shock: Age 59 of 82, time-this-age:7.0068
SNW_VFI_MAIN_BISEC_VEC 1 Period Unemp Shock: Age 60 of 82, time-this-age:7.0328
SNW_VFI_MAIN_BISEC_VEC 1 Period Unemp Shock: Age 61 of 82, time-this-age:6.8954
SNW_VFI_MAIN_BISEC_VEC 1 Period Unemp Shock: Age 62 of 82, time-this-age:6.9436
SNW_VFI_MAIN_BISEC_VEC 1 Period Unemp Shock: Age 63 of 82, time-this-age:6.983
SNW_VFI_MAIN_BISEC_VEC 1 Period Unemp Shock: Age 64 of 82, time-this-age:6.9707
SNW_VFI_MAIN_BISEC_VEC 1 Period Unemp Shock: Age 65 of 82, time-this-age:6.9944
SNW_VFI_MAIN_BISEC_VEC 1 Period Unemp Shock: Age 66 of 82, time-this-age:7.3946
SNW_VFI_MAIN_BISEC_VEC 1 Period Unemp Shock: Age 67 of 82, time-this-age:7.0114
SNW_VFI_MAIN_BISEC_VEC 1 Period Unemp Shock: Age 68 of 82, time-this-age:7.109
SNW_VFI_MAIN_BISEC_VEC 1 Period Unemp Shock: Age 69 of 82, time-this-age:7.0221
SNW_VFI_MAIN_BISEC_VEC 1 Period Unemp Shock: Age 70 of 82, time-this-age:7.0655
SNW_VFI_MAIN_BISEC_VEC 1 Period Unemp Shock: Age 71 of 82, time-this-age:6.8624
SNW_VFI_MAIN_BISEC_VEC 1 Period Unemp Shock: Age 72 of 82, time-this-age:6.8953
SNW_VFI_MAIN_BISEC_VEC 1 Period Unemp Shock: Age 73 of 82, time-this-age:6.9772
SNW_VFI_MAIN_BISEC_VEC 1 Period Unemp Shock: Age 74 of 82, time-this-age:6.9265
SNW_VFI_MAIN_BISEC_VEC 1 Period Unemp Shock: Age 75 of 82, time-this-age:6.9556
SNW_VFI_MAIN_BISEC_VEC 1 Period Unemp Shock: Age 76 of 82, time-this-age:6.8726
SNW_VFI_MAIN_BISEC_VEC 1 Period Unemp Shock: Age 77 of 82, time-this-age:7.1171
SNW_VFI_MAIN_BISEC_VEC 1 Period Unemp Shock: Age 78 of 82, time-this-age:7.0941
SNW_VFI_MAIN_BISEC_VEC 1 Period Unemp Shock: Age 79 of 82, time-this-age:6.6593
SNW_VFI_MAIN_BISEC_VEC 1 Period Unemp Shock: Age 80 of 82, time-this-age:6.504
SNW_VFI_MAIN_BISEC_VEC 1 Period Unemp Shock: Age 81 of 82, time-this-age:6.3068
SNW_VFI_MAIN_BISEC_VEC 1 Period Unemp Shock: Age 82 of 82, time-this-age:6.6383
SNW_VFI_MAIN_BISEC_VEC 1 Period Unemp Shock: Age 83 of 82, time-this-age:8.1596
Completed SNW_VFI_MAIN_BISEC_VEC 1 Period Unemp Shock;SNW_MP_PARAM=default_docdense;SNW_MP_CONTROL=d

```

```

XXXXXXXXXXXXXXXXXXXXXXXXXXXXXXXXXXXXXXXXXXXXXXXXXXXXXXXXXXXX
CONTAINER NAME: mp_outcomes ND Array (Matrix etc)
XXXXXXXXXXXXXXXXXXXXXXXXXXXXXXXXXXXXXXXXXXXXXXXXXXXXXXXXXXXX

```

	i	idx	ndim	numel	rowN	colN	sum	mean	std
V_VFI	1	1	6	4.37e+07	83	5.265e+05	-8.759e+08	-20.044	27.874
ap_VFI	2	2	6	4.37e+07	83	5.265e+05	1.3809e+09	31.599	36.658
cons_VFI	3	3	6	4.37e+07	83	5.265e+05	2.105e+08	4.8169	8.3229

```

xxx TABLE:V_VFI XXXXXXXXXXXXXXXXXXXXXXX
c1 c2 c3 c4 c5 c526496 c526497 c526498

```

	-----	-----	-----	-----	-----	-----	-----	-----
r1	-369.35	-369.07	-367.11	-361.97	-353.39	-6.8096	-6.6548	-6.500
r2	-357.14	-356.86	-354.97	-349.98	-341.85	-6.618	-6.4683	-6.318
r3	-345.28	-344.99	-343.18	-338.45	-330.78	-6.4227	-6.278	-6.132
r4	-334.13	-333.86	-332.12	-327.68	-320.43	-6.2297	-6.0896	-5.948
r5	-324.01	-323.75	-322.06	-317.88	-310.99	-6.0467	-5.9107	-5.773
r79	-13.388	-13.378	-13.307	-13.12	-12.781	-0.2305	-0.21962	-0.2093
r80	-11.919	-11.908	-11.837	-11.653	-11.317	-0.17582	-0.16751	-0.1596
r81	-10.133	-10.122	-10.051	-9.8679	-9.5372	-0.12032	-0.11462	-0.1092
r82	-7.7774	-7.767	-7.6957	-7.5131	-7.1868	-0.066524	-0.063355	-0.06039
r83	-5.0665	-5.0529	-4.9595	-4.7226	-4.3206	-0.021146	-0.020134	-0.01918

xxx TABLE:ap\_VFI xxxxxxxxxxxxxxxxxxxxxxx

	-----	-----	-----	-----	-----	-----	-----	-----
	c1	c2	c3	c4	c5	c526496	c526497	c
r1	0.0041199	0.0043268	0.0080703	0.013905	0.032959	110.07	115.71	1
r2	0.0041199	0.0041199	0.0070902	0.013905	0.032284	110.04	115.69	1
r3	0.0041199	0.0041199	0.0054862	0.013905	0.030609	110	115.66	1
r4	0.0041199	0.0041199	0.0046552	0.013905	0.029711	110.29	115.97	1
r5	0.0035447	0.0040795	0.0041199	0.013905	0.028846	110.59	116.28	1
r79	0	0	0.00041185	0.0041199	0.013905	81.091	85.231	8
r80	0	0	0	0.0041199	0.013905	75.865	79.539	8
r81	0	0	0	0.0020033	0.013501	67.78	70.52	7
r82	0	0	0	0.00051498	0.010558	50.126	53.467	5
r83	0	0	0	0	0	0	0	0

xxx TABLE:cons\_VFI xxxxxxxxxxxxxxxxxxxxxxx

	-----	-----	-----	-----	-----	-----	-----	-----
	c1	c2	c3	c4	c5	c526496	c526497	c526498
r1	0.043302	0.04363	0.04363	0.047957	0.048689	9.4621	9.6396	9.8066
r2	0.043302	0.043837	0.04461	0.047957	0.049364	9.6318	9.8014	9.9571
r3	0.043302	0.043837	0.046214	0.047957	0.051039	9.8074	9.9664	10.108
r4	0.044033	0.044568	0.047776	0.048687	0.052666	9.971	10.118	10.244
r5	0.04532	0.04532	0.049023	0.049398	0.054241	10.123	10.258	10.369
r79	0.22617	0.2267	0.23002	0.23643	0.24634	34.787	36.471	38.418
r80	0.22617	0.2267	0.23043	0.23643	0.24634	40.001	42.15	44.426
r81	0.22617	0.2267	0.23043	0.23854	0.24675	48.074	51.158	54.236
r82	0.22617	0.2267	0.23043	0.24003	0.24969	65.719	68.202	71.583
r83	0.19737	0.19791	0.20163	0.21175	0.23145	115.84	121.66	127.68

Difference Between Value and Choices In Unemployment and Future Periods

```
V_VFI_wthtrumpchk_drop = V_VFI_ss - V_VFI_wthtrumpchk;
ap_VFI_wthtrumpchk_drop = ap_VFI_ss - ap_VFI_wthtrumpchecks;
cons_VFI_wthtrumpchk_drop = cons_VFI_ss - cons_VFI_wthtrumpchk;
```

## 6.1.2 Define Parameter Frames

Define the matrix dimensions names and dimension vector values. Policy and Value Functions share the same ND dimensional structure.

% Grids:

```
age_grid = 18:100;
agrid = mp_params('agrid');
eta_H_grid = mp_params('eta_H_grid');
eta_S_grid = mp_params('eta_S_grid');
ar_st_eta_HS_grid = string(cellstr([num2str(eta_H_grid', 'hz=%3.2f;'), num2str(eta_S_grid', 'wz=%3.2
```

```

edu_grid = [0,1];
marry_grid = [0,1];
kids_grid = (1:1:mp_params('n_kidsgrid'))';
% NaN(n_jgrid,n_agrid,n_etagrid,n_educgrid,n_marriedgrid,n_kidsgrid);
cl_mp_datasetdesc = {};
cl_mp_datasetdesc{1} = containers.Map({'name', 'labval'}, {'age', age_grid});
cl_mp_datasetdesc{2} = containers.Map({'name', 'labval'}, {'savings', agrid});
cl_mp_datasetdesc{3} = containers.Map({'name', 'labval'}, {'eta', 1:length(eta_H_grid)});
cl_mp_datasetdesc{4} = containers.Map({'name', 'labval'}, {'edu', edu_grid});
cl_mp_datasetdesc{5} = containers.Map({'name', 'labval'}, {'marry', marry_grid});
cl_mp_datasetdesc{6} = containers.Map({'name', 'labval'}, {'kids', kids_grid});

```

### 6.1.3 Analyze Savings and Shocks

First, analyze Savings Levels and Shocks, Aggregate Over All Others, and do various other calculations.

```

% Generate some Data
mp_support_graph = containers.Map('KeyType', 'char', 'ValueType', 'any');
mp_support_graph('cl_st_xtitle') = {'Savings States, a'};
mp_support_graph('st_legend_loc') = 'eastoutside';
mp_support_graph('bl_graph_logy') = true; % do not log
mp_support_graph('it_legend_select') = 15; % how many shock legends to show
mp_support_graph('cl_colors') = 'jet';

MEAN(VAL(A,Z) - VAL(A,Z|CARESActChecks)), MEAN(AP(A,Z) - AP(A,Z|CARESActChecks)),
MEAN(C(A,Z) - C(A,Z|CARESActChecks))

Tabulate value and policies along savings and shocks:

% Set
% NaN(n_jgrid,n_agrid,n_etagrid,n_educgrid,n_marriedgrid,n_kidsgrid);
ar_permute = [1,4,5,6,3,2];
% Value Function
tb_az_v = ff_summ_nd_array("MEAN(v(A,Z) - v(A,Z|CARESActChecks))", V_VFI_wthtrumpchk_drop, true, ["m

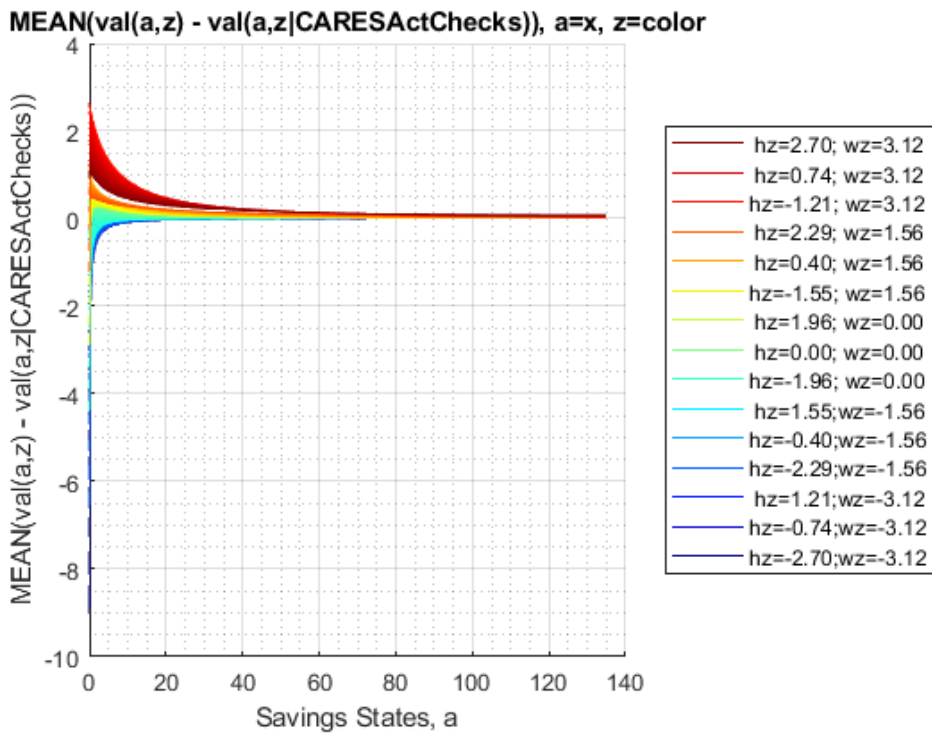
xxx  MEAN(v(A,Z) - v(A,Z|CARESActChecks))  xxxxxxxxxxxxxxxxxxxxxxxxxxxxxxxx
      group      savings      mean_eta_1      mean_eta_2      mean_eta_3      mean_eta_4      mean_eta_5
      -----      -
      1              0          -9.0028          -8.1198          -7.2767          -6.4867          -5.7583

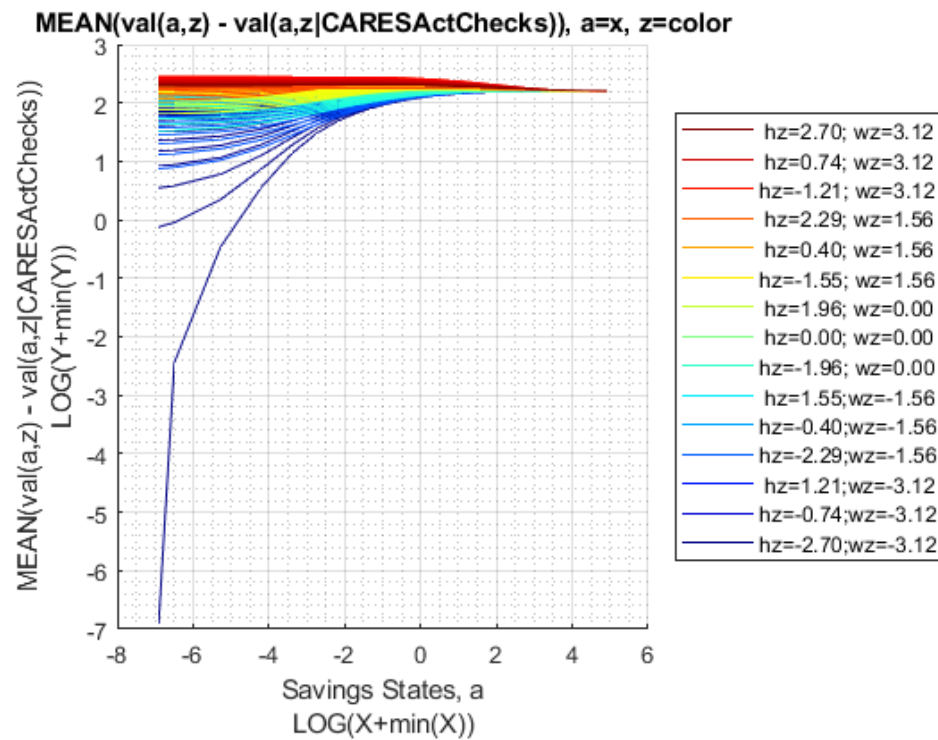
```

```
% Consumption Choices
tb_az_c = ff_summ_nd_array("MEAN(C(A,Z) - C(A,Z|CARESActChecks))", cons_VFI_wthtrumpchk_drop, true,
```

xxx	MEAN(C(A,Z) - C(A,Z CARESActChecks))	xxxxxxxxxxxxxxxxxxxxxxxxxxxxxxxx	xxxxxxxxxxxxxxxxxxxxxxxxxxxxxxxx	xxxxxxxxxxxxxxxxxxxxxxxxxxxxxxxx	xxxxxxxxxxxxxxxxxxxxxxxxxxxxxxxx	xxxxxxxxxxxxxxxxxxxxxxxxxxxxxxxx
group	savings	mean_eta_1	mean_eta_2	mean_eta_3	mean_eta_4	mean_eta_5
1	0	-0.048192	-0.047194	-0.046217	-0.045225	-0.044179

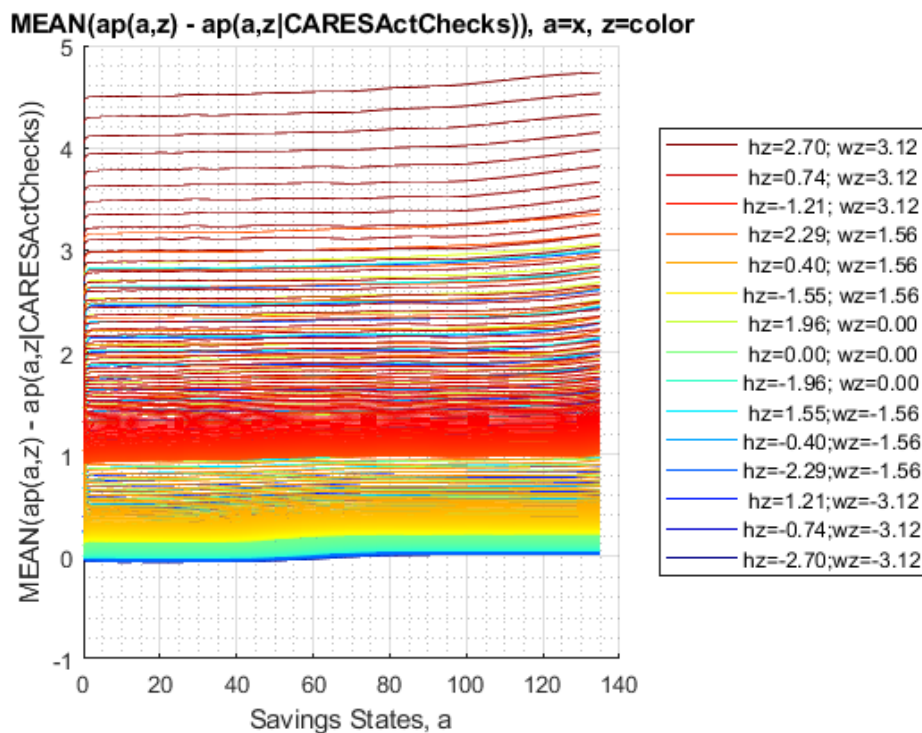
```
mp_support_graph('cl_st_graph_title') = {'MEAN(val(a,z) - val(a,z|CARESActChecks)), a=x, z=color'};
mp_support_graph('cl_st_ytitle') = {'MEAN(val(a,z) - val(a,z|CARESActChecks))'};
ff_graph_grid((tb_az_v{1:end, 3:end})', ar_st_eta_HS_grid, agrid, mp_support_graph);
```

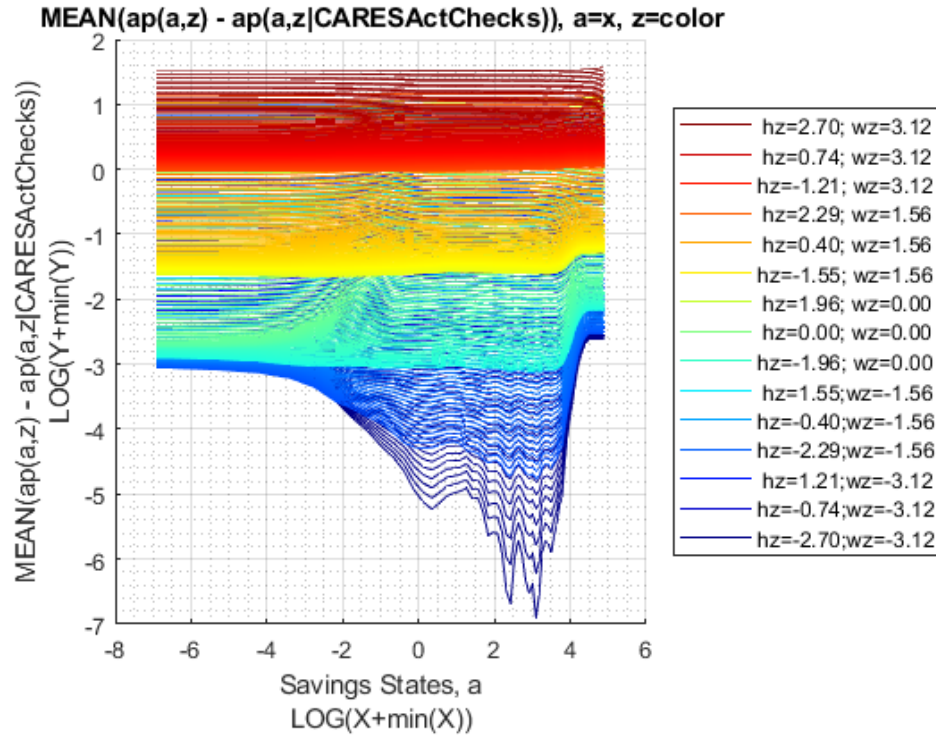




Graph Mean Savings Choices Change:

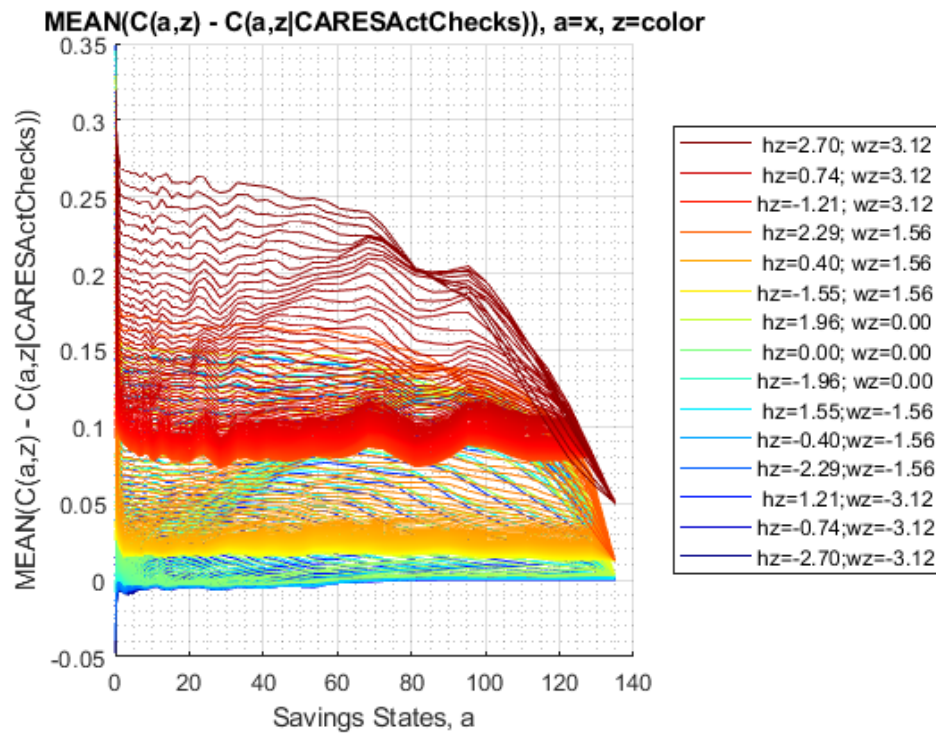
```
mp_support_graph('cl_st_graph_title') = {'MEAN(ap(a,z) - ap(a,z|CARESActChecks)), a=x, z=color'};
mp_support_graph('cl_st_ytitle') = {'MEAN(ap(a,z) - ap(a,z|CARESActChecks))'};
ff_graph_grid((tb_az_ap{1:end, 3:end})', ar_st_eta_HS_grid, agrid, mp_support_graph);
```

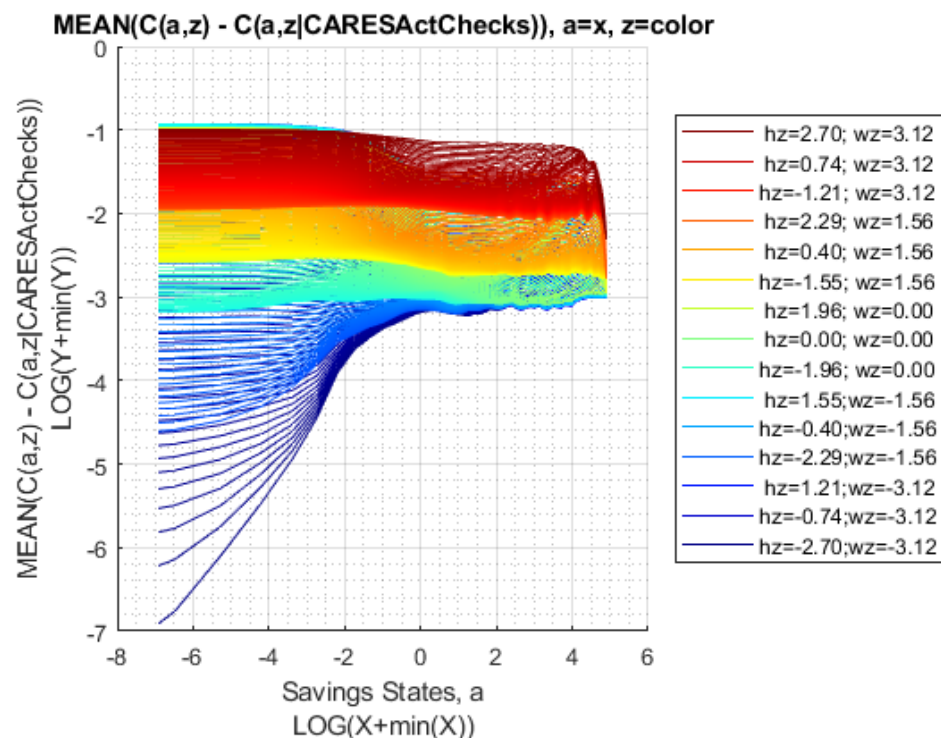




Graph Mean Consumption Change:

```
mp_support_graph('cl_st_graph_title') = {'MEAN(C(a,z) - C(a,z|CARESActChecks)), a=x, z=color'};
mp_support_graph('cl_st_ytitle') = {'MEAN(C(a,z) - C(a,z|CARESActChecks))'};
ff_graph_grid((tb_az_c{1:end, 3:end})', ar_st_eta_HS_grid, agrid, mp_support_graph);
```





#### 6.1.4 Analyze Kids and Marriage and Age

Aggregating over education, savings, and shocks, what are the differential effects of Marriage and Age.

```
% Generate some Data
mp_support_graph = containers.Map('KeyType', 'char', 'ValueType', 'any');
ar_row_grid = [...
    "k0M0", "K1M0", "K2M0", "K3M0", "K4M0", ...
    "k0M1", "K1M1", "K2M1", "K3M1", "K4M1"];
mp_support_graph('cl_st_xtitle') = {'Age'};
mp_support_graph('st_legend_loc') = 'best';
mp_support_graph('bl_graph_logy') = true; % do not log
mp_support_graph('st_rounding') = '6.2f'; % format shock legend
mp_support_graph('cl_scatter_shapes') = {...
    'o', 'd', 's', 'x', '*'}, ...
    'o', 'd', 's', 'x', '*'};
mp_support_graph('cl_colors') = {...
    'red', 'red', 'red', 'red', 'red'...
    'blue', 'blue', 'blue', 'blue', 'blue'};

MEAN(V(KM,J) - V(KM,J | CARESActChecks)), MEAN(ap(KM,J) - ap(KM,J | CARESActChecks)),
MEAN(c(KM,J) - c(KM,J | CARESActChecks))

Tabulate value and policies:

% Set
% NaN(n_jgrid,n_agrid,n_etagrid,n_educgrid,n_marriedgrid,n_kidsgrid);
ar_permute = [2,3,4,1,6,5];
% Value Function
tb_az_v = ff_summ_nd_array("MEAN(V(KM,J) - V(KM,J | CARESActChecks))", V_VFI_wthtrumpchk_drop, true,

xxx MEAN(V(KM,J) - V(KM,J | CARESActChecks)) xxxxxxxxxxxxxxxxxxxxxxxxxxxxxxxx
group kids marry mean_age_18 mean_age_19 mean_age_20 mean_age_21 mean_age_2
-----
1 1 0 0.2332 0.22485 0.21742 0.22953 0.23963
```

2	2	0	0.066539	0.065877	0.068247	0.098285	0.12333
3	3	0	-0.16926	-0.15841	-0.1423	-0.093192	-0.051804
4	4	0	-0.44442	-0.42121	-0.39008	-0.32042	-0.26131
5	5	0	-0.73932	-0.70328	-0.65682	-0.56749	-0.49136
6	1	1	0.54283	0.53403	0.52485	0.52685	0.52859
7	2	1	0.572	0.56458	0.55612	0.56246	0.56751
8	3	1	0.52502	0.52141	0.51661	0.52951	0.5404
9	4	1	0.46008	0.46188	0.46209	0.48277	0.50057
10	5	1	0.29213	0.30189	0.31023	0.34193	0.36924

% Aprime Choice

tb\_az\_ap = ff\_summ\_nd\_array("MEAN(ap(KM,J) - ap(KM,J | CARESActChecks))", ap\_VFI\_wthtrumpchk\_drop, t

```

xxx MEAN(ap(KM,J) - ap(KM,J | CARESActChecks)) xxxxxxxxxxxxxxxxxxxxxxxxxxxxxxxx
  group  kids  marry  mean_age_18  mean_age_19  mean_age_20  mean_age_21  mean_age_2
-----  ----  -----  -
1      1      0      0.53409     0.53149     0.52842     0.56711     0.60568
2      2      0      0.51704     0.51346     0.50927     0.54742     0.58546
3      3      0      0.50183     0.49768     0.49316     0.53101     0.56887
4      4      0      0.48856     0.48424     0.47955     0.51731     0.55508
5      5      0      0.47499     0.47072     0.46598     0.50375     0.54161
6      1      1      1.1088      1.1527      1.1974      1.2901      1.3837
7      2      1      1.0065      1.0431      1.0802      1.164       1.2484
8      3      1      0.92804     0.96014     0.99224     1.0702      1.1489
9      4      1      0.84205     0.86965     0.89728     0.97107     1.0451
10     5      1      0.71408     0.73273     0.7514      0.8152      0.87929

```

% Consumption Choices

tb\_az\_c = ff\_summ\_nd\_array("MEAN(c(KM,J) - c(KM,J | CARESActChecks))", cons\_VFI\_wthtrumpchk\_drop, tr

```

xxx MEAN(c(KM,J) - c(KM,J | CARESActChecks)) xxxxxxxxxxxxxxxxxxxxxxxxxxxxxxxx
  group  kids  marry  mean_age_18  mean_age_19  mean_age_20  mean_age_21  mean_age_2
-----  ----  -----  -
1      1      0      0.047456    0.05006     0.053131    0.053501    0.053678
2      2      0      0.051258    0.054838    0.059034    0.060117    0.06099
3      3      0      0.055768    0.059917    0.064439    0.065978    0.067166
4      4      0      0.057894    0.062211    0.066905    0.068696    0.070118
5      5      0      0.059903    0.064171    0.068906    0.070851    0.07233
6      1      1      0.0854      0.090837    0.096389    0.10046     0.10399
7      2      1      0.079182    0.084761    0.090437    0.095109    0.099255
8      3      1      0.078652    0.083563    0.089111    0.093893    0.098067
9      4      1      0.082412    0.086456    0.091037    0.093958    0.096652
10     5      1      0.085584    0.089889    0.094581    0.097555    0.10014

```

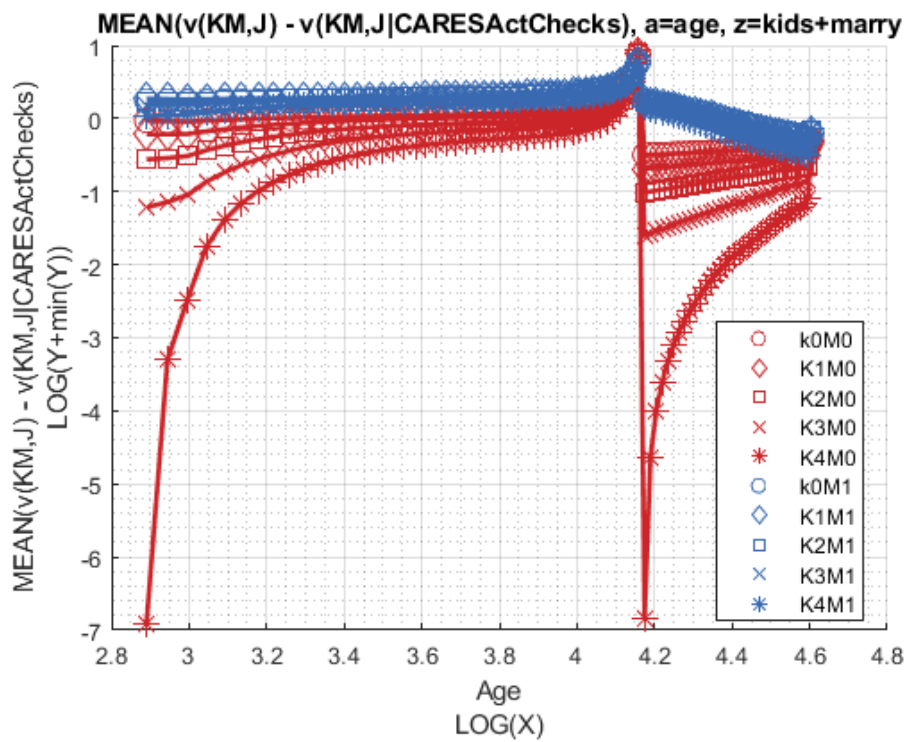
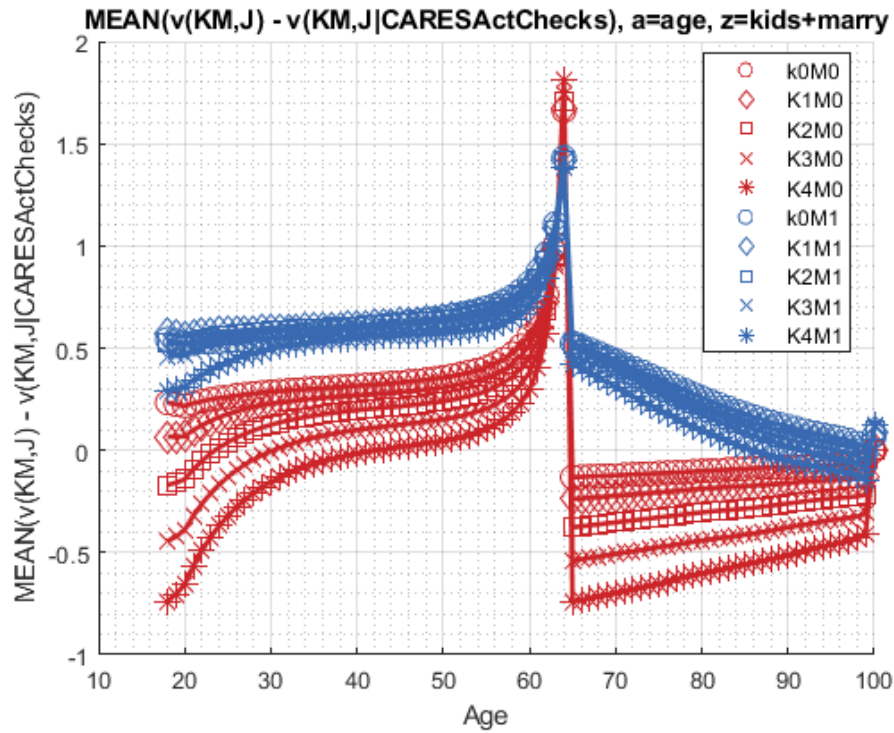
Graph Mean Values Change:

```

mp_support_graph('cl_st_graph_title') = {'MEAN(v(KM,J) - v(KM,J|CARESActChecks), a=age, z=kids+marry}
mp_support_graph('cl_st_ytitle') = {'MEAN(v(KM,J) - v(KM,J|CARESActChecks)'};
ff_graph_grid((tb_az_v{1:end, 4:end}), ar_row_grid, age_grid, mp_support_graph);

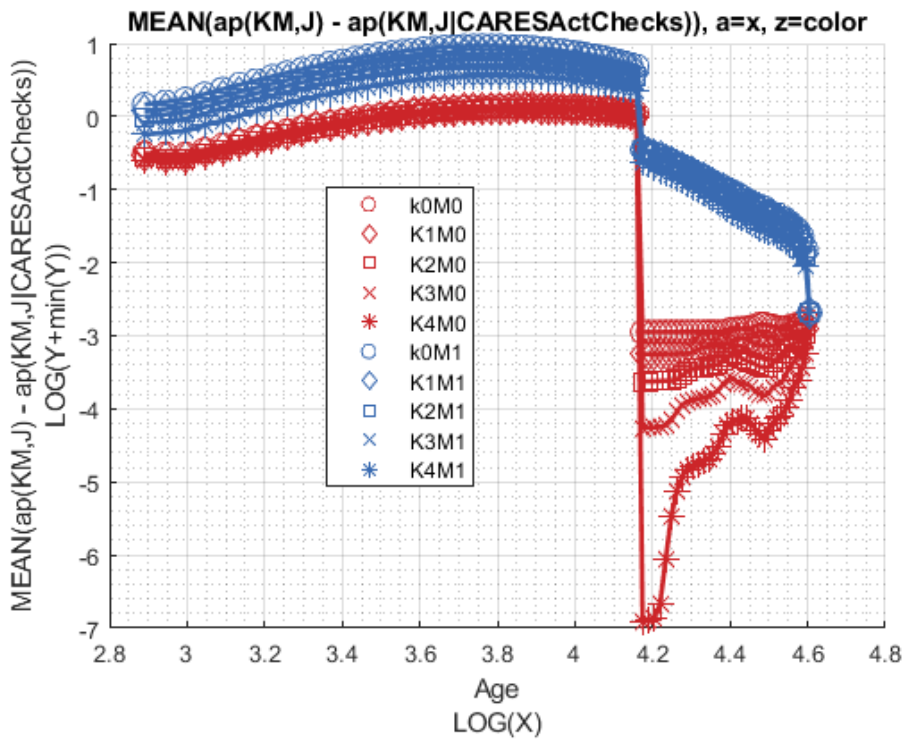
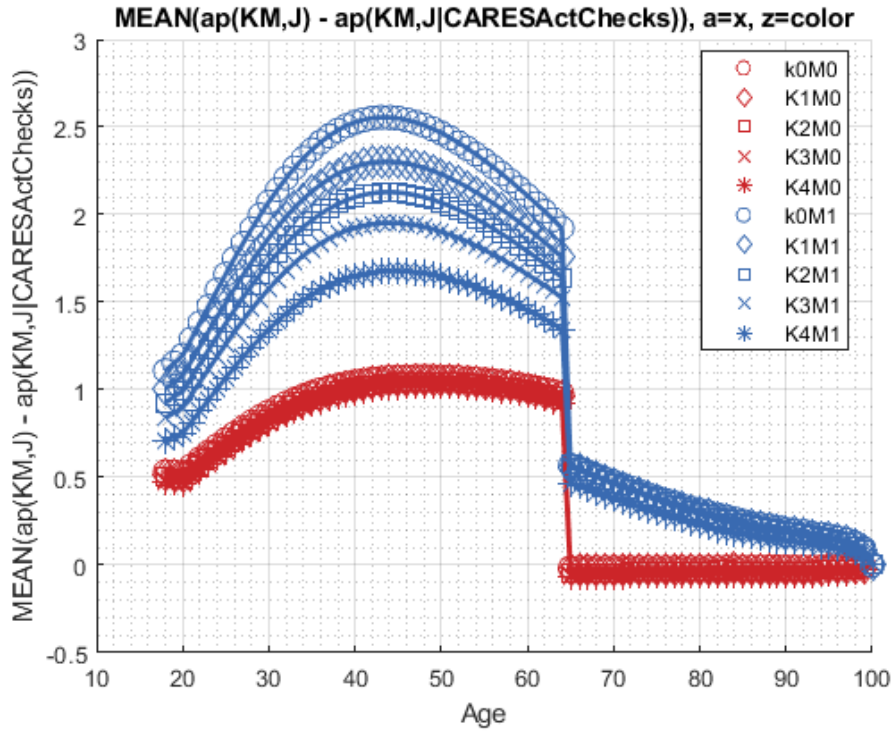
```





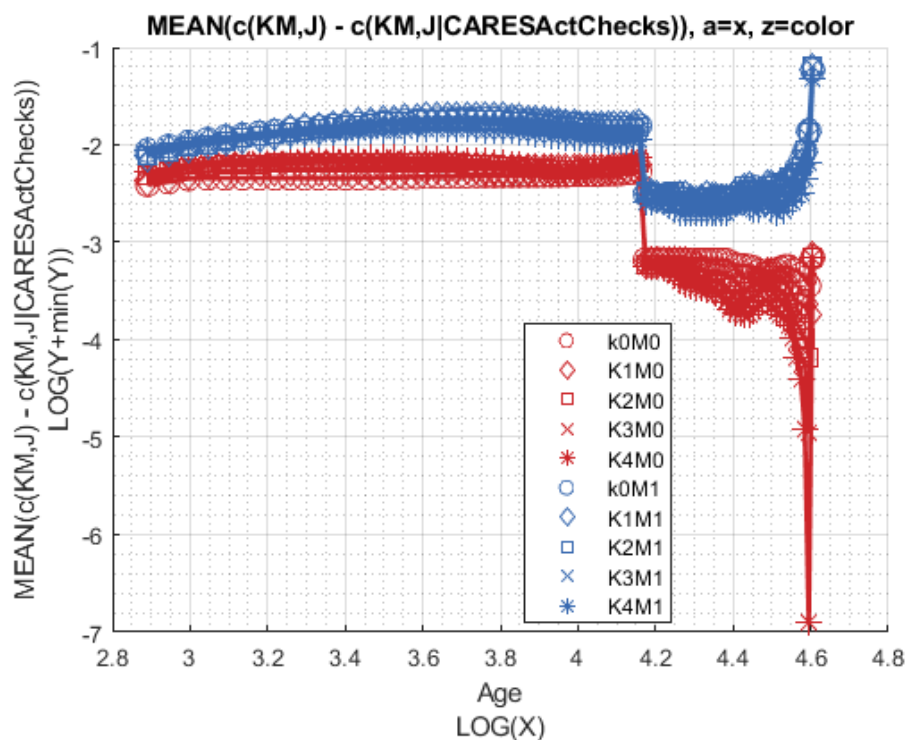
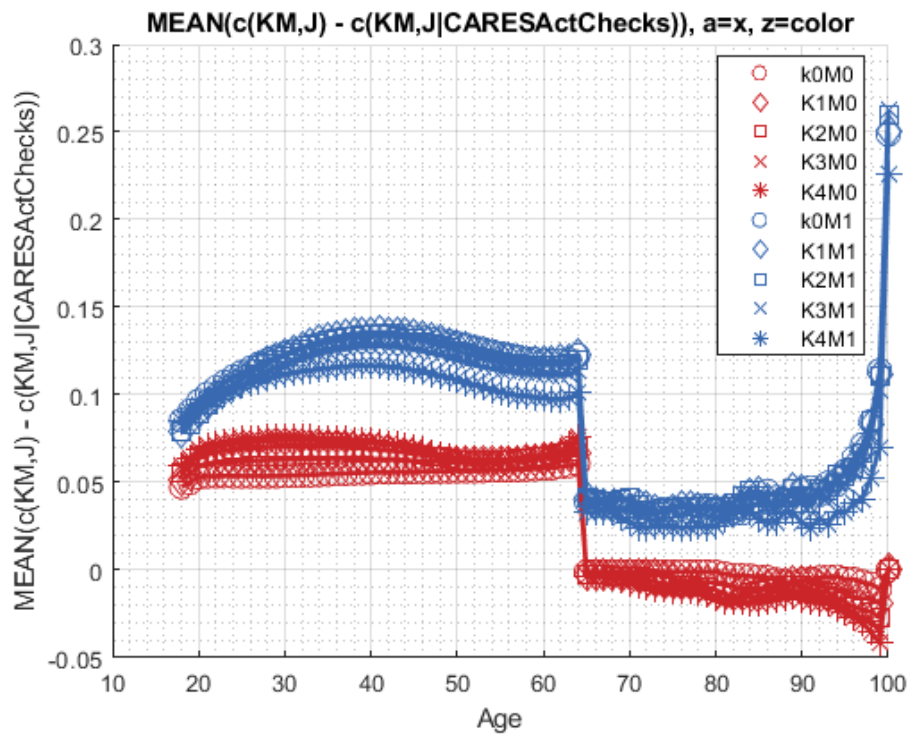
Graph Mean Savings Choices Change:

```
mp_support_graph('cl_st_graph_title') = {'MEAN(ap(KM,J) - ap(KM,J|CARESActChecks))', a=x, z=color'};
mp_support_graph('cl_st_ytitle') = {'MEAN(ap(KM,J) - ap(KM,J|CARESActChecks))'};
ff_graph_grid((tb_az_ap{1:end, 4:end}), ar_row_grid, age_grid, mp_support_graph);
```



Graph Mean Consumption Change:

```
mp_support_graph('cl_st_graph_title') = {'MEAN(c(KM,J) - c(KM,J|CARESActChecks))', a=x, z=color'};
mp_support_graph('cl_st_ytitle') = {'MEAN(c(KM,J) - c(KM,J|CARESActChecks))'};
ff_graph_grid((tb_az_c{1:end, 4:end}), ar_row_grid, age_grid, mp_support_graph);
```



### 6.1.5 Analyze Education and Marriage and Age

Aggregating over education, savings, and shocks, what are the differential effects of Marriage and Age.

```
% Generate some Data
```

```
mp_support_graph = containers.Map('KeyType', 'char', 'ValueType', 'any');
```

```
ar_row_grid = ["E0M0", "E1M0", "E0M1", "E1M1"];
```

```
mp_support_graph('cl_st_xtitle') = {'Age'};
```

```
mp_support_graph('st_legend_loc') = 'best';
```

```
mp_support_graph('bl_graph_logy') = true; % do not log
```

```
mp_support_graph('st_rounding') = '6.2f'; % format shock legend
mp_support_graph('cl_scatter_shapes') = {'*', 'p', '*', 'p' };
mp_support_graph('cl_colors') = {'red', 'red', 'blue', 'blue'};
```

```
MEAN(v(EKM,J) - v(EKM,J|CARESAActChecks)), MEAN(ap(EM,J) - ap(EM,J|CARESAActChecks)),
MEAN(c(EM,J) - c(EM,J|CARESAActChecks))
```

Tabulate value and policies:

```
% Set
% NaN(n_jgrid,n_agrid,n_etagrid,n_educgrid,n_marriedgrid,n_kidsgrid);
ar_permute = [2,3,6,1,4,5];
% Value Function
tb_az_v = ff_summ_nd_array("MEAN(v(EM,J) - v(EM,J|CARESAActChecks))", V_VFI_wthtrumpchk_drop, true, [
```

```
xxx MEAN(v(EM,J) - v(EM,J|CARESAActChecks)) xxxxxxxxxxxxxxxxxxxxxxxxxxxxxxxx
  group   edu   marry   mean_age_18   mean_age_19   mean_age_20   mean_age_21   mean_age_22
  -----   ---   -----   -----
  1         0     0      -0.20644     -0.19866     -0.18731     -0.152        -0.12059
  2         1     0      -0.21487     -0.19821     -0.17411     -0.10932     -0.056018
  3         0     1       0.49975     0.50183     0.50278     0.51591     0.52735
  4         1     1       0.45707     0.45169     0.44517     0.4615      0.47518
```

```
% Aprime Choice
tb_az_ap = ff_summ_nd_array("MEAN(ap(EM,J) - ap(EM,J|CARESAActChecks))", ap_VFI_wthtrumpchk_drop, true,
```

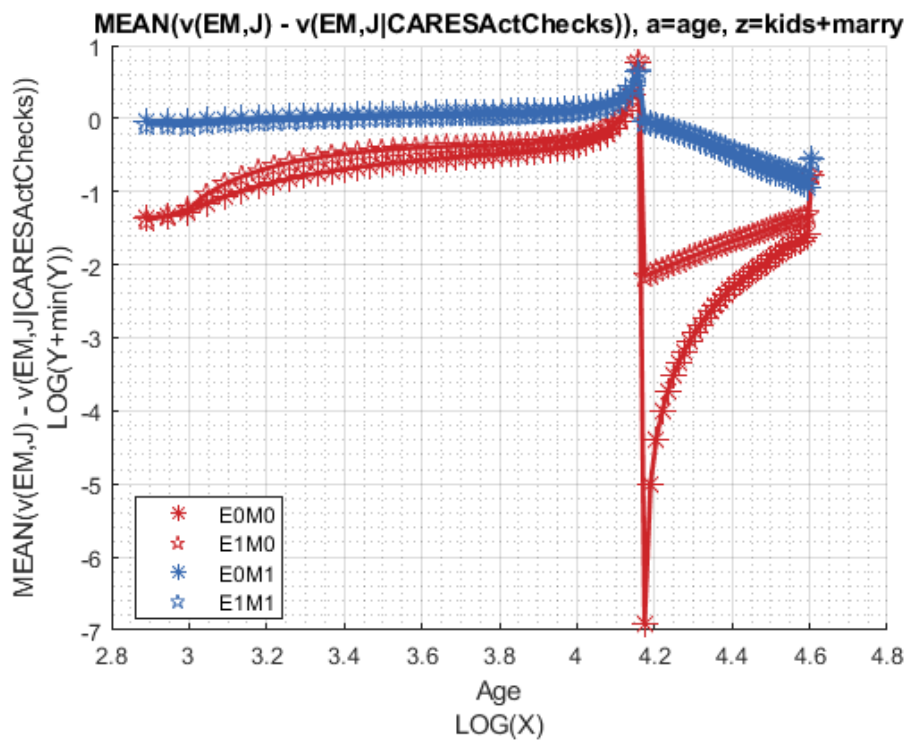
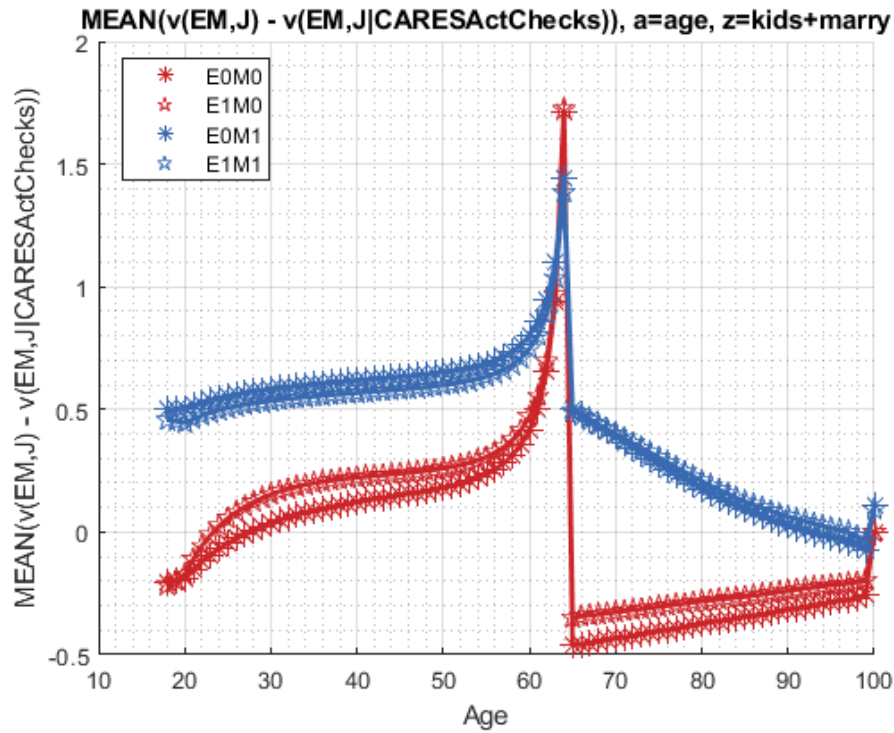
```
xxx MEAN(ap(EM,J) - ap(EM,J|CARESAActChecks)) xxxxxxxxxxxxxxxxxxxxxxxxxxxxxxxx
  group   edu   marry   mean_age_18   mean_age_19   mean_age_20   mean_age_21   mean_age_22
  -----   ---   -----   -----
  1         0     0       0.51372     0.51186     0.50965     0.53259     0.55496
  2         1     0       0.49288     0.48717     0.4809      0.53405     0.58772
  3         0     1       0.88501     0.91449     0.94426     1.0019      1.0594
  4         1     1       0.95477     0.98885     1.0231      1.1223      1.2227
```

```
% Consumption Choices
tb_az_c = ff_summ_nd_array("MEAN(c(EM,J) - c(EM,J|CARESAActChecks))", cons_VFI_wthtrumpchk_drop, true,
```

```
xxx MEAN(c(EM,J) - c(EM,J|CARESAActChecks)) xxxxxxxxxxxxxxxxxxxxxxxxxxxxxxxx
  group   edu   marry   mean_age_18   mean_age_19   mean_age_20   mean_age_21   mean_age_22
  -----   ---   -----   -----
  1         0     0       0.044034    0.045896    0.048105    0.048949    0.049779
  2         1     0       0.064877    0.070583    0.076861    0.078708    0.079934
  3         0     1       0.068818    0.072249    0.075948    0.078738    0.08143
  4         1     1       0.095673    0.10195     0.10867     0.11365     0.11781
```

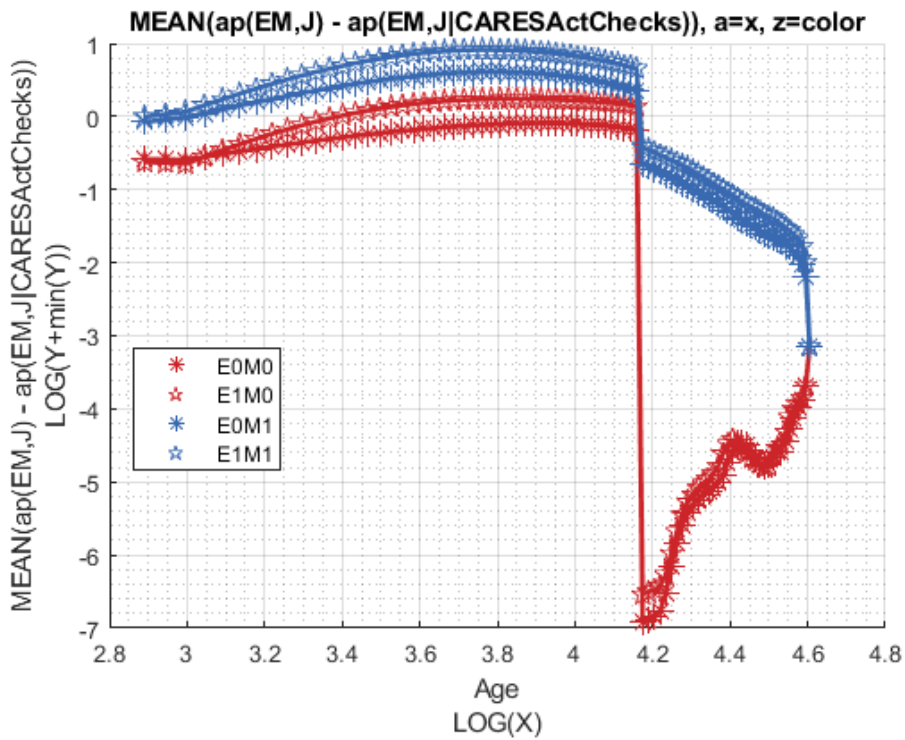
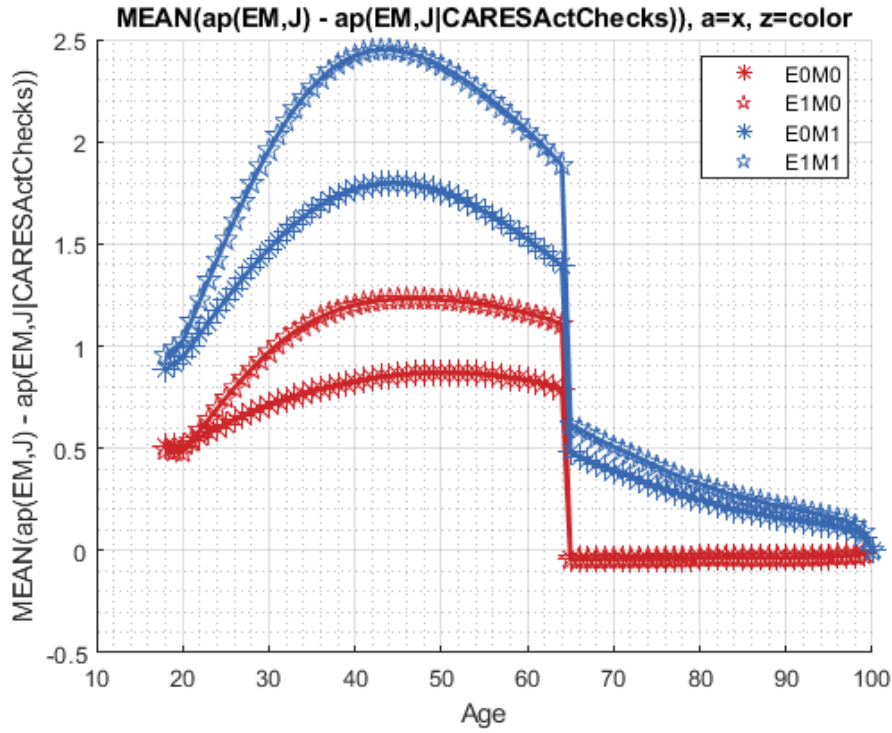
Graph Mean Values Change:

```
mp_support_graph('cl_st_graph_title') = {'MEAN(v(EM,J) - v(EM,J|CARESAActChecks))', a=age, z=kids+marr
mp_support_graph('cl_st_ytitle') = {'MEAN(v(EM,J) - v(EM,J|CARESAActChecks))'};
ff_graph_grid((tb_az_v{1:end, 4:end}), ar_row_grid, age_grid, mp_support_graph);
```



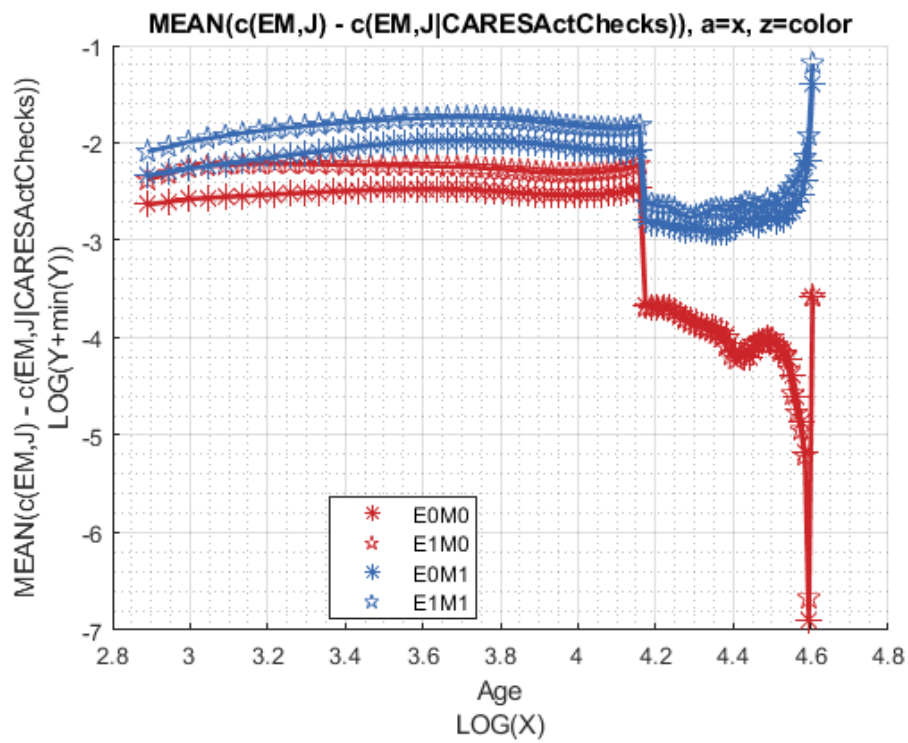
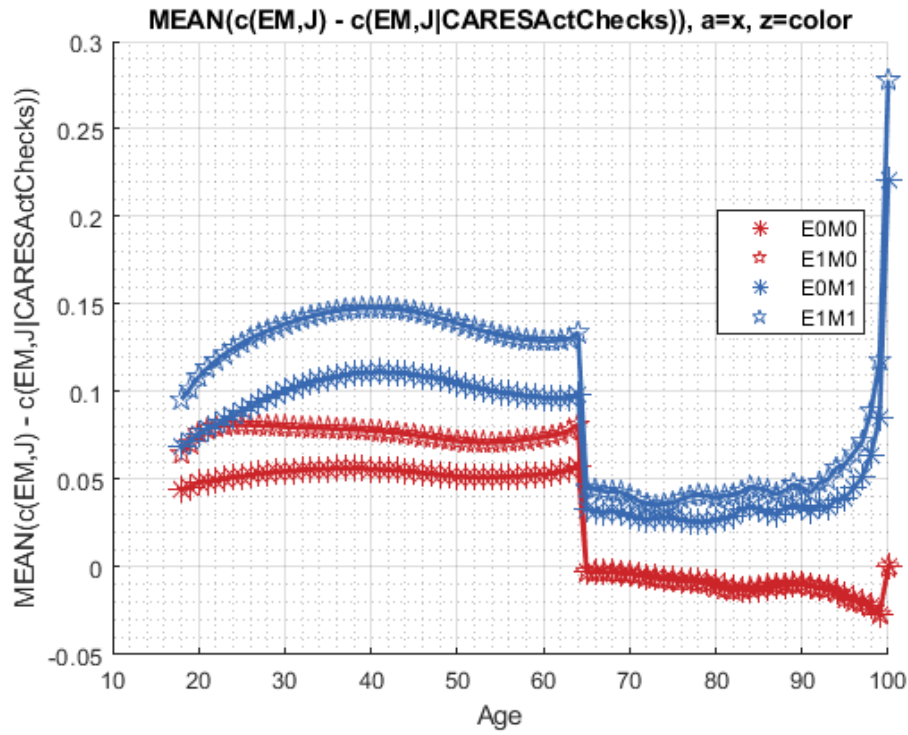
Graph Mean Savings Choices Change:

```
mp_support_graph('cl_st_graph_title') = {'MEAN(ap(EM,J) - ap(EM,J|CARESActChecks))', a=x, z=color'};
mp_support_graph('cl_st_ytitle') = {'MEAN(ap(EM,J) - ap(EM,J|CARESActChecks))'};
ff_graph_grid((tb_az_ap{1:end, 4:end}), ar_row_grid, age_grid, mp_support_graph);
```



Graph Mean Consumption Change:

```
mp_support_graph('cl_st_graph_title') = {'MEAN(c(EM,J) - c(EM,J|CARESActChecks))', a=x, z=color'};
mp_support_graph('cl_st_ytitle') = {'MEAN(c(EM,J) - c(EM,J|CARESActChecks))'};
ff_graph_grid((tb_az_c{1:end, 4:end}), ar_row_grid, age_grid, mp_support_graph);
```







# Chapter 7

## Household Life Cycle Distribution

### 7.1 Distribution Grid Search

This is the example vignette for function: `snw_ds_main_grid_search` from the [PrjOptiSNW Package](#). This function solves for vfi and gets distribution induced by policy functions and exogenous distributions. Grid Search for VFI and Grid Search also for Distribution. The results are illustrative of the differences between using grid search and exact solution. The grid search solution here is not fully vectorized but loops over the state-space.

#### 7.1.1 Test SNW\_DS\_MAIN\_GRID\_SEARCH Defaults More Dense

Rather than solving for "docdense", this solves for "moredense", which has fewer shocks, in order to save time given the relatively slow speed of this algorithm.

```
mp_params = snw_mp_param('default_moredense');
mp_controls = snw_mp_control('default_test');
mp_controls('bl_print_vfi') = false;
mp_controls('bl_print_ds') = false;
mp_controls('bl_print_ds_verbose') = false;
[Phi_true,Phi_adj,A_agg,Y_inc_agg,it,mp_dsvfi_results] = snw_ds_main_grid_search(mp_params, mp_contr
```

Elapsed time is 13045.688258 seconds.

Completed SNW\_VFI\_MAIN\_GRID\_SEARCH;SNW\_MP\_PARAM=default\_moredense;SNW\_MP\_CONTROL=default\_test

Elapsed time is 13841.078692 seconds.

Completed SNW\_DS\_MAIN;SNW\_MP\_PARAM=;default\_moredense;SNW\_MP\_CONTROL=;default\_test

```
Phi_true = Phi_true/sum(Phi_true(:));
```

#### 7.1.2 Show All Info in mp\_dsvfi\_results More Dense

```
mp_cl_mt_xyz_of_s = mp_dsvfi_results('mp_cl_mt_xyz_of_s');
disp(mp_cl_mt_xyz_of_s('tb_outcomes'))
```

	mean	unweighted_sum	sd	coefofvar	gini	min
	-----	-----	-----	-----	-----	-----
a_ss	4.2955	5130.2	8.2965	1.9314	0.74079	0
ap_ss	33.948	11476	25.584	0.75362	0.43382	1
cons_ss	1.1795	1.585e+07	1.0182	0.86318	0.40848	0.035637
v_ss	-19.79	-1.1145e+07	35.654	-1.8016	-0.774	-868.79
n_ss	2.3554	21	1.4375	0.61029	0.3128	1
y_all	1.6272	2.3969e+07	1.8982	1.1665	0.50121	0.038108
y_head_inc	1.2682	5.6172e+05	1.5441	1.2175	0.50432	0.038108

y_head_earn	1.0492	2628.2	1.4242	1.3574	0.60462	0
y_spouse_inc	0.35895	55552	0.96039	2.6755	0.85307	0
yshr_interest	0.11509	1.0971e+06	0.17681	1.5363	0.70728	0
yshr_wage	0.78433	2.4004e+06	0.34004	0.43354	0.19505	0
yshr_SS	0.10058	67295	0.23745	2.3608	0.91583	0
yshr_tax	0.17694	7.7853e+05	0.040535	0.22909	0.13026	0.036506
yshr_nttxss	0.076363	7.1123e+05	0.25868	3.3875	1.4024	-0.89715

### 7.1.3 More Dense Param Results Define Frames

Define the matrix dimensions names and dimension vector values. Probability mass matrixes, Policy and Value Functions share the same ND dimensional structure.

```
% Grids:
age_grid = 18:100;
agrid = mp_params('agrid');
eta_H_grid = mp_params('eta_H_grid');
eta_S_grid = mp_params('eta_S_grid');
ar_st_eta_HS_grid = string(cellstr([num2str(eta_H_grid', 'hz=%3.2f;'), num2str(eta_S_grid', 'wz=%3.2f;')]);
edu_grid = [0,1];
marry_grid = [0,1];
kids_grid = (1:1:mp_params('n_kidsgrid'))';
% NaN(n_jgrid,n_agrid,n_etagrid,n_educgrid,n_marriedgrid,n_kidsgrid);
cl_mp_datasetdesc = {};
cl_mp_datasetdesc{1} = containers.Map({'name', 'labval'}, {'age', age_grid});
cl_mp_datasetdesc{2} = containers.Map({'name', 'labval'}, {'savings', agrid});
cl_mp_datasetdesc{3} = containers.Map({'name', 'labval'}, {'eta', 1:length(eta_H_grid)});
cl_mp_datasetdesc{4} = containers.Map({'name', 'labval'}, {'edu', edu_grid});
cl_mp_datasetdesc{5} = containers.Map({'name', 'labval'}, {'marry', marry_grid});
cl_mp_datasetdesc{6} = containers.Map({'name', 'labval'}, {'kids', kids_grid});
```

### 7.1.4 Analyze Probability Mass Along Age Dimensions

Where are the mass at? Analyze mass given state space components.

```
% Get the Joint distribution over all states
% Define Graph Inputs
mp_support_graph = containers.Map('KeyType', 'char', 'ValueType', 'any');
mp_support_graph('st_legend_loc') = 'best';
mp_support_graph('bl_graph_logy') = false; % do not log

Exogenous Permanent States Mass: Life Cycle, Edu and Marraige

Tabulate value and policies along savings and shocks:

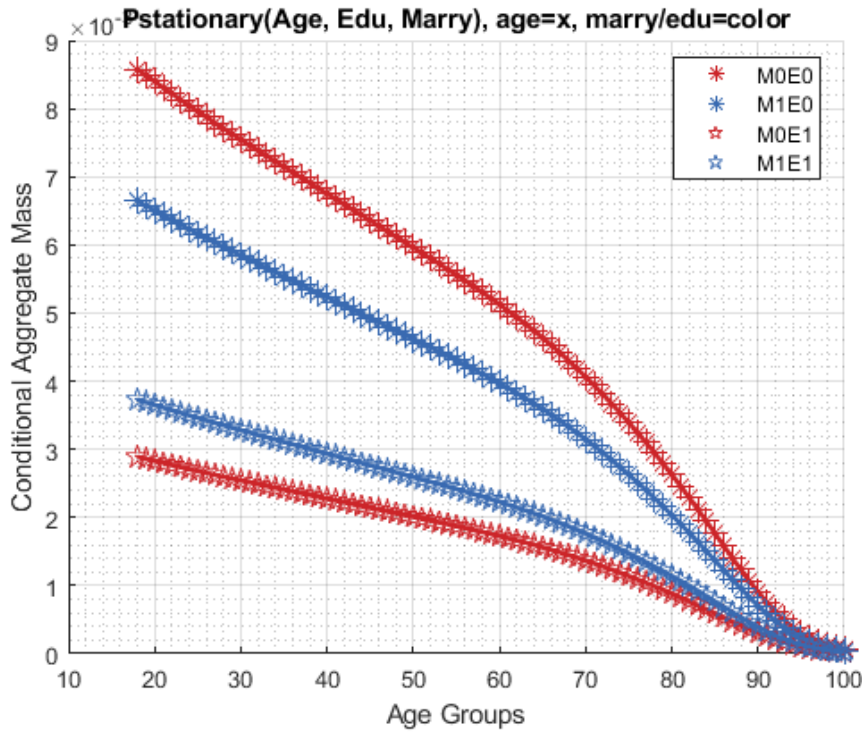
% NaN(n_jgrid,n_agrid,n_etagrid,n_educgrid,n_marriedgrid,n_kidsgrid);
ar_permute = [2,3,6,1,5,4];
% Value Function
tb_prob_aem = ff_summ_nd_array("P(Age, EDU, MARRY)", Phi_true, true, ["sum"], 3, 1, cl_mp_datasetdesc);

xxx P(Age, EDU, MARRY)) xxxxxxxxxxxxxxxxxxxxxxxxxxxxxxxx
  group  marry  edu  sum_age_18  sum_age_19  sum_age_20  sum_age_21  sum_age_22  s
-----  -----  ---  -
  1      0      0  0.0085768  0.0084866  0.0083969  0.0083078  0.0082194  0
  2      1      0  0.0066438  0.0065739  0.0065044  0.0064354  0.0063669  0
  3      0      1  0.0028875  0.0028571  0.0028227  0.002797  0.0027672  0
  4      1      1  0.0037292  0.0036899  0.0036509  0.0036122  0.0035738  0

mp_support_graph('cl_st_graph_title') = {'Pstationary(Age, Edu, Marry), age=x, marry/edu=color'};
mp_support_graph('cl_st_ytitle') = {'Conditional Aggregate Mass'};
```

```

ar_row_grid = ["M0E0", "M1E0", "M0E1", "M1E1"];
mp_support_graph('cl_st_xtitle') = {'Age Groups'};
mp_support_graph('cl_scatter_shapes') = {'*', '*', 'p', 'p' };
mp_support_graph('cl_colors') = {'red', 'blue', 'red', 'blue'};
ff_graph_grid((tb_prob_aem{1:end, 4:end}), ar_row_grid, age_grid, mp_support_graph);
    
```



Kids and Marry By Age Mass

```

% NaN(n_jgrid,n_agrid,n_etagrid,n_educgrid,n_marriedgrid,n_kidsgrid);
ar_permute = [2,3,4,1,6,5];
% Value Function
tb_prob_amarrykids = ff_summ_nd_array("P(Age, Kids, Marry)", Phi_true, true, ["sum"], 3, 1, cl_mp_d
    
```

xxx	P(Age, Kids, Marry))			xxxxxxxxxxxxxxxxxxxxxxxxxxxxxxxx				
group	kids	marry	sum_age_18	sum_age_19	sum_age_20	sum_age_21	sum_age_22	
1	1	0	0.0091249	0.0080278	0.0071652	0.0064765	0.0059205	
2	2	0	0.0013699	0.0019743	0.0022187	0.0022858	0.0022687	
3	3	0	0.00071266	0.00098425	0.0013537	0.0016929	0.0019639	
4	4	0	0.00020622	0.00027865	0.00037326	0.00049476	0.00062818	
5	5	0	5.0761e-05	7.8715e-05	0.000113	0.00015485	0.00020534	
6	1	1	0.0055624	0.0046679	0.0039774	0.0034368	0.0030088	
7	2	1	0.0027682	0.0025539	0.0023005	0.0020611	0.0018525	
8	3	1	0.0014982	0.0021823	0.0025943	0.0028096	0.002896	
9	4	1	0.00041197	0.00064648	0.00095224	0.0012491	0.0015009	
10	5	1	0.00013221	0.0002132	0.00033097	0.00049097	0.00068255	

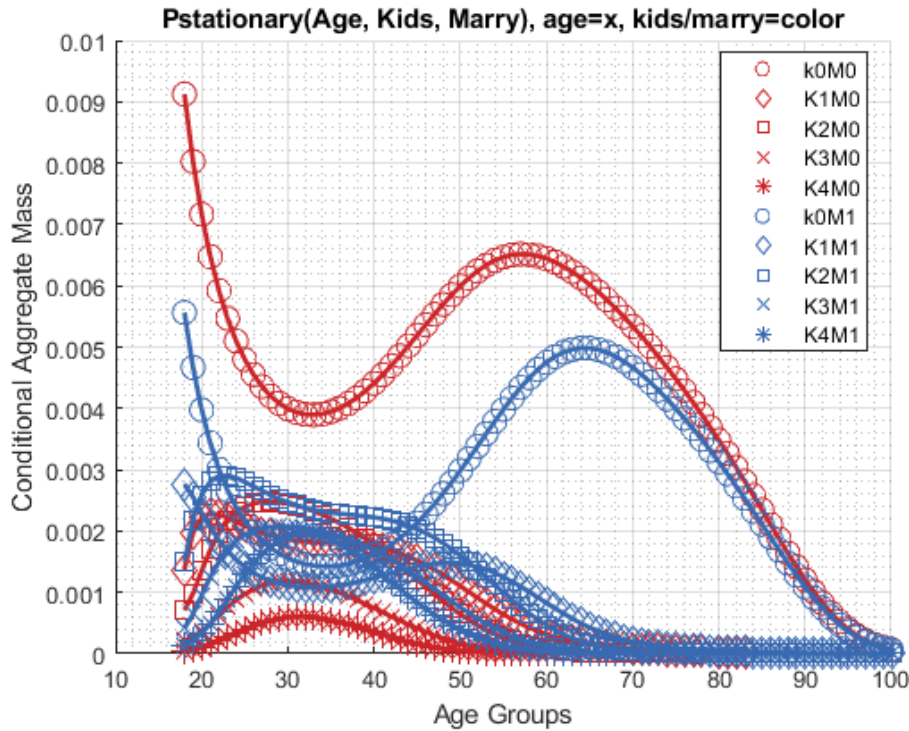
```

mp_support_graph('cl_st_graph_title') = {'Pstationary(Age, Kids, Marry), age=x, kids/marry=color'};
mp_support_graph('cl_st_ytitle') = {'Conditional Aggregate Mass'};
ar_row_grid = [...
    "k0M0", "K1M0", "K2M0", "K3M0", "K4M0", ...
    "k0M1", "K1M1", "K2M1", "K3M1", "K4M1"];
mp_support_graph('cl_scatter_shapes') = {...
    'o', 'd', 's', 'x', '*', ...
    
```

```

'o', 'd', 's', 'x', '*'};
mp_support_graph('cl_colors') = {...
    'red', 'red', 'red', 'red', 'red'...
    'blue', 'blue', 'blue', 'blue', 'blue'};
mp_support_graph('cl_st_xtitle') = {'Age Groups'};
ff_graph_grid((tb_prob_amarrykids{1:end, 4:end}), ar_row_grid, age_grid, mp_support_graph);

```



### 7.1.5 Analyze Probability Mass Asset and Shock Dimensions

Where are the mass at?

```

% Define Graph Inputs
mp_support_graph = containers.Map('KeyType', 'char', 'ValueType', 'any');
mp_support_graph('st_legend_loc') = 'best';
mp_support_graph('bl_graph_logy') = false; % do not log

```

Asset and Shock Mass

```

% NaN(n_jgrid,n_agrid,n_etagrid,n_educgrid,n_marriedgrid,n_kidsgrid);
ar_permute = [1,4,5,6,3,2];
% Value Function
tb_prob_az = ff_summ_nd_array("P(A,Z)", Phi_true, true, ["sum"], 4, 1, cl_mp_datasetdesc, ar_permut

```

xxx P(A,Z)	xxxxxxxxxxxxxxxxxxxxxxxxxxxxxxxx						
group	savings	sum_eta_1	sum_eta_2	sum_eta_3	sum_eta_4	sum_eta_5	sum_et
-----	-----	-----	-----	-----	-----	-----	-----
1	0	1.7754e-05	0.00011362	0.00037708	0.00061913	0.00056244	0.0003
2	4e-05	2.8763e-07	1.3442e-06	4.0195e-06	3.6795e-07	6.5205e-06	1.2822
3	0.00032	8.5896e-07	2.1837e-06	1.5288e-05	9.7352e-06	3.0233e-05	2.2281
4	0.00108	2.4168e-06	6.6439e-06	8.5514e-06	8.806e-06	1.0167e-05	3.836
5	0.00256	7.7644e-07	6.7137e-06	3.5185e-05	3.6273e-05	1.2262e-05	6.4167
6	0.005	1.615e-07	5.6988e-06	1.2805e-05	1.6079e-05	5.4165e-05	1.0241
7	0.00864	2.9022e-07	1.5618e-05	1.5907e-05	7.5335e-05	2.1309e-05	1.7692
8	0.01372	9.2058e-08	2.2512e-06	1.6629e-05	2.2447e-05	0.00010906	1.9013

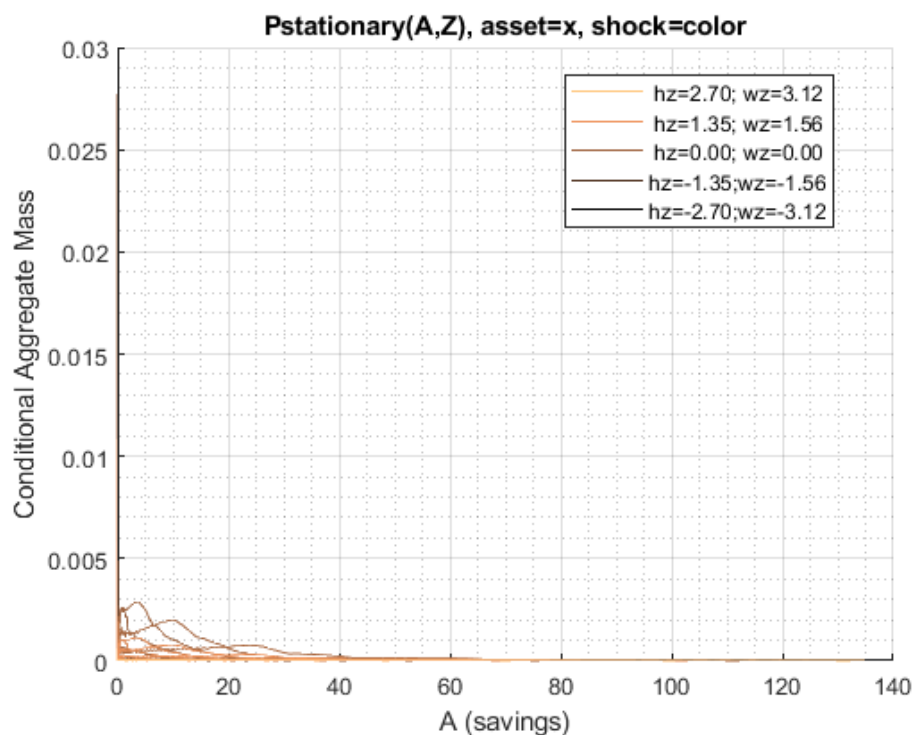
9	0.02048	1.493e-07	5.139e-06	1.987e-05	2.7684e-05	1.8495e-05	2.0213
10	0.02916	2.2636e-07	2.1911e-06	2.2674e-05	4.0829e-05	5.6366e-05	5.2344
11	0.04	3.6847e-07	3.2622e-06	3.5384e-05	3.9524e-05	3.7428e-05	6.0069
12	0.05324	2.7682e-07	2.8958e-06	5.7484e-05	3.6034e-05	3.501e-05	4.0214
13	0.06912	3.353e-07	2.6767e-06	1.4572e-05	3.8273e-05	2.474e-05	2.563
14	0.08788	3.0394e-07	2.2742e-06	1.4027e-05	3.4255e-05	3.7729e-05	1.5417
15	0.10976	2.5858e-07	1.9422e-06	1.2587e-05	3.4742e-05	2.7058e-05	2.4059
16	0.135	2.7326e-07	1.9079e-06	1.2852e-05	3.438e-05	3.6783e-05	1.6552
17	0.16384	2.7552e-07	1.9749e-06	1.5066e-05	3.5948e-05	3.0858e-05	2.8702
18	0.19652	3.0673e-07	2.1238e-06	2.128e-05	3.877e-05	3.75e-05	1.7398
19	0.23328	3.2755e-07	2.1478e-06	1.0054e-05	3.8731e-05	3.1329e-05	2.6872
20	0.27436	3.5257e-07	2.2995e-06	1.0938e-05	4.2758e-05	4.3572e-05	1.8163
21	0.32	4.0641e-07	2.5518e-06	1.1635e-05	4.5919e-05	3.416e-05	3.1068
22	0.37044	4.4361e-07	2.8814e-06	1.2784e-05	4.688e-05	4.9116e-05	2.2826
23	0.42592	4.7158e-07	3.2535e-06	1.3383e-05	5.1616e-05	4.104e-05	2.9579
24	0.48668	5.1923e-07	3.4305e-06	1.432e-05	5.2283e-05	5.1981e-05	2.8417
25	0.55296	5.437e-07	3.6017e-06	1.5469e-05	5.6439e-05	5.2035e-05	3.2783
26	0.625	5.5347e-07	3.8425e-06	1.5479e-05	5.5965e-05	5.6994e-05	2.7605
27	0.70304	5.568e-07	3.7614e-06	1.5095e-05	5.8432e-05	5.4503e-05	3.5853
28	0.78732	5.7466e-07	3.7497e-06	1.502e-05	5.7903e-05	5.6109e-05	2.9314
29	0.87808	5.7563e-07	3.8005e-06	1.4892e-05	5.6949e-05	5.3853e-05	3.2364
30	0.97556	5.7132e-07	3.8705e-06	1.5095e-05	5.6906e-05	5.5758e-05	2.9176
31	1.08	5.726e-07	3.8645e-06	1.5349e-05	5.6413e-05	5.4339e-05	3.1568
32	1.1916	5.6625e-07	3.7872e-06	1.484e-05	5.448e-05	5.7108e-05	2.7934
33	1.3107	5.4238e-07	3.6971e-06	1.4269e-05	5.2724e-05	5.4906e-05	3.2967
34	1.4375	5.3278e-07	3.5724e-06	1.3626e-05	4.9663e-05	5.6325e-05	2.6723
35	1.5722	5.0996e-07	3.485e-06	1.3686e-05	4.6691e-05	5.5236e-05	3.069
36	1.715	5.0398e-07	3.4238e-06	1.3137e-05	4.7646e-05	5.6783e-05	2.8995
37	1.8662	4.767e-07	3.3615e-06	1.2844e-05	3.4086e-05	5.6434e-05	3.0261
38	2.0261	4.684e-07	3.2063e-06	1.2531e-05	3.2602e-05	5.8615e-05	2.8719
39	2.1949	4.5256e-07	3.1314e-06	1.2176e-05	3.2249e-05	5.8445e-05	3.0339
40	2.3728	4.2248e-07	3.093e-06	1.2003e-05	3.0763e-05	6.0571e-05	2.7865
41	2.56	4.0678e-07	2.958e-06	1.1808e-05	3.0172e-05	6.0706e-05	3.0549
42	2.7568	3.9214e-07	2.8541e-06	1.1601e-05	2.9569e-05	6.2065e-05	2.9269
43	2.9635	3.6841e-07	2.7289e-06	1.1074e-05	2.8387e-05	6.2402e-05	3.0802
44	3.1803	3.4717e-07	2.6124e-06	1.0683e-05	2.5913e-05	6.3791e-05	2.948
45	3.4074	3.2367e-07	2.453e-06	1.0352e-05	2.5365e-05	6.4051e-05	3.198
46	3.645	3.0387e-07	2.3261e-06	9.9363e-06	2.5054e-05	6.4312e-05	3.0105
47	3.8934	2.8153e-07	2.1577e-06	9.4355e-06	2.4465e-05	6.3912e-05	3.2461
48	4.1529	2.5915e-07	2.0525e-06	8.9454e-06	2.4289e-05	6.2333e-05	3.3681
49	4.4237	2.3743e-07	1.8857e-06	8.3087e-06	2.2777e-05	6.0276e-05	3.3448
50	4.706	2.1918e-07	1.7288e-06	7.9955e-06	2.2245e-05	5.8169e-05	3.4403
51	5	1.9952e-07	1.5877e-06	7.4469e-06	2.1203e-05	5.5849e-05	3.516
52	5.306	1.8097e-07	1.466e-06	6.9877e-06	2.0273e-05	5.2403e-05	3.5974
53	5.6243	1.6229e-07	1.3297e-06	6.4332e-06	1.9708e-05	4.7628e-05	3.6187
54	5.9551	1.4898e-07	1.2561e-06	6.0843e-06	1.9174e-05	4.4076e-05	3.7855
55	6.2986	1.3486e-07	1.128e-06	5.585e-06	1.771e-05	4.0303e-05	3.7916
56	6.655	1.2261e-07	1.0323e-06	5.2044e-06	1.6634e-05	3.8461e-05	3.8144
57	7.0246	1.0954e-07	9.419e-07	4.8168e-06	1.5965e-05	3.7804e-05	4.0109
58	7.4077	9.7875e-08	8.5816e-07	4.4452e-06	1.4933e-05	3.5109e-05	4.0919
59	7.8045	8.546e-08	7.7452e-07	4.0603e-06	1.4176e-05	3.2431e-05	4.1509
60	8.2152	7.3682e-08	6.8673e-07	3.7298e-06	1.328e-05	2.9425e-05	4.2677
61	8.64	6.477e-08	6.1848e-07	3.4011e-06	1.2396e-05	2.7206e-05	4.266
62	9.0792	5.531e-08	5.4066e-07	3.0693e-06	1.1543e-05	2.5521e-05	4.3977
63	9.5331	4.7541e-08	4.7103e-07	2.763e-06	1.0681e-05	2.4224e-05	4.4506
64	10.002	4.0248e-08	4.0902e-07	2.4495e-06	9.8848e-06	2.2907e-05	4.4746
65	10.486	3.4304e-08	3.5272e-07	2.1931e-06	9.3275e-06	2.2397e-05	4.3939
66	10.985	2.8818e-08	3.0078e-07	1.8744e-06	8.5509e-06	2.0402e-05	4.185

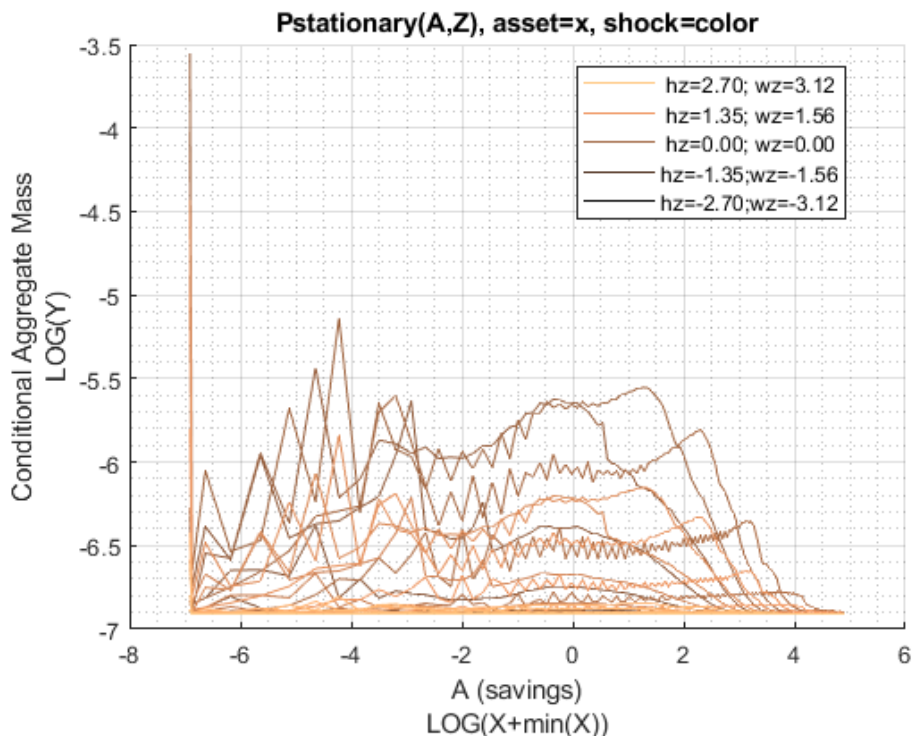
67	11.5	2.381e-08	2.5613e-07	1.6478e-06	7.8158e-06	1.8976e-05	4.0119
68	12.031	1.9337e-08	2.1722e-07	1.4123e-06	7.0946e-06	1.7273e-05	3.7509
69	12.577	1.5777e-08	1.8339e-07	1.2258e-06	6.3824e-06	1.6049e-05	3.4531
70	13.14	1.2851e-08	1.5121e-07	1.0425e-06	5.5804e-06	1.4547e-05	3.2353
71	13.72	1.0265e-08	1.2303e-07	8.8363e-07	4.9327e-06	1.3365e-05	2.8115
72	14.316	7.9662e-09	9.9864e-08	7.4205e-07	4.3605e-06	1.2054e-05	2.5938
73	14.93	6.2761e-09	8.0975e-08	6.2212e-07	3.8095e-06	1.0943e-05	2.5285
74	15.561	4.9435e-09	6.4741e-08	5.1199e-07	3.2737e-06	9.9099e-06	2.404
75	16.209	3.9203e-09	5.1535e-08	4.1842e-07	2.8741e-06	8.6393e-06	2.2512
76	16.875	3.0965e-09	4.1106e-08	3.4266e-07	2.4563e-06	7.837e-06	2.0909
77	17.559	2.4345e-09	3.245e-08	2.7852e-07	2.0728e-06	6.9943e-06	1.9281
78	18.261	1.8995e-09	2.5906e-08	2.2453e-07	1.8078e-06	6.1702e-06	1.838
79	18.982	1.4113e-09	2.0505e-08	1.7857e-07	1.4705e-06	5.4235e-06	1.6869
80	19.722	1.0589e-09	1.5945e-08	1.4273e-07	1.2186e-06	4.7175e-06	1.4272
81	20.48	7.4099e-10	1.2449e-08	1.1516e-07	1.0016e-06	4.0402e-06	1.2422
82	21.258	5.3869e-10	9.3255e-09	9.1737e-08	8.0834e-07	3.454e-06	1.0801
83	22.055	3.8509e-10	7.0555e-09	7.294e-08	6.5411e-07	2.9309e-06	9.4775
84	22.871	2.8297e-10	5.0721e-09	5.6197e-08	5.2093e-07	2.5225e-06	8.5883
85	23.708	2.0045e-10	3.6381e-09	4.3661e-08	4.1573e-07	2.1339e-06	7.5613
86	24.565	1.4573e-10	2.6214e-09	3.2964e-08	3.3317e-07	1.8413e-06	7.1167
87	25.442	1.0412e-10	1.9298e-09	2.4937e-08	2.6889e-07	1.5139e-06	6.1692
88	26.34	7.2935e-11	1.3869e-09	1.8357e-08	2.1245e-07	1.2556e-06	5.9791

```

mp_support_graph('cl_st_graph_title') = {'Pstationary(A,Z), asset=x, shock=color'};
mp_support_graph('cl_st_ytitle') = {'Conditional Aggregate Mass'};
mp_support_graph('cl_st_xtitle') = {'A (savings)'};
mp_support_graph('st_rowvar_name') = 'z=';
mp_support_graph('it_legend_select') = 5;
mp_support_graph('st_rounding') = '6.2f';
mp_support_graph('bl_graph_logy') = true;
mp_support_graph('cl_colors') = 'copper';
ff_graph_grid((tb_prob_az{1:end}, 3:end)', ar_st_eta_HS_grid, agrid, mp_support_graph);% Consumption

```





Asset Mass by Age

```
% NaN(n_jgrid,n_agrid,n_etagrid,n_educgrid,n_marriedgrid,n_kidsgrid);
ar_permute = [3,4,5,6,1,2];
% Value Function
tb_prob_age = ff_summ_nd_array("P(A,Z)", Phi_true, true, ["sum"], 4, 1, cl_mp_datasetdesc, ar_perm
```

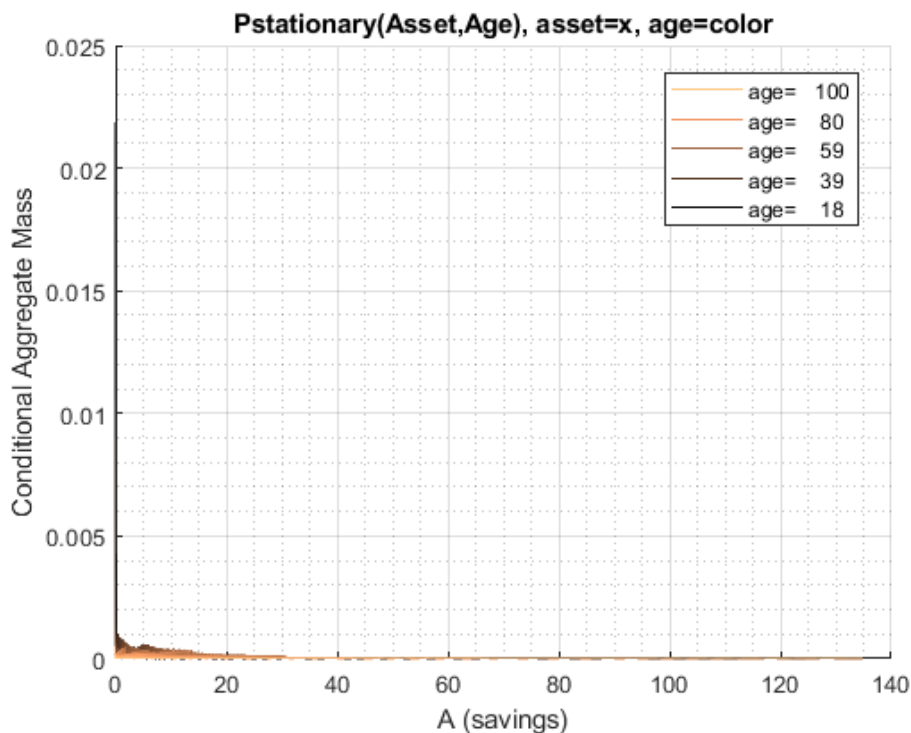
xxx	P(A,Z)	xxxxxxxxxxxxxxxxxxxxxxxxxxxxxxxx					
group	savings	sum_age_18	sum_age_19	sum_age_20	sum_age_21	sum_age_22	sum_ag
1	0	0.021837	0.002388	0.0018389	0.0064409	0.0087881	0.01
2	4e-05	0	2.3862e-06	2.8257e-06	1.5227e-05	0.0005064	7.2295
3	0.00032	0	3.749e-05	3.8393e-05	0.00067452	0.0013202	3.5912
4	0.00108	0	0.00031485	0.0003134	0.00027522	6.8839e-05	0.0001
5	0.00256	0	0.0012853	0.0012851	0.0015569	8.2445e-05	6.9654
6	0.005	0	0.00034215	0.00051426	0.0020793	0.00015903	0.0001
7	0.00864	0	0.0028722	0.0026464	0.00031254	0.00033461	0.0001
8	0.01372	0	0.003431	0.003249	0.00031772	0.00028917	0.0001
9	0.02048	0	0.00028503	0.00067598	0.00043826	0.00042815	0.0003
10	0.02916	0	0.004274	0.0016076	0.00077901	0.00039339	0.0003
11	0.04	0	0.0024741	0.0016863	0.0015146	0.0012551	0.0003
12	0.05324	0	0.00012193	0.0017565	0.00025805	0.00022615	0.001
13	0.06912	0	0.00044563	0.00062939	0.00029172	0.00029416	0.000
14	0.08788	0	2.7692e-05	0.00011258	0.00015714	0.00018719	0.0002
15	0.10976	0	6.2377e-05	8.9179e-06	7.7238e-05	0.00018316	0.0001
16	0.135	0	0.00067668	0.00016484	0.00010206	0.00022055	0.0002
17	0.16384	0	5.8231e-06	5.0833e-05	0.00019203	0.00023346	0.0002
18	0.19652	0	3.2338e-05	4.7739e-05	0.00021932	0.00024025	0.0002
19	0.23328	0	2.7827e-05	0.00062964	0.00031839	0.00035773	0.0002
20	0.27436	0	3.3098e-06	0.00010242	0.00072231	0.0003499	0.0003
21	0.32	0	4.0326e-05	0.00030725	0.00040297	0.00025423	0.0003
22	0.37044	0	0.00023294	0.00035244	0.00045546	0.00075563	0.0003
23	0.42592	0	0.00029162	0.00046138	0.00031538	0.00034379	0.000

24	0.48668	0	0.0002901	0.00049108	0.00051896	0.00038724	0.000
25	0.55296	0	0.00034886	0.00054564	0.0003598	0.00041642	0.0004
26	0.625	0	0.00050916	0.00043448	0.00029056	0.00033958	0.0003
27	0.70304	0	0.00039586	0.00037749	0.00035324	0.00035324	0.0003
28	0.78732	0	0.00020681	0.00035156	0.00038514	0.00031557	0.0003
29	0.87808	0	1.4297e-05	5.5411e-05	0.00015561	0.00033422	0.0002
30	0.97556	0	1.5592e-05	6.288e-05	0.00029113	0.00022006	0.0002
31	1.08	0	2.009e-06	8.4115e-05	0.00014086	0.00019115	0.0002
32	1.1916	0	2.1045e-05	0.00010101	0.00015504	0.00012678	0.0001
33	1.3107	0	1.4435e-06	6.9572e-05	5.1203e-05	0.00020997	0.0001
34	1.4375	0	5.1689e-07	4.651e-05	7.846e-05	7.725e-05	0.0001
35	1.5722	0	4.7793e-07	4.484e-06	2.0179e-05	8.927e-05	0.0001
36	1.715	0	2.3446e-06	4.8601e-06	2.089e-05	4.4483e-05	0.0001
37	1.8662	0	2.6545e-07	5.0217e-06	2.8241e-05	3.3543e-05	5.1577
38	2.0261	0	5.4286e-07	3.5584e-06	1.983e-05	3.2623e-05	4.7562
39	2.1949	0	1.5332e-06	2.2585e-05	9.6032e-06	3.0291e-05	4.164
40	2.3728	0	4.1159e-06	1.2542e-05	1.5038e-05	2.1111e-05	4.7981
41	2.56	0	4.9992e-06	9.9161e-06	2.4244e-05	2.6564e-05	3.3403
42	2.7568	0	7.7981e-06	1.5369e-05	2.0348e-05	3.8876e-05	3.2557
43	2.9635	0	1.0694e-05	1.9867e-05	2.6661e-05	3.3652e-05	4.0382
44	3.1803	0	1.3309e-05	1.8776e-05	4.5294e-05	3.4882e-05	4.4248
45	3.4074	0	1.3226e-05	2.3002e-05	3.5636e-05	3.4395e-05	4.1287
46	3.645	0	3.533e-06	2.5709e-05	3.2868e-05	4.0509e-05	3.8809
47	3.8934	0	1.8503e-05	2.4946e-05	2.6065e-05	3.9174e-05	3.9923

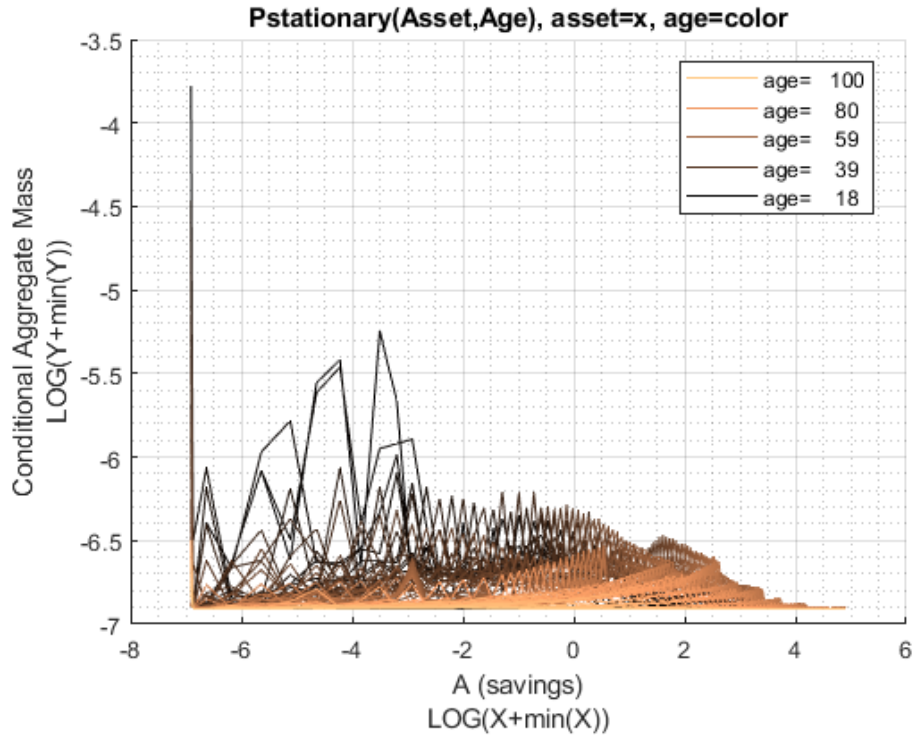
```

mp_support_graph('cl_st_graph_title') = {'Pstationary(Asset,Age), asset=x, age=color'};
mp_support_graph('cl_st_ytitle') = {'Conditional Aggregate Mass'};
mp_support_graph('cl_st_xtitle') = {'A (savings)'};
mp_support_graph('st_rowvar_name') = 'age=';
mp_support_graph('it_legend_select') = 5;
mp_support_graph('st_rounding') = '6.0f';
mp_support_graph('bl_graph_logy') = true;
mp_support_graph('cl_colors') = 'copper';
ff_graph_grid((tb_prob_age{1:end, 3:end}),' age_grid, agrid, mp_support_graph);% Consumption Choice

```







### 7.1.6 Probability Statistics A, C and V Conditional on Ages

Where are the mass at?

```

ap_ss = mp_dsvfi_results('ap_ss');
c_ss = mp_dsvfi_results('cons_ss');
v_ss = mp_dsvfi_results('v_ss');
n_ss = mp_dsvfi_results('n_ss');

y_head_inc = mp_dsvfi_results('y_head_inc_ss');
y_spouse_inc = mp_dsvfi_results('y_spouse_inc_ss');

yshr_wage = mp_dsvfi_results('yshr_wage_ss');
yshr_SS = mp_dsvfi_results('yshr_SS_ss');
yshr_nttxss = mp_dsvfi_results('yshr_nttxss_ss');

for it_ctr=1:size(ap_ss, 1)
    if (ismember(it_ctr, round(linspace(1, size(ap_ss, 1), 3))))
        display(['age = ' num2str(age_grid(it_ctr))]);

        % construct input data
        Phi_true_age = Phi_true(it_ctr, :, :, :, :);
        ap_ss_age = ap_ss(it_ctr, :, :, :, :);
        c_ss_age = c_ss(it_ctr, :, :, :, :);
        v_ss_age = v_ss(it_ctr, :, :, :, :);
        n_ss_age = n_ss(it_ctr, :, :, :, :);

        y_head_inc_age = y_head_inc(it_ctr, :, :, :, :);
        y_spouse_inc_age = y_spouse_inc(it_ctr, :, :, :, :);
        yshr_wage_age = yshr_wage(it_ctr, :, :, :, :);
        yshr_SS_age = yshr_SS(it_ctr, :, :, :, :);
        yshr_nttxss_age = yshr_nttxss(it_ctr, :, :, :, :);

        mp_cl_ar_xyz_of_s = containers.Map('KeyType','char', 'ValueType','any');

```

```

mp_cl_ar_xyz_of_s('ap_ss') = {ap_ss_age(:), zeros(1)};
mp_cl_ar_xyz_of_s('c_ss') = {c_ss_age(:), zeros(1)};
mp_cl_ar_xyz_of_s('v_ss') = {v_ss_age(:), zeros(1)};
mp_cl_ar_xyz_of_s('n_ss') = {n_ss_age(:), zeros(1)};
mp_cl_ar_xyz_of_s('y_head_inc') = {y_head_inc_age(:), zeros(1)};
mp_cl_ar_xyz_of_s('y_spouse') = {y_spouse_inc_age(:), zeros(1)};
mp_cl_ar_xyz_of_s('yshr_wage') = {yshr_wage_age(:), zeros(1)};
mp_cl_ar_xyz_of_s('yshr_SS') = {yshr_SS_age(:), zeros(1)};
mp_cl_ar_xyz_of_s('yshr_nttxss') = {yshr_nttxss_age(:), zeros(1)};
mp_cl_ar_xyz_of_s('ar_st_y_name') = ["ap_ss", "c_ss", "v_ss", "n_ss", ...
    "y_head_inc", "y_spouse", "yshr_wage", "yshr_SS", "yshr_nttxss"];

% controls
mp_support = containers.Map('KeyType','char', 'ValueType','any');
mp_support('ar_fl_percentiles') = [0.01 10 25 50 75 90 99.99];
mp_support('bl_display_final') = true;
mp_support('bl_display_detail') = false;
mp_support('bl_display_drvm2outcomes') = false;
mp_support('bl_display_drvstats') = false;
mp_support('bl_display_drvm2covcor') = false;

% Call Function
mp_cl_mt_xyz_of_s = ff_simu_stats(Phi_true_age(:)/sum(Phi_true_age,'all'), mp_cl_ar_xyz_of_s
end
end

age =18
xxx tb_outcomes: all stats xxx

```

OriginalVariableNames	ap_ss	c_ss	v_ss	n_ss	y_head_inc
{'mean' }	10.116	0.75737	-37.592	1.9854	0.84341
{'unweighted_sum' }	11476	2.4405e+05	-7.8955e+05	21	4422.1
{'sd' }	6.9537	0.67774	55.748	1.0848	0.90505
{'coefofvar' }	0.68742	0.89486	-1.483	0.54639	1.0731
{'gini' }	0.32034	0.41117	-0.64344	0.268	0.41353
{'min' }	1	0.035637	-868.79	1	0.038108
{'max' }	151	18.059	25.518	6	13.784
{'pYis0' }	0	0	0	0	0
{'pYls0' }	0	0	0.8166	0	0
{'pYgr0' }	1	1	0.1834	1	1
{'pYisMINY' }	0.11052	0.0014188	7.8342e-06	0.41786	0.0033703
{'pYisMAXY' }	0	0	0	0.0060544	0
{'p0_01' }	1	0.035637	-746.63	1	0.038108
{'p10' }	1	0.24578	-86.517	1	0.14676
{'p25' }	7	0.3161	-50.751	1	0.28802
{'p50' }	9	0.51551	-25.389	2	0.56523
{'p75' }	11	0.88958	-5.527	3	1.1092
{'p90' }	23	1.5797	6.0744	4	2.1768
{'p99_99' }	52	6.8857	23.692	6	8.3836
{'fl_cov_ap_ss' }	48.354	1.9167	116.57	0.29345	1.7747
{'fl_cor_ap_ss' }	1	0.4067	0.3007	0.038901	0.28199
{'fl_cov_c_ss' }	1.9167	0.45934	20.369	0.067217	0.59824
{'fl_cor_c_ss' }	0.4067	1	0.5391	0.091423	0.9753
{'fl_cov_v_ss' }	116.57	20.369	3107.8	2.9005	24.615
{'fl_cor_v_ss' }	0.3007	0.5391	1	0.047962	0.48787
{'fl_cov_n_ss' }	0.29345	0.067217	2.9005	1.1768	-1.236e-17
{'fl_cor_n_ss' }	0.038901	0.091423	0.047962	1	-1.2589e-17

{'fl_cov_y_head_inc' }	1.7747	0.59824	24.615	-1.236e-17	0.81911
{'fl_cor_y_head_inc' }	0.28199	0.9753	0.48787	-1.2589e-17	1
{'fl_cov_y_spouse' }	3.1074	0.081697	4.9476	0.13364	0.021751
{'fl_cor_y_spouse' }	0.77947	0.21026	0.15481	0.21488	0.04192
{'fl_cov_yshr_wage' }	3.7471e-30	2.4421e-31	-9.1828e-31	1.0754e-30	8.1847e-31
{'fl_cor_yshr_wage' }	4.0447e-16	2.7046e-16	-1.2364e-17	7.4411e-16	6.788e-16
{'fl_cov_yshr_SS' }	0	0	0	0	0
{'fl_cor_yshr_SS' }	NaN	NaN	NaN	NaN	NaN
{'fl_cov_yshr_nttxss' }	0.16611	0.021334	1.8609	0.0077776	0.025219
{'fl_cor_yshr_nttxss' }	0.58487	0.77071	0.81728	0.17554	0.68223
{'fracByP0_01' }	0.010925	6.6761e-05	0.0030452	0.21046	0.00015228
{'fracByP10' }	0.010925	0.050401	0.44014	0.21046	0.019229
{'fracByP25' }	0.148	0.072459	0.71161	0.21046	0.096342
{'fracByP50' }	0.28531	0.21889	0.94673	0.53024	0.29663
{'fracByP75' }	0.60536	0.47077	1.0363	0.77109	0.59361
{'fracByP90' }	0.758	0.70215	1.0323	0.92834	0.84502
{'fracByP99_99' }	0.99975	0.99993	1	1	1

age =59

xxx tb\_outcomes: all stats xxx

OriginalVariableNames	ap_ss	c_ss	v_ss	n_ss	y_head_inc
{'mean' }	55.659	1.287	-12.919	1.7239	1.8545
{'unweighted_sum' }	11476	2.6894e+05	-1.1138e+05	21	13268
{'sd' }	23.095	1.0938	20.385	0.90777	2.0429
{'coefofvar' }	0.41494	0.84994	-1.5779	0.52659	1.1016
{'gini' }	0.22938	0.40011	-0.80515	0.23461	0.47957
{'min' }	1	0.055882	-235.34	1	0.059541
{'max' }	151	32.48	14.759	6	23.47
{'pYis0' }	0	0	0	0	0
{'pYls0' }	0	0	0.74277	0	0
{'pYgr0' }	1	1	0.25723	1	1
{'pYisMINY' }	0.0037896	2.9499e-05	3.9537e-07	0.48835	9.9096e-05
{'pYisMAXY' }	4.9199e-06	2.3292e-08	0	0.0036816	2.0186e-06
{'p0_01' }	1	0.05663	-137.64	1	0.059554
{'p10' }	28	0.31379	-41.113	1	0.39098
{'p25' }	41	0.59299	-18.867	1	0.6458
{'p50' }	55	1.065	-7.2226	2	1.1351
{'p75' }	70	1.6559	0.35778	2	2.1525
{'p90' }	85	2.4892	6.453	3	4.19
{'p99_99' }	146	15.179	14.69	6	22.847
{'fl_cov_ap_ss' }	533.38	21.832	417.21	2.9474	37.948
{'fl_cor_ap_ss' }	1	0.86423	0.88619	0.14059	0.80428
{'fl_cov_c_ss' }	21.832	1.1965	14.391	0.23796	2.0766
{'fl_cor_c_ss' }	0.86423	1	0.64539	0.23965	0.92925
{'fl_cov_v_ss' }	417.21	14.391	415.54	3.8082	23.854
{'fl_cor_v_ss' }	0.88619	0.64539	1	0.2058	0.5728
{'fl_cov_n_ss' }	2.9474	0.23796	3.8082	0.82404	0.062177
{'fl_cor_n_ss' }	0.14059	0.23965	0.2058	1	0.033527
{'fl_cov_y_head_inc' }	37.948	2.0766	23.854	0.062177	4.1736
{'fl_cor_y_head_inc' }	0.80428	0.92925	0.5728	0.033527	1
{'fl_cov_y_spouse' }	5.9801	0.27801	4.7175	0.2771	0.1726
{'fl_cor_y_spouse' }	0.2311	0.22684	0.20654	0.27244	0.075404
{'fl_cov_yshr_wage' }	-1.3386	-0.041425	-1.1118	-0.0063156	-0.054208
{'fl_cor_yshr_wage' }	-0.6493	-0.42426	-0.61101	-0.07794	-0.29725
{'fl_cov_yshr_SS' }	0	0	0	0	0
{'fl_cor_yshr_SS' }	NaN	NaN	NaN	NaN	NaN
{'fl_cov_yshr_nttxss' }	0.76653	0.028255	0.72181	0.0084863	0.047728

{'fl_cor_yshr_nttxss'}	0.88794	0.69107	0.94731	0.2501	0.62501
{'fracByP0_01' }	6.8085e-05	5.4514e-06	0.0013821	0.28329	4.1425e-06
{'fracByP10' }	0.031672	0.019903	0.46352	0.28329	0.013283
{'fracByP25' }	0.1219	0.075667	0.79865	0.28329	0.054393
{'fracByP50' }	0.34388	0.22765	1.0532	0.72028	0.1806
{'fracByP75' }	0.62522	0.48161	1.1105	0.72028	0.41873
{'fracByP90' }	0.8294	0.71297	1.0711	0.85389	0.65167
{'fracByP99_99' }	0.9998	0.99881	1	1	0.99935
age =100					
xxx tb_outcomes: all stats xxx					
OriginalVariableNames	ap_ss	c_ss	v_ss	n_ss	y_head_inc
-----	-----	-----	-----	-----	-----
{'mean' }	1	0.33746	-3.2579	1.4797	0.23579
{'unweighted_sum' }	1	2.8049e+05	789.51	21	483.8
{'sd' }	1.088e-14	0.23923	1.2254	0.50567	0.022052
{'coefofvar' }	1.088e-14	0.70891	-0.37615	0.34173	0.093527
{'gini' }	0	0.29996	-0.20031	0.12034	0.044484
{'min' }	1	0.19737	-11.197	1	0.22
{'max' }	1	141.61	0.99282	6	5.666
{'pYis0' }	0	0	0	0	0
{'pYls0' }	0	0	0.99204	0	0
{'pYgr0' }	1	1	0.007965	1	1
{'pYisMINY' }	1	0.34474	1.4552e-10	0.5232	0.48869
{'pYisMAXY' }	1	0	0	4.2206e-08	0
{'p0_01' }	1	0.19737	-7.038	1	0.22
{'p10' }	1	0.19737	-4.0665	1	0.22
{'p25' }	1	0.19737	-4.0665	1	0.22
{'p50' }	1	0.23607	-3.7707	1	0.2202
{'p75' }	1	0.36676	-2.6758	2	0.266
{'p90' }	1	0.59408	-1.2803	2	0.26717
{'p99_99' }	1	2.9028	0.51281	4	0.31843
{'fl_cov_ap_ss' }	1.1838e-28	4.4139e-31	3.5754e-30	4.121e-29	2.8489e-30
{'fl_cor_ap_ss' }	1	1.6958e-16	2.6816e-16	7.4904e-15	1.1874e-14
{'fl_cov_c_ss' }	4.4139e-31	0.057229	0.23842	0.059118	0.0016668
{'fl_cor_c_ss' }	1.6958e-16	1	0.81327	0.48871	0.31595
{'fl_cov_v_ss' }	3.5754e-30	0.23842	1.5017	0.20689	0.012148
{'fl_cor_v_ss' }	2.6816e-16	0.81327	1	0.33387	0.44951
{'fl_cov_n_ss' }	4.121e-29	0.059118	0.20689	0.2557	0.0018516
{'fl_cor_n_ss' }	7.4904e-15	0.48871	0.33387	1	0.16604
{'fl_cov_y_head_inc' }	2.8489e-30	0.0016668	0.012148	0.0018516	0.0004863
{'fl_cor_y_head_inc' }	1.1874e-14	0.31595	0.44951	0.16604	1
{'fl_cov_y_spouse' }	-3.2619e-31	0.050594	0.17973	0.052581	0.00064389
{'fl_cor_y_spouse' }	-1.2267e-16	0.86534	0.60012	0.42546	0.11947
{'fl_cov_yshr_wage' }	-6.2277e-32	0.040102	0.18489	0.087766	0.00067273
{'fl_cor_yshr_wage' }	-2.5076e-17	0.73439	0.66096	0.76038	0.13365
{'fl_cov_yshr_SS' }	-3.036e-30	-0.041567	-0.19392	-0.089099	-0.00074396
{'fl_cor_yshr_SS' }	-1.2162e-15	-0.75734	-0.68973	-0.768	-0.14704
{'fl_cov_yshr_nttxss' }	-3.8383e-30	0.045721	0.21331	0.096069	0.00089733
{'fl_cor_yshr_nttxss' }	-1.4131e-15	0.76558	0.69726	0.76104	0.163
{'fracByP0_01' }	1	0.20164	0.00049502	0.35357	0.45597
{'fracByP10' }	1	0.20164	0.5347	0.35357	0.45597
{'fracByP25' }	1	0.20164	0.5347	0.35357	0.45597
{'fracByP50' }	1	0.31034	0.64676	0.35357	0.46775
{'fracByP75' }	1	0.52813	0.89014	0.99419	0.87014
{'fracByP90' }	1	0.73972	0.97784	0.99419	0.88578
{'fracByP99_99' }	1	0.9992	1	0.99999	0.99992



```
xxx TABLE:cons_VFI xxxxxxxxxxxxxxxxxxxxxx
```

	c1	c2	c3	c4	c5	c526496	c526497	c526498
r1	0.036717	0.037251	0.040426	0.04363	0.048012	9.6396	9.8066	9.9533
r2	0.036717	0.037251	0.040477	0.04461	0.049364	9.8014	9.9571	10.088
r3	0.036717	0.037251	0.040477	0.046214	0.051039	9.9664	10.108	10.22
r4	0.038144	0.038678	0.041903	0.047776	0.052666	10.118	10.244	10.339
r5	0.039534	0.040068	0.043323	0.04929	0.054241	10.258	10.369	10.446
r79	0.19737	0.19791	0.20163	0.21175	0.23093	35.811	37.046	38.418
r80	0.19737	0.19791	0.20163	0.21175	0.23145	40.207	42.15	44.426
r81	0.19737	0.19791	0.20163	0.21175	0.23145	48.541	51.158	54.236
r82	0.19737	0.19791	0.20163	0.21175	0.23145	66.71	69.193	71.724
r83	0.19737	0.19791	0.20163	0.21175	0.23145	116.82	122.65	128.66

```
Completed SNW_DS_MAIN;SNW_MP_PARAM=default_docdense;SNW_MP_CONTROL=default_test;time=2153.0961
```

```
% [Phi_true,Phi_adj] = snw_ds_main(mp_params, mp_controls);
Phi_true = Phi_true/sum(Phi_true(:));
```

## 7.2.2 Show All Info in mp\_dsvfi\_results More Dense

```
mp_cl_mt_xyz_of_s = mp_dsvfi_results('mp_cl_mt_xyz_of_s');
disp(mp_cl_mt_xyz_of_s('tb_outcomes'))
```

	mean	unweighted_sum	sd	coefofvar	gini	min
a_ss	4.3602	2228	6.8796	1.5778	0.6755	0
ap_ss	4.4621	5.3216e+08	6.9169	1.5501	0.67638	0
cons_ss	1.0635	5.0787e+07	0.6938	0.65237	0.33936	0.036717
v_ss	-36.615	-4.0773e+08	24.55	-0.67049	-0.33945	-615.77
n_ss	2.3554	21	1.4375	0.61029	0.3128	1
y_all	1.4189	8.353e+07	1.4929	1.0521	0.47667	0
y_head_inc	1.1081	1.9253e+06	1.013	0.91419	0.42164	0.038108
y_head_earn	0.88655	19732	0.92804	1.0468	0.53121	0
y_spouse_inc	0.35797	4.827e+05	0.95437	2.6661	0.85269	0
yshr_interest	0.12865	3.8438e+06	0.17577	1.3663	0.65781	0
yshr_wage	0.77402	8.8881e+06	0.33679	0.43512	0.2062	0
yshr_SS	0.097329	29012	0.2266	2.3282	0.91382	0
yshr_tax	0.17833	2.8338e+06	0.035661	0.19998	0.11386	0.036506
yshr_nttxss	0.080996	2.8048e+06	0.24691	3.0485	1.2592	-0.89715

## 7.2.3 More Dense Param Results Define Frames

Define the matrix dimensions names and dimension vector values. Probability mass matrixes, Policy and Value Functions share the same ND dimensional structure.

```
% Grids:
```

```
age_grid = 18:100;
agrid = mp_params('agrid');
eta_H_grid = mp_params('eta_H_grid');
eta_S_grid = mp_params('eta_S_grid');
ar_st_eta_HS_grid = string(cellstr([num2str(eta_H_grid', 'hz=%3.2f;'), num2str(eta_S_grid', 'wz=%3.2f;')]);
edu_grid = [0,1];
marry_grid = [0,1];
kids_grid = (1:1:mp_params('n_kidsgrid'))';
% NaN(n_jgrid,n_agrid,n_etagrid,n_educgrid,n_marriedgrid,n_kidsgrid);
cl_mp_datasetdesc = {};
```

```

cl_mp_datasetdesc{1} = containers.Map({'name', 'labval'}, {'age', age_grid});
cl_mp_datasetdesc{2} = containers.Map({'name', 'labval'}, {'savings', agrid});
cl_mp_datasetdesc{3} = containers.Map({'name', 'labval'}, {'eta', 1:length(eta_H_grid)});
cl_mp_datasetdesc{4} = containers.Map({'name', 'labval'}, {'edu', edu_grid});
cl_mp_datasetdesc{5} = containers.Map({'name', 'labval'}, {'marry', marry_grid});
cl_mp_datasetdesc{6} = containers.Map({'name', 'labval'}, {'kids', kids_grid});

```

## 7.2.4 Analyze Probability Mass Along Age Dimensions

Where are the mass at? Analyze mass given state space components.

```

% Get the Joint distribution over all states
% Define Graph Inputs
mp_support_graph = containers.Map('KeyType', 'char', 'ValueType', 'any');
mp_support_graph('st_legend_loc') = 'best';
mp_support_graph('bl_graph_logy') = false; % do not log

```

Exogenous Permanent States Mass: Life Cycle, Edu and Marraige

Tabulate value and policies along savings and shocks:

```

% NaN(n_jgrid,n_agrid,n_etagrid,n_educgrid,n_marriedgrid,n_kidsgrid);
ar_permute = [2,3,6,1,5,4];
% Value Function
tb_prob_aem = ff_summ_nd_array("P(Age, EDU, MARRY)", Phi_true, true, ["sum"], 3, 1, cl_mp_datasetde

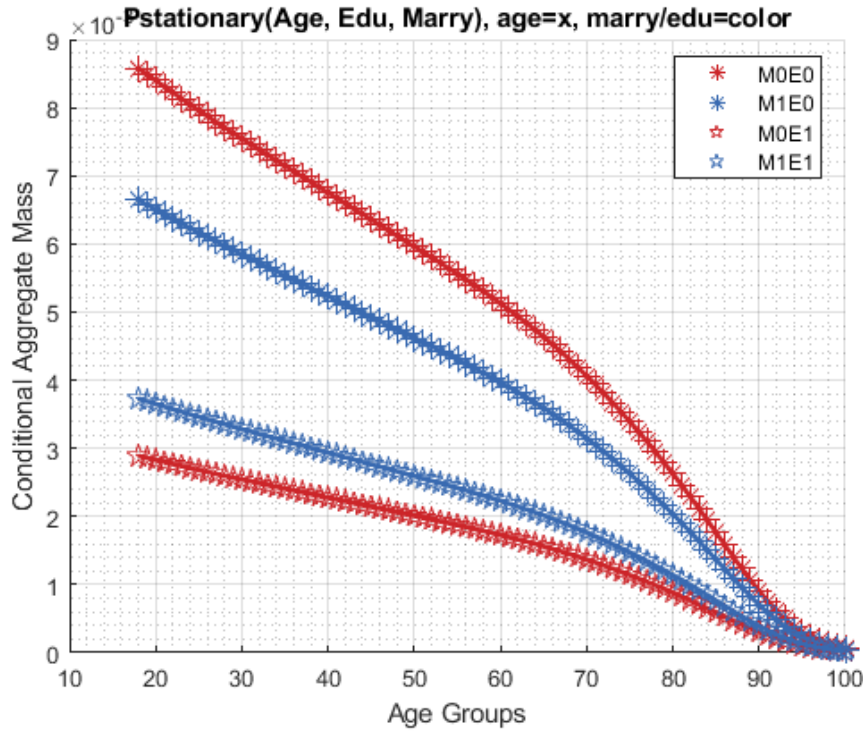
```

xxx	P(Age, EDU, MARRY))			xxxxxxxxxxxxxxxxxxxxxxxxxxxxxxxx					
	group	marry	edu	sum_age_18	sum_age_19	sum_age_20	sum_age_21	sum_age_22	s
	-----	-----	---	-----	-----	-----	-----	-----	-
	1	0	0	0.0085768	0.0084866	0.0083969	0.0083078	0.0082194	0
	2	1	0	0.0066438	0.0065739	0.0065044	0.0064354	0.0063669	
	3	0	1	0.0028875	0.0028571	0.002827	0.002797	0.0027672	0
	4	1	1	0.0037292	0.0036899	0.0036509	0.0036122	0.0035738	0

```

mp_support_graph('cl_st_graph_title') = {'Pstationary(Age, Edu, Marry), age=x, marry/edu=color'};
mp_support_graph('cl_st_ytitle') = {'Conditional Aggregate Mass'};
ar_row_grid = ["MOEO", "M1EO", "MOE1", "M1E1"];
mp_support_graph('cl_st_xtitle') = {'Age Groups'};
mp_support_graph('cl_scatter_shapes') = {'*', '*', 'p', 'p'};
mp_support_graph('cl_colors') = {'red', 'blue', 'red', 'blue'};
ff_graph_grid((tb_prob_aem{1:end, 4:end}), ar_row_grid, age_grid, mp_support_graph);

```



Kids and Marry By Age Mass

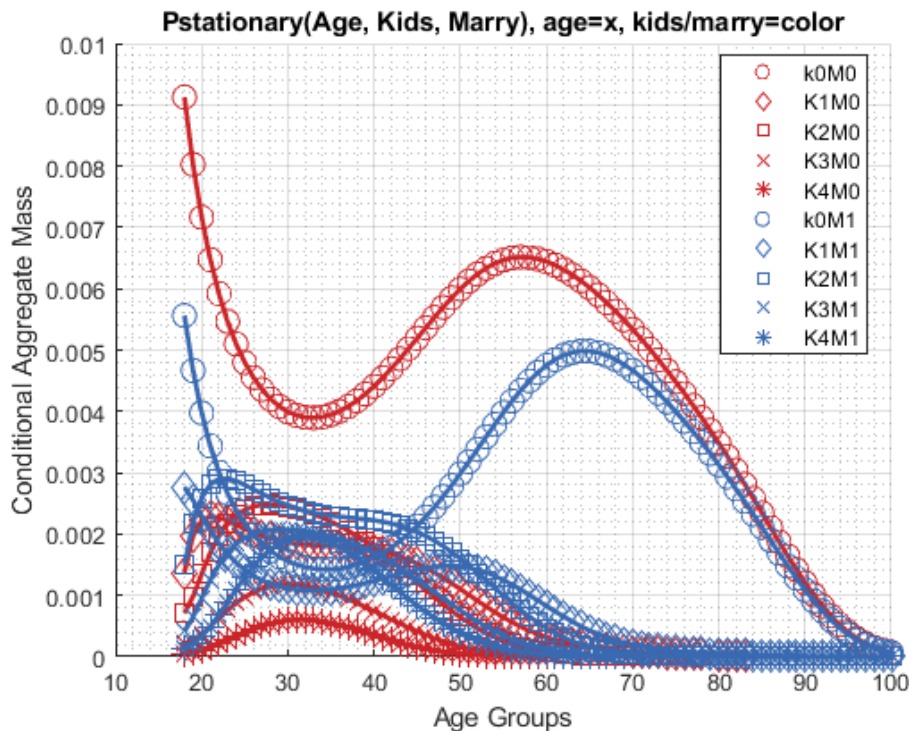
```
% NaN(n_jgrid,n_agrid,n_etagrid,n_educgrid,n_marriedgrid,n_kidsgrid);
ar_permute = [2,3,4,1,6,5];
% Value Function
tb_prob_amarrykids = ff_summ_nd_array("P(Age, Kids, Marry)", Phi_true, true, ["sum"], 3, 1, cl_mp_d
```

xxx	P(Age, Kids, Marry)			xxxxxxxxxxxxxxxxxxxxxxxxxxxxxxxx				
group	kids	marry	sum_age_18	sum_age_19	sum_age_20	sum_age_21	sum_age_22	
1	1	0	0.0091249	0.0080278	0.0071652	0.0064765	0.0059205	
2	2	0	0.0013699	0.0019743	0.0022187	0.0022858	0.0022687	
3	3	0	0.00071266	0.00098425	0.0013537	0.0016929	0.0019639	
4	4	0	0.00020622	0.00027865	0.00037326	0.00049476	0.00062818	
5	5	0	5.0761e-05	7.8715e-05	0.000113	0.00015485	0.00020534	
6	1	1	0.0055624	0.0046679	0.0039774	0.0034368	0.0030088	
7	2	1	0.0027682	0.0025539	0.0023005	0.0020611	0.0018525	
8	3	1	0.0014982	0.0021823	0.0025943	0.0028096	0.002896	
9	4	1	0.00041197	0.00064648	0.00095224	0.0012491	0.0015009	
10	5	1	0.00013221	0.0002132	0.00033097	0.00049097	0.00068255	

```
mp_support_graph('cl_st_graph_title') = {'Pstationary(Age, Kids, Marry), age=x, kids/marry=color'};
mp_support_graph('cl_st_ytitle') = {'Conditional Aggregate Mass'};
ar_row_grid = [...
    "k0M0", "K1M0", "K2M0", "K3M0", "K4M0", ...
    "k0M1", "K1M1", "K2M1", "K3M1", "K4M1"];
mp_support_graph('cl_scatter_shapes') = {...
    'o', 'd', 's', 'x', '*'}, ...
    'o', 'd', 's', 'x', '*'};
mp_support_graph('cl_colors') = {...
    'red', 'red', 'red', 'red', 'red'...
    'blue', 'blue', 'blue', 'blue', 'blue'};
mp_support_graph('cl_st_xtitle') = {'Age Groups'};
```



```
ff_graph_grid((tb_prob_amarrykids{1:end, 4:end}), ar_row_grid, age_grid, mp_support_graph);
```



### 7.2.5 Analyze Probability Mass Asset and Shock Dimensions

Where are the mass at?

```
% Define Graph Inputs
mp_support_graph = containers.Map('KeyType', 'char', 'ValueType', 'any');
mp_support_graph('st_legend_loc') = 'best';
mp_support_graph('bl_graph_logy') = false; % do not log
```

Asset and Shock Mass

```
% NaN(n_jgrid,n_agrid,n_etagrid,n_educgrid,n_marriedgrid,n_kidsgrid);
ar_permute = [1,4,5,6,3,2];
% Value Function
tb_prob_az = ff_summ_nd_array("P(A,Z)", Phi_true, true, ["sum"], 4, 1, cl_mp_datasetdesc, ar_permute);
```

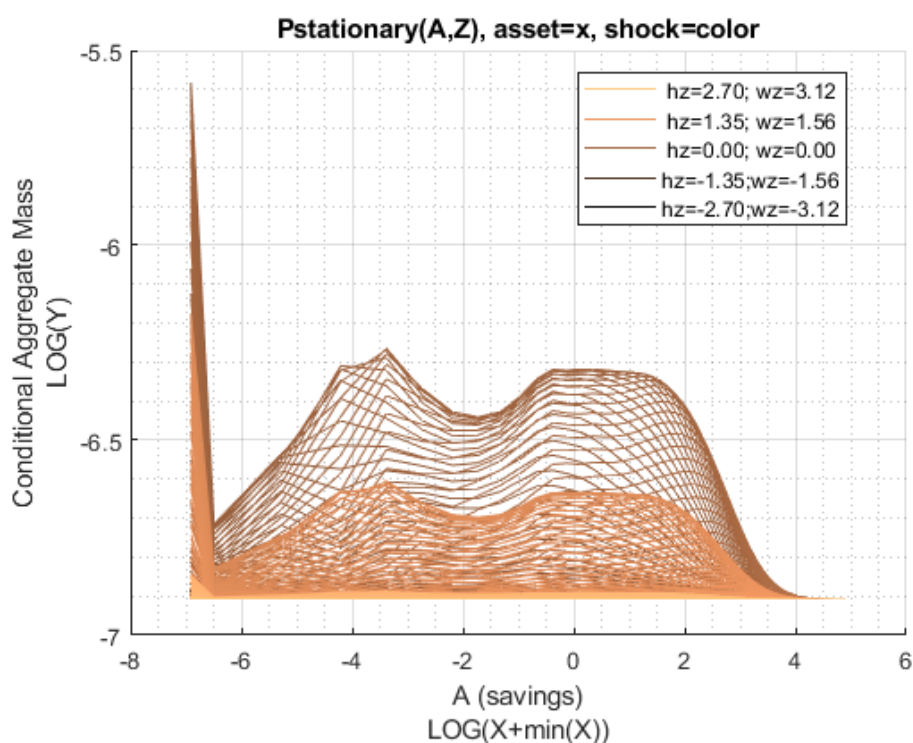
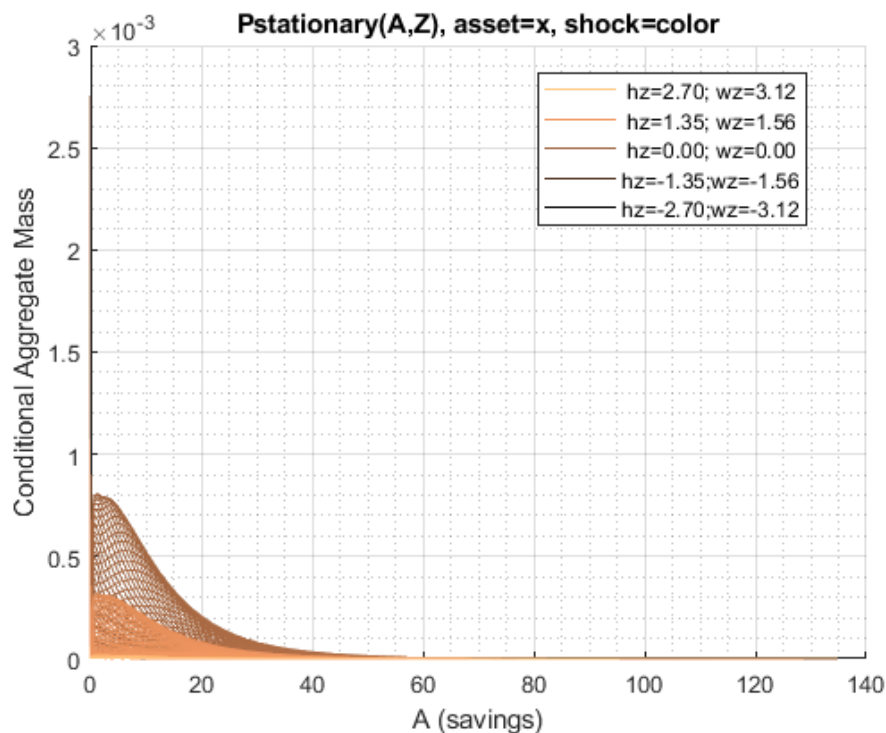
xxx	P(A,Z)	xxxxxxxxxxxxxxxxxxxxxxxxxxxxxxxx						
group	savings	sum_eta_1	sum_eta_2	sum_eta_3	sum_eta_4	sum_eta_5	sum	
1	0	1.6729e-07	1.4316e-07	2.1759e-07	3.1665e-07	4.509e-07	6.3	
2	0.00051498	3.7493e-10	3.6049e-10	6.2649e-10	1.1273e-09	2.1799e-09	4.4	
3	0.0041199	7.5745e-10	6.6694e-10	1.0474e-09	1.5976e-09	2.4182e-09	3.6	
4	0.013905	1.6314e-09	1.4169e-09	2.1927e-09	3.2778e-09	4.8429e-09	7.1	
5	0.032959	5.5034e-09	4.7405e-09	7.269e-09	1.0722e-08	1.5557e-08	2.2	
6	0.064373	6.5761e-09	5.6858e-09	8.729e-09	1.2871e-08	1.8634e-08	2.6	

```
mp_support_graph('cl_st_graph_title') = {'Pstationary(A,Z), asset=x, shock=color'};
mp_support_graph('cl_st_ytitle') = {'Conditional Aggregate Mass'};
mp_support_graph('cl_st_xtitle') = {'A (savings)'};
mp_support_graph('st_rowvar_name') = 'z=';
mp_support_graph('it_legend_select') = 5;
mp_support_graph('st_rounding') = '6.2f';
```

```

mp_support_graph('bl_graph_logy') = true;
mp_support_graph('cl_colors') = 'copper';
ff_graph_grid((tb_prob_az{1:end, 3:end})', ar_st_eta_HS_grid, agrid, mp_support_graph);% Consumption

```



Asset Mass by Age

```

% NaN(n_jgrid,n_agrid,n_etagrid,n_educgrid,n_marriedgrid,n_kidsgrid);
ar_permute = [3,4,5,6,1,2];
% Value Function
tb_prob_age = ff_summ_nd_array("P(A,Z)", Phi_true, true, ["sum"], 4, 1, cl_mp_datasetdesc, ar_perm

```

xxx	P(A,Z))	xxxxxxxxxxxxxxxxxxxxxxxxxxxxxxxx						
group	savings	sum_age_18	sum_age_19	sum_age_20	sum_age_21	sum_age_22	sum	
-----	-----	-----	-----	-----	-----	-----	-----	-----
1	0	0.021837	0.0023506	0.0017989	0.0039364	0.0058286	0.	
2	0.00051498	0	0.00039478	0.00037898	0.0011264	0.00064408	0.0	
3	0.0041199	0	0.0020814	0.0019874	0.0019922	0.00088345	0.0	
4	0.013905	0	0.0038512	0.0031528	0.0016753	0.0011288	0.0	
5	0.032959	0	0.0059559	0.0036616	0.0019605	0.0014625	0.	
6	0.064373	0	0.0019624	0.0026806	0.0015589	0.0012782	0.	
7	0.11124	0	0.0010231	0.0010755	0.0008941	0.0009494	0.	
8	0.17664	0	0.00067266	0.00082141	0.0009652	0.0010565	0.	
9	0.26367	0	0.00045811	0.00086333	0.0011647	0.0011767	0.	
10	0.37542	0	0.00053656	0.001129	0.0012812	0.0011528	0.	
11	0.51498	0	0.00090841	0.0013729	0.0012822	0.0012345	0	
12	0.68544	0	0.00097635	0.0011151	0.0011024	0.001139	0.	
13	0.88989	0	0.00023558	0.00050592	0.00075138	0.00094942	0	
14	1.1314	0	4.591e-05	0.00027667	0.00049327	0.00061366	0.0	
15	1.4131	0	1.7547e-05	0.00019582	0.00030348	0.00040728	0.0	
16	1.7381	0	8.2268e-06	6.7346e-05	0.00015086	0.00025852	0.0	
17	2.1094	0	6.1503e-06	3.6395e-05	9.6376e-05	0.00016375	0.0	
18	2.5301	0	1.345e-05	3.725e-05	7.4002e-05	0.00012113	0.0	
19	3.0034	0	2.2526e-05	4.8231e-05	7.8125e-05	0.00011085	0.0	
20	3.5323	0	2.9888e-05	5.5596e-05	8.1028e-05	0.00010487	0.0	
21	4.1199	0	3.0433e-05	5.4594e-05	7.2792e-05	9.1925e-05	0.0	
22	4.7693	0	2.0409e-05	3.7846e-05	5.5558e-05	7.2536e-05	8.9	
23	5.4836	0	5.1452e-06	1.8425e-05	3.2883e-05	4.8468e-05	6.5	
24	6.2658	0	7.3282e-07	5.3334e-06	1.4182e-05	2.7049e-05	4.1	
25	7.1191	0	1.062e-07	1.2922e-06	4.9633e-06	1.2247e-05	2.3	
26	8.0466	0	1.7779e-08	5.0549e-07	2.0442e-06	5.3225e-06	1.1	
27	9.0514	0	3.0263e-09	3.0488e-07	1.0981e-06	2.7972e-06	5.7	
28	10.136	0	1.2227e-10	1.6491e-07	5.5442e-07	1.5926e-06	3.3	
29	11.305	0	0	4.8394e-08	2.2296e-07	8.1497e-07	1.9	
30	12.56	0	0	9.3997e-09	7.016e-08	3.1478e-07	1.0	
31	13.905	0	0	1.808e-09	2.0992e-08	9.9385e-08	4.7	
32	15.342	0	0	4.1404e-10	6.2716e-09	3.4866e-08	1.9	
33	16.875	0	0	9.9687e-11	1.6909e-09	1.3108e-08	6.2	
34	18.507	0	0	2.1381e-11	4.7515e-10	4.3065e-09	2.1	
35	20.241	0	0	8.897e-13	1.3917e-10	1.2185e-09	8.3	
36	22.08	0	0	0	2.966e-11	3.6653e-10	2.8	
37	24.027	0	0	0	3.6991e-12	1.1419e-10	8.4	
38	26.085	0	0	0	7.8046e-13	2.4029e-11	2.7	
39	28.258	0	0	0	1.7968e-13	4.0593e-12	8.1	
40	30.548	0	0	0	8.7684e-15	1.0642e-12	1.7	
41	32.959	0	0	0	0	1.9771e-13	3.6	
42	35.493	0	0	0	0	1.5011e-14	9.2	
43	38.154	0	0	0	0	2.3721e-15	1.	
44	40.945	0	0	0	0	3.0185e-16	1.7	
45	43.868	0	0	0	0	6.4297e-18	3.2	
46	46.928	0	0	0	0	0	3.4	
47	50.126	0	0	0	0	...		

```

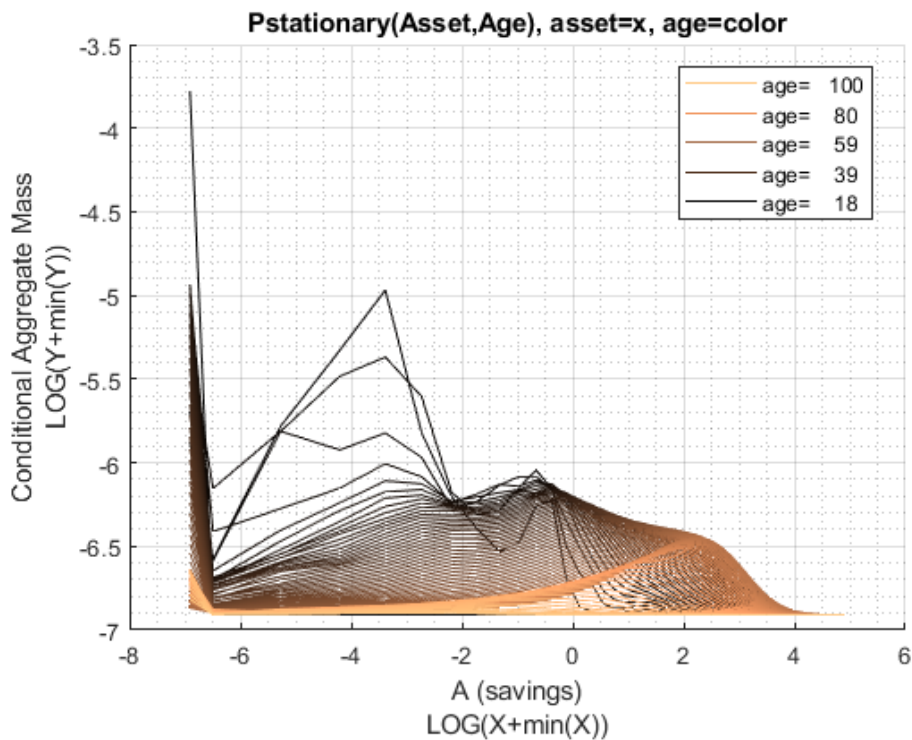
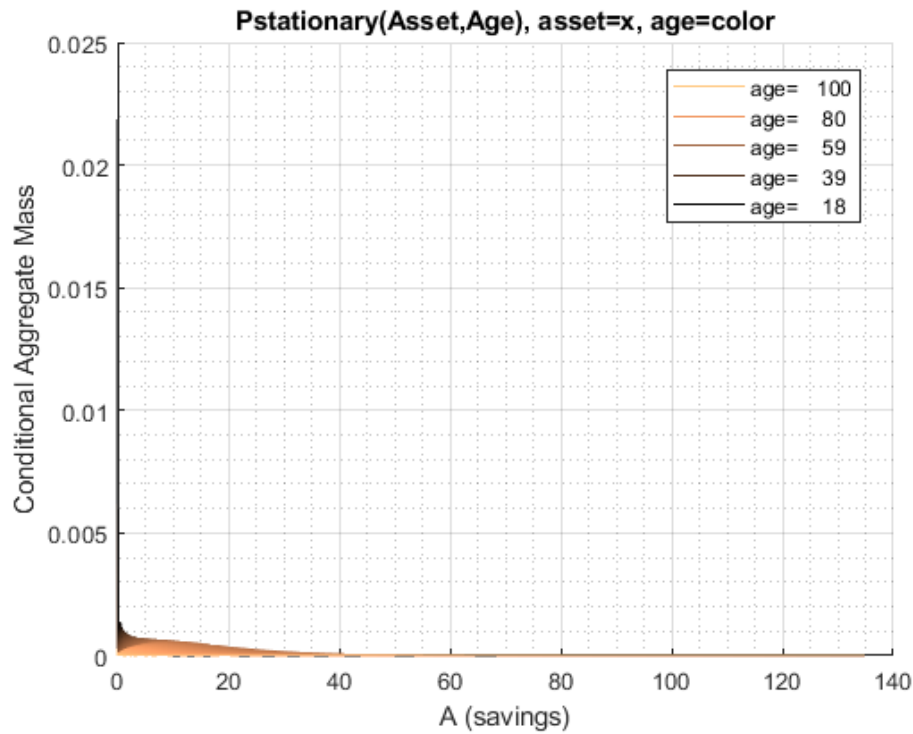
mp_support_graph('cl_st_graph_title') = {'Pstationary(Asset,Age), asset=x, age=color'};
mp_support_graph('cl_st_ytitle') = {'Conditional Aggregate Mass'};
mp_support_graph('cl_st_xtitle') = {'A (savings)'};
mp_support_graph('st_rowvar_name') = 'age=';
mp_support_graph('it_legend_select') = 5;
mp_support_graph('st_rounding') = '6.0f';

```

```

mp_support_graph('bl_graph_logy') = true;
mp_support_graph('cl_colors') = 'copper';
ff_graph_grid((tb_prob_age{1:end, 3:end}),'', age_grid, agrid, mp_support_graph);% Consumption Choice

```



## 7.2.6 Probability Statistics A, C and V Conditional on Ages

Where are the mass at?

```

ap_ss = mp_dsvfi_results('ap_ss');
c_ss = mp_dsvfi_results('cons_ss');

```

```

v_ss = mp_dsvfi_results('v_ss');
n_ss = mp_dsvfi_results('n_ss');

y_head_inc = mp_dsvfi_results('y_head_inc_ss');
y_spouse_inc = mp_dsvfi_results('y_spouse_inc_ss');

yshr_wage = mp_dsvfi_results('yshr_wage_ss');
yshr_SS = mp_dsvfi_results('yshr_SS_ss');
yshr_nttxss = mp_dsvfi_results('yshr_nttxss_ss');

for it_ctr=1:size(ap_ss, 1)
    if (ismember(it_ctr, round(linspace(1, size(ap_ss, 1), 3))))
        display(['age = ' num2str(age_grid(it_ctr))]);

        % construct input data
        Phi_true_age = Phi_true(it_ctr, :, :, : ,: ,:);
        ap_ss_age = ap_ss(it_ctr, :, :, : ,: ,:);
        c_ss_age = c_ss(it_ctr, :, :, : ,: ,:);
        v_ss_age = v_ss(it_ctr, :, :, : ,: ,:);
        n_ss_age = n_ss(it_ctr, :, :, : ,: ,:);

        y_head_inc_age = y_head_inc(it_ctr, :, :, : ,: ,:);
        y_spouse_inc_age = y_spouse_inc(it_ctr, :, :, : ,: ,:);
        yshr_wage_age = yshr_wage(it_ctr, :, :, : ,: ,:);
        yshr_SS_age = yshr_SS(it_ctr, :, :, : ,: ,:);
        yshr_nttxss_age = yshr_nttxss(it_ctr, :, :, : ,: ,:);

        mp_cl_ar_xyz_of_s = containers.Map('KeyType','char', 'ValueType','any');
        mp_cl_ar_xyz_of_s('ap_ss') = {ap_ss_age(:), zeros(1)};
        mp_cl_ar_xyz_of_s('c_ss') = {c_ss_age(:), zeros(1)};
        mp_cl_ar_xyz_of_s('v_ss') = {v_ss_age(:), zeros(1)};
        mp_cl_ar_xyz_of_s('n_ss') = {n_ss_age(:), zeros(1)};
        mp_cl_ar_xyz_of_s('y_head_inc') = {y_head_inc_age(:), zeros(1)};
        mp_cl_ar_xyz_of_s('y_spouse') = {y_spouse_inc_age(:), zeros(1)};
        mp_cl_ar_xyz_of_s('yshr_wage') = {yshr_wage_age(:), zeros(1)};
        mp_cl_ar_xyz_of_s('yshr_SS') = {yshr_SS_age(:), zeros(1)};
        mp_cl_ar_xyz_of_s('yshr_nttxss') = {yshr_nttxss_age(:), zeros(1)};
        mp_cl_ar_xyz_of_s('ar_st_y_name') = ["ap_ss", "c_ss", "v_ss", "n_ss",...
            "y_head_inc", "y_spouse", "yshr_wage", "yshr_SS", "yshr_nttxss"];

        % controls
        mp_support = containers.Map('KeyType','char', 'ValueType','any');
        mp_support('ar_fl_percentiles') = [0.01 10 25 50 75 90 99.99];
        mp_support('bl_display_final') = true;
        mp_support('bl_display_detail') = false;
        mp_support('bl_display_drvm2outcomes') = false;
        mp_support('bl_display_drvstats') = false;
        mp_support('bl_display_drvm2covcor') = false;

        % Call Function
        mp_cl_mt_xyz_of_s = ff_simu_stats(Phi_true_age(:)/sum(Phi_true_age,'all'), mp_cl_ar_xyz_of_s
    end
end

age =18
xxx tb_outcomes: all stats xxx
OriginalVariableNames      ap_ss      c_ss      v_ss      n_ss      y_head_inc
-----

```

{'mean'}	}	0.13209	0.63361	-59.72	1.9854	0.71265
{'unweighted_sum'}	}	1.0935e+07	8.5257e+05	-1.1176e+07	21	15541
{'sd'}	}	0.34847	0.37861	29.967	1.0848	0.54567
{'coefofvar'}	}	2.6381	0.59754	-0.50178	0.54639	0.76569
{'gini'}	}	0.7705	0.3109	-0.25126	0.268	0.36259
{'min'}	}	0	0.036717	-615.77	1	0.038108
{'max'}	}	145.08	10.204	-3.7499	6	13.784
{'pYis0'}	}	0.10805	0	0	0	0
{'pYls0'}	}	0	0	1	0	0
{'pYgr0'}	}	0.89195	1	0	1	1
{'pYisMINY'}	}	0.10805	1.3288e-05	5.8837e-08	0.41786	2.5312e-05
{'pYisMAXY'}	}	0	0	0	0.0060544	0
{'p0_01'}	}	0	0.047727	-352.03	1	0.046651
{'p10'}	}	0	0.24819	-96.425	1	0.23528
{'p25'}	}	0.012214	0.36957	-70.656	1	0.35258
{'p50'}	}	0.032959	0.55272	-52.866	2	0.56523
{'p75'}	}	0.076248	0.80075	-39.739	3	0.90612
{'p90'}	}	0.4782	1.1197	-31.147	4	1.3579
{'p99_99'}	}	5.4534	3.6548	-10.999	6	6.8484
{'fl_cov_ap_ss'}	}	0.12143	0.055156	2.4756	0.02663	0.050357
{'fl_cor_ap_ss'}	}	1	0.41805	0.23707	0.070443	0.26483
{'fl_cov_c_ss'}	}	0.055156	0.14335	8.0725	0.076682	0.18653
{'fl_cor_c_ss'}	}	0.41805	1	0.7115	0.1867	0.90288
{'fl_cov_v_ss'}	}	2.4756	8.0725	898	0.45095	10.05
{'fl_cor_v_ss'}	}	0.23707	0.7115	1	0.013872	0.61462
{'fl_cov_n_ss'}	}	0.02663	0.076682	0.45095	1.1768	-4.12e-18
{'fl_cor_n_ss'}	}	0.070443	0.1867	0.013872	1	-6.96e-18
{'fl_cov_y_head_inc'}	}	0.050357	0.18653	10.05	-4.12e-18	0.29776
{'fl_cor_y_head_inc'}	}	0.26483	0.90288	0.61462	-6.96e-18	1
{'fl_cov_y_spouse'}	}	0.18246	0.071672	3.4951	0.13323	0.010455
{'fl_cor_y_spouse'}	}	0.91943	0.33241	0.2048	0.21565	0.033645
{'fl_cov_yshr_wage'}	}	7.6315e-33	1.7081e-32	-2.0646e-31	3.5437e-31	6.4579e-33
{'fl_cor_yshr_wage'}	}	9.8628e-17	2.0318e-16	-3.1028e-17	1.4712e-15	5.3299e-17
{'fl_cov_yshr_SS'}	}	0	0	0	0	0
{'fl_cor_yshr_SS'}	}	NaN	NaN	NaN	NaN	NaN
{'fl_cov_yshr_nttxss'}	}	0.0057593	0.011163	0.86319	0.007516	0.01319
{'fl_cor_yshr_nttxss'}	}	0.48714	0.86903	0.84902	0.20421	0.71249
{'fracByP0_01'}	}	0	7.1734e-06	0.00073274	0.21046	7.788e-06
{'fracByP10'}	}	0	0.030664	0.21367	0.21046	0.027495
{'fracByP25'}	}	0.0067284	0.10372	0.4286	0.21046	0.092606
{'fracByP50'}	}	0.046851	0.29072	0.67444	0.53024	0.26377
{'fracByP75'}	}	0.13176	0.54795	0.87012	0.77109	0.5245
{'fracByP90'}	}	0.35932	0.76949	0.95644	0.92834	0.74403
{'fracByP99_99'}	}	0.99576	0.99938	0.99998	1	0.99912

age =59

xxx tb\_outcomes: all stats xxx

OriginalVariableNames	ap_ss	c_ss	v_ss	n_ss	y_head_inc	
{'mean'}	}	9.6978	1.2003	-27.032	1.7239	1.6127
{'unweighted_sum'}	}	1.1254e+07	1.0744e+06	-5.7273e+06	21	45380
{'sd'}	}	9.5091	0.76817	15.51	0.90777	1.276
{'coefofvar'}	}	0.98054	0.64	-0.57376	0.52659	0.79122
{'gini'}	}	0.47956	0.33158	-0.29874	0.23461	0.38177
{'min'}	}	0	0.05663	-230.76	1	0.059541
{'max'}	}	158.47	12.271	-1.694	6	23.47
{'pYis0'}	}	0.004589	0	0	0	0

{'pYls0'}	0	0	1	0	0
{'pYgr0'}	0.99541	1	0	1	1
{'pYisMINY'}	0.004589	9.8045e-06	2.9682e-09	0.48835	9.869e-06
{'pYisMAXY'}	9.1885e-09	2.1301e-11	5.3537e-07	0.0036816	1.4932e-06
{'p0_01'}	0	0.07838	-123.12	1	0.08341
{'p10'}	1.2229	0.40584	-47.779	1	0.49527
{'p25'}	3.196	0.6516	-33.261	1	0.77993
{'p50'}	7.0976	1.0499	-23.135	2	1.2719
{'p75'}	13.089	1.547	-16.274	2	2.0397
{'p90'}	21.159	2.1475	-11.776	3	3.1029
{'p99_99'}	112.62	8.4781	-2.7295	6	15.937
{'fl_cov_ap_ss'}	90.423	6.9267	101.69	0.81683	10.484
{'fl_cor_ap_ss'}	1	0.94827	0.68949	0.094628	0.86408
{'fl_cov_c_ss'}	6.9267	0.59008	8.839	0.23092	0.85409
{'fl_cor_c_ss'}	0.94827	1	0.74189	0.33116	0.87137
{'fl_cov_v_ss'}	101.69	8.839	240.55	2.5586	13.062
{'fl_cor_v_ss'}	0.68949	0.74189	1	0.18173	0.66001
{'fl_cov_n_ss'}	0.81683	0.23092	2.5586	0.82404	0.055266
{'fl_cor_n_ss'}	0.094628	0.33116	0.18173	1	0.047713
{'fl_cov_y_head_inc'}	10.484	0.85409	13.062	0.055266	1.6281
{'fl_cor_y_head_inc'}	0.86408	0.87137	0.66001	0.047713	1
{'fl_cov_y_spouse'}	2.2203	0.24459	3.6105	0.27625	0.1162
{'fl_cor_y_spouse'}	0.20978	0.28607	0.20915	0.27342	0.08182
{'fl_cov_yshr_wage'}	-0.53029	-0.034916	-0.87809	0.0021706	-0.036142
{'fl_cor_yshr_wage'}	-0.55378	-0.45137	-0.56221	0.023745	-0.28128
{'fl_cov_yshr_SS'}	0	0	0	0	0
{'fl_cor_yshr_SS'}	NaN	NaN	NaN	NaN	NaN
{'fl_cov_yshr_nttxss'}	0.19504	0.017838	0.43624	0.0074857	0.026908
{'fl_cor_yshr_nttxss'}	0.67474	0.76393	0.92529	0.27128	0.69373
{'fracByP0_01'}	0	6.875e-06	0.00049633	0.28329	5.7641e-06
{'fracByP10'}	0.0057779	0.026049	0.23158	0.28329	0.022494
{'fracByP25'}	0.040074	0.091752	0.44951	0.28329	0.082256
{'fracByP50'}	0.16977	0.26933	0.70658	0.72028	0.24076
{'fracByP75'}	0.42173	0.53549	0.88743	0.72028	0.48935
{'fracByP90'}	0.67785	0.76094	0.96591	0.85389	0.72071
{'fracByP99_99'}	0.99869	0.99925	0.99999	1	0.99889

age =100

xxx tb\_outcomes: all stats xxx

OriginalVariableNames	ap_ss	c_ss	v_ss	n_ss	y_head_inc	y_s
{'mean'}	0	0.33019	-4.3147	1.4797	0.2355	0
{'unweighted_sum'}	0	1.2179e+05	-3630.5	21	209.83	
{'sd'}	0	0.23351	1.1931	0.50567	0.021892	
{'coefofvar'}	NaN	0.7072	-0.27653	0.34173	0.092957	
{'gini'}	NaN	0.2934	-0.14462	0.12034	0.043711	0
{'min'}	0	0.19737	-12.197	1	0.22	
{'max'}	0	141.61	-0.0071775	6	5.666	
{'pYis0'}	1	0	0	0	0	0
{'pYls0'}	0	0	1	0	0	
{'pYgr0'}	0	1	0	1	1	0
{'pYisMINY'}	1	0.35707	1.4848e-10	0.5232	0.50347	0
{'pYisMAXY'}	1	0	0	4.2206e-08	0	1.03
{'p0_01'}	0	0.19737	-8.038	1	0.22	
{'p10'}	0	0.19737	-5.0665	1	0.22	
{'p25'}	0	0.19737	-5.0665	1	0.22	
{'p50'}	0	0.23607	-5.0103	1	0.22	
{'p75'}	0	0.34876	-3.7889	2	0.266	0

{'p90'	}	0	0.58892	-2.3842	2	0.26656	0
{'p99_99'	}	0	2.8508	-0.49608	4	0.31126	0
{'fl_cov_ap_ss'	}	0	0	0	0	0	0
{'fl_cor_ap_ss'	}	NaN	NaN	NaN	NaN	NaN	NaN
{'fl_cov_c_ss'	}	0	0.054526	0.22623	0.059682	0.0015233	0.
{'fl_cor_c_ss'	}	NaN	1	0.812	0.50545	0.298	0
{'fl_cov_v_ss'	}	0	0.22623	1.4236	0.21735	0.011521	0
{'fl_cor_v_ss'	}	NaN	0.812	1	0.36026	0.44106	0
{'fl_cov_n_ss'	}	0	0.059682	0.21735	0.2557	0.0018733	0.
{'fl_cor_n_ss'	}	NaN	0.50545	0.36026	1	0.16923	0
{'fl_cov_y_head_inc'	}	0	0.0015233	0.011521	0.0018733	0.00047925	0.00
{'fl_cor_y_head_inc'	}	NaN	0.298	0.44106	0.16923	1	0
{'fl_cov_y_spouse'	}	0	0.050691	0.18354	0.052581	0.00064761	0.
{'fl_cor_y_spouse'	}	NaN	0.88823	0.62943	0.42546	0.12104	0
{'fl_cov_yshr_wage'	}	0	0.040339	0.19022	0.087809	0.00068213	0.
{'fl_cor_yshr_wage'	}	NaN	0.75656	0.69819	0.76049	0.13646	0
{'fl_cov_yshr_SS'	}	0	-0.041495	-0.19728	-0.089315	-0.00073742	-0
{'fl_cor_yshr_SS'	}	NaN	-0.77343	-0.71963	-0.76875	-0.14661	-0
{'fl_cov_yshr_nttxss'	}	0	0.045639	0.21697	0.096294	0.00089018	0
{'fl_cor_yshr_nttxss'	}	NaN	0.78185	0.72746	0.76178	0.16266	0
{'fracByP0_01'	}	NaN	0.21345	0.00043423	0.35357	0.47033	0
{'fracByP10'	}	NaN	0.21345	0.51425	0.35357	0.47033	0
{'fracByP25'	}	NaN	0.21345	0.51425	0.35357	0.47033	0
{'fracByP50'	}	NaN	0.33309	0.6114	0.35357	0.47033	0
{'fracByP75'	}	NaN	0.53778	0.8525	0.99419	0.87579	0
{'fracByP90'	}	NaN	0.74393	0.95864	0.99419	0.8936	0
{'fracByP99_99'	}	NaN	0.99922	0.99999	0.99999	0.99991	0

### 7.3 Distribution Exact Savings Choices Vectorized

This is the example vignette for function: `snw_ds_main_vec` from the [PrjOptiSNW Package](#). This function solves for vfi and gets distribution induced by policy functions and exogenous distributions. Vectorized vfi and distribution methods.

#### 7.3.1 Test SNW\_DS\_MAIN\_VEC

Call the function with testing defaults.

```
% mp_params = snw_mp_param('default_dense');
mp_params = snw_mp_param('default_docdense');
mp_controls = snw_mp_control('default_test');
mp_controls('bl_print_vfi') = false;
mp_controls('bl_print_ds') = true;
mp_controls('bl_print_ds_verbose') = false;
[Phi_true,Phi_adj,A_agg,Y_inc_agg,it,mp_dsvfi_results] = snw_ds_main_vec(mp_params, mp_controls);
```

Completed SNW\_VFI\_MAIN\_BISEC\_VEC;SNW\_MP\_PARAM=default\_docdense;SNW\_MP\_CONTROL=default\_test;time=543.

```
-----
XXXXXXXXXXXXXXXXXXXXXXXXXXXXXXXXXXXXXXXXXXXXXXXXXXXXXXXXXXXX
CONTAINER NAME: mp_outcomes ND Array (Matrix etc)
XXXXXXXXXXXXXXXXXXXXXXXXXXXXXXXXXXXXXXXXXXXXXXXXXXXXXXXXXXXX
      i      idx      ndim      numel      rowN      colN      sum      mean      std
-----
V_VFI      1      1      6      4.37e+07      83      5.265e+05      -8.6673e+08      -19.834      28.17
ap_VFI      2      2      6      4.37e+07      83      5.265e+05      1.4164e+09      32.412      36.
cons_VFI      3      3      6      4.37e+07      83      5.265e+05      2.131e+08      4.8764      8.326
```



xxx TABLE:V\_VFI xxxxxxxxxxxxxxxxxxxxxxx

	c1	c2	c3	c4	c5	c526496	c526497	c526498
r1	-376.05	-375.66	-373.17	-367.4	-358.05	-6.68	-6.5297	-6.379
r2	-363.8	-363.41	-360.93	-355.25	-346.25	-6.4892	-6.3437	-6.197
r3	-351.75	-351.36	-348.9	-343.44	-334.9	-6.2948	-6.1538	-6.011
r4	-339.81	-339.45	-337.16	-332.06	-324.04	-6.095	-5.9584	-5.8
r5	-328.99	-328.65	-326.51	-321.72	-314.17	-5.9054	-5.7725	-5.637
r79	-14.033	-14.02	-13.926	-13.689	-13.287	-0.22848	-0.21775	-0.2076
r80	-12.564	-12.55	-12.457	-12.22	-11.818	-0.17427	-0.16611	-0.1584
r81	-10.778	-10.764	-10.671	-10.434	-10.032	-0.11927	-0.11368	-0.1084
r82	-8.4226	-8.4089	-8.3155	-8.0786	-7.6766	-0.06597	-0.06284	-0.05992
r83	-5.0665	-5.0529	-4.9595	-4.7226	-4.3206	-0.020968	-0.019972	-0.01903

xxx TABLE:ap\_VFI xxxxxxxxxxxxxxxxxxxxxxx

	c1	c2	c3	c4	c5	c526496	c526497	c526498	c526499
r1	0	0	0.0005656	0.0075134	0.022901	114.76	120.42	126.29	132
r2	0	0	0.00051498	0.0065334	0.021549	114.87	120.54	126.42	132
r3	0	0	0.00051498	0.0049294	0.019875	114.98	120.67	126.57	132
r4	0	0	0.00051498	0.0047937	0.019672	115.74	121.44	127.36	133
r5	0	0	0.00048517	0.0046683	0.019484	116.51	122.22	128.16	134
r79	0	0	0	0	0.00051498	81.091	85.68	90.325	94.
r80	0	0	0	0	0	76.669	80.55	84.292	88.
r81	0	0	0	0	0	68.313	71.52	74.459	77.
r82	0	0	0	0	0	50.126	53.467	56.953	58.
r83	0	0	0	0	0	0	0	0	0

xxx TABLE:cons\_VFI xxxxxxxxxxxxxxxxxxxxxxx

	c1	c2	c3	c4	c5	c526496	c526497	c526498
r1	0.036717	0.037251	0.040426	0.04363	0.048012	9.6396	9.8066	9.9533
r2	0.036717	0.037251	0.040477	0.04461	0.049364	9.8014	9.9571	10.088
r3	0.036717	0.037251	0.040477	0.046214	0.051039	9.9664	10.108	10.22
r4	0.038144	0.038678	0.041903	0.047776	0.052666	10.118	10.244	10.339
r5	0.039534	0.040068	0.043323	0.04929	0.054241	10.258	10.369	10.446
r79	0.19737	0.19791	0.20163	0.21175	0.23093	35.811	37.046	38.418
r80	0.19737	0.19791	0.20163	0.21175	0.23145	40.207	42.15	44.426
r81	0.19737	0.19791	0.20163	0.21175	0.23145	48.541	51.158	54.236
r82	0.19737	0.19791	0.20163	0.21175	0.23145	66.71	69.193	71.724
r83	0.19737	0.19791	0.20163	0.21175	0.23145	116.82	122.65	128.66

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 SNW\_DS\_MAIN\_VEC ACUMU MASS: Finished Age Group:13 of 82, time-this-age:14.4545

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SNW\_DS\_MAIN\_VEC ACUMU MASS: Finished Age Group:70 of 82, time-this-age:12.1532  
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 SNW\_DS\_MAIN NORMALIZE MASS: Finished Age Group:71 of 82, time-this-age:0.053119  
 SNW\_DS\_MAIN NORMALIZE MASS: Finished Age Group:72 of 82, time-this-age:0.062005  
 SNW\_DS\_MAIN NORMALIZE MASS: Finished Age Group:73 of 82, time-this-age:0.05542  
 SNW\_DS\_MAIN NORMALIZE MASS: Finished Age Group:74 of 82, time-this-age:0.060745  
 SNW\_DS\_MAIN NORMALIZE MASS: Finished Age Group:75 of 82, time-this-age:0.05168  
 SNW\_DS\_MAIN NORMALIZE MASS: Finished Age Group:76 of 82, time-this-age:0.051709  
 SNW\_DS\_MAIN NORMALIZE MASS: Finished Age Group:77 of 82, time-this-age:0.058973  
 SNW\_DS\_MAIN NORMALIZE MASS: Finished Age Group:78 of 82, time-this-age:0.059053  
 SNW\_DS\_MAIN NORMALIZE MASS: Finished Age Group:79 of 82, time-this-age:0.069633  
 SNW\_DS\_MAIN NORMALIZE MASS: Finished Age Group:80 of 82, time-this-age:0.046625  
 SNW\_DS\_MAIN NORMALIZE MASS: Finished Age Group:81 of 82, time-this-age:0.069697  
 SNW\_DS\_MAIN NORMALIZE MASS: Finished Age Group:82 of 82, time-this-age:0.049734  
 SNW\_DS\_MAIN NORMALIZE MASS: Finished Age Group:83 of 82, time-this-age:0.046755  
 SNW\_DS\_MAIN: Share of population with assets equal to upper bound on asset grid:6.8049e-06  
 SNW\_DS\_MAIN: Accidental bequests are thrown in the ocean  
 SNW\_DS\_MAIN\_VEC tax and spend;it=1;err=0.014163  
 SNW\_DS\_MAIN\_VEC tax and spend;it=2;err=0.011847  
 SNW\_DS\_MAIN\_VEC tax and spend;it=3;err=0.0098976  
 SNW\_DS\_MAIN\_VEC tax and spend;it=4;err=0.0082601  
 SNW\_DS\_MAIN\_VEC tax and spend;it=5;err=0.0068875  
 SNW\_DS\_MAIN\_VEC tax and spend;it=6;err=0.0057387  
 SNW\_DS\_MAIN\_VEC tax and spend;it=7;err=0.0047786  
 SNW\_DS\_MAIN\_VEC tax and spend;it=8;err=0.0039772  
 SNW\_DS\_MAIN\_VEC tax and spend;it=9;err=0.0033087  
 SNW\_DS\_MAIN\_VEC tax and spend;it=10;err=0.0027516  
 SNW\_DS\_MAIN\_VEC tax and spend;it=11;err=0.0022876  
 SNW\_DS\_MAIN\_VEC tax and spend;it=12;err=0.0019014  
 SNW\_DS\_MAIN\_VEC tax and spend;it=13;err=0.0015801  
 SNW\_DS\_MAIN\_VEC tax and spend;it=14;err=0.0013128  
 SNW\_DS\_MAIN\_VEC tax and spend;it=15;err=0.0010906  
 SNW\_DS\_MAIN\_VEC tax and spend;it=16;err=0.00090591  
 SNW\_DS\_MAIN\_VEC tax and spend;it=17;err=0.00075241  
 SNW\_DS\_MAIN\_VEC tax and spend;it=18;err=0.00062488  
 SNW\_DS\_MAIN\_VEC tax and spend;it=19;err=0.00051892  
 SNW\_DS\_MAIN\_VEC tax and spend;it=20;err=0.00043091

SNW\_DS\_MAIN\_VEC tax and spend;it=21;err=0.00035781  
 SNW\_DS\_MAIN\_VEC tax and spend;it=22;err=0.0002971  
 SNW\_DS\_MAIN\_VEC tax and spend;it=23;err=0.00024668  
 SNW\_DS\_MAIN\_VEC tax and spend;it=24;err=0.00020481  
 SNW\_DS\_MAIN\_VEC tax and spend;it=25;err=0.00017004  
 SNW\_DS\_MAIN\_VEC tax and spend;it=26;err=0.00014118  
 SNW\_DS\_MAIN\_VEC tax and spend;it=27;err=0.00011721  
 SNW\_DS\_MAIN\_VEC tax and spend;it=28;err=9.7309e-05  
 SNW\_DS\_MAIN\_VEC: Number of a2-adjustments (for taxation) used to balance the government budget= 28  
 SNW\_DS\_MAIN\_VEC: Old and updated value of a2=1.5286 1.4349  
 SNW\_DS\_MAIN\_VEC: Aggregates: Cons., Gov. cons., Save, Assets, Income, Bequests 48.70063 11.4200  
 SNW\_DS\_MAIN\_VEC: Resource constraint: C\_t+A\_{t+1}+G\_t=A\_t+Y\_t 264.4537 264.6461  
 Completed SNW\_DS\_MAIN\_VEC;SNW\_MP\_PARAM=default\_docdense;SNW\_MP\_CONTROL=default\_test;time=1820.5957  
 xxx tb\_outcomes: all stats xxx

OriginalVariableNames	a_ss	ap_ss	cons_ss	n_ss	y_all
{'mean'}	4.3602	4.4621	1.0635	2.3554	1.4661
{'unweighted_sum'}	2228	5.3216e+08	5.0787e+07	21	8.3558e+07
{'sd'}	6.8796	6.9169	0.6938	1.4375	1.4665
{'coefofvar'}	1.5778	1.5501	0.65237	0.61029	1.0003
{'gini'}	0.6755	0.67638	0.33936	0.3128	0.44546
{'min'}	0	0	0.036717	1	0.038108
{'max'}	135	163.73	141.61	6	50.873
{'pYis0'}	0.11808	0.097968	0	0	0
{'pYls0'}	0	0	0	0	0
{'pYgr0'}	0.88192	0.90203	1	1	1
{'pYisMINY'}	0.11808	0.097968	8.6094e-07	0.36005	8.6094e-07
{'pYisMAXY'}	6.8049e-06	2.2836e-12	0	0.041101	2.2836e-12
{'p0_01'}	0	0	0.066342	1	0.069931
{'p0_1'}	0	0	0.10404	1	0.11208
{'p1'}	0	0	0.18515	1	0.20327
{'p5'}	0	0	0.27323	1	0.26924
{'p10'}	0	0.00051498	0.35662	1	0.34663
{'p20'}	0.064373	0.083002	0.49455	1	0.49947
{'p25'}	0.17664	0.20935	0.56067	1	0.57738
{'p30'}	0.37542	0.39434	0.62765	1	0.65537
{'p40'}	0.88989	0.90689	0.76677	2	0.82916
{'p50'}	1.7381	1.6906	0.91665	2	1.0312
{'p60'}	3.0034	2.8912	1.0828	2	1.2832
{'p70'}	4.7693	4.7054	1.2762	3	1.6179
{'p75'}	5.4836	5.9044	1.3916	3	1.8375
{'p80'}	7.1191	7.4694	1.5274	4	2.1165
{'p90'}	12.56	12.521	1.9354	5	3.0585
{'p95'}	16.875	17.769	2.3449	5	4.0476
{'p99'}	30.548	31.792	3.4017	6	6.9072
{'p99_9'}	56.953	57.866	5.2893	6	14.815
{'p99_99'}	90.439	90.717	7.5592	6	21.023
{'fl_cov_a_ss'}	47.329	47.318	3.476	-1.478	4.5793
{'fl_cor_a_ss'}	1	0.99439	0.72826	-0.14945	0.45389
{'fl_cov_ap_ss'}	47.318	47.844	3.5799	-1.4406	5.4304
{'fl_cor_ap_ss'}	0.99439	1	0.74597	-0.14488	0.53534
{'fl_cov_cons_ss'}	3.476	3.5799	0.48135	0.23978	0.7718
{'fl_cor_cons_ss'}	0.72826	0.74597	1	0.24042	0.75854
{'fl_cov_n_ss'}	-1.478	-1.4406	0.23978	2.0664	0.36196
{'fl_cor_n_ss'}	-0.14945	-0.14488	0.24042	1	0.1717
{'fl_cov_y_all'}	4.5793	5.4304	0.7718	0.36196	2.1507
{'fl_cor_y_all'}	0.45389	0.53534	0.75854	0.1717	1

{'fl_cov_y_head_inc' }	3.9427	4.2301	0.5704	0.09459	1.1331
{'fl_cor_y_head_inc' }	0.56573	0.60369	0.81157	0.064956	0.76267
{'fl_cov_y_head_earn' }	1.8957	2.208	0.43323	0.19345	0.98441
{'fl_cor_y_head_earn' }	0.29692	0.34397	0.67286	0.14501	0.7233
{'fl_cov_y_spouse_inc' }	0.63663	1.2003	0.2014	0.26737	1.0177
{'fl_cor_y_spouse_inc' }	0.096963	0.18183	0.30417	0.19489	0.7271
{'fl_cov_yshr_interest' }	0.80041	0.75231	0.03747	-0.072581	-0.014203
{'fl_cor_yshr_interest' }	0.6619	0.61877	0.30725	-0.28725	-0.055097
{'fl_cov_yshr_wage' }	-0.80811	-0.71978	-0.0042544	0.17131	0.10973
{'fl_cor_yshr_wage' }	-0.34878	-0.30898	-0.018207	0.35386	0.22217
{'fl_cov_yshr_SS' }	0.007703	-0.03253	-0.033215	-0.098733	-0.095531
{'fl_cor_yshr_SS' }	0.0049412	-0.020754	-0.21127	-0.3031	-0.28746
{'fl_cov_yshr_tax' }	0.10041	0.11154	0.018848	0.013683	0.039306
{'fl_cor_yshr_tax' }	0.40929	0.45221	0.76179	0.26692	0.75157
{'fl_cov_yshr_nttxss' }	0.09271	0.14407	0.052063	0.11242	0.13484
{'fl_cor_yshr_nttxss' }	0.054578	0.084358	0.30392	0.31672	0.37237
{'fracByP0_01' }	0	0	5.4726e-06	0.15286	4.2573e-06
{'fracByP0_1' }	0	0	8.2626e-05	0.15286	6.3235e-05
{'fracByP1' }	0	0	0.0013773	0.15286	0.0010873
{'fracByP5' }	0	0	0.010075	0.15286	0.0076055
{'fracByP10' }	0	1.8925e-07	0.024991	0.15286	0.018124
{'fracByP20' }	0.00071111	0.0007016	0.065093	0.15286	0.047
{'fracByP25' }	0.0023543	0.0022849	0.089893	0.15286	0.065314
{'fracByP30' }	0.0065355	0.0056773	0.11782	0.15286	0.086292
{'fracByP40' }	0.023222	0.019937	0.1833	0.40183	0.1368
{'fracByP50' }	0.057104	0.048358	0.26234	0.40183	0.20002
{'fracByP60' }	0.11454	0.098974	0.35614	0.40183	0.27863
{'fracByP70' }	0.2027	0.18293	0.46671	0.56321	0.37699
{'fracByP75' }	0.23918	0.24222	0.52936	0.56321	0.43577
{'fracByP80' }	0.32171	0.31675	0.59788	0.75407	0.50297
{'fracByP90' }	0.55921	0.53294	0.75856	0.8953	0.67532
{'fracByP95' }	0.69427	0.69899	0.85803	0.8953	0.79442
{'fracByP99' }	0.90202	0.9039	0.96048	1	0.93109
{'fracByP99_9' }	0.9849	0.98396	0.99413	1	0.988
{'fracByP99_99' }	0.99794	0.99764	0.99921	1	0.99841

```
% [Phi_true,Phi_adj] = snw_ds_main(mp_params, mp_controls);
Phi_true = Phi_true/sum(Phi_true(:));
```

### 7.3.2 Show All Info in mp\_dsvfi\_results

```
mp_cl_mt_xyz_of_s = mp_dsvfi_results('mp_cl_mt_xyz_of_s');
disp(mp_cl_mt_xyz_of_s('tb_outcomes'))
```

	mean	unweighted_sum	sd	coefofvar	gini	min
	-----	-----	-----	-----	-----	-----
a_ss	4.3602	2228	6.8796	1.5778	0.6755	0
ap_ss	4.4621	5.3216e+08	6.9169	1.5501	0.67638	0
cons_ss	1.0635	5.0787e+07	0.6938	0.65237	0.33936	0.036717
n_ss	2.3554	21	1.4375	0.61029	0.3128	1
y_all	1.4661	8.3558e+07	1.4665	1.0003	0.44546	0.038108
y_head_inc	1.1081	1.9253e+06	1.013	0.91419	0.42164	0.038108
y_head_earn	0.88655	19732	0.92804	1.0468	0.53121	0
y_spouse_inc	0.35797	4.827e+05	0.95437	2.6661	0.85269	0
yshr_interest	0.12865	3.8438e+06	0.17577	1.3663	0.65781	0
yshr_wage	0.77402	8.8881e+06	0.33679	0.43512	0.2062	0
yshr_SS	0.097329	29012	0.2266	2.3282	0.91382	0

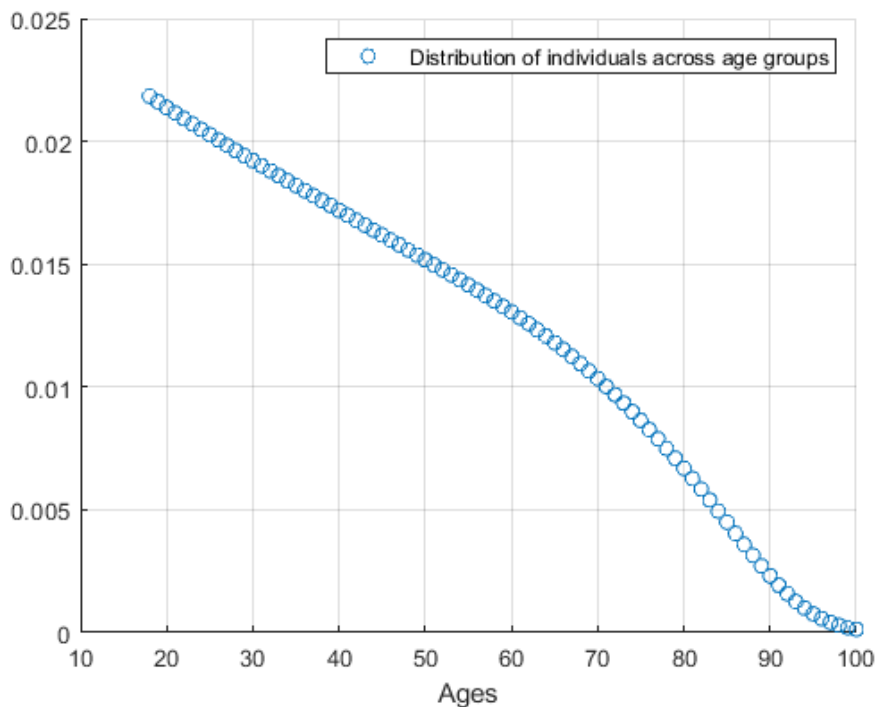
yshr_tax	0.17833	2.8338e+06	0.035661	0.19998	0.11386	0.036506
yshr_nttxss	0.080996	2.8048e+06	0.24691	3.0485	1.2592	-0.89715

### 7.3.3 Show Distribution by Age

Note that the age-distribution is exogenously determined by the age-specific survival rate. From: `load('Mortality_prob_by_age_18_99.mat','mort_prob') psi_full=1-mort_prob;`

First, we generate a vector for the age-specific mass, and visualize this.

```
ar_fl_phi_true_age = NaN([size(Phi_true,1),1]);
for it_age_ctr=1:size(Phi_true,1)
    ar_fl_phi_true_age(it_age_ctr,1) = sum(Phi_true(it_age_ctr,:));
end
ar_ages = 18:(18+size(Phi_true,1)-1);
% Graph
figure();
h1 = scatter(ar_ages, ar_fl_phi_true_age);
grid on;
legend1 = sprintf('Distribution of individuals across age groups');
legend({legend1});
xlabel("Ages");
```



Second, given some overall age span from age  $X_l$  to  $X_u$ , we consider  $G$  segments within, and the conditional probability of mass in each of the  $G$  segments within  $X_l$  to  $X_u$  bounds.

```
% Overall prime-age
it_age_min = 18;
it_age_max = 65;
ar_ages_18t65 = ((ar_ages<=it_age_max) & (ar_ages>=it_age_min));
ar_fl_phi_true_age_18t65 = ar_fl_phi_true_age(ar_ages_18t65);
fl_total_mass_18t65 = sum(ar_fl_phi_true_age_18t65);
% Sub-segments
ar_it_lower = [18, 25, 55]';
ar_it_higher = [24, 54, 65]';
ar_fl_p_agegrp_condi_18t65 = NaN([length(ar_it_lower),1]);
```

```

for it_age_ctr=1:length(ar_it_lower)
    it_age_lower = ar_it_lower(it_age_ctr);
    it_age_higher = ar_it_higher(it_age_ctr);
    ar_ages_subgrp = ((ar_ages<=it_age_higher) & (ar_ages>=it_age_lower));
    ar_fl_phi_true_age_subgrp = ar_fl_phi_true_age(ar_ages_subgrp);
    ar_fl_p_agegrp_condi_18t65(it_age_ctr) = sum(ar_fl_phi_true_age_subgrp)/fl_total_mass_18t65;
end
disp(['sum of ar_fl_p_agegrp_condi_18t65=' num2str(sum(ar_fl_p_agegrp_condi_18t65))]);

sum of ar_fl_p_agegrp_condi_18t65=1

disp(table(ar_fl_p_agegrp_condi_18t65, ar_it_lower, ar_it_higher));

```

ar_fl_p_agegrp_condi_18t65	ar_it_lower	ar_it_higher
-----	-----	-----
0.18278	18	24
0.64041	25	54
0.17681	55	65

## 7.4 Distribution with One Period Policy Shift

This is the example vignette for function: [snw\\_ds\\_main\\_vec](#) from the [PrjOptiSNW Package](#).

### 7.4.1 One-period Deviation from Steady-State given Alternative Policy Function

In addition to solving for distribution given one policy function, [snw\\_ds\\_main\\_vec](#) can also solve for the distributional shift from "steady-state" with a one-period policy shift.

If a 6th parameter, PHI\_ADJ\_BASE, is provided to [snw\\_ds\\_main\\_vec](#), solve for next-period forward distribution conditional on PHI\_ADJ\_BASE, using the policy function provided to [snw\\_ds\\_main\\_vec](#) as the 3rd and 4th parameters.

When PHI\_ADJ\_BASE is provided, if the AP\_SS, CONS\_SS policy functions inputs are from the same problem that generated PHI\_ADJ\_BASE, output PHI\_ADJ will be identical to PHI\_ADJ\_BASE. However, if AP\_SS, CONS\_SS are different policy functions from those that induced PHI\_ADJ\_BASE, PHI\_ADJ output will be different from PHI\_ADJ\_BASE input.

This allows for obtaining the distributional impact of a one period policy, allowing for deviation from "steady-state" distribution. This is used to solve for the distribution after one-period MIT shock, given stimulus checks provided in that period.

This is used to model the distributional effects of CARES Act, the two rounds of Trump Stimulus Checks, on household asset distribution when then receive the Biden stimulus checks from the the American Recovery Act. In effect, we have two MIT shock periods.

### 7.4.2 Solve for "Steady-State" Policy and Value Functions

Steady-state policy and value functions

```

% mp_params = snw_mp_param('default_dense');
mp_params = snw_mp_param('default_docdense');
% mp_params = snw_mp_param('default_moredense_a65zh133zs5_e2m2');
mp_controls = snw_mp_control('default_test');
mp_controls('bl_print_vfi') = false;
mp_controls('bl_print_vfi_verbose') = false;
mp_controls('bl_print_ds') = false;
mp_controls('bl_print_ds_verbose') = false;
[V_ss,ap_ss,cons_ss,mp_valpol_more_ss] = snw_vfi_main_bisec_vec(mp_params, mp_controls);

```



```
Completed SNW_VFI_MAIN_BISEC_VEC;SNW_MP_PARAM=default_docdense;SNW_MP_CONTROL=default_test;time=550.
```

### 7.4.3 Solve for "Steady-State" Distribution

Solve for steady-state distributions, using steady-state policy functions.

```
[Phi_true_ss,Phi_adj_ss,A_agg_ss,Y_inc_agg_ss,~,mp_dsvfi_results_ss] = ...
    snw_ds_main_vec(mp_params, mp_controls, ap_ss, cons_ss);
```

```
Completed SNW_VFI_MAIN_BISEC_VEC;SNW_MP_PARAM=default_docdense;SNW_MP_CONTROL=default_test;time=547.
Completed SNW_DS_MAIN_VEC;SNW_MP_PARAM=default_docdense;SNW_MP_CONTROL=default_test;time=1786.6361
```

```
% [Phi_true,Phi_adj] = snw_ds_main(mp_params, mp_controls);
Phi_true_ss = Phi_true_ss/sum(Phi_true_ss(:));
```

Show distributional results.

```
mp_cl_mt_xyz_of_s = mp_dsvfi_results_ss('mp_cl_mt_xyz_of_s');
disp(mp_cl_mt_xyz_of_s('tb_outcomes'));
```

	mean	unweighted_sum	sd	coefofvar	gini	min
	-----	-----	-----	-----	-----	-----
a_ss	4.3602	2228	6.8796	1.5778	0.6755	0
ap_ss	4.4621	5.3216e+08	6.9169	1.5501	0.67638	0
cons_ss	1.0635	5.0787e+07	0.6938	0.65237	0.33936	0.036717
n_ss	2.3554	21	1.4375	0.61029	0.3128	1
y_all	1.4661	8.3558e+07	1.4665	1.0003	0.44546	0.038108
y_head_inc	1.1081	1.9253e+06	1.013	0.91419	0.42164	0.038108
y_head_earn	0.88655	19732	0.92804	1.0468	0.53121	0
y_spouse_inc	0.35797	4.827e+05	0.95437	2.6661	0.85269	0
yshr_interest	0.12865	3.8438e+06	0.17577	1.3663	0.65781	0
yshr_wage	0.77402	8.8881e+06	0.33679	0.43512	0.2062	0
yshr_SS	0.097329	29012	0.2266	2.3282	0.91382	0
yshr_tax	0.17833	2.8338e+06	0.035661	0.19998	0.11386	0.036506
yshr_nttxss	0.080996	2.8048e+06	0.24691	3.0485	1.2592	-0.89715

### 7.4.4 Solve for Policy Function Under Trump Stimulus

Same continuation value as prior (steady-state continuation), but now solve for new policy (one round) due to Trump stimulus. Same tax rate in covid and other years, manna-from-heaven. This calls the [snw\\_vfi\\_main\\_bisec\\_vec\\_stimulus](#) function, which provides the stimulus checks as a function of income and family status.

```
mp_params('a2_covidyr') = mp_params('a2_covidyr_manna_heaven');
[~,ap_trumpchecks,cons_trumpchecks, mp_valpol_more_trumpchecks] = ...
    snw_vfi_main_bisec_vec_stimulus(mp_params, mp_controls, V_ss);
```

```
Completed SNW_VFI_MAIN_BISEC_VEC 1 Period Unemp Shock;SNW_MP_PARAM=default_docdense;SNW_MP_CONTROL=d
```

### 7.4.5 Solve for Updated Distribution given Trump Stimulus

Fixing mass at their steady-state distribution, policy functions shift to the Trump stimulus policies, resolve for one-period forward distribution. The distributional code is almost identical, except uses steady-state distribution as the "base" distribution via parameter PHI\_ADJ\_SS.

```
[Phi_true_trumpchecks,Phi_adj_trumpchecks,...
    A_agg_trumpchecks,Y_inc_agg_trumpchecks,~,mp_dsvfi_results_trumpchecks] = snw_ds_main_vec(...
    mp_params, mp_controls, ...
    ap_trumpchecks, cons_trumpchecks, ...
```

```

mp_valpol_more_trumpchecks, ...
Phi_adj_ss);

Completed SNW_DS_MAIN_VEC;SNW_MP_PARAM=default_docdense;SNW_MP_CONTROL=default_test;time=1546.0593

Phi_true_trumpchecks = Phi_true_trumpchecks/sum(Phi_true_trumpchecks(:));

Show distributional results.

mp_cl_mt_xyz_of_s = mp_dsvfi_results_trumpchecks('mp_cl_mt_xyz_of_s');
disp(mp_cl_mt_xyz_of_s('tb_outcomes'));

```

	mean	unweighted_sum	sd	coefofvar	gini	min
	-----	-----	-----	-----	-----	-----
a_ss	4.3988	2228	6.8731	1.5625	0.66733	0
ap_ss	4.5367	5.326e+08	6.9044	1.5219	0.66162	0
cons_ss	1.0761	5.0871e+07	0.68968	0.64091	0.33326	0.048012
n_ss	2.3554	21	1.4375	0.61029	0.3128	1
y_all	1.4676	8.3558e+07	1.4664	0.99915	0.44498	0.038108
y_head_inc	1.1097	1.9253e+06	1.0127	0.9126	0.42095	0.038108
y_head_earn	0.88655	19732	0.92804	1.0468	0.53121	0
y_spouse_inc	0.35797	4.827e+05	0.95437	2.6661	0.85269	0
yshr_interest	0.13035	3.8438e+06	0.1754	1.3457	0.64346	0
yshr_wage	0.77264	8.8881e+06	0.33616	0.43508	0.21167	0
yshr_SS	0.097017	29012	0.22582	2.3276	0.91391	0
yshr_tax	0.17842	2.8338e+06	0.035595	0.1995	0.11358	0.036506
yshr_nttxss	0.081403	2.8048e+06	0.24609	3.0231	1.249	-0.89715

#### 7.4.6 Debug Check, SNW\_DS\_MAIN\_VEC with Steady State Policies

This is to confirm that code is working properly. If we use steady-state policy functions and also provide as a sixth parameter the steady-state distribution, PHI\_ADJ\_SS, to `snw_ds_main_vec`, we should get back the same distribution, PHI\_TRUE\_SS\_WITH\_EXISTDIST\_DEBUG, which is the same as PHI\_ADJ\_SS. See that the distributional outputs at the end of this subsection is the same as the distributional table before the table directly prior.

```

[Phi_true_ss_with_existdist_debug,~,~,~,~,mp_dsvfi_results_ss_with_existdist_debug] = snw_ds_main_vec(
mp_params, mp_controls, ...
ap_ss, cons_ss, ...
mp_valpol_more_ss, ...
Phi_adj_ss);

Completed SNW_DS_MAIN_VEC;SNW_MP_PARAM=default_docdense;SNW_MP_CONTROL=default_test;time=1848.7637

Phi_true_ss_with_existdist_debug = Phi_true_ss_with_existdist_debug/sum(Phi_true_ss_with_existdist_d

Show distributional results.

mp_cl_mt_xyz_of_s = mp_dsvfi_results_ss_with_existdist_debug('mp_cl_mt_xyz_of_s');
disp(mp_cl_mt_xyz_of_s('tb_outcomes'));

```

	mean	unweighted_sum	sd	coefofvar	gini	min
	-----	-----	-----	-----	-----	-----
a_ss	4.3602	2228	6.8796	1.5778	0.6755	0
ap_ss	4.4621	5.3216e+08	6.9169	1.5501	0.67638	0
cons_ss	1.0635	5.0787e+07	0.6938	0.65237	0.33936	0.036717
n_ss	2.3554	21	1.4375	0.61029	0.3128	1
y_all	1.4661	8.3558e+07	1.4665	1.0003	0.44546	0.038108
y_head_inc	1.1081	1.9253e+06	1.013	0.91419	0.42164	0.038108

y_head_earn	0.88655	19732	0.92804	1.0468	0.53121	0
y_spouse_inc	0.35797	4.827e+05	0.95437	2.6661	0.85269	0
yshr_interest	0.12865	3.8438e+06	0.17577	1.3663	0.65781	0
yshr_wage	0.77402	8.8881e+06	0.33679	0.43512	0.2062	0
yshr_SS	0.097329	29012	0.2266	2.3282	0.91382	0
yshr_tax	0.17833	2.8338e+06	0.035661	0.19998	0.11386	0.036506
yshr_nttxss	0.080996	2.8048e+06	0.24691	3.0485	1.2592	-0.89715



# Chapter 8

## Value of Each Check

### 8.1 2020 V and C without Unemployment

This is the example vignette for function: `snw_a4chk_wrk_bisec_vec` from the [PrjOptiSNW Package](#). This function solves for the V(states, check) for individuals working. Dense solution. Bisection, most time for the test here taken to generate the income matrixes. But these can be generated out of the check loops.

#### 8.1.1 Test SNW\_A4CHK\_WRK\_BISEC\_VEC Defaults Dense

Call the function with default parameters. Solve first for non-covid value and policy. Then depending on 2020 taxes, solve for 2020 policy and value.

```
mp_params = snw_mp_param('default_docdense');
% mp_params = snw_mp_param('default_dense');
mp_params('beta') = 0.95;
mp_controls = snw_mp_control('default_test');
mp_controls('bl_print_vfi') = false;
mp_controls('bl_timer') = true;
[V_ss,~,cons_ss,~] = snw_vfi_main_bisec_vec(mp_params, mp_controls);
```

Completed SNW\_VFI\_MAIN\_BISEC\_VEC;SNW\_MP\_PARAM=default\_docdense;SNW\_MP\_CONTROL=default\_test;time=501.

```
-----
XXXXXXXXXXXXXXXXXXXXXXXXXXXXXXXXXXXXXXXXXXXX
CONTAINER NAME: mp_outcomes ND Array (Matrix etc)
XXXXXXXXXXXXXXXXXXXXXXXXXXXXXXXXXXXXXXXXXXXX
```

	i	idx	ndim	numel	rowN	colN	sum	mean	std
V_VFI	1	1	6	4.37e+07	83	5.265e+05	-6.6619e+08	-15.245	21.86
ap_VFI	2	2	6	4.37e+07	83	5.265e+05	1.3967e+09	31.962	36.42
cons_VFI	3	3	6	4.37e+07	83	5.265e+05	2.3276e+08	5.3263	8.441

```
xxx TABLE:V_VFI XXXXXXXXXXXXXXXXXXXXXXXX
```

	c1	c2	c3	c4	c5	c526496	c526497	c526498
r1	-293.96	-293.57	-291.09	-285.44	-276.41	-4.3584	-4.2643	-4.171
r2	-284.42	-284.03	-281.55	-275.97	-267.24	-4.2519	-4.1612	-4.071
r3	-274.87	-274.48	-272.03	-266.62	-258.33	-4.1429	-4.0559	-3.969
r4	-265.22	-264.86	-262.58	-257.53	-249.74	-4.0309	-3.9475	-3.864
r5	-256.51	-256.17	-254.04	-249.3	-241.96	-3.9252	-3.8452	-3.765
r79	-13.642	-13.628	-13.535	-13.298	-12.896	-0.22092	-0.21058	-0.2008

r80	-12.283	-12.269	-12.176	-11.939	-11.537	-0.16979	-0.16182	-0.154
r81	-10.605	-10.591	-10.498	-10.261	-9.8589	-0.11712	-0.11163	-0.1064
r82	-8.3494	-8.3358	-8.2424	-8.0055	-7.6035	-0.065333	-0.062242	-0.0593
r83	-5.0665	-5.0529	-4.9595	-4.7226	-4.3206	-0.020968	-0.019972	-0.01903

```
xxx TABLE:ap_VFI xxxxxxxxxxxxxxxxxxxxxxxx
```

	c1	c2	c3	c4	c5	c526496	c526497	c526498	c526499
r1	0	0	0.00051498	0.0066578	0.021589	112.13	117.67	123.4	129.3
r2	0	0	0.00051498	0.0057684	0.020245	112.17	117.71	123.43	129.3
r3	0	0	0.00020768	0.0041456	0.018539	112.2	117.73	123.45	129.3
r4	0	0	0.00010346	0.0041199	0.018307	112.86	118.39	124.11	130.0
r5	0	0	5.2907e-06	0.0041199	0.018091	113.53	119.07	124.79	130.7
r79	0	0	0	0	0	81.091	85.364	89.335	93.25
r80	0	0	0	0	0	76.124	79.747	83.431	86.98
r81	0	0	0	0	0	67.945	70.639	73.673	76.99
r82	0	0	0	0	0	50.126	53.467	56.302	57.88
r83	0	0	0	0	0	0	0	0	0

```
xxx TABLE:cons_VFI xxxxxxxxxxxxxxxxxxxxxxxx
```

	c1	c2	c3	c4	c5	c526496	c526497	c526498
r1	0.036717	0.037251	0.040477	0.044486	0.049324	12.265	12.55	12.844
r2	0.036717	0.037251	0.040477	0.045375	0.050668	12.501	12.787	13.082
r3	0.036717	0.037251	0.040784	0.046998	0.052374	12.755	13.042	13.337
r4	0.038144	0.038678	0.042314	0.048449	0.054031	13	13.289	13.584
r5	0.039534	0.040068	0.043802	0.049839	0.055635	13.236	13.525	13.821
r79	0.19737	0.19791	0.20163	0.21175	0.23145	35.811	37.362	39.409
r80	0.19737	0.19791	0.20163	0.21175	0.23145	40.752	42.953	45.286
r81	0.19737	0.19791	0.20163	0.21175	0.23145	48.909	52.039	55.022
r82	0.19737	0.19791	0.20163	0.21175	0.23145	66.71	69.193	72.375
r83	0.19737	0.19791	0.20163	0.21175	0.23145	116.82	122.65	128.66

```
welf_checks = 2; % 2 checks is $200 dollar of welfare checks
xi=1; % xi=0 full income loss from covid shock, xi=1, no covid income losses
b=1; % when xi=1, b does not matter, no income losses
TR = 100/58056;
mp_params('TR') = TR;
mp_params('xi') = xi;
mp_params('b') = b;
% if = mp_params('a2_covidyr_manna_heaven'), V_emp_2020 same as V_ss if b=1
% or xi=1.
% if = mp_params('a2_covidyr_tax_fully_pay'), V_emp_2020 differ due to 2020
% tax differences
mp_params('a2_covidyr') = mp_params('a2_covidyr_manna_heaven');
% mp_params('a2_covidyr') = mp_params('a2_covidyr_tax_fully_pay');
[V_emp_2020,~,cons_emp_2020,~] = snw_vfi_main_bisec_vec(mp_params, mp_controls, V_ss);
```

Completed SNW\_VFI\_MAIN\_BISEC\_VEC 1 Period Unemp Shock;SNW\_MP\_PARAM=default\_docdense;SNW\_MP\_CONTROL=

```
xxxxxxxxxxxxxxxxxxxxxxxxxxxxxxxxxxxxxxxxxxxxxxxxxxxxxxxxxxxxxxxxxxxxxxxx
CONTAINER NAME: mp_outcomes ND Array (Matrix etc)
xxxxxxxxxxxxxxxxxxxxxxxxxxxxxxxxxxxxxxxxxxxxxxxxxxxxxxxxxxxxxxxxxxxxxxxx
```

i	idx	ndim	numel	rowN	colN	sum	mean	std
-	---	----	-----	----	-----	-----	-----	-----

V_VFI	1	1	6	4.37e+07	83	5.265e+05	-6.6619e+08	-15.245	21.86
ap_VFI	2	2	6	4.37e+07	83	5.265e+05	1.3967e+09	31.962	36.42
cons_VFI	3	3	6	4.37e+07	83	5.265e+05	2.3276e+08	5.3263	8.441

xxx TABLE:V\_VFI xxxxxxxxxxxxxxxxxxxxxxxx

	c1	c2	c3	c4	c5	c526496	c526497	c526498
r1	-293.96	-293.57	-291.09	-285.44	-276.41	-4.3584	-4.2643	-4.171
r2	-284.42	-284.03	-281.55	-275.97	-267.24	-4.2519	-4.1612	-4.071
r3	-274.87	-274.48	-272.03	-266.62	-258.33	-4.1429	-4.0559	-3.969
r4	-265.22	-264.86	-262.58	-257.53	-249.74	-4.0309	-3.9475	-3.864
r5	-256.51	-256.17	-254.04	-249.3	-241.96	-3.9252	-3.8452	-3.765
r79	-13.642	-13.628	-13.535	-13.298	-12.896	-0.22092	-0.21058	-0.2008
r80	-12.283	-12.269	-12.176	-11.939	-11.537	-0.16979	-0.16182	-0.154
r81	-10.605	-10.591	-10.498	-10.261	-9.8589	-0.11712	-0.11163	-0.1064
r82	-8.3494	-8.3358	-8.2424	-8.0055	-7.6035	-0.065333	-0.062242	-0.0593
r83	-5.0665	-5.0529	-4.9595	-4.7226	-4.3206	-0.020968	-0.019972	-0.01903

xxx TABLE:ap\_VFI xxxxxxxxxxxxxxxxxxxxxxxx

	c1	c2	c3	c4	c5	c526496	c526497	c526498	c5264
r1	0	0	0.00051498	0.0066578	0.021589	112.13	117.67	123.4	129.3
r2	0	0	0.00051498	0.0057684	0.020245	112.17	117.71	123.43	129.3
r3	0	0	0.00020768	0.0041456	0.018539	112.2	117.73	123.45	129.3
r4	0	0	0.00010346	0.0041199	0.018307	112.86	118.39	124.11	130.0
r5	0	0	5.2907e-06	0.0041199	0.018091	113.53	119.07	124.79	130.7
r79	0	0	0	0	0	81.091	85.364	89.335	93.25
r80	0	0	0	0	0	76.124	79.747	83.431	86.98
r81	0	0	0	0	0	67.945	70.639	73.673	76.99
r82	0	0	0	0	0	50.126	53.467	56.302	57.88
r83	0	0	0	0	0	0	0	0	0

xxx TABLE:cons\_VFI xxxxxxxxxxxxxxxxxxxxxxxx

	c1	c2	c3	c4	c5	c526496	c526497	c526498
r1	0.036717	0.037251	0.040477	0.044486	0.049324	12.265	12.55	12.844
r2	0.036717	0.037251	0.040477	0.045375	0.050668	12.501	12.787	13.082
r3	0.036717	0.037251	0.040784	0.046998	0.052374	12.755	13.042	13.337
r4	0.038144	0.038678	0.042314	0.048449	0.054031	13	13.289	13.584
r5	0.039534	0.040068	0.043802	0.049839	0.055635	13.236	13.525	13.821
r79	0.19737	0.19791	0.20163	0.21175	0.23145	35.811	37.362	39.409
r80	0.19737	0.19791	0.20163	0.21175	0.23145	40.752	42.953	45.286
r81	0.19737	0.19791	0.20163	0.21175	0.23145	48.909	52.039	55.022
r82	0.19737	0.19791	0.20163	0.21175	0.23145	66.71	69.193	72.375
r83	0.19737	0.19791	0.20163	0.21175	0.23145	116.82	122.65	128.66

[V\_W\_2020, C\_W\_2020] = snw\_a4chk\_wrk\_bisec\_vec(welf\_checks, V\_emp\_2020, cons\_emp\_2020, mp\_params, mp

Completed SNW\_A4CHK\_WRK\_BISEC\_VEC;SNW\_MP\_PARAM=st\_biden\_or\_trump\_undefined;welf\_checks=2;TR=0.001722

xx

CONTAINER NAME: mp\_container\_map ND Array (Matrix etc)

xx

i	idx	ndim	numel	rowN	colN	sum	mean
-	---	----	-----	----	-----	-----	-----

C_W	1	1	6	4.37e+07	83	5.265e+05	2.3278e+08	5.3269
C_W_minus_C_ss	2	2	6	4.37e+07	83	5.265e+05	25096	0.00057428
V_W	3	3	6	4.37e+07	83	5.265e+05	-6.6561e+08	-15.231
V_W_minus_V_ss	4	4	6	4.37e+07	83	5.265e+05	5.8108e+05	0.013297
mn_MPC	5	5	6	4.37e+07	83	5.265e+05	7.2848e+06	0.1667

```
mn_V_W_gain_check = V_W_2020 - V_emp_2020;
mn_MPC_W_gain_share_check = (C_W_2020 - cons_emp_2020)./(welf_checks*mp_params('TR'));
```

### 8.1.2 Dense Param Results Define Frames

Define the matrix dimensions names and dimension vector values. Policy and Value Functions share the same ND dimensional structure.

```
% Grids:
age_grid = 18:100;
agrid = mp_params('agrid');
eta_H_grid = mp_params('eta_H_grid');
eta_S_grid = mp_params('eta_S_grid');
ar_st_eta_HS_grid = string(cellstr([num2str(eta_H_grid', 'hz=%3.2f;'), num2str(eta_S_grid', 'wz=%3.2f;')]);
edu_grid = [0,1];
marry_grid = [0,1];
kids_grid = (1:1:mp_params('n_kidsgrid'))';
% NaN(n_jgrid,n_agrid,n_etagrid,n_educgrid,n_marriedgrid,n_kidsgrid);
cl_mp_datasetdesc = {};
cl_mp_datasetdesc{1} = containers.Map({'name', 'labval'}, {'age', age_grid});
cl_mp_datasetdesc{2} = containers.Map({'name', 'labval'}, {'savings', agrid});
cl_mp_datasetdesc{3} = containers.Map({'name', 'labval'}, {'eta', 1:length(eta_H_grid)});
cl_mp_datasetdesc{4} = containers.Map({'name', 'labval'}, {'edu', edu_grid});
cl_mp_datasetdesc{5} = containers.Map({'name', 'labval'}, {'marry', marry_grid});
cl_mp_datasetdesc{6} = containers.Map({'name', 'labval'}, {'kids', kids_grid});
```

### 8.1.3 Analyze Difference in V and C with Check

The difference between V and V with Check, marginal utility gain given the check.

```
% Generate some Data
mp_support_graph = containers.Map('KeyType', 'char', 'ValueType', 'any');
mp_support_graph('cl_st_xtitle') = {'Savings States, a'};
mp_support_graph('st_legend_loc') = 'eastoutside';
mp_support_graph('bl_graph_logy') = true; % do not log
mp_support_graph('it_legend_select') = 21; % how many shock legends to show
mp_support_graph('cl_colors') = 'jet';
```

```
MEAN(MN_V_GAIN_CHECK(A,Z))
```

Tabulate value and policies along savings and shocks:

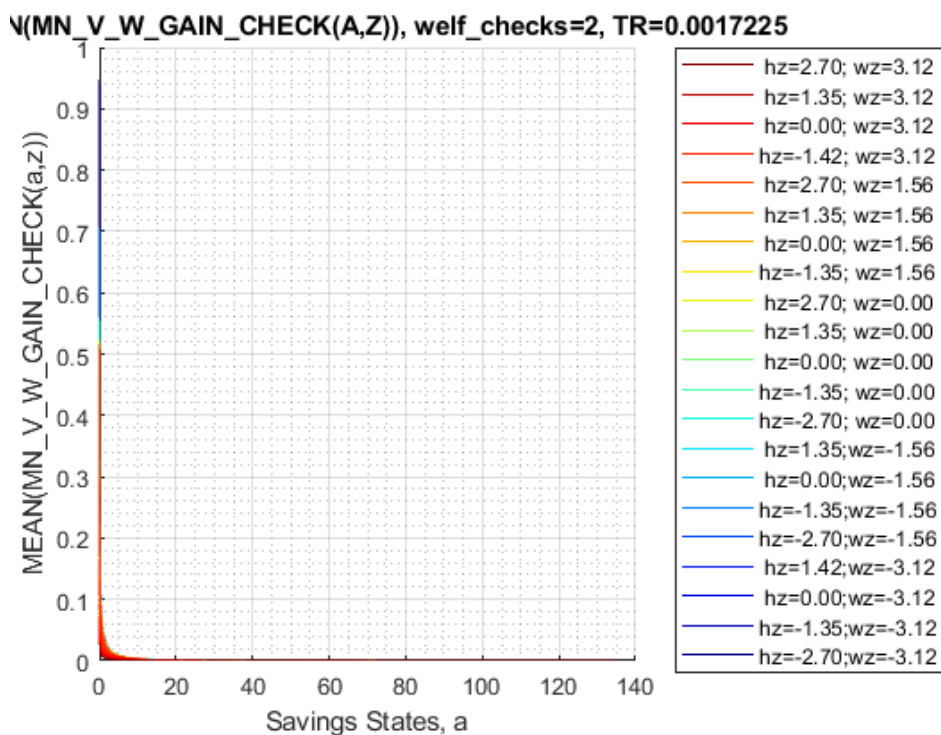
```
% Set
ar_permute = [1,4,5,6,3,2];
% Value Function
st_title = ['MEAN(MN_V_W_GAIN_CHECK(A,Z)), welf_checks=' num2str(welf_checks) ', TR=' num2str(mp_par
tb_az_v = ff_summ_nd_array(st_title, mn_V_W_gain_check, true, ["mean"], 4, 1, cl_mp_datasetdesc, ar_

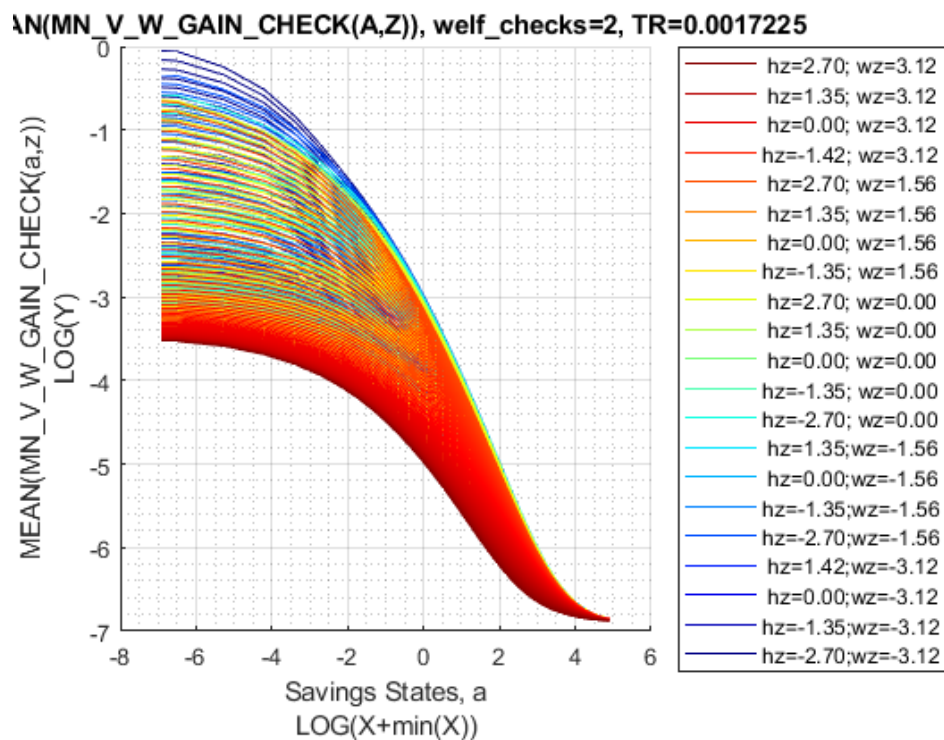
xxx MEAN(MN_V_W_GAIN_CHECK(A,Z)), welf_checks=2, TR=0.0017225 xxxxxxxxxxxxxxxxxxxxxxxxxxxxxxxx
group      savings      mean_eta_1      mean_eta_2      mean_eta_3      mean_eta_4      mean_eta_5      mea
-----
1          0          0.94877        0.84952        0.761          0.68204        0.61169
```



3      0.0041199      0.78107      0.71106      0.6451      0.58402      0.52829

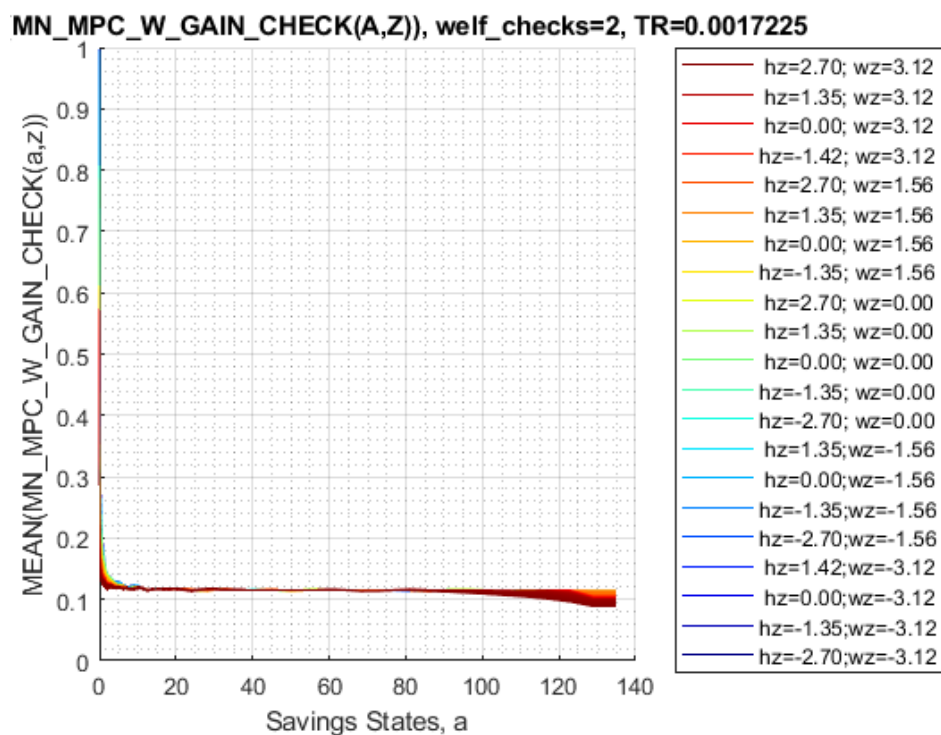
```
st_title = ['MEAN(MN\V\W\_GAIN\_CHECK(A,Z)), welf\_checks=' num2str(welf_checks) ', TR=' num2str(m
mp_support_graph('cl_st_graph_title') = {st_title};
mp_support_graph('cl_st_ytitle') = {'MEAN(MN\V\W\_GAIN\_CHECK(a,z))'};
ff_graph_grid((tb_az_v{1:end, 3:end})', ar_st_eta_HS_grid, agrid, mp_support_graph);
```

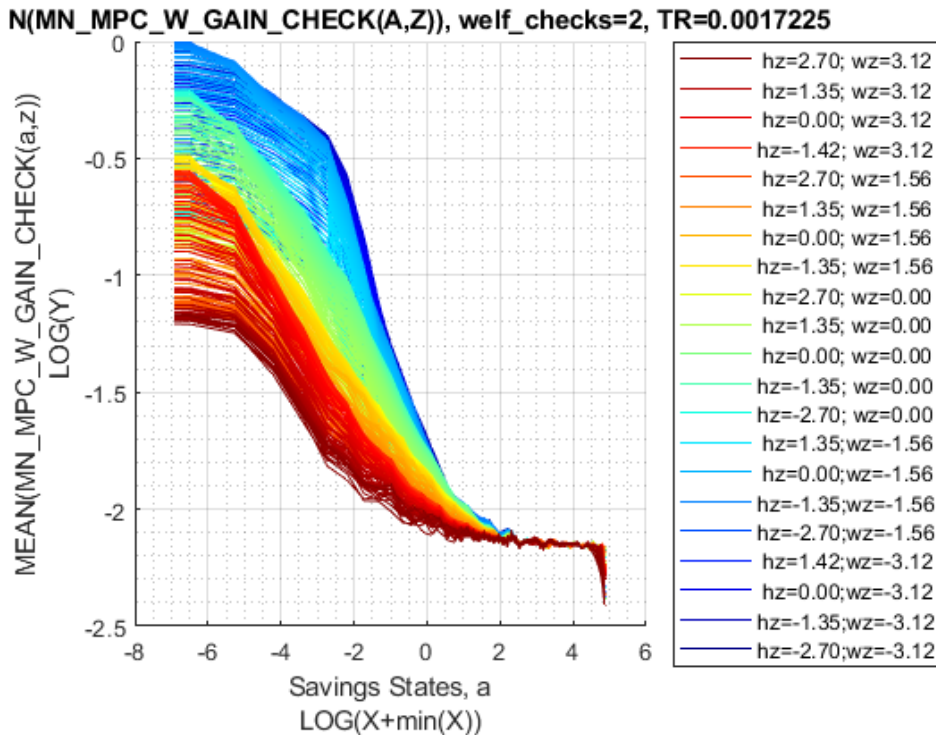




Graph Mean Consumption (*MPC: Share of Check Consumed*):

```
st_title = ['MEAN(MN\MPC_W_GAIN_CHECK(A,Z)), welf_checks=' num2str(welf_checks) ', TR=' num2str
mp_support_graph('cl_st_graph_title') = {st_title};
mp_support_graph('cl_st_ytitle') = {'MEAN(MN\MPC_W_GAIN_CHECK(a,z))'};
ff_graph_grid((tb_az_c{1:end, 3:end}'), ar_st_eta_HS_grid, agrid, mp_support_graph);
```





### 8.1.4 Analyze Kids and Marriage and Age

Aggregating over education, savings, and shocks, what are the differential effects of Marriage and Age.

```
% Generate some Data
mp_support_graph = containers.Map('KeyType', 'char', 'ValueType', 'any');
ar_row_grid = [...
    "k0M0", "K1M0", "K2M0", "K3M0", "K4M0", ...
    "k0M1", "K1M1", "K2M1", "K3M1", "K4M1"];
mp_support_graph('cl_st_xtitle') = {'Age'};
mp_support_graph('st_legend_loc') = 'best';
mp_support_graph('bl_graph_logy') = true; % do not log
mp_support_graph('st_rounding') = '6.2f'; % format shock legend
mp_support_graph('cl_scatter_shapes') = {...
    'o', 'd', 's', 'x', '*', ...
    'o', 'd', 's', 'x', '*'};
mp_support_graph('cl_colors') = {...
    'red', 'red', 'red', 'red', 'red'...
    'blue', 'blue', 'blue', 'blue', 'blue'};
```

MEAN(VAL(KM,J)), MEAN(AP(KM,J)), MEAN(C(KM,J))

Tabulate value and policies:

```
% Set
% NaN(n_jgrid,n_agrid,n_etagrid,n_educgrid,n_marriedgrid,n_kidsgrid);
ar_permute = [2,3,4,1,6,5];
% Value Function
st_title = ['MEAN(MN_V_W_GAIN_CHECK(KM,J)), welf_checks=' num2str(welf_checks) ', TR=' num2str(mp_pa
tb_az_v = ff_summ_nd_array(st_title, mn_V_W_gain_check, true, ["mean"], 3, 1, cl_mp_datasetdesc, ar_
```

xxx	MEAN(MN_V_W_GAIN_CHECK(KM,J)), welf_checks=2, TR=0.0017225 xxxxxxxxxxxxxxxxxxxxxxxxxxxxxxx						
group	kids	marry	mean_age_18	mean_age_19	mean_age_20	mean_age_21	mean_age_2
-----	----	-----	-----	-----	-----	-----	-----
1	1	0	0.028443	0.027382	0.02607	0.023829	0.021959

2	2	0	0.039131	0.037712	0.035894	0.032743	0.030106
3	3	0	0.04572	0.04432	0.04241	0.038719	0.035631
4	4	0	0.051937	0.050449	0.048354	0.044164	0.040661
5	5	0	0.056986	0.0555	0.053326	0.04875	0.044927
6	1	1	0.008385	0.0079795	0.0075874	0.0068616	0.0062549
7	2	1	0.011253	0.010708	0.010181	0.0092041	0.0083817
8	3	1	0.013554	0.012928	0.012313	0.011136	0.010147
9	4	1	0.016251	0.015529	0.014803	0.013404	0.012225
10	5	1	0.019768	0.018969	0.018139	0.016444	0.015026

% Consumption Function

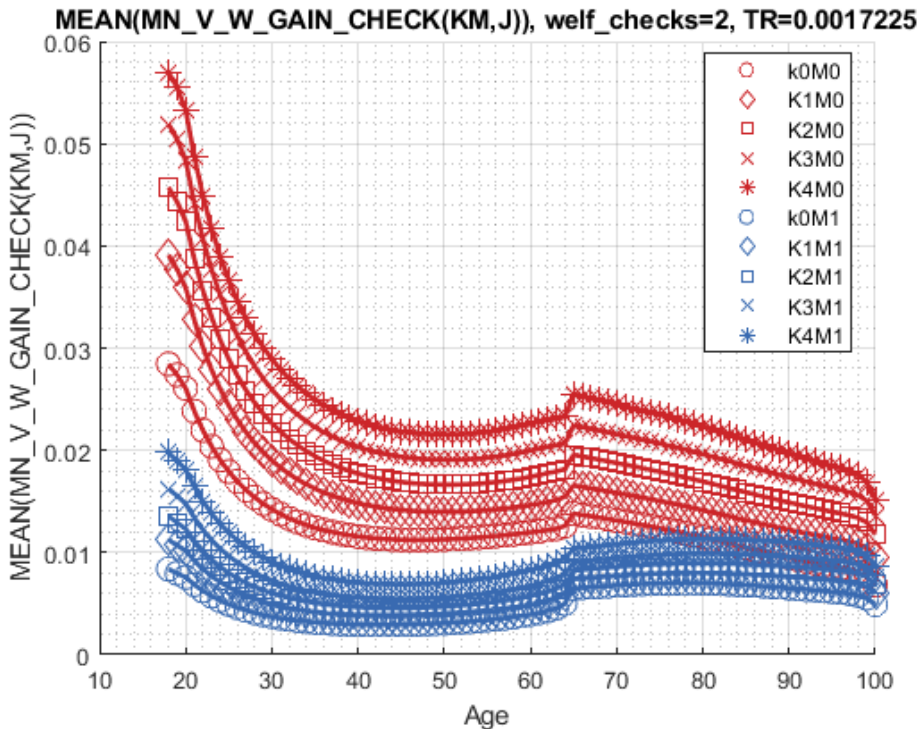
```
st_title = ['MEAN(MN_MPC_W_GAIN_CHECK(KM,J)), welf_checks=' num2str(welf_checks) ', TR=' num2str(mp_
tb_az_c = ff_summ_nd_array(st_title, mn_MPC_W_gain_share_check, true, ["mean"], 3, 1, cl_mp_datasetd
```

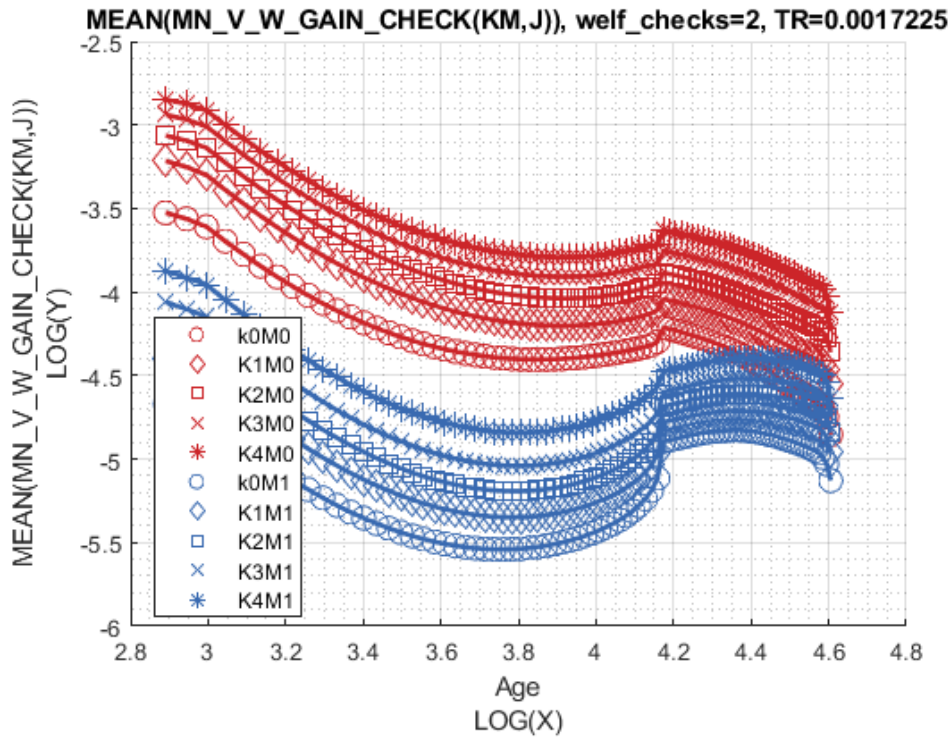
```
xxx MEAN(MN_MPC_W_GAIN_CHECK(KM,J)), welf_checks=2, TR=0.0017225 xxxxxxxxxxxxxxxxxxxxxxxxxxxxxxxx
group kids marry mean_age_18 mean_age_19 mean_age_20 mean_age_21 mean_age_2
-----
```

1	1	0	0.067542	0.074752	0.091075	0.088909	0.086942
2	2	0	0.075256	0.083119	0.10165	0.099284	0.097581
3	3	0	0.086542	0.095859	0.11593	0.11256	0.10948
4	4	0	0.091496	0.10076	0.12129	0.11824	0.11514
5	5	0	0.098346	0.10645	0.12728	0.12409	0.12073
6	1	1	0.10277	0.10672	0.1125	0.11137	0.11019
7	2	1	0.10343	0.1077	0.11433	0.11354	0.11208
8	3	1	0.10875	0.11374	0.12309	0.11975	0.11861
9	4	1	0.11014	0.11556	0.12324	0.12217	0.12228
10	5	1	0.1166	0.1232	0.13246	0.13017	0.12661

Graph Mean Values:

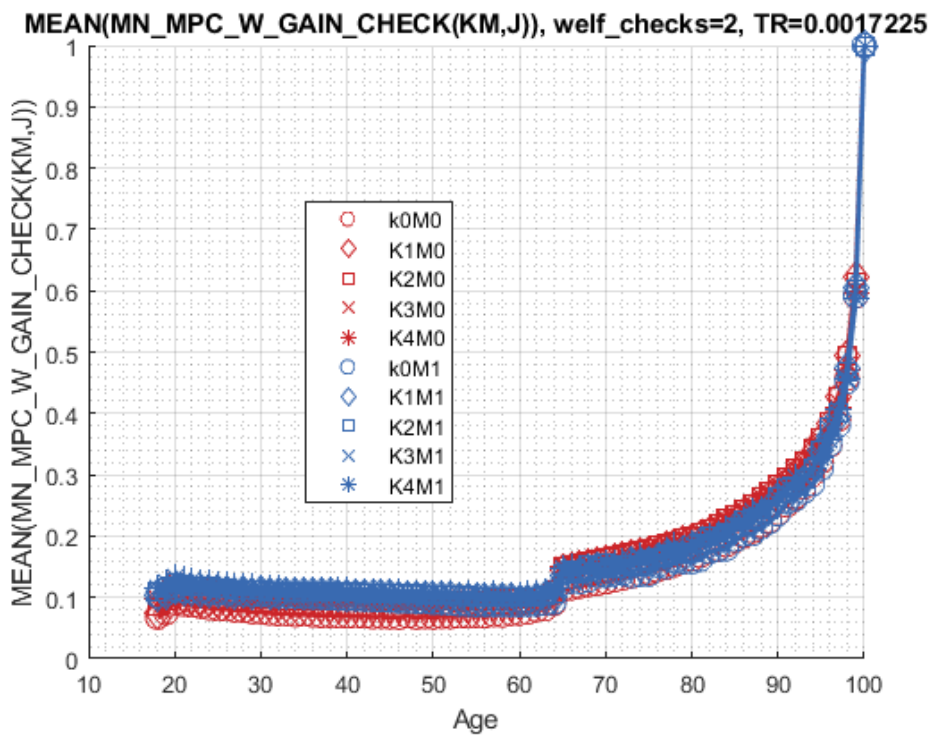
```
st_title = ['MEAN(MN_V_W_GAIN_CHECK(KM,J)), welf_checks=' num2str(welf_checks) ', TR=' num2str(
mp_support_graph('cl_st_graph_title') = {st_title};
mp_support_graph('cl_st_ytitle') = {'MEAN(MN_V_W_GAIN_CHECK(KM,J))'};
ff_graph_grid((tb_az_v{1:end, 4:end}), ar_row_grid, age_grid, mp_support_graph);
```

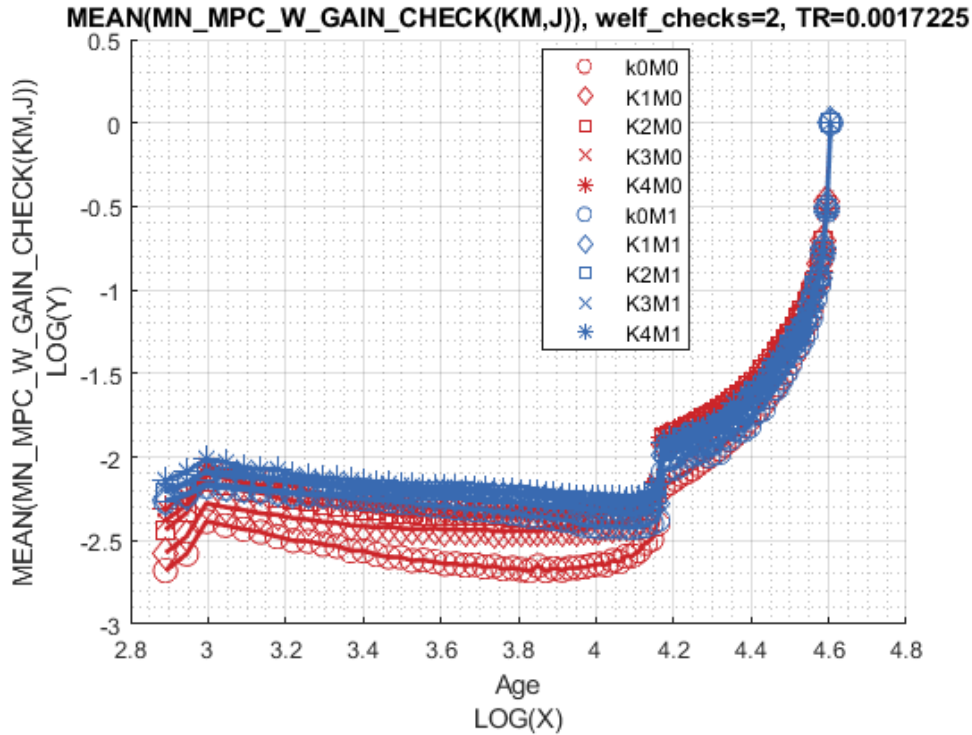




Graph Mean Consumption (*MPC: Share of Check Consumed*):

```
st_title = ['MEAN(MN\MPC\_W\_GAIN\_CHECK(KM,J)), welf\_checks=' num2str(welf_checks) ', TR=' num2str(
mp_support_graph('cl_st_graph_title') = {st_title};
mp_support_graph('cl_st_ytitle') = {'MEAN(MN\MPC\_W\_GAIN\_CHECK(KM,J))'};
ff_graph_grid((tb_az_c{1:end, 4:end}), ar_row_grid, age_grid, mp_support_graph);
```





### 8.1.5 Analyze Education and Marriage

Aggregating over education, savings, and shocks, what are the differential effects of Marriage and Age.

```
% Generate some Data
mp_support_graph = containers.Map('KeyType', 'char', 'ValueType', 'any');
ar_row_grid = ["E0M0", "E1M0", "E0M1", "E1M1"];
mp_support_graph('cl_st_xtitle') = {'Age'};
mp_support_graph('st_legend_loc') = 'best';
mp_support_graph('bl_graph_logy') = true; % do not log
mp_support_graph('st_rounding') = '6.2f'; % format shock legend
mp_support_graph('cl_scatter_shapes') = {'*', 'p', '*', 'p'};
mp_support_graph('cl_colors') = {'red', 'red', 'blue', 'blue'};
```

```
MEAN(VA(EM,J)), MEAN(AP(EM,J)), MEAN(C(EM,J))
```

Tabulate value and policies:

```
% Set
% NaN(n_jgrid,n_agrid,n_etagrid,n_educgrid,n_marriedgrid,n_kidsgrid);
ar_permute = [2,3,6,1,4,5];
% Value Function
st_title = ['MEAN(MN_V_W_GAIN_CHECK(EM,J)), welf_checks=' num2str(welf_checks) ', TR=' num2str(mp_pa
tb_az_v = ff_summ_nd_array(st_title, mn_V_W_gain_check, true, ["mean"], 3, 1, cl_mp_datasetdesc, ar_
```

```
xxx MEAN(MN_V_W_GAIN_CHECK(EM,J)), welf_checks=2, TR=0.0017225 xxxxxxxxxxxxxxxxxxxxxxxxxxxxxxxx
```

group	edu	marry	mean_age_18	mean_age_19	mean_age_20	mean_age_21	mean_age_22
1	0	0	0.045692	0.044619	0.043207	0.040746	0.03856
2	1	0	0.043194	0.041526	0.039215	0.034536	0.030754
3	0	1	0.014697	0.014079	0.01347	0.012491	0.01163
4	1	1	0.012987	0.012367	0.011739	0.010329	0.009184

```
% Consumption
st_title = ['MEAN(MN_MPC_W_GAIN_CHECK(EM,J)), welf_checks=' num2str(welf_checks) ', TR=' num2str(mp_
```

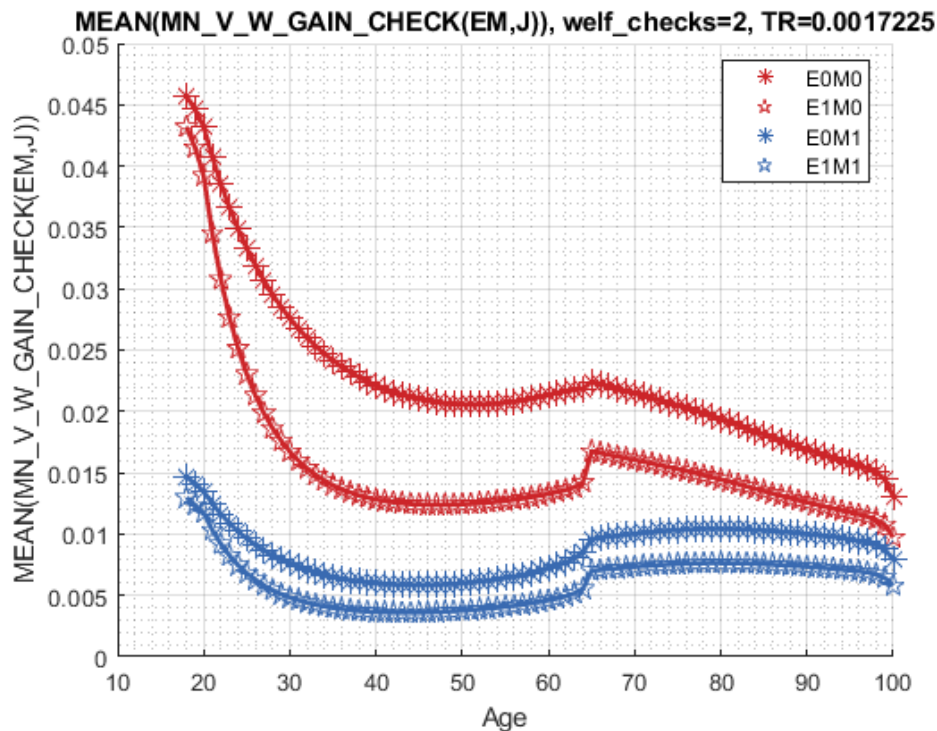
```
tb_az_c = ff_summ_nd_array(st_title, mn_MPC_W_gain_share_check, true, ["mean"], 3, 1, cl_mp_datasetd
```

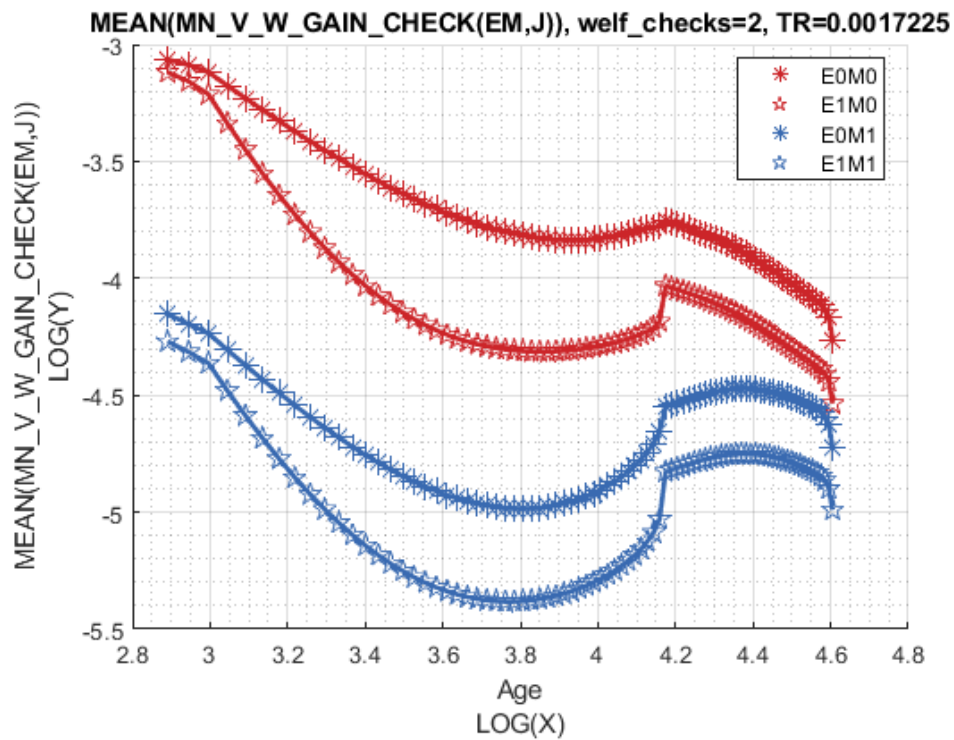
```
xxx MEAN(MN_MPC_W_GAIN_CHECK(EM,J)), welf_checks=2, TR=0.0017225 xxxxxxxxxxxxxxxxxxxxxxxxxxxxxxx
```

group	edu	marry	mean_age_18	mean_age_19	mean_age_20	mean_age_21	mean_age_22
1	0	0	0.075296	0.080407	0.092505	0.091671	0.091522
2	1	0	0.092377	0.10397	0.13038	0.12556	0.12042
3	0	1	0.099842	0.10362	0.10816	0.10847	0.10824
4	1	1	0.11684	0.12315	0.13408	0.13033	0.12767

Graph Mean Values:

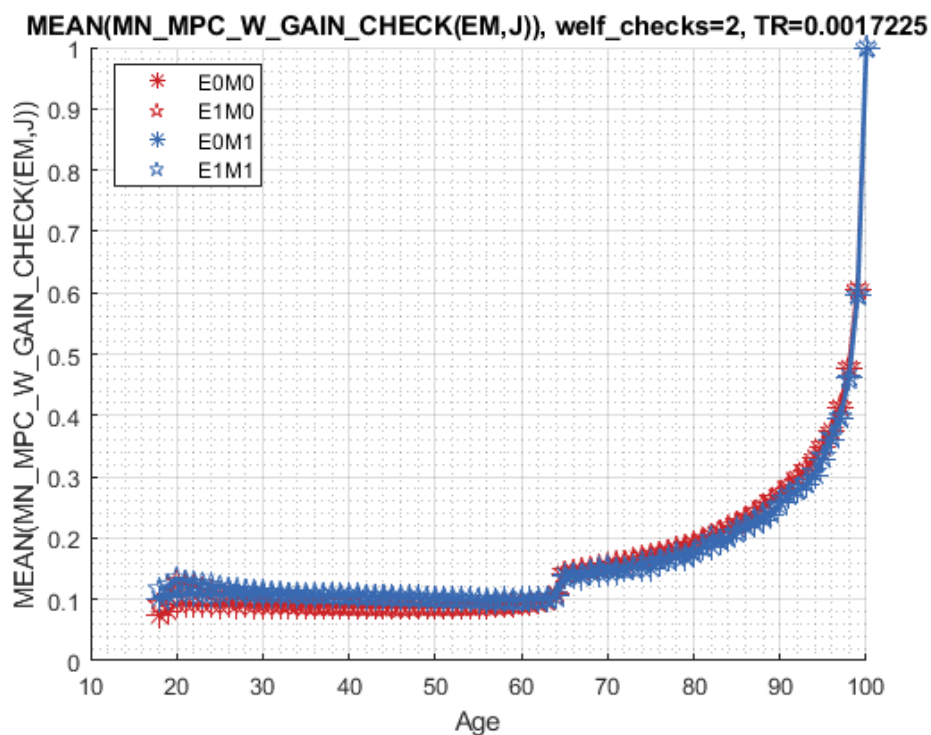
```
st_title = ['MEAN(MN_V_W_GAIN_CHECK(EM,J)), welf_checks=' num2str(welf_checks) ', TR=' num2str(
mp_support_graph('cl_st_graph_title') = {st_title};
mp_support_graph('cl_st_ytitle') = {'MEAN(MN_V_W_GAIN_CHECK(EM,J))'};
ff_graph_grid((tb_az_v{1:end, 4:end}), ar_row_grid, age_grid, mp_support_graph);
```





Graph Mean Consumption (*MPC: Share of Check Consumed*):

```
st_title = ['MEAN(MN\MPC\_W\_GAIN\_CHECK(EM,J)), welf\_checks=' num2str(welf_checks) ', TR=' num2str(
mp_support_graph('cl_st_graph_title') = {st_title};
mp_support_graph('cl_st_ytitle') = {'MEAN(MN\MPC\_W\_GAIN\_CHECK(EM,J))'};
ff_graph_grid((tb_az_c{1:end, 4:end}), ar_row_grid, age_grid, mp_support_graph);
```











```

XXXXXXXXXXXXXXXXXXXXXXXXXXXXXXXXXXXXXXXXXXXXXXXXXXXXXXXXXXXX
      i      idx      ndim      numel      rowN      colN      sum      mean
      -      ---      ----      -
C_U      1      1      6      4.37e+07      83      5.265e+05      2.2891e+08      5.2
C_U_minus_C_unemp      2      2      6      4.37e+07      83      5.265e+05      31259      0.00071
V_U      3      3      6      4.37e+07      83      5.265e+05      -6.8723e+08      -15.
V_U_minus_V_unemp      4      4      6      4.37e+07      83      5.265e+05      9.9746e+05      0.022
mn_MPC_unemp      5      5      6      4.37e+07      83      5.265e+05      9.0737e+06      0.20

```

```

mn_V_U_gain_check = V_U_2020 - V_unemp_2020;
mn_MPC_U_gain_share_check = (C_U_2020 - cons_unemp_2020)./(welf_checks*mp_params('TR'));

```

## 8.2.2 Dense Param Results Define Frames

Define the matrix dimensions names and dimension vector values. Policy and Value Functions share the same ND dimensional structure.

```

% Grids:
age_grid = 18:100;
agrid = mp_params('agrid');
eta_H_grid = mp_params('eta_H_grid');
eta_S_grid = mp_params('eta_S_grid');
ar_st_eta_HS_grid = string(cellstr([num2str(eta_H_grid), 'hz=%3.2f;'], num2str(eta_S_grid), 'wz=%3.2f;'));
edu_grid = [0,1];
marry_grid = [0,1];
kids_grid = (1:1:mp_params('n_kidsgrid'))';
% NaN(n_jgrid,n_agrid,n_etagrid,n_educgrid,n_marriedgrid,n_kidsgrid);
cl_mp_datasetdesc = {};
cl_mp_datasetdesc{1} = containers.Map({'name', 'labval'}, {'age', age_grid});
cl_mp_datasetdesc{2} = containers.Map({'name', 'labval'}, {'savings', agrid});
cl_mp_datasetdesc{3} = containers.Map({'name', 'labval'}, {'eta', 1:length(eta_H_grid)});
cl_mp_datasetdesc{4} = containers.Map({'name', 'labval'}, {'edu', edu_grid});
cl_mp_datasetdesc{5} = containers.Map({'name', 'labval'}, {'marry', marry_grid});
cl_mp_datasetdesc{6} = containers.Map({'name', 'labval'}, {'kids', kids_grid});

```

## 8.2.3 Analyze Difference in V and C with Check

The difference between V and V with Check, marginal utility gain given the check.

```

% Generate some Data
mp_support_graph = containers.Map('KeyType', 'char', 'ValueType', 'any');
mp_support_graph('cl_st_xtitle') = {'Savings States', 'a'};
mp_support_graph('st_legend_loc') = 'eastoutside';
mp_support_graph('bl_graph_logy') = true; % do not log
mp_support_graph('it_legend_select') = 21; % how many shock legends to show
mp_support_graph('cl_colors') = 'jet';

```

```
MEAN(MN_V_GAIN_CHECK(A,Z))
```

Tabulate value and policies along savings and shocks:

```

% Set
ar_permute = [1,4,5,6,3,2];
% Value Function
st_title = ['MEAN(MN_V_U_GAIN_CHECK(A,Z)), welf_checks=' num2str(welf_checks) ', TR=' num2str(mp_params('TR'))'];
tb_az_v = ff_summ_nd_array(st_title, mn_V_U_gain_check, true, ["mean"], 4, 1, cl_mp_datasetdesc, ar_permute);

```

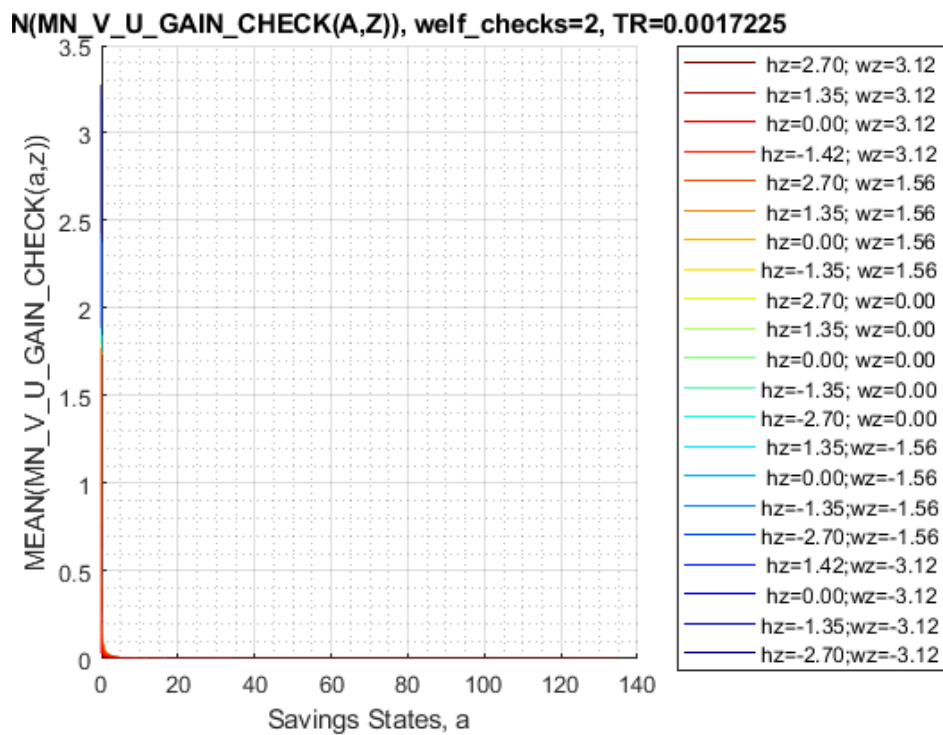
```

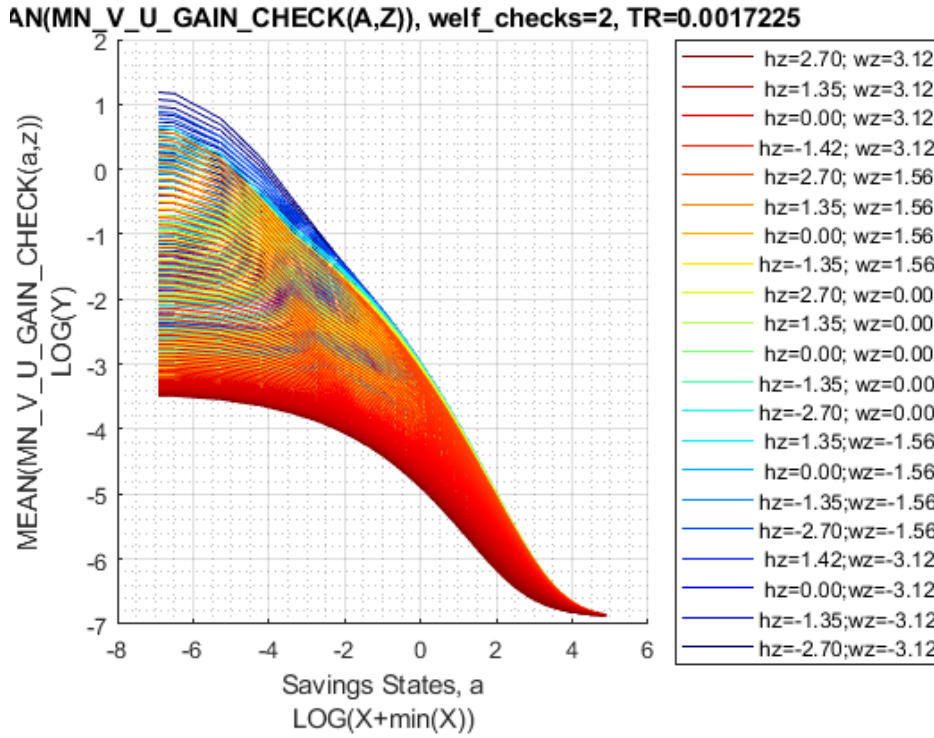
xxx MEAN(MN_V_U_GAIN_CHECK(A,Z)), welf_checks=2, TR=0.0017225 xxxxxxxxxxxxxxxxxxxxxxxxxxxxxxxx
  group      savings      mean_eta_1      mean_eta_2      mean_eta_3      mean_eta_4      mean_eta_5      mea
  -----

```

1                    0                    3.2784                    2.9257                    2.61                    2.3278                    2.0757

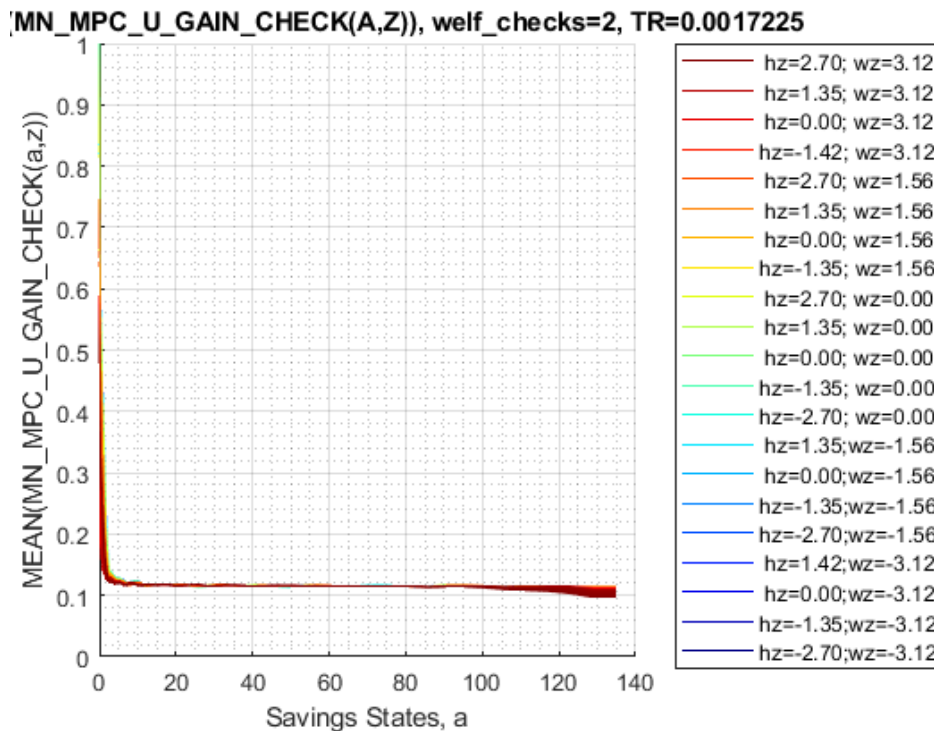
```
st_title = ['MEAN(MN\V\U\_GAIN\_CHECK(A,Z)), welf\_checks=' num2str(welf_checks) ', TR=' num2str(m
mp_support_graph('cl_st_graph_title') = {st_title};
mp_support_graph('cl_st_ytitle') = {'MEAN(MN\V\U\_GAIN\_CHECK(a,z))'};
ff_graph_grid((tb_az_v{1:end, 3:end})', ar_st_eta_HS_grid, agrid, mp_support_graph);
```

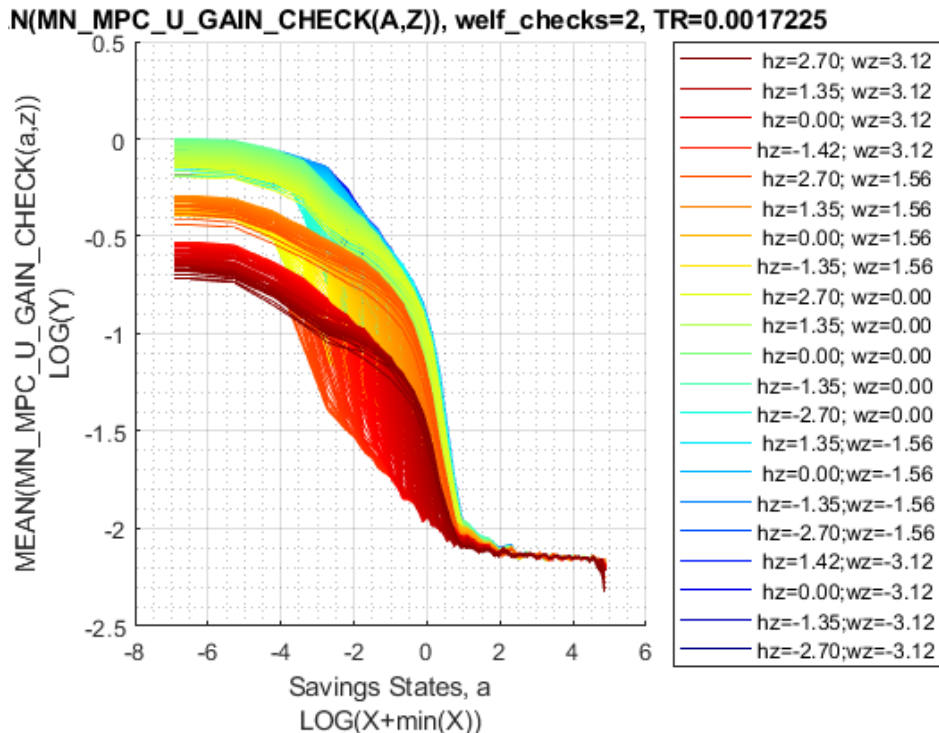




Graph Mean Consumption (*MPC: Share of Check Consumed*):

```
st_title = ['MEAN(MN_MPC_U_GAIN_CHECK(A,Z)), welf_checks=' num2str(welf_checks) ', TR=' num2str
mp_support_graph('cl_st_graph_title') = {st_title};
mp_support_graph('cl_st_ytitle') = {'MEAN(MN_MPC_U_GAIN_CHECK(a,z))'};
ff_graph_grid((tb_az_c{1:end, 3:end}'), ar_st_eta_HS_grid, agrid, mp_support_graph);
```





### 8.2.4 Analyze Kids and Marriage and Age

Aggregating over education, savings, and shocks, what are the differential effects of Marriage and Age.

```
% Generate some Data
mp_support_graph = containers.Map('KeyType', 'char', 'ValueType', 'any');
ar_row_grid = [...
    "k0M0", "K1M0", "K2M0", "K3M0", "K4M0", ...
    "k0M1", "K1M1", "K2M1", "K3M1", "K4M1"];
mp_support_graph('cl_st_xtitle') = {'Age'};
mp_support_graph('st_legend_loc') = 'best';
mp_support_graph('bl_graph_logy') = true; % do not log
mp_support_graph('st_rounding') = '6.2f'; % format shock legend
mp_support_graph('cl_scatter_shapes') = {...
    'o', 'd', 's', 'x', '*', ...
    'o', 'd', 's', 'x', '*'};
mp_support_graph('cl_colors') = {...
    'red', 'red', 'red', 'red', 'red'...
    'blue', 'blue', 'blue', 'blue', 'blue'};
```

MEAN(VAL(KM,J)), MEAN(AP(KM,J)), MEAN(C(KM,J))

Tabulate value and policies:

```
% Set
% NaN(n_jgrid,n_agrid,n_etagrid,n_educgrid,n_marriedgrid,n_kidsgrid);
ar_permute = [2,3,4,1,6,5];
% Value Function
st_title = ['MEAN(MN_V_U_GAIN_CHECK(KM,J)), welf_checks=' num2str(welf_checks) ', TR=' num2str(mp_pa
tb_az_v = ff_summ_nd_array(st_title, mn_V_U_gain_check, true, ["mean"], 3, 1, cl_mp_datasetdesc, ar_
```

xxx	MEAN(MN_V_U_GAIN_CHECK(KM,J)), welf_checks=2, TR=0.0017225 xxxxxxxxxxxxxxxxxxxxxxxxxxxxxxx						
group	kids	marry	mean_age_18	mean_age_19	mean_age_20	mean_age_21	mean_age_2
-----	----	-----	-----	-----	-----	-----	-----
1	1	0	0.05653	0.055715	0.054794	0.04982	0.045679

2	2	0	0.078925	0.077839	0.076575	0.069564	0.063719
3	3	0	0.094952	0.093819	0.09245	0.084005	0.076969
4	4	0	0.10891	0.1077	0.1062	0.09651	0.088441
5	5	0	0.12087	0.11965	0.11809	0.10735	0.098413
6	1	1	0.020237	0.019467	0.018733	0.016911	0.015385
7	2	1	0.026775	0.025778	0.024831	0.02242	0.020395
8	3	1	0.032414	0.031263	0.030161	0.027239	0.024791
9	4	1	0.038629	0.037309	0.036028	0.032548	0.029638
10	5	1	0.047127	0.045665	0.044235	0.039997	0.03645

% Consumption Function

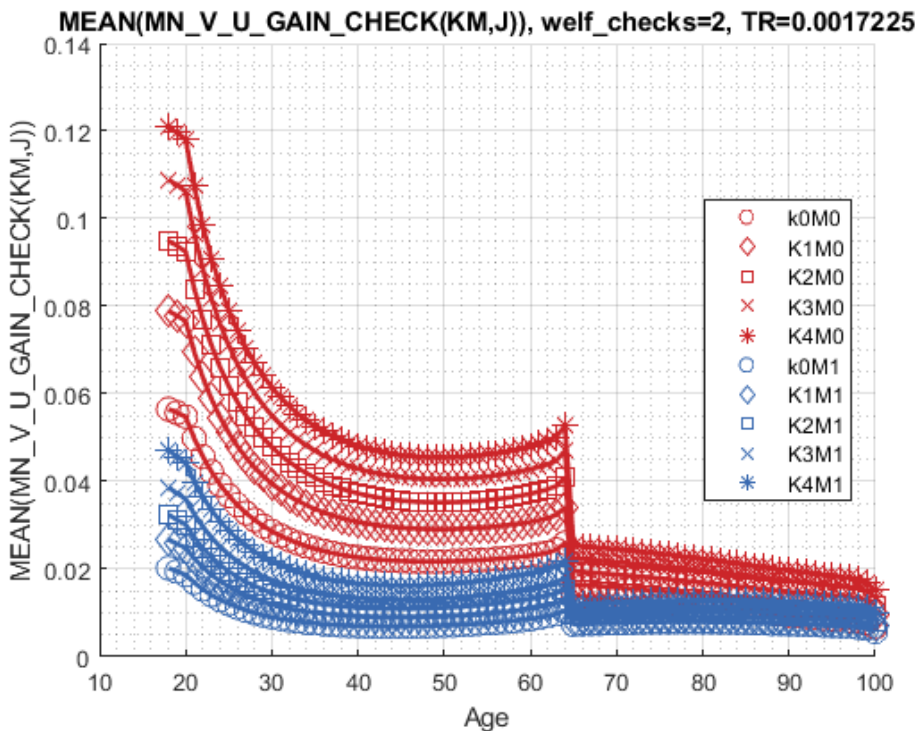
```
st_title = ['MEAN(MN_MPC_U_GAIN_CHECK(KM,J))', welf_checks=' num2str(welf_checks) ', TR=' num2str(mp_
tb_az_c = ff_summ_nd_array(st_title, mn_MPC_U_gain_share_check, true, ["mean"], 3, 1, cl_mp_datasetd
```

```
xxx MEAN(MN_MPC_U_GAIN_CHECK(KM,J)), welf_checks=2, TR=0.0017225 xxxxxxxxxxxxxxxxxxxxxxxxxxxxxxxx
  group  kids  marry  mean_age_18  mean_age_19  mean_age_20  mean_age_21  mean_age_2
-----  ----  -----  -
```

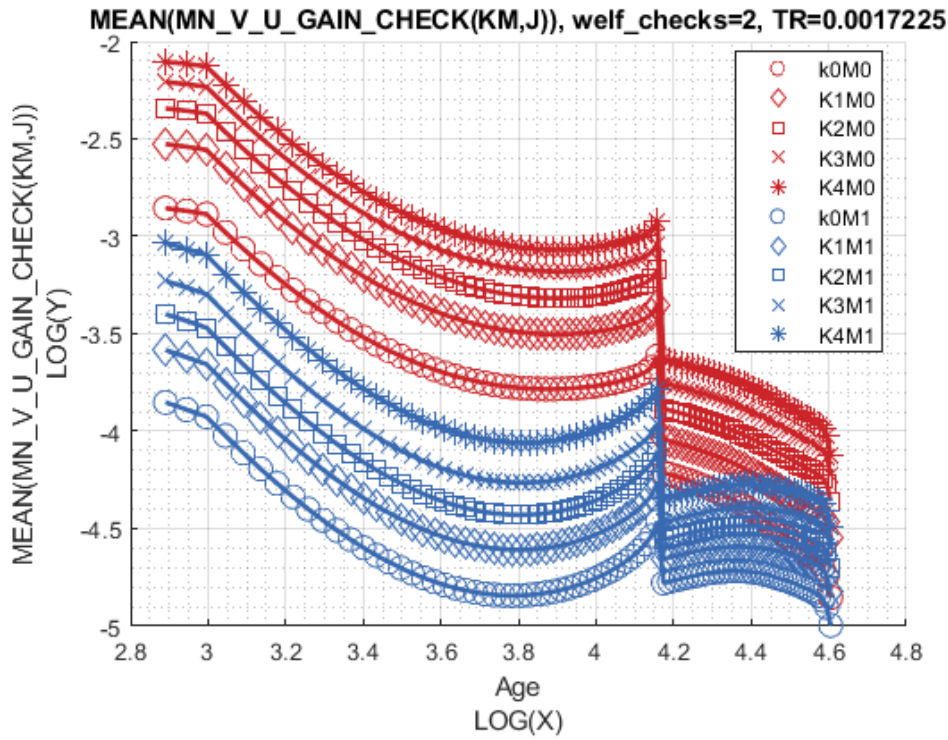
1	1	0	0.16534	0.16905	0.17306	0.17381	0.17437
2	2	0	0.1737	0.17744	0.18164	0.18288	0.18395
3	3	0	0.18114	0.18464	0.18867	0.18992	0.19103
4	4	0	0.18485	0.18821	0.19215	0.19339	0.19447
5	5	0	0.18839	0.19152	0.19526	0.19638	0.19735
6	1	1	0.16189	0.16482	0.1704	0.16811	0.17036
7	2	1	0.16399	0.1672	0.1718	0.17073	0.17219
8	3	1	0.16993	0.17298	0.17649	0.17652	0.17818
9	4	1	0.17337	0.17752	0.17974	0.17989	0.18201
10	5	1	0.18363	0.18473	0.18799	0.18953	0.18894

Graph Mean Values:

```
st_title = ['MEAN(MN_V_U_GAIN_CHECK(KM,J))', welf_checks=' num2str(welf_checks) ', TR=' num2str(
mp_support_graph('cl_st_graph_title') = {st_title};
mp_support_graph('cl_st_ytitle') = {'MEAN(MN_V_U_GAIN_CHECK(KM,J))'};
ff_graph_grid((tb_az_v{1:end, 4:end}), ar_row_grid, age_grid, mp_support_graph);
```



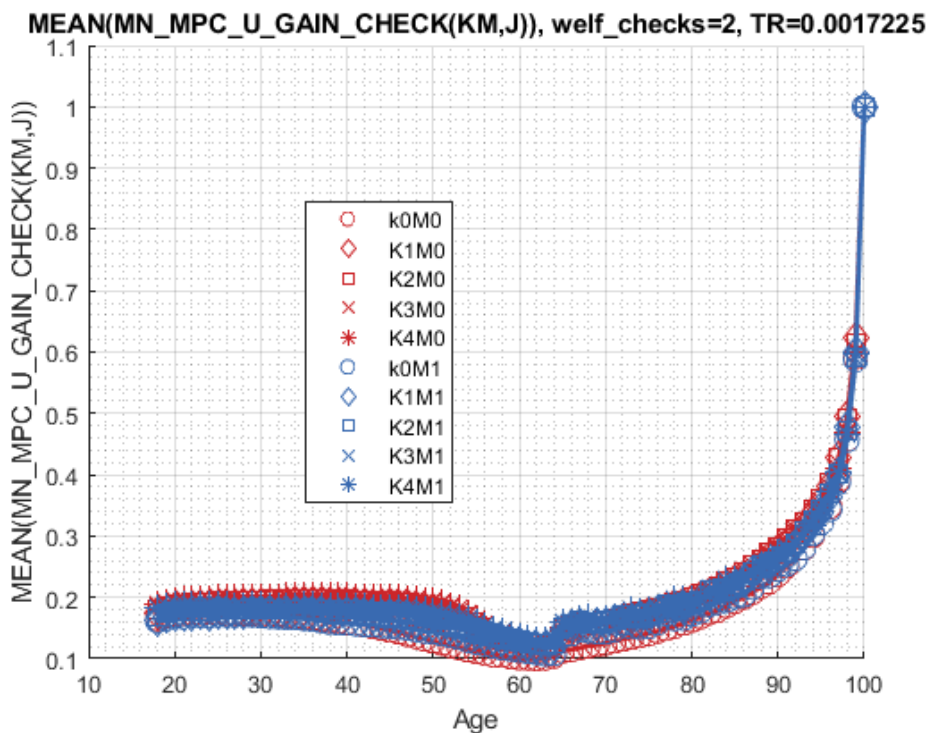


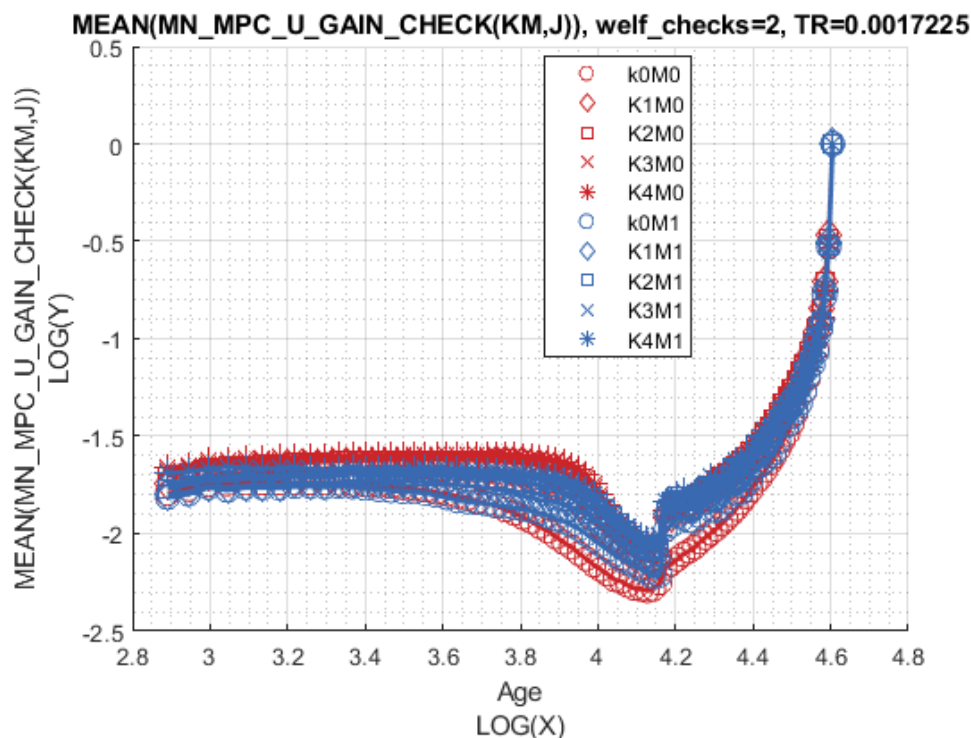


Graph Mean Consumption (*MPC: Share of Check Consumed*):

```

st_title = ['MEAN(MN\MPC\_U\_GAIN\_CHECK(KM,J)), welf\_checks=' num2str(welf_checks) ', TR=' num2str
mp_support_graph('cl_st_graph_title') = {st_title};
mp_support_graph('cl_st_ytitle') = {'MEAN(MN\MPC\_U\_GAIN\_CHECK(KM,J))'};
ff_graph_grid((tb_az_c{1:end, 4:end}), ar_row_grid, age_grid, mp_support_graph);
    
```





### 8.2.5 Analyze Education and Marriage

Aggregating over education, savings, and shocks, what are the differential effects of Marriage and Age.

```
% Generate some Data
mp_support_graph = containers.Map('KeyType', 'char', 'ValueType', 'any');
ar_row_grid = ["E0M0", "E1M0", "E0M1", "E1M1"];
mp_support_graph('cl_st_xtitle') = {'Age'};
mp_support_graph('st_legend_loc') = 'best';
mp_support_graph('bl_graph_logy') = true; % do not log
mp_support_graph('st_rounding') = '6.2f'; % format shock legend
mp_support_graph('cl_scatter_shapes') = {'*', 'p', '*', 'p'};
mp_support_graph('cl_colors') = {'red', 'red', 'blue', 'blue'};
MEAN(VA(EM,J)), MEAN(AP(EM,J)), MEAN(C(EM,J))
```

Tabulate value and policies:

```
% Set
% NaN(n_jgrid,n_agrid,n_etagrid,n_educgrid,n_marriedgrid,n_kidsgrid);
ar_permute = [2,3,6,1,4,5];
% Value Function
st_title = ['MEAN(MN_V_U_GAIN_CHECK(EM,J)), welf_checks=' num2str(welf_checks) ', TR=' num2str(mp_pa
tb_az_v = ff_summ_nd_array(st_title, mn_V_U_gain_check, true, ["mean"], 3, 1, cl_mp_datasetdesc, ar_
```

```
xxx MEAN(MN_V_U_GAIN_CHECK(EM,J)), welf_checks=2, TR=0.0017225 xxxxxxxxxxxxxxxxxxxxxxxxxxxxxxxx
group   edu   marry   mean_age_18   mean_age_19   mean_age_20   mean_age_21   mean_age_22
-----
1       0       0       0.0932       0.092347     0.091343     0.086009     0.081278
2       1       0       0.090875     0.089539     0.087898     0.076892     0.068011
3       0       1       0.034609     0.033465     0.032367     0.030037     0.027999
4       1       1       0.031464     0.030328     0.029228     0.025609     0.022664
```

% Consumption

```
st_title = ['MEAN(MN_MPC_U_GAIN_CHECK(EM,J)), welf_checks=' num2str(welf_checks) ', TR=' num2str(mp_
```

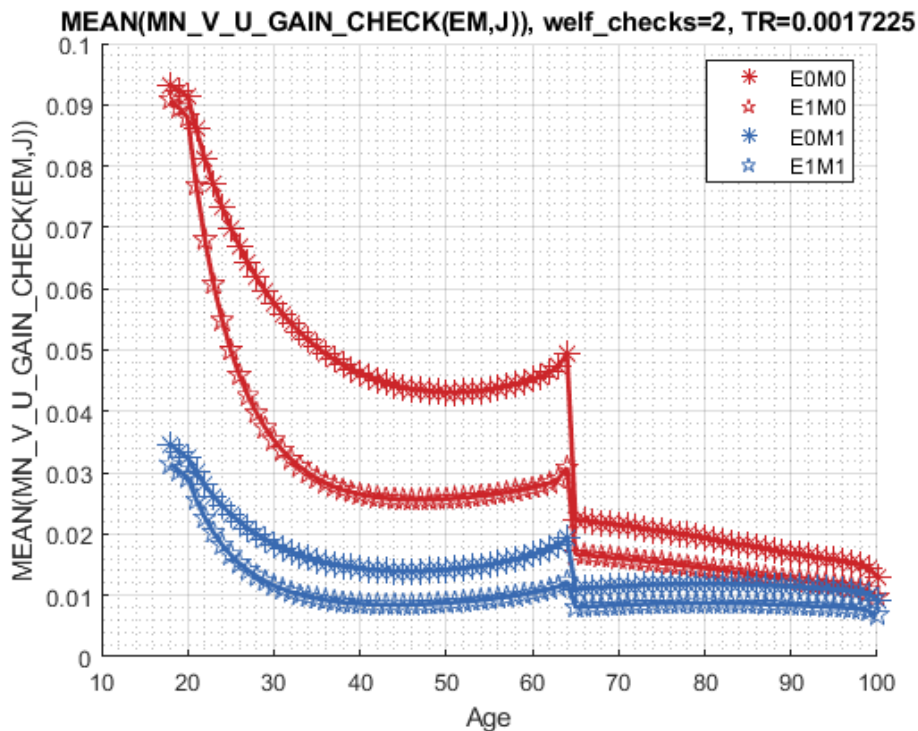
```
tb_az_c = ff_summ_nd_array(st_title, mn_MPC_U_gain_share_check, true, ["mean"], 3, 1, cl_mp_datasetd
```

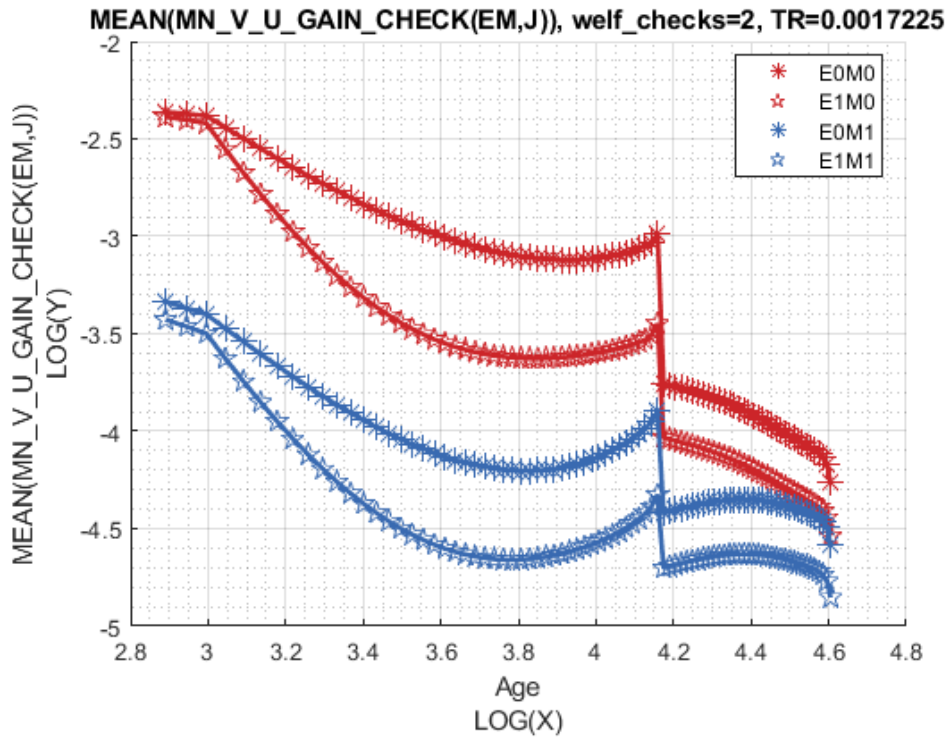
```
xxx MEAN(MN_MPC_U_GAIN_CHECK(EM,J)), welf_checks=2, TR=0.0017225 xxxxxxxxxxxxxxxxxxxxxxxxxxxxxxx
```

group	edu	marry	mean_age_18	mean_age_19	mean_age_20	mean_age_21	mean_age_22
1	0	0	0.17201	0.17468	0.17758	0.17848	0.17931
2	1	0	0.18536	0.18966	0.19474	0.19608	0.19716
3	0	1	0.16432	0.16694	0.16991	0.16969	0.17077
4	1	1	0.1768	0.17996	0.18466	0.18422	0.1859

Graph Mean Values:

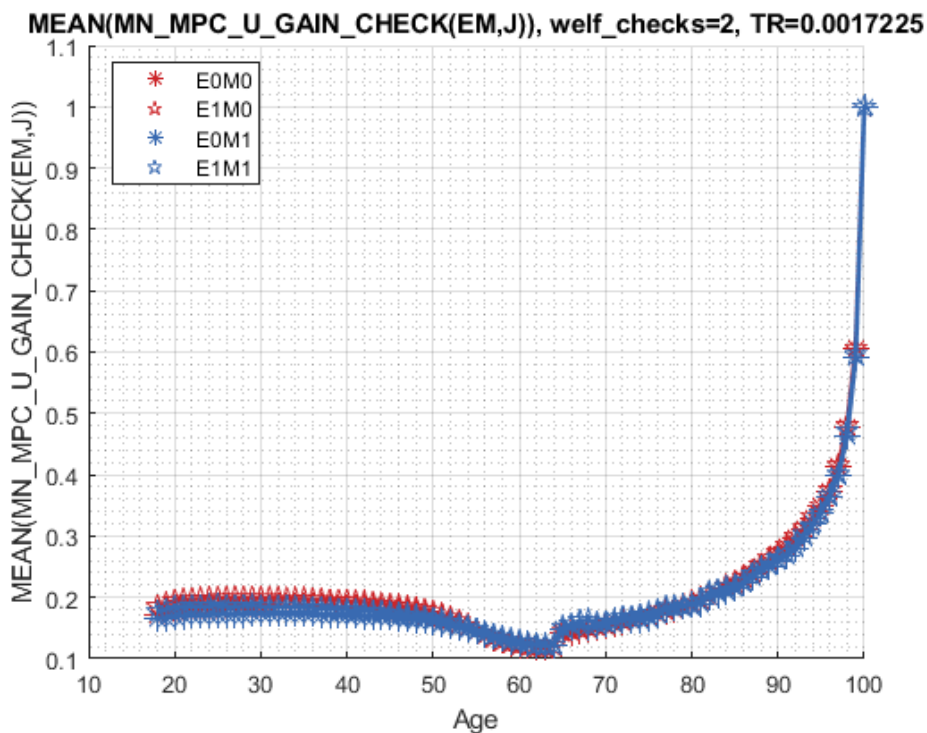
```
st_title = ['MEAN(MN_V_U_GAIN_CHECK(EM,J)), welf_checks=' num2str(welf_checks) ', TR=' num2str(
mp_support_graph('cl_st_graph_title') = {st_title};
mp_support_graph('cl_st_ytitle') = {'MEAN(MN_V_U_GAIN_CHECK(EM,J))'};
ff_graph_grid((tb_az_v{1:end, 4:end}), ar_row_grid, age_grid, mp_support_graph);
```

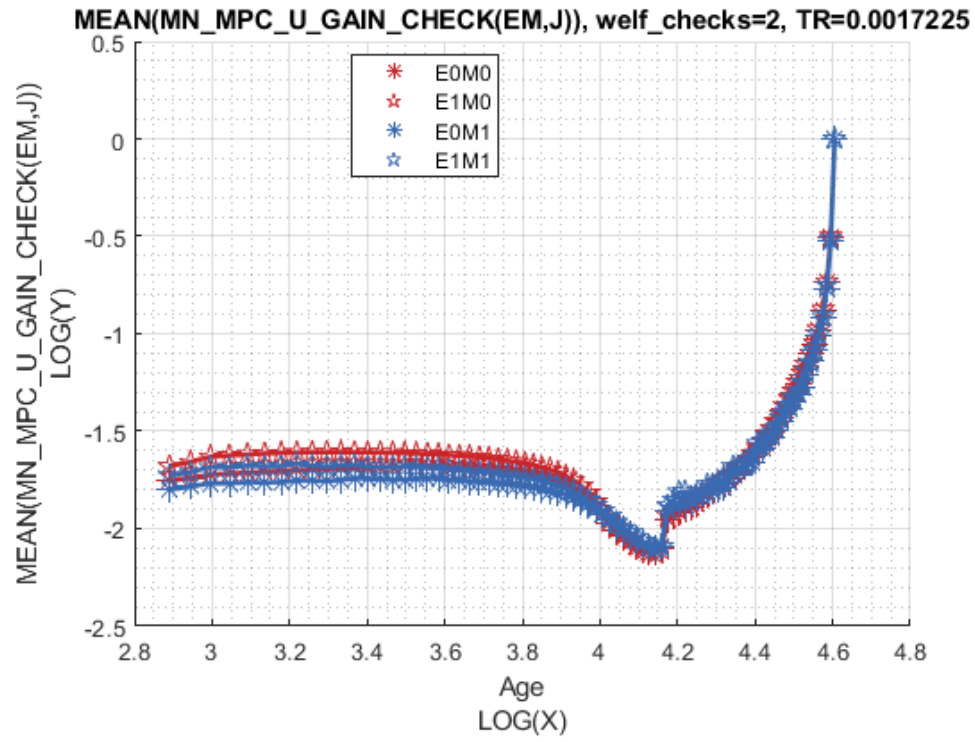




Graph Mean Consumption (*MPC: Share of Check Consumed*):

```
st_title = ['MEAN(MN\MPC_U_GAIN_CHECK(EM,J)), welf_checks=' num2str(welf_checks) ', TR=' num2str(
mp_support_graph('cl_st_graph_title') = {st_title};
mp_support_graph('cl_st_ytitle') = {'MEAN(MN\MPC_U_GAIN_CHECK(EM,J))'};
ff_graph_grid((tb_az_c{1:end, 4:end}), ar_row_grid, age_grid, mp_support_graph);
```







## Chapter 9

# 2019/2020 and 2007/2008 V and C Full State Space

### 9.1 2020 Full States EV and EC of One Check

This is the example vignette for function: [snw\\_evuvw20\\_jaeemk](#) from the [PrjOptiSNW Package](#). 2020 integrated over VU and VW. Average C or V given unemployment probabilities.

#### 9.1.1 Test SNW\_EVUVW20\_JAEEMK Defaults

Call the function with defaults.

```
clear all;
st_solu_type = 'biseq_vec';

% Solve the VFI Problem and get Value Function
mp_params = snw_mp_param('default_docdense');
mp_params('beta') = 0.95;
mp_controls = snw_mp_control('default_test');

% set Unemployment Related Variables
xi=0.5; % Proportional reduction in income due to unemployment (xi=0 refers to 0 labor income; xi=1
b=0; % Unemployment insurance replacement rate (b=0 refers to no UI benefits; b=1 refers to 100 perc
TR=100/58056; % Value of a welfare check (can receive multiple checks). TO DO: Update with alternati

mp_params('xi') = xi;
mp_params('b') = b;
mp_params('TR') = TR;

% Solve for Unemployment Values
mp_controls('bl_print_vfi') = false;
mp_controls('bl_print_ds') = false;
mp_controls('bl_print_ds_verbose') = false;
mp_controls('bl_print_precompute') = false;
mp_controls('bl_print_precompute_verbose') = false;
mp_controls('bl_print_a4chk') = false;
mp_controls('bl_print_a4chk_verbose') = false;
mp_controls('bl_print_evuvw20_jaeemk') = false;
mp_controls('bl_print_evuvw20_jaeemk_verbose') = false;

Solve the model:

%% A. Solve VFI
% 2. Solve VFI and Distributon
```

```
% Solve the Model to get V working and unemployed
% solved with calibrated regular a2
[V_ss,ap_ss,cons_ss,mp_valpol_more_ss] = snw_vfi_main_bisec_vec(mp_params, mp_controls);
```

Completed SNW\_VFI\_MAIN\_BISEC\_VEC;SNW\_MP\_PARAM=default\_docdense;SNW\_MP\_CONTROL=default\_test;time=524.

```
-----
XXXXXXXXXXXXXXXXXXXXXXXXXXXXXXXXXXXXXXXXXXXX
CONTAINER NAME: mp_outcomes ND Array (Matrix etc)
XXXXXXXXXXXXXXXXXXXXXXXXXXXXXXXXXXXXXXXXXXXX
```

	i	idx	ndim	numel	rowN	colN	sum	mean	std
V_VFI	1	1	6	4.37e+07	83	5.265e+05	-6.6619e+08	-15.245	21.86
ap_VFI	2	2	6	4.37e+07	83	5.265e+05	1.3967e+09	31.962	36.42
cons_VFI	3	3	6	4.37e+07	83	5.265e+05	2.3276e+08	5.3263	8.441

xxx TABLE:V\_VFI XXXXXXXXXXXXXXXXXXXXXXX

	c1	c2	c3	c4	c5	c526496	c526497	c526498
r1	-293.96	-293.57	-291.09	-285.44	-276.41	-4.3584	-4.2643	-4.171
r2	-284.42	-284.03	-281.55	-275.97	-267.24	-4.2519	-4.1612	-4.071
r3	-274.87	-274.48	-272.03	-266.62	-258.33	-4.1429	-4.0559	-3.969
r4	-265.22	-264.86	-262.58	-257.53	-249.74	-4.0309	-3.9475	-3.864
r5	-256.51	-256.17	-254.04	-249.3	-241.96	-3.9252	-3.8452	-3.765
r79	-13.642	-13.628	-13.535	-13.298	-12.896	-0.22092	-0.21058	-0.2008
r80	-12.283	-12.269	-12.176	-11.939	-11.537	-0.16979	-0.16182	-0.154
r81	-10.605	-10.591	-10.498	-10.261	-9.8589	-0.11712	-0.11163	-0.1064
r82	-8.3494	-8.3358	-8.2424	-8.0055	-7.6035	-0.065333	-0.062242	-0.0593
r83	-5.0665	-5.0529	-4.9595	-4.7226	-4.3206	-0.020968	-0.019972	-0.01903

xxx TABLE:ap\_VFI XXXXXXXXXXXXXXXXXXXXXXX

	c1	c2	c3	c4	c5	c526496	c526497	c526498	c526499
r1	0	0	0.00051498	0.0066578	0.021589	112.13	117.67	123.4	129.3
r2	0	0	0.00051498	0.0057684	0.020245	112.17	117.71	123.43	129.3
r3	0	0	0.00020768	0.0041456	0.018539	112.2	117.73	123.45	129.3
r4	0	0	0.00010346	0.0041199	0.018307	112.86	118.39	124.11	130.0
r5	0	0	5.2907e-06	0.0041199	0.018091	113.53	119.07	124.79	130.7
r79	0	0	0	0	0	81.091	85.364	89.335	93.25
r80	0	0	0	0	0	76.124	79.747	83.431	86.98
r81	0	0	0	0	0	67.945	70.639	73.673	76.99
r82	0	0	0	0	0	50.126	53.467	56.302	57.88
r83	0	0	0	0	0	0	0	0	0

xxx TABLE:cons\_VFI XXXXXXXXXXXXXXXXXXXXXXX

	c1	c2	c3	c4	c5	c526496	c526497	c526498
r1	0.036717	0.037251	0.040477	0.044486	0.049324	12.265	12.55	12.844
r2	0.036717	0.037251	0.040477	0.045375	0.050668	12.501	12.787	13.082
r3	0.036717	0.037251	0.040784	0.046998	0.052374	12.755	13.042	13.337
r4	0.038144	0.038678	0.042314	0.048449	0.054031	13	13.289	13.584
r5	0.039534	0.040068	0.043802	0.049839	0.055635	13.236	13.525	13.821
r79	0.19737	0.19791	0.20163	0.21175	0.23145	35.811	37.362	39.409
r80	0.19737	0.19791	0.20163	0.21175	0.23145	40.752	42.953	45.286
r81	0.19737	0.19791	0.20163	0.21175	0.23145	48.909	52.039	55.022





r1	0	0	0	0	0.0083625	107.54	113.09	118.82	124.74	130.86
r2	0	0	0	0	0.0074731	107.45	112.99	118.72	124.64	130.75
r3	0	0	0	0	0.0058503	107.33	112.88	118.61	124.52	130.64
r4	0	0	0	0	0.0049981	107.54	113.08	118.81	124.73	130.85
r5	0	0	0	0	0.004174	107.76	113.3	119.03	124.95	131.07
r79	0	0	0	0	0	80.462	84.34	88.311	92.234	96.324
r80	0	0	0	0	0	75.113	78.736	82.42	85.975	90.439
r81	0	0	0	0	0	66.945	69.639	72.673	76.669	81.091
r82	0	0	0	0	0	50.126	53.467	55.311	56.953	60.587
r83	0	0	0	0	0	0	0	0	0	0

```
xxx TABLE:cons_VFI xxxxxxxxxxxxxxxxxxxxxxx
```

	c1	c2	c3	c4	c5	c526496	c526497	c526498
r1	0.018623	0.019158	0.022901	0.033062	0.044486	11.989	12.265	12.55
r2	0.018623	0.019158	0.022901	0.033062	0.045375	12.223	12.501	12.787
r3	0.018623	0.019158	0.022901	0.033062	0.046998	12.476	12.755	13.042
r4	0.019354	0.019888	0.023632	0.033792	0.048579	12.72	13	13.289
r5	0.020066	0.020601	0.024344	0.034504	0.050114	12.955	13.236	13.525
r79	0.19737	0.19791	0.20163	0.21175	0.23145	35.417	37.362	39.409
r80	0.19737	0.19791	0.20163	0.21175	0.23145	40.752	42.953	45.286
r81	0.19737	0.19791	0.20163	0.21175	0.23145	48.909	52.039	55.022
r82	0.19737	0.19791	0.20163	0.21175	0.23145	65.719	68.202	72.375
r83	0.19737	0.19791	0.20163	0.21175	0.23145	115.84	121.66	127.68

```
%% B. Solve Dist
```

```
[Phi_true] = snw_ds_main_vec(mp_params, mp_controls, ap_ss, cons_ss);
```

```
Completed SNW_DS_MAIN_VEC;SNW_MP_PARAM=default_docdense;SNW_MP_CONTROL=default_test;time=929.8427
```

```
Previous code
```

```
%% Solve the Model to get V working and unemployed
% [V_ss,ap_ss,cons_ss,mp_valpol_more_ss] = snw_vfi_main_bisec_vec(mp_params, mp_controls);
%% Solve unemployment
% [V_unemp,~,cons_unemp,~] = snw_vfi_main_bisec_vec(mp_params, mp_controls, V_ss);
% [Phi_true] = snw_ds_main(mp_params, mp_controls, ap_ss, cons_ss, mp_valpol_more_ss);
```

### 9.1.2 Precompute

```
inc_VFI = mp_valpol_more_ss('inc_VFI');
spouse_inc_VFI = mp_valpol_more_ss('spouse_inc_VFI');
total_inc_VFI = inc_VFI + spouse_inc_VFI;
% Get Matrixes
cl_st_precompute_list = {'a', ...
    'inc', 'inc_unemp', 'spouse_inc', 'spouse_inc_unemp', 'ref_earn_wageind_grid'};
mp_controls('bl_print_precompute_verbose') = false;
[mp_precompute_res] = snw_hh_precompute(mp_params, mp_controls, cl_st_precompute_list, ap_ss, Phi_tr
```

```
Wage quintile cutoffs=0.4645    0.71528    1.0335    1.5632
```

```
Completed SNW_HH_PRECOMPUTE;SNW_MP_PARAM=default_docdense;SNW_MP_CONTROL=default_test;time cost=274.
```

### 9.1.3 Solve for 2020 Evuvw With 0 and 2 Checks

```
% Call Function
```

```
welf_checks = 0;
```

```
[ev20_jaeemk_check0, ec20_jaeemk_check0] = snw_evuvw20_jaeemk(...
```

```

welf_checks, st_solu_type, mp_params, mp_controls, ...
V_ss_2020, cons_ss_2020, V_unemp_2020, cons_unemp_2020, mp_precompute_res);

Completed SNW_A4CHK_WRK_BISEC_VEC;SNW_MP_PARAM=st_biden_or_trump_undefined;welf_checks=0;TR=0.001722
Completed SNW_A4CHK_UNEMP_BISEC_VEC;welf_checks=0;TR=0.0017225;xi=0.5;b=0;SNW_MP_PARAM=default_docde
Completed SNW_EVUVW20_JAEEMK;SNW_MP_PARAM=default_docdense;SNW_MP_CONTROL=default_test;timeEUEC=8.01

% Call Function
welf_checks = 2;
[ev20_jaeemk_check2, ec20_jaeemk_check2] = snw_evuvw20_jaeemk(...
    welf_checks, st_solu_type, mp_params, mp_controls, ...
    V_ss_2020, cons_ss_2020, V_unemp_2020, cons_unemp_2020, mp_precompute_res);

Completed SNW_A4CHK_WRK_BISEC_VEC;SNW_MP_PARAM=st_biden_or_trump_undefined;welf_checks=2;TR=0.001722
Completed SNW_A4CHK_UNEMP_BISEC_VEC;welf_checks=2;TR=0.0017225;xi=0.5;b=0;SNW_MP_PARAM=default_docde
Completed SNW_EVUVW20_JAEEMK;SNW_MP_PARAM=default_docdense;SNW_MP_CONTROL=default_test;timeEUEC=7.97

Differences between Checks in Expected Value and Expected Consumption

mn_V_U_gain_check = ev20_jaeemk_check2 - ev20_jaeemk_check0;
mn_MPC_U_gain_share_check = (ec20_jaeemk_check2 - ec20_jaeemk_check0)./(welf_checks*mp_params('TR'))

```

#### 9.1.4 Param Results Define Frames

Define the matrix dimensions names and dimension vector values. Policy and Value Functions share the same ND dimensional structure.

```

% Grids:
age_grid = 18:100;
agrid = mp_params('agrid');
eta_H_grid = mp_params('eta_H_grid');
eta_S_grid = mp_params('eta_S_grid');
ar_st_eta_HS_grid = string(cellstr([num2str(eta_H_grid', 'hz=%3.2f;'), num2str(eta_S_grid', 'wz=%3.2
edu_grid = [0,1];
marry_grid = [0,1];
kids_grid = (1:1:mp_params('n_kidsgrid'))';
% NaN(n_jgrid,n_agrid,n_etaagrid,n_eduagrid,n_marriedgrid,n_kidsgrid);
cl_mp_datasetdesc = {};
cl_mp_datasetdesc{1} = containers.Map({'name', 'labval'}, {'age', age_grid});
cl_mp_datasetdesc{2} = containers.Map({'name', 'labval'}, {'savings', agrid});
cl_mp_datasetdesc{3} = containers.Map({'name', 'labval'}, {'eta', 1:length(eta_H_grid)});
cl_mp_datasetdesc{4} = containers.Map({'name', 'labval'}, {'edu', edu_grid});
cl_mp_datasetdesc{5} = containers.Map({'name', 'labval'}, {'marry', marry_grid});
cl_mp_datasetdesc{6} = containers.Map({'name', 'labval'}, {'kids', kids_grid});

```

#### 9.1.5 Analyze Difference in V and C with Check

The difference between V and V with Check, marginal utility gain given the check.

```

% Generate some Data
mp_support_graph = containers.Map('KeyType', 'char', 'ValueType', 'any');
mp_support_graph('cl_st_xtitle') = {'Savings States', 'a'};
mp_support_graph('st_legend_loc') = 'eastoutside';
mp_support_graph('bl_graph_logy') = true; % do not log
mp_support_graph('it_legend_select') = 21; % how many shock legends to show
mp_support_graph('cl_colors') = 'jet';

```

```
MEAN(MN_V_GAIN_CHECK(A,Z))
```

Tabulate value and policies along savings and shocks:

```
% Set
```

```

ar_permute = [1,4,5,6,3,2];
% Value Function
st_title = ['MEAN(MN_V_U_GAIN_CHECK(A,Z)), welf_checks=' num2str(welf_checks) ', TR=' num2str(mp_par
tb_az_v = ff_summ_nd_array(st_title, mn_V_U_gain_check, true, ["mean"], 4, 1, cl_mp_datasetdesc, ar_

```

```

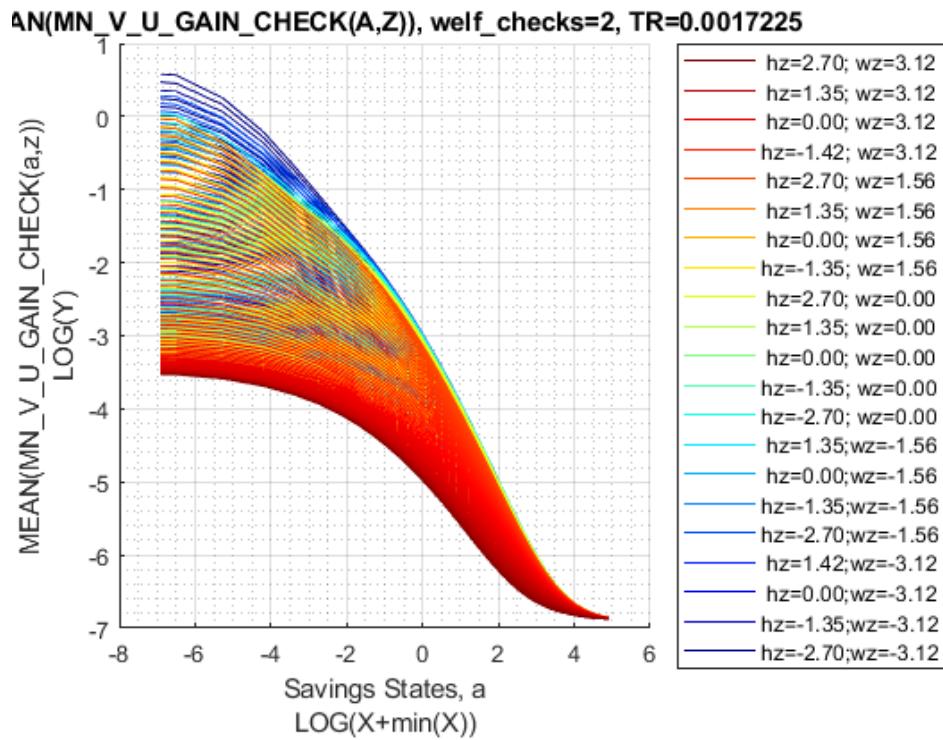
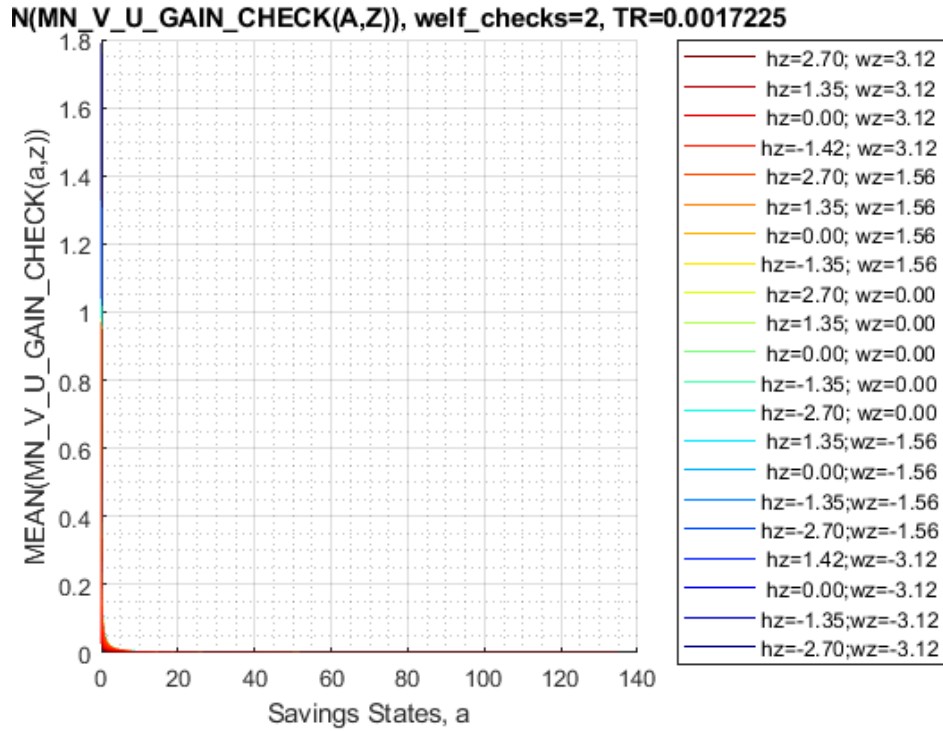
xxx MEAN(MN_V_U_GAIN_CHECK(A,Z)), welf_checks=2, TR=0.0017225 xxxxxxxxxxxxxxxxxxxxxxxxxxxxxxx
  group      savings      mean_eta_1      mean_eta_2      mean_eta_3      mean_eta_4      mean_eta_5      mea
  -----      -
      1          0          1.7895          1.5987          1.4282          1.2759          1.1399

```

```

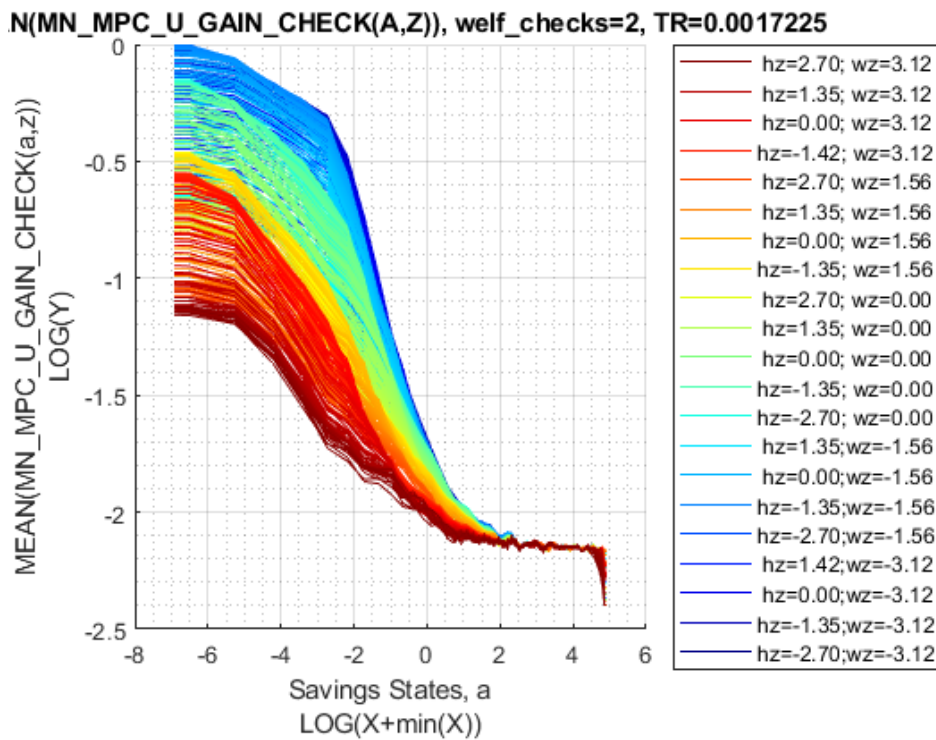
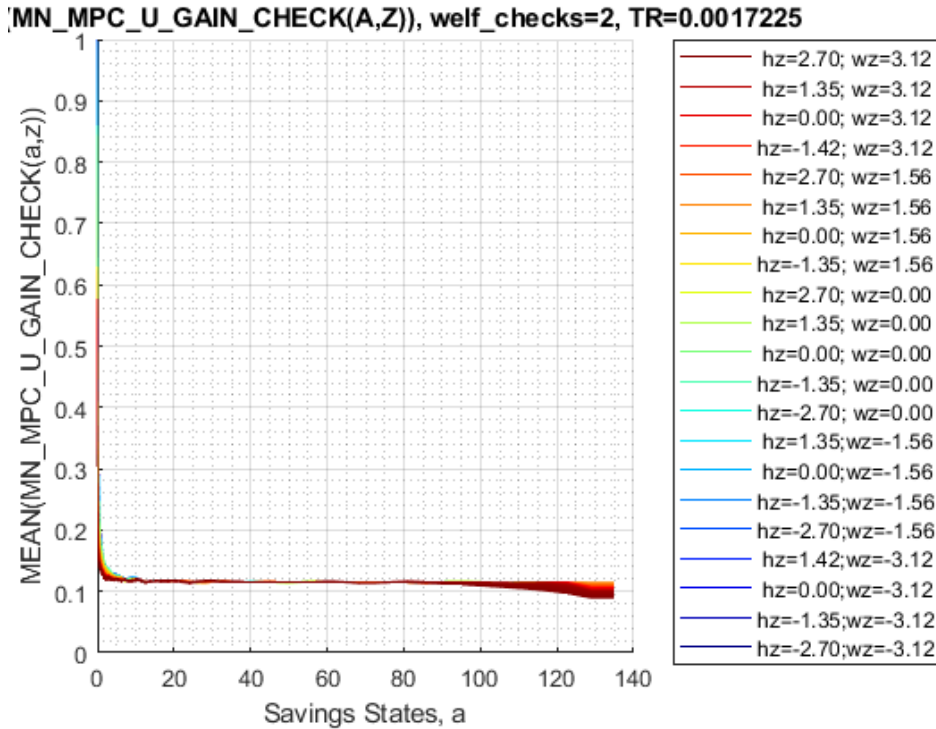
st_title = ['MEAN(MN_V_U_GAIN_CHECK(A,Z)), welf_checks=' num2str(welf_checks) ', TR=' num2str(m
mp_support_graph('cl_st_graph_title') = {st_title};
mp_support_graph('cl_st_ytitle') = {'MEAN(MN_V_U_GAIN_CHECK(a,z))'};
ff_graph_grid((tb_az_v{1:end, 3:end}),' ar_st_eta_HS_grid, agrid, mp_support_graph);

```



Graph Mean Consumption (MPC: Share of Check Consumed):

```
st_title = ['MEAN(MN\MPC\U\GAIN\CHECK(A,Z)), welf_checks=' num2str(welf_checks) ', TR=' num2str
mp_support_graph('cl_st_graph_title') = {st_title};
mp_support_graph('cl_st_ytitle') = {'MEAN(MN\MPC\U\GAIN\CHECK(a,z))'};
ff_graph_grid((tb_az_c{1:end, 3:end}),' ar_st_eta_HS_grid, agrid, mp_support_graph);
```



### 9.1.6 Analyze Marginal Value and MPC over $Y(a, \eta)$ , Conditional On Kids, Marry, Age, Education

Income is generated by savings and shocks, what are the income levels generated by all the shock and savings points conditional on kids, marital status, age and educational levels. Plot on the Y axis MPC, and plot on the X axis income levels, use colors to first distinguish between different a levels, then use colors to distinguish between different  $\eta$  levels.

Set Up date, Select Age 38, unmarried, no kids, lower education:

```

% NaN(n_jgrid,n_agrid,n_etagrid,n_educgrid,n_marriedgrid,n_kidsgrid);
% 38 year old, unmarried, no kids, lower educated
% Only Household Head Shock Matters so select up to 'n_eta_H_grid'
mn_total_inc_jemk = total_inc_VFI(20, :, 1:mp_params('n_eta_H_grid'), 1, 1, 1);
mn_V_W_gain_check_use = ev20_jaeemk_check2 - ev20_jaeemk_check0;
mn_C_W_gain_check_use = ec20_jaeemk_check2 - ec20_jaeemk_check0;

```

Select Age, Education, Marital, Kids Count:s

```

% Selections
it_age = 21; % +18
it_marital = 1; % 1 = unmarried
it_kids = 1; % 1 = kids is zero
it_educ = 1; % 1 = lower education
% Select: NaN(n_jgrid,n_agrid,n_etagrid,n_educgrid,n_marriedgrid,n_kidsgrid);
mn_C_W_gain_check_jemk = mn_C_W_gain_check_use(it_age, :, 1:mp_params('n_eta_H_grid'), it_educ, it_m
mn_V_W_gain_check_jemk = mn_V_W_gain_check_use(it_age, :, 1:mp_params('n_eta_H_grid'), it_educ, it_m
% Reshape, so shock is the first dim, a is the second
mt_total_inc_jemk = permute(mn_total_inc_jemk, [3, 2, 1]);
mt_C_W_gain_check_jemk = permute(mn_C_W_gain_check_jemk, [3, 2, 1]);
mt_C_W_gain_check_jemk(mt_C_W_gain_check_jemk <= 1e-10) = 1e-10;
mt_V_W_gain_check_jemk = permute(mn_V_W_gain_check_jemk, [3, 2, 1]);
mt_V_W_gain_check_jemk(mt_V_W_gain_check_jemk <= 1e-10) = 1e-10;
% Generate meshed a and shock grid
[mt_eta_H, mt_a] = ndgrid(eta_H_grid(1:mp_params('n_eta_H_grid')), agrid);

```

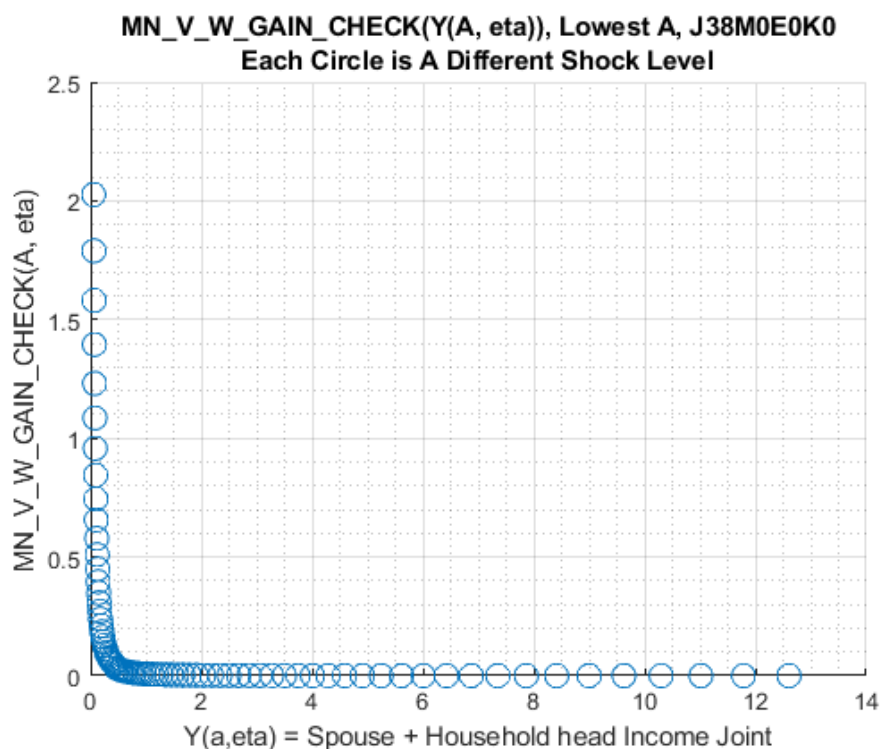
### 9.1.7 Marginal Value Gains, Color as Shock, Conditional on Age, Marital, Kids, and Education

How do shocks and a impact marginal value. First plot one asset level, variation comes only from increasingly higher shocks:

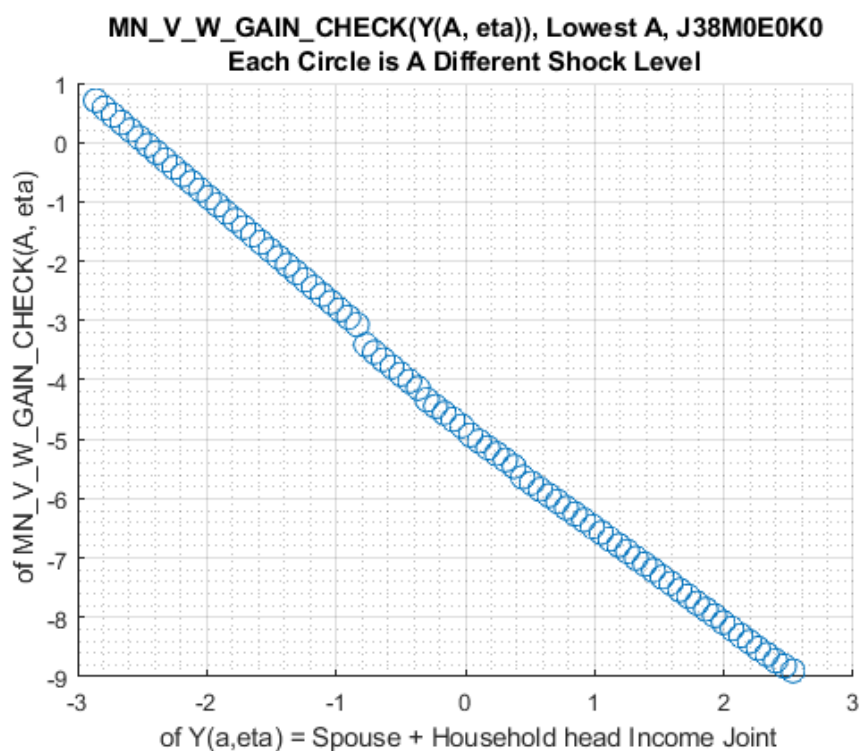
```

figure();
it_a = 1;
scatter(mt_total_inc_jemk(:, it_a), (mt_V_W_gain_check_jemk(:, it_a)), 100);
title({'MN\_V\_W\_GAIN\_CHECK(Y(A, eta)), Lowest A, J38MOEOKO', ...
      'Each Circle is A Different Shock Level'});
xlabel('Y(a, eta) = Spouse + Household head Income Joint');
ylabel('MN\_V\_W\_GAIN\_CHECK(A, eta)');
grid on;
grid minor;

```



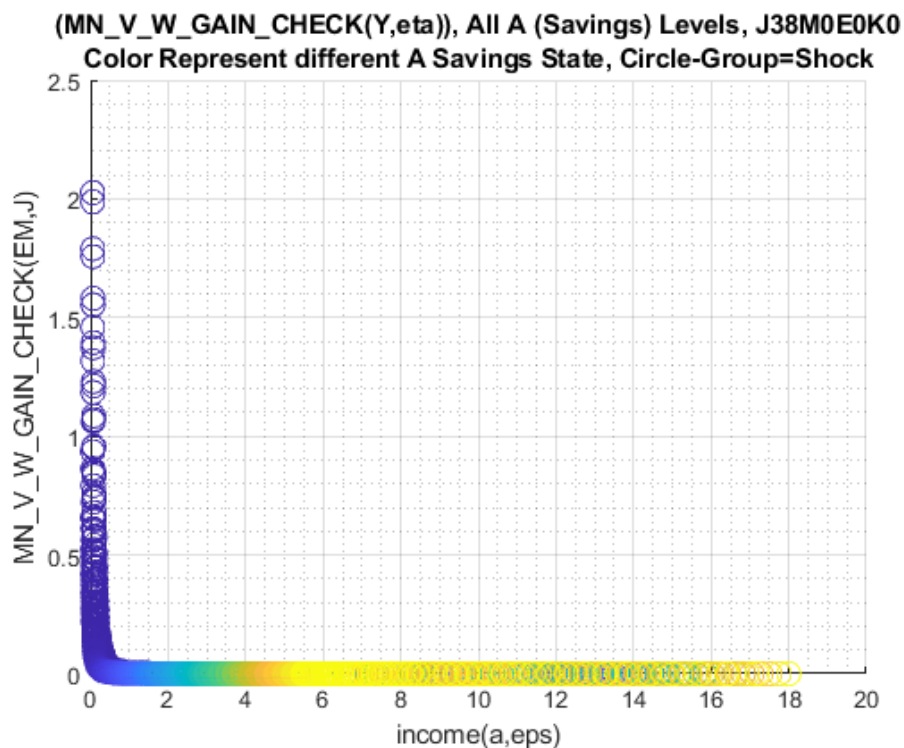
```
figure();
it_shock = 1;
scatter(log(mt_total_inc_jemk(:,it_a)), log(mt_V_W_gain_check_jemk(:,it_a)), 100);
title({'MN_V_W_GAIN_CHECK(Y(A, eta)), Lowest A, J38M0E0K0', ...
      'Each Circle is A Different Shock Level'});
xlabel(' of Y(a,eta) = Spouse + Household head Income Joint');
ylabel(' of MN_V_W_GAIN_CHECK(A, eta)');
grid on;
grid minor;
```



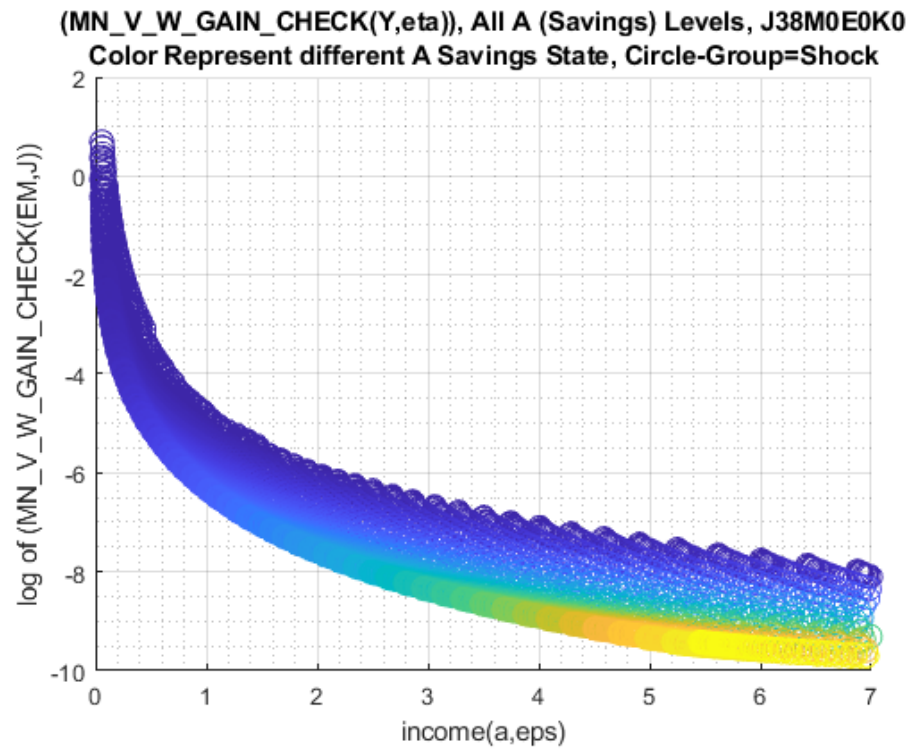


Plot all asset levels:

```
figure();
scatter(mt_total_inc_jemk(:), (mt_V_W_gain_check_jemk(:)), 100, mt_a(:));
title({'(MN_V_W_GAIN_CHECK(Y,eta)), All A (Savings) Levels, J38M0E0K0', ...
      'Color Represent different A Savings State, Circle-Group=Shock'});
xlabel('income(a,eps)');
ylabel('MN_V_W_GAIN_CHECK(EM,J)');
grid on;
grid minor;
```



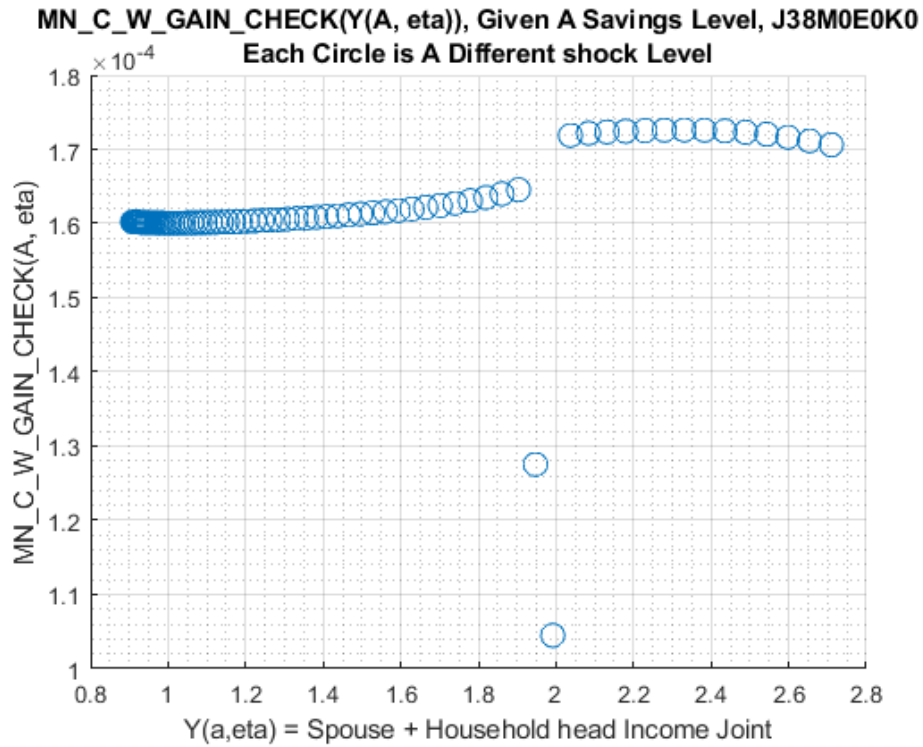
```
figure();
scatter(mt_total_inc_jemk(:), log(mt_V_W_gain_check_jemk(:)), 100, mt_a(:));
title({'(MN_V_W_GAIN_CHECK(Y,eta)), All A (Savings) Levels, J38M0E0K0', ...
      'Color Represent different A Savings State, Circle-Group=Shock'});
xlabel('income(a,eps)');
ylabel('log of (MN_V_W_GAIN_CHECK(EM,J))');
xlim([0,7]);
grid on;
grid minor;
```



### 9.1.8 Marginal Consumption Gains, Color as Shock, Conditional on Age, Marital, Kids, and Education

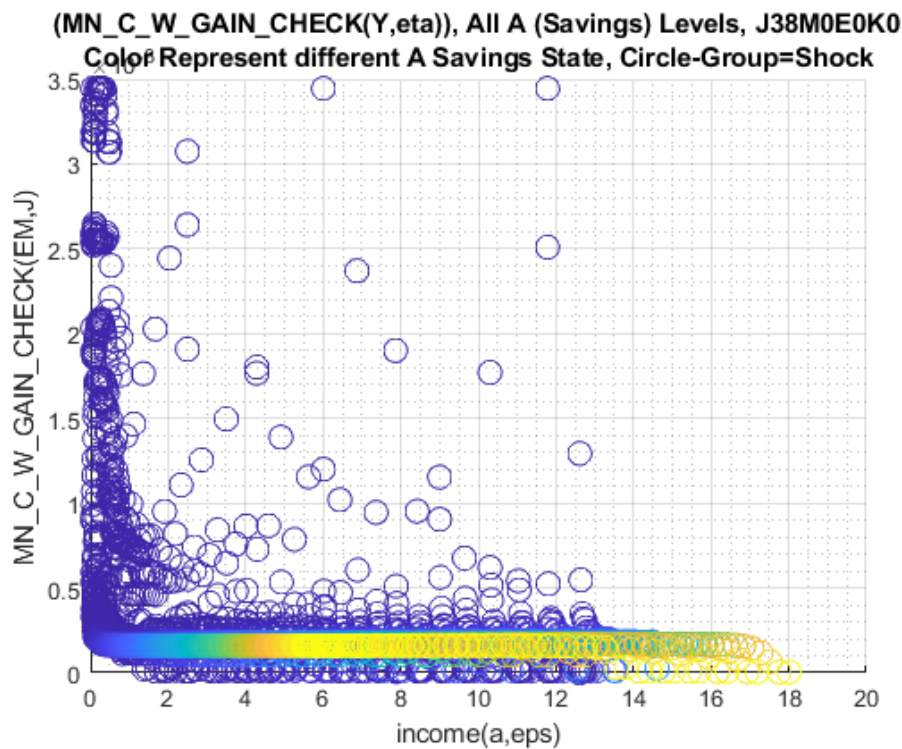
How do shocks and  $a$  impact marginal value. First plot one asset level, variation comes only from increasingly higher shocks:

```
figure();
it_a = 50;
scatter(log(mt_total_inc_jemk(:,it_a)), mt_C_W_gain_check_jemk(:,it_a), 100);
title({'MN\C\W\_GAIN\_CHECK(Y(A, eta)), Given A Savings Level, J38M0E0K0', ...
      'Each Circle is A Different shock Level'});
xlabel('Y(a,eta) = Spouse + Household head Income Joint');
ylabel('MN\C\W\_GAIN\_CHECK(A, eta)');
grid on;
grid minor;
```



Plot all asset levels:

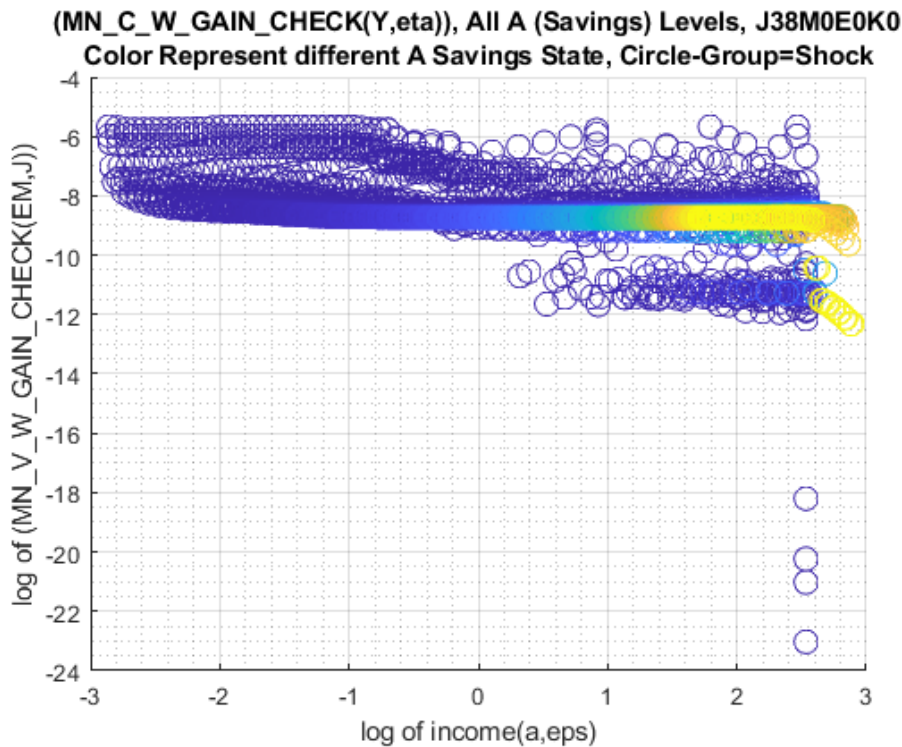
```
figure();
scatter((mt_total_inc_jemk(:)), (mt_C_W_gain_check_jemk(:)), 100, mt_a(:));
title({'(MN\C\W\_GAIN\_CHECK(Y,eta)), All A (Savings) Levels, J38M0E0K0', ...
      'Color Represent different A Savings State, Circle-Group=Shock'});
xlabel('income(a,eps)');
ylabel('MN\C\W\_GAIN\_CHECK(EM,J)');
grid on;
grid minor;
```



```

figure();
scatter(log(mt_total_inc_jemk(:)), log(mt_C_W_gain_check_jemk(:)), 100, mt_a(:));
title({'(MN\C\W\GAIN\CHECK(Y,eta)), All A (Savings) Levels, J38M0E0K0', ...
      'Color Represent different A Savings State, Circle-Group=Shock'});
xlabel('log of income(a,eps)');
ylabel('log of (MN\V\W\GAIN\CHECK(EM,J))');
grid on;
grid minor;

```



### 9.1.9 Analyze Kids and Marriage and Age

Aggregating over education, savings, and shocks, what are the differential effects of Marriage and Age.

```

% Generate some Data
mp_support_graph = containers.Map('KeyType', 'char', 'ValueType', 'any');
ar_row_grid = [...
    "k0M0", "k1M0", "k2M0", "k3M0", "k4M0", ...
    "k0M1", "k1M1", "k2M1", "k3M1", "k4M1"];
mp_support_graph('cl_st_xtitle') = {'Age'};
mp_support_graph('st_legend_loc') = 'best';
mp_support_graph('bl_graph_logy') = true; % do not log
mp_support_graph('st_rounding') = '6.2f'; % format shock legend
mp_support_graph('cl_scatter_shapes') = {...
    'o', 'd', 's', 'x', '*'}, ...
    'o', 'd', 's', 'x', '*'};
mp_support_graph('cl_colors') = {...
    'red', 'red', 'red', 'red', 'red'}...
    'blue', 'blue', 'blue', 'blue', 'blue'};

MEAN(VAL(KM,J)), MEAN(AP(KM,J)), MEAN(C(KM,J))

Tabulate value and policies:

% Set
% NaN(n_jgrid,n_agrid,n_etagrid,n_educgrid,n_marriedgrid,n_kidsgrid);
ar_permute = [2,3,4,1,6,5];

```

% Value Function

```
st_title = ['MEAN(MN_V_U_GAIN_CHECK(KM,J)), welf_checks=' num2str(welf_checks) ', TR=' num2str(mp_pa
tb_az_v = ff_summ_nd_array(st_title, mn_V_U_gain_check, true, ["mean"], 3, 1, cl_mp_datasetdesc, ar
```

```
xxx MEAN(MN_V_U_GAIN_CHECK(KM,J)), welf_checks=2, TR=0.0017225 xxxxxxxxxxxxxxxxxxxxxxxxxxxxxxx
```

group	kids	marry	mean_age_18	mean_age_19	mean_age_20	mean_age_21	mean_age_2
1	1	0	0.038527	0.037553	0.036379	0.033145	0.030452
2	2	0	0.053415	0.052114	0.050493	0.045939	0.042139
3	3	0	0.063389	0.062083	0.060366	0.054947	0.050428
4	4	0	0.072383	0.070992	0.069108	0.062921	0.057762
5	5	0	0.079913	0.078518	0.076562	0.069748	0.06407
6	1	1	0.012602	0.012065	0.01155	0.010426	0.0094863
7	2	1	0.01678	0.016072	0.015393	0.013895	0.012637
8	3	1	0.020271	0.019456	0.018665	0.016854	0.015337
9	4	1	0.024225	0.023287	0.022361	0.020206	0.018399
10	5	1	0.029524	0.028487	0.02744	0.02482	0.022631

% Consumption Function

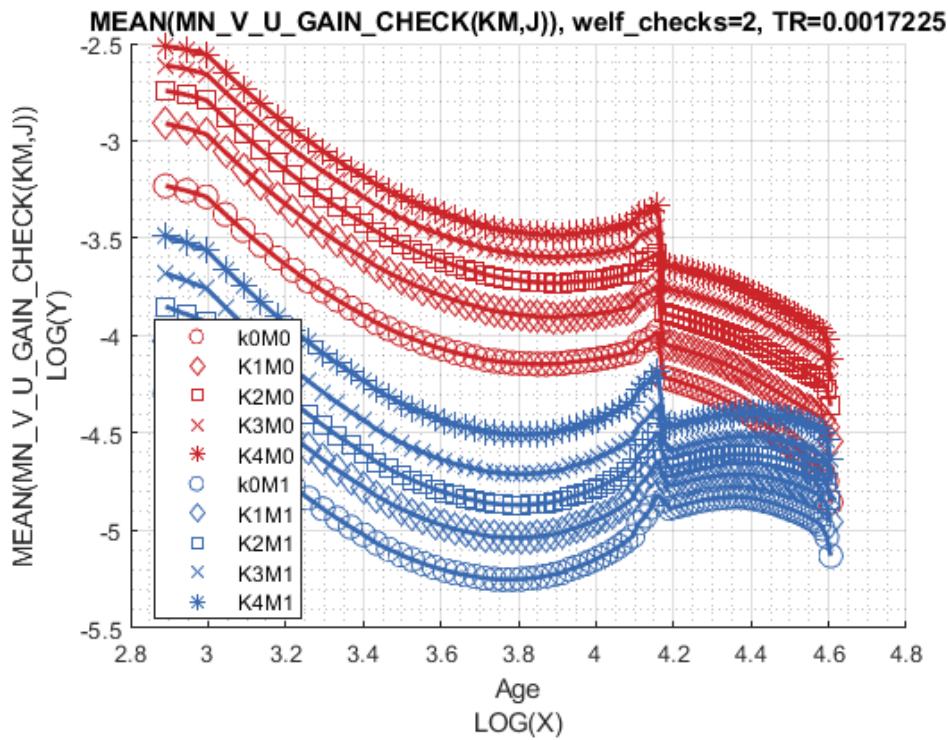
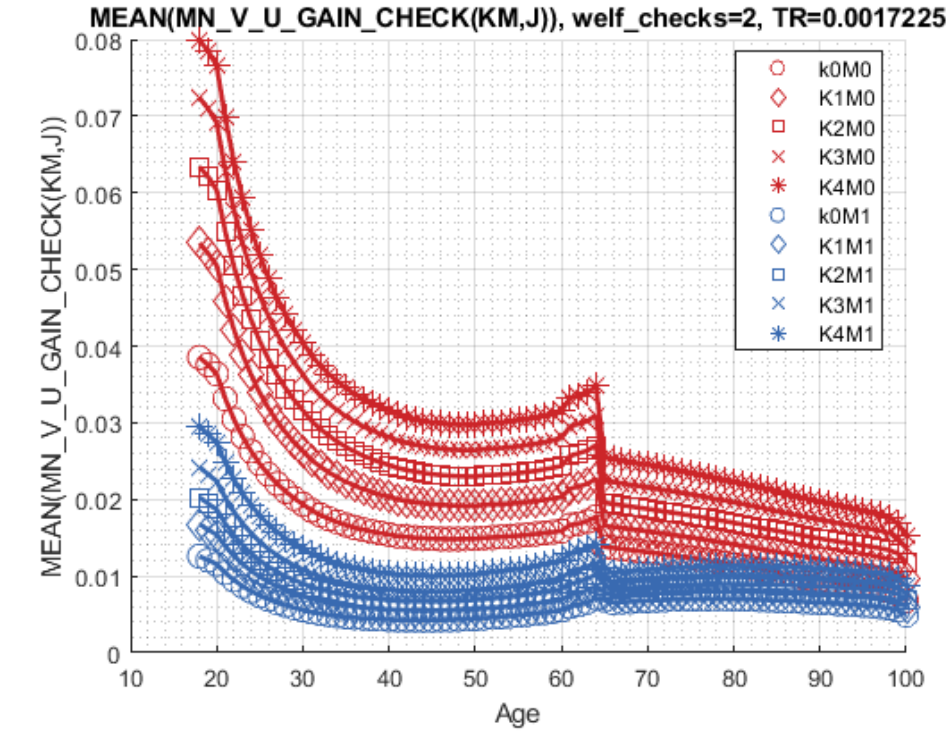
```
st_title = ['MEAN(MN_MPC_U_GAIN_CHECK(KM,J)), welf_checks=' num2str(welf_checks) ', TR=' num2str(mp_
tb_az_c = ff_summ_nd_array(st_title, mn_MPC_U_gain_share_check, true, ["mean"], 3, 1, cl_mp_datasetd
```

```
xxx MEAN(MN_MPC_U_GAIN_CHECK(KM,J)), welf_checks=2, TR=0.0017225 xxxxxxxxxxxxxxxxxxxxxxxxxxxxxxx
```

group	kids	marry	mean_age_18	mean_age_19	mean_age_20	mean_age_21	mean_age_2
1	1	0	0.084608	0.090543	0.10335	0.10135	0.099555
2	2	0	0.09227	0.09874	0.1136	0.11143	0.10989
3	3	0	0.10204	0.1099	0.12674	0.12369	0.12091
4	4	0	0.10652	0.1144	0.13184	0.12908	0.1263
5	5	0	0.1125	0.11953	0.13744	0.13456	0.13155
6	1	1	0.11122	0.11518	0.12131	0.11968	0.11893
7	2	1	0.11206	0.11641	0.12306	0.12166	0.12056
8	3	1	0.1176	0.12247	0.1311	0.12797	0.12718
9	4	1	0.11929	0.12501	0.13176	0.1305	0.13114
10	5	1	0.1264	0.13179	0.1402	0.13884	0.13503

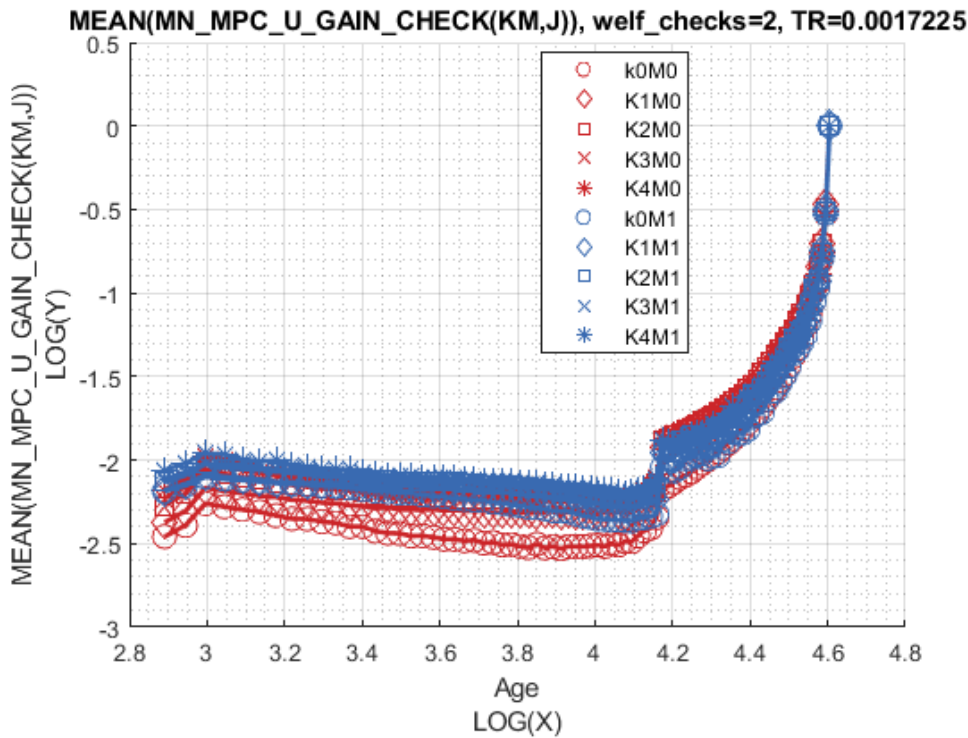
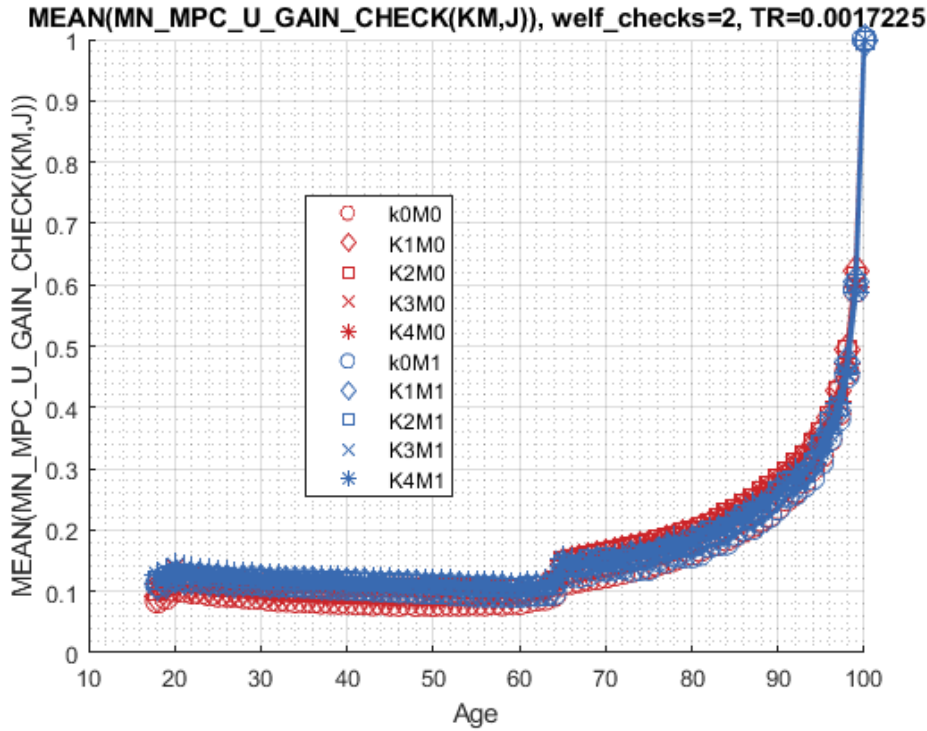
Graph Mean Values:

```
st_title = ['MEAN(MN\V\U\_GAIN\_CHECK(KM,J)), welf\_checks=' num2str(welf_checks) ', TR=' num2str(
mp_support_graph('cl_st_graph_title') = {st_title};
mp_support_graph('cl_st_ytitle') = {'MEAN(MN\V\U\_GAIN\_CHECK(KM,J))'};
ff_graph_grid((tb_az_v{1:end, 4:end}), ar_row_grid, age_grid, mp_support_graph);
```



Graph Mean Consumption (*MPC: Share of Check Consumed*):

```
st_title = ['MEAN(MN\MPC\U\_GAIN\_CHECK(KM,J)), welf_checks=' num2str(welf_checks) ', TR=' num2str(
mp_support_graph('cl_st_graph_title') = {st_title};
mp_support_graph('cl_st_ytitle') = {'MEAN(MN\MPC\U\_GAIN\_CHECK(KM,J))'};
ff_graph_grid((tb_az_c{1:end, 4:end}), ar_row_grid, age_grid, mp_support_graph);
```



### 9.1.10 Analyze Education and Marriage

Aggregating over education, savings, and shocks, what are the differential effects of Marriage and Age.

```
% Generate some Data
mp_support_graph = containers.Map('KeyType', 'char', 'ValueType', 'any');
ar_row_grid = ["E0M0", "E1M0", "E0M1", "E1M1"];
mp_support_graph('cl_st_xtitle') = {'Age'};
mp_support_graph('st_legend_loc') = 'best';
mp_support_graph('bl_graph_logy') = true; % do not log
```

```
mp_support_graph('st_rounding') = '6.2f'; % format shock legend
mp_support_graph('cl_scatter_shapes') = {'*', 'p', '*', 'p' };
mp_support_graph('cl_colors') = {'red', 'red', 'blue', 'blue'};
```

```
MEAN(VAL(EM,J)), MEAN(AP(EM,J)), MEAN(C(EM,J))
```

Tabulate value and policies:

```
% Set
% NaN(n_jgrid,n_agrid,n_etagrid,n_educgrid,n_marriedgrid,n_kidsgrid);
ar_permute = [2,3,6,1,4,5];
% Value Function
st_title = ['MEAN(MN_V_U_GAIN_CHECK(EM,J)), welf_checks=' num2str(welf_checks) ', TR=' num2str(mp_pa
tb_az_v = ff_summ_nd_array(st_title, mn_V_U_gain_check, true, ["mean"], 3, 1, cl_mp_datasetdesc, ar_
```

```
xxx MEAN(MN_V_U_GAIN_CHECK(EM,J)), welf_checks=2, TR=0.0017225 xxxxxxxxxxxxxxxxxxxxxxxxxxxxxxx
  group   edu   marry   mean_age_18   mean_age_19   mean_age_20   mean_age_21   mean_age_22
  -----   ---   -----   -----
  1         0     0     0.062745     0.06175     0.060482     0.056976     0.053863
  2         1     0     0.060305     0.058754     0.056681     0.049704     0.044078
  3         0     1     0.021795     0.020987     0.020201     0.018731     0.017442
  4         1     1     0.019567     0.01876     0.017963     0.015749     0.013955
```

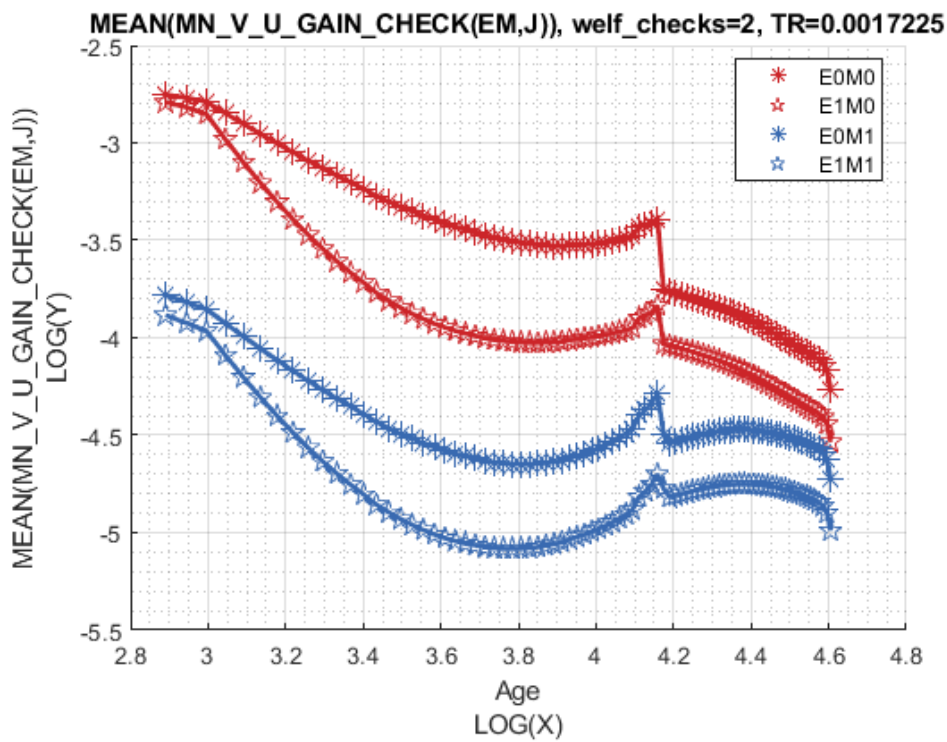
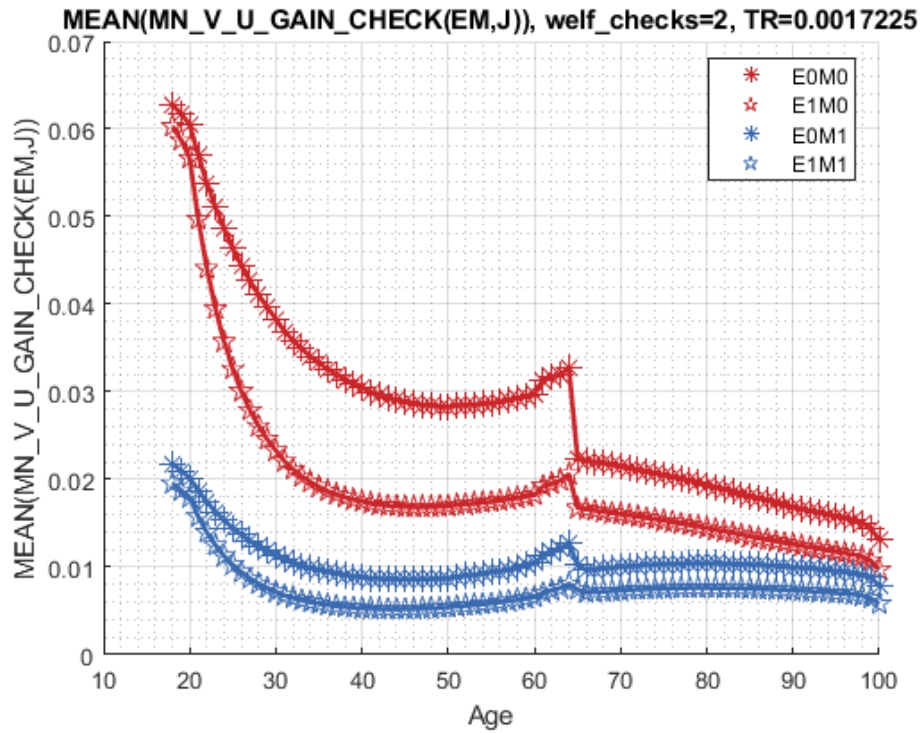
```
% Consumption
st_title = ['MEAN(MN_MPC_U_GAIN_CHECK(EM,J)), welf_checks=' num2str(welf_checks) ', TR=' num2str(mp_
tb_az_c = ff_summ_nd_array(st_title, mn_MPC_U_gain_share_check, true, ["mean"], 3, 1, cl_mp_datasetd
```

```
xxx MEAN(MN_MPC_U_GAIN_CHECK(EM,J)), welf_checks=2, TR=0.0017225 xxxxxxxxxxxxxxxxxxxxxxxxxxxxxxx
  group   edu   marry   mean_age_18   mean_age_19   mean_age_20   mean_age_21   mean_age_22
  -----   ---   -----   -----
  1         0     0     0.091431     0.09559     0.10516     0.10437     0.10421
  2         1     0     0.10775     0.11765     0.14003     0.13567     0.13107
  3         0     1     0.1091     0.11287     0.1172     0.11714     0.11697
  4         1     1     0.12553     0.13148     0.14177     0.13832     0.13616
```

Graph Mean Values:

```
st_title = ['MEAN(MN\V\U\_GAIN\_CHECK(EM,J)), welf\_checks=' num2str(welf_checks) ', TR=' num2str(
mp_support_graph('cl_st_graph_title') = {st_title};
mp_support_graph('cl_st_ytitle') = {'MEAN(MN\V\U\_GAIN\_CHECK(EM,J))'};
ff_graph_grid((tb_az_v{1:end, 4:end}), ar_row_grid, age_grid, mp_support_graph);
```

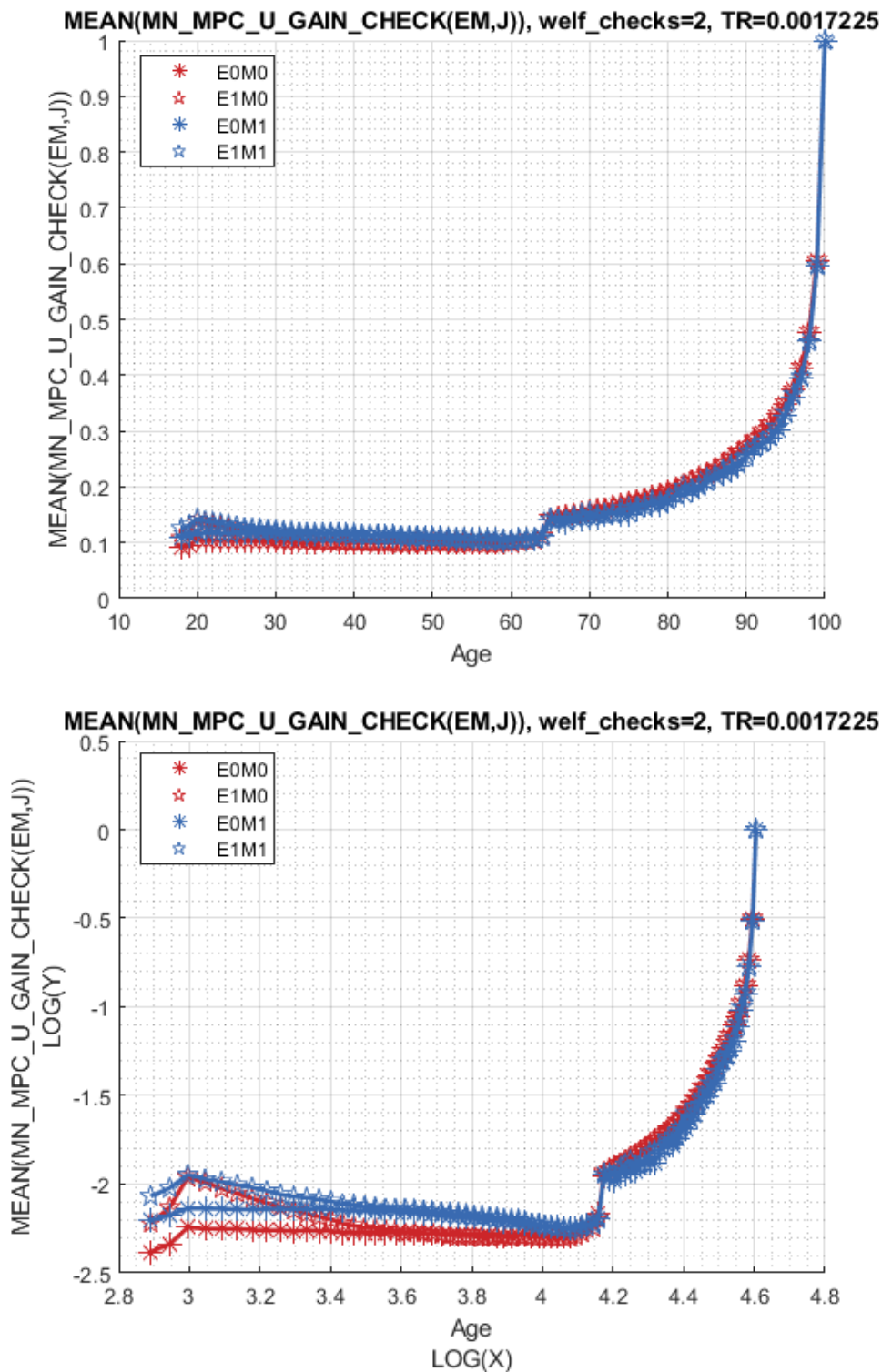




Graph Mean Consumption (MPC: Share of Check Consumed):

```

st_title = ['MEAN(MN\MPC\U\_GAIN\_CHECK(EM,J)), welf\_checks=' num2str(welf_checks) ', TR=' num2str
mp_support_graph('cl_st_graph_title') = {st_title};
mp_support_graph('cl_st_ytitle') = {'MEAN(MN\MPC\U\_GAIN\_CHECK(EM,J))'};
ff_graph_grid((tb_az_c{1:end, 4:end}), ar_row_grid, age_grid, mp_support_graph);
    
```



## 9.2 2019 (Biden/Trump Checks) Full States EV and EC of Two Checks

This is the example vignette for function: [snw\\_evuvw19\\_jaemk\\_foc](#) from the [PrjOptiSNW Package](#). 2019 integrated over VU and VW, given optimal savings choices, unemployment shocks and various expectations.

Given 2020 JAEEMK (age, endogenous savings, education, income shock, marital status, kids count), what is the expected value for the planner given 2020 JAEEMK and transition between 2019 to 2020

JAEEMK given some stimulus check assignment based on 2019 information? (Stimulus amount set by WELF\_CHECKS). This is similar to [snw\\_evuvw19\\_jaeemk](#), except the solution here, under [snw\\_evuvw19\\_jaeemk\\_foc](#), relies on First Order Conditions, and are hence faster.

Despite the name, this function supports solving the 2019 looking into 2020 as well as the 2007 looking into 2008 problems. The idea is that the planner only has information from 2019 and from 2007, and must allocate using those information. Stimulus, however, is given in 2020 and in 2008. So the planner needs to consider expected values in consumption or welfare given the transition probabilities of states in 2007 to 2008 and in 2019 to 2020. The [snw\\_evuvw19\\_jmky](#) file then aggregates the full state-space results to just JMKY state-space, which is the extend of information available to the planner.

### 9.2.1 Test SNW\_EVUVW19\_JAEEMK Defaults for 2019

Call the function with defaults parameters.

```
clear all;
% Solution types
st_biden_or_trump = 'bidenchk';
st_solu_type = 'bisec_vec';

% Solve the VFI Problem and get Value Function
mp_params = snw_mp_param('default_docdense');
% mp_params = snw_mp_param('default_dense');
mp_params('beta') = 0.95;
mp_params('st_biden_or_trump') = st_biden_or_trump;
% mp_params = snw_mp_param('default_dense');
mp_controls = snw_mp_control('default_test');

% set Unemployment Related Variables
mp_params('a2_covidyr') = mp_params('a2_covidyr_manna_heaven');
% mp_params('a2_covidyr') = mp_params('a2_covidyr_tax_fully_pay');

% Solve for Unemployment Values
mp_controls('bl_print_vfi') = false;
mp_controls('bl_print_vfi_verbose') = true;
mp_controls('bl_print_ds') = false;
mp_controls('bl_print_ds_verbose') = false;
mp_controls('bl_print_precompute') = false;
mp_controls('bl_print_precompute_verbose') = false;
mp_controls('bl_print_a4chk') = false;
mp_controls('bl_print_a4chk_verbose') = false;
mp_controls('bl_print_evuvw20_jaeemk') = false;
mp_controls('bl_print_evuvw20_jaeemk_verbose') = false;

% Solve the Model to get V working and unemployed
[V_ss,ap_ss,cons_ss,mp_valpol_more_ss] = snw_vfi_main_bisec_vec(mp_params, mp_controls);

Completed SNW_VFI_MAIN_BISEC_VEC;SNW_MP_PARAM=default_docdense;SNW_MP_CONTROL=default_test;time=519.
-----
XXXXXXXXXXXXXXXXXXXXXXXXXXXXXXXXXXXXXXXXXXXXXXXXXXXXXXXXXXXX
CONTAINER NAME: mp_outcomes ND Array (Matrix etc)
XXXXXXXXXXXXXXXXXXXXXXXXXXXXXXXXXXXXXXXXXXXXXXXXXXXXXXXXXXXX

```

	i	idx	ndim	numel	rowN	colN	sum	mean	std
V_VFI	1	1	6	4.37e+07	83	5.265e+05	-6.6619e+08	-15.245	21.86
ap_VFI	2	2	6	4.37e+07	83	5.265e+05	1.3967e+09	31.962	36.42
cons_VFI	3	3	6	4.37e+07	83	5.265e+05	2.3276e+08	5.3263	8.441



	i	idx	ndim	numel	rowN	colN	sum	mean	std
V_VFI	1	1	6	4.37e+07	83	5.265e+05	-6.6619e+08	-15.245	21.86
ap_VFI	2	2	6	4.37e+07	83	5.265e+05	1.3967e+09	31.962	36.42
cons_VFI	3	3	6	4.37e+07	83	5.265e+05	2.3276e+08	5.3263	8.441

xxx TABLE:V\_VFI xxxxxxxxxxxxxxxxxxxxxxx

	c1	c2	c3	c4	c5	c526496	c526497	c526498
r1	-293.96	-293.57	-291.09	-285.44	-276.41	-4.3584	-4.2643	-4.171
r2	-284.42	-284.03	-281.55	-275.97	-267.24	-4.2519	-4.1612	-4.071
r3	-274.87	-274.48	-272.03	-266.62	-258.33	-4.1429	-4.0559	-3.969
r4	-265.22	-264.86	-262.58	-257.53	-249.74	-4.0309	-3.9475	-3.864
r5	-256.51	-256.17	-254.04	-249.3	-241.96	-3.9252	-3.8452	-3.765
r79	-13.642	-13.628	-13.535	-13.298	-12.896	-0.22092	-0.21058	-0.2008
r80	-12.283	-12.269	-12.176	-11.939	-11.537	-0.16979	-0.16182	-0.154
r81	-10.605	-10.591	-10.498	-10.261	-9.8589	-0.11712	-0.11163	-0.1064
r82	-8.3494	-8.3358	-8.2424	-8.0055	-7.6035	-0.065333	-0.062242	-0.0593
r83	-5.0665	-5.0529	-4.9595	-4.7226	-4.3206	-0.020968	-0.019972	-0.01903

xxx TABLE:ap\_VFI xxxxxxxxxxxxxxxxxxxxxxx

	c1	c2	c3	c4	c5	c526496	c526497	c526498	c526499
r1	0	0	0.00051498	0.0066578	0.021589	112.13	117.67	123.4	129.3
r2	0	0	0.00051498	0.0057684	0.020245	112.17	117.71	123.43	129.3
r3	0	0	0.00020768	0.0041456	0.018539	112.2	117.73	123.45	129.3
r4	0	0	0.00010346	0.0041199	0.018307	112.86	118.39	124.11	130.0
r5	0	0	5.2907e-06	0.0041199	0.018091	113.53	119.07	124.79	130.7
r79	0	0	0	0	0	81.091	85.364	89.335	93.25
r80	0	0	0	0	0	76.124	79.747	83.431	86.98
r81	0	0	0	0	0	67.945	70.639	73.673	76.99
r82	0	0	0	0	0	50.126	53.467	56.302	57.88
r83	0	0	0	0	0	0	0	0	0

xxx TABLE:cons\_VFI xxxxxxxxxxxxxxxxxxxxxxx

	c1	c2	c3	c4	c5	c526496	c526497	c526498
r1	0.036717	0.037251	0.040477	0.044486	0.049324	12.265	12.55	12.844
r2	0.036717	0.037251	0.040477	0.045375	0.050668	12.501	12.787	13.082
r3	0.036717	0.037251	0.040784	0.046998	0.052374	12.755	13.042	13.337
r4	0.038144	0.038678	0.042314	0.048449	0.054031	13	13.289	13.584
r5	0.039534	0.040068	0.043802	0.049839	0.055635	13.236	13.525	13.821
r79	0.19737	0.19791	0.20163	0.21175	0.23145	35.811	37.362	39.409
r80	0.19737	0.19791	0.20163	0.21175	0.23145	40.752	42.953	45.286
r81	0.19737	0.19791	0.20163	0.21175	0.23145	48.909	52.039	55.022
r82	0.19737	0.19791	0.20163	0.21175	0.23145	66.71	69.193	72.375
r83	0.19737	0.19791	0.20163	0.21175	0.23145	116.82	122.65	128.66

% Solve unemployment, different income than under ss due to income losses

mp\_params('xi') = 0.50;

mp\_params('b') = 0.50;

[V\_unemp\_2020,~,cons\_unemp\_2020,~] = snw\_vfi\_main\_bisec\_vec(mp\_params, mp\_controls, V\_ss);

Completed SNW\_VFI\_MAIN\_BISEC\_VEC 1 Period Unemp Shock;SNW\_MP\_PARAM=default\_docdense;SNW\_MP\_CONTROL=d

```

-----
XXXXXXXXXXXXXXXXXXXXXXXXXXXXXXXXXXXXXXXXXXXX
CONTAINER NAME: mp_outcomes ND Array (Matrix etc)
XXXXXXXXXXXXXXXXXXXXXXXXXXXXXXXXXXXXXXXXXXXX

```

	i	idx	ndim	numel	rowN	colN	sum	mean	std
V_VFI	1	1	6	4.37e+07	83	5.265e+05	-6.7567e+08	-15.462	22.25
ap_VFI	2	2	6	4.37e+07	83	5.265e+05	1.3783e+09	31.541	36.3
cons_VFI	3	3	6	4.37e+07	83	5.265e+05	2.3114e+08	5.2893	8.440

```

xxx TABLE:V_VFI XXXXXXXXXXXXXXXXXXXXXXX

```

	c1	c2	c3	c4	c5	c526496	c526497	c526498
r1	-302.8	-302.11	-297.97	-290.4	-280.12	-4.3991	-4.3032	-4.208
r2	-293.25	-292.57	-288.43	-280.86	-270.8	-4.2921	-4.1998	-4.108
r3	-283.7	-283.02	-278.88	-271.34	-261.75	-4.1826	-4.094	-4.006
r4	-273.72	-273.09	-269.23	-262.13	-253.1	-4.0721	-3.987	-3.902
r5	-264.7	-264.11	-260.51	-253.79	-245.27	-3.9679	-3.8861	-3.805
r79	-13.642	-13.628	-13.535	-13.298	-12.896	-0.22191	-0.21148	-0.2016
r80	-12.283	-12.269	-12.176	-11.939	-11.537	-0.17053	-0.16249	-0.154
r81	-10.605	-10.591	-10.498	-10.261	-9.8589	-0.11764	-0.11208	-0.1068
r82	-8.3494	-8.3358	-8.2424	-8.0055	-7.6035	-0.065608	-0.062497	-0.05959
r83	-5.0665	-5.0529	-4.9595	-4.7226	-4.3206	-0.021056	-0.020052	-0.01911

```

xxx TABLE:ap_VFI XXXXXXXXXXXXXXXXXXXXXXX

```

	c1	c2	c3	c4	c5	c526496	c526497	c526498	c526499	c
r1	0	0	0	0.0011815	0.013905	109.98	115.52	121.26	127.18	1
r2	0	0	0	0.00090277	0.013905	109.95	115.49	121.22	127.14	1
r3	0	0	0	0.00051498	0.013905	109.9	115.45	121.18	127.1	1
r4	0	0	0	0.00051498	0.013905	110.34	115.88	121.61	127.53	1
r5	0	0	0	0.00048777	0.013905	110.79	116.33	122.06	127.98	
r79	0	0	0	0	0	80.974	84.852	88.823	92.746	9
r80	0	0	0	0	0	75.619	79.241	82.926	86.481	9
r81	0	0	0	0	0	67.445	70.139	73.173	76.669	8
r82	0	0	0	0	0	50.126	53.467	55.806	57.389	6
r83	0	0	0	0	0	0	0	0	0	

```

xxx TABLE:cons_VFI XXXXXXXXXXXXXXXXXXXXXXX

```

	c1	c2	c3	c4	c5	c526496	c526497	c526498
r1	0.027723	0.028258	0.031999	0.040974	0.048028	11.989	12.265	12.55
r2	0.027723	0.028258	0.031999	0.041253	0.048028	12.223	12.501	12.787
r3	0.027723	0.028258	0.031999	0.041641	0.048028	12.476	12.755	13.042
r4	0.028805	0.029339	0.033081	0.042722	0.049108	12.72	13	13.289
r5	0.029859	0.030394	0.034135	0.043802	0.050161	12.955	13.236	13.525
r79	0.19737	0.19791	0.20163	0.21175	0.23145	35.417	37.362	39.409
r80	0.19737	0.19791	0.20163	0.21175	0.23145	40.752	42.953	45.286
r81	0.19737	0.19791	0.20163	0.21175	0.23145	48.909	52.039	55.022
r82	0.19737	0.19791	0.20163	0.21175	0.23145	66.215	68.697	72.375
r83	0.19737	0.19791	0.20163	0.21175	0.23145	116.33	122.15	128.17

```

[Phi_true] = snw_ds_main(mp_params, mp_controls, ap_ss, cons_emp_2020, mp_valpol_more_ss);

```

Completed SNW\_DS\_MAIN;SNW\_MP\_PARAM=default\_docdense;SNW\_MP\_CONTROL=default\_test;time=1473.2344

```
% Get Matrixes
cl_st_precompute_list = {'a', ...
    'inc', 'inc_unemp', 'spouse_inc', 'spouse_inc_unemp', 'ref_earn_wageind_grid',...
    'ar_z_ctr_amz'};
% cl_st_precompute_list = {'a', ...
%     'inc', 'inc_unemp', 'spouse_inc', 'spouse_inc_unemp', 'ref_earn_wageind_grid',...
%     'ap_idx_lower_ss', 'ap_idx_higher_ss', 'ap_idx_lower_weight_ss'};
mp_controls('bl_print_precompute_verbose') = false;
[mp_precompute_res] = snw_hh_precompute(mp_params, mp_controls, cl_st_precompute_list, ap_ss, Phi_tr
```

Wage quintile cutoffs=0.4645 0.71528 1.0335 1.5632

Completed SNW\_HH\_PRECOMPUTE;SNW\_MP\_PARAM=default\_docdense;SNW\_MP\_CONTROL=default\_test;time cost=279.

### 9.2.2 Solve for 2019 Evuvw With 0 and 2 Checks

Solve for 0 and 2 checks, by finding the increase to asset state-space that is equivalent to the check increase, so that the problem can be solved without increasing the state-space.

```
% Call Function
welf_checks = 0;
[ev19_jaeemk_check0, ec19_jaeemk_check0, ev20_jaeemk_check0, ec20_jaeemk_check0] = snw_evuvw19_jaeemk(
    welf_checks, st_solu_type, mp_params, mp_controls, ...
    V_emp_2020, ap_ss, cons_emp_2020, V_unemp_2020, cons_unemp_2020, mp_precompute_res);
```

Completed SNW\_A4CHK\_WRK\_BISEC\_VEC;SNW\_MP\_PARAM=bidenchk;welf\_checks=0;TR=0.0015999;SNW\_MP\_PARAM=defa

Completed SNW\_A4CHK\_UNEMP\_BISEC\_VEC;welf\_checks=0;TR=0.0015999;xi=0.5;b=0.5;SNW\_MP\_PARAM=default\_doc

Completed SNW\_EVUVW20\_JAEEMK;SNW\_MP\_PARAM=default\_docdense;SNW\_MP\_CONTROL=default\_test;timeEUEC=8.35

Completed SNW\_EVUVW19\_JAEEMK\_FOC;st\_biden\_or\_trump=bidenchk;SNW\_MP\_PARAM=default\_docdense;SNW\_MP\_CON

```
-----
XXXXXXXXXXXXXXXXXXXXXXXXXXXXXXXXXXXXXXXXXXXXXXXXXXXX
CONTAINER NAME: mp_outcomes ND Array (Matrix etc)
XXXXXXXXXXXXXXXXXXXXXXXXXXXXXXXXXXXXXXXXXXXXXXXXXXXX
```

	i	idx	ndim	numel	rowN	colN	sum	mean
	-	---	----	-----	----	-----	-----	-----
ec19_jaeemk	1	1	6	4.3173e+07	82	5.265e+05	1.9673e+08	4.5568
ec20_jaeemk	2	2	6	4.37e+07	83	5.265e+05	2.3259e+08	5.3225
ev19_jaeemk	3	3	6	4.3173e+07	82	5.265e+05	-6.4971e+08	-15.049
ev20_jaeemk	4	4	6	4.37e+07	83	5.265e+05	-6.683e+08	-15.293

```
xxx TABLE:ec19_jaeemk XXXXXXXXXXXXXXXXXXXXXXXX
      c1          c2          c3          c4          c5          c526496    c526497    c526498
```

	c1	c2	c3	c4	c5	c526496	c526497	c526498
	-----	-----	-----	-----	-----	-----	-----	-----
r1	0.036494	0.036494	0.037029	0.041925	0.048857	12.017	12.289	12.569
r2	0.036494	0.036494	0.037029	0.041745	0.049665	12.261	12.534	12.815
r3	0.037912	0.037912	0.038127	0.041994	0.050655	12.495	12.77	13.052
r4	0.039293	0.039293	0.039401	0.043382	0.052052	12.753	13.028	13.311
r5	0.040635	0.040635	0.04064	0.044725	0.053494	13.002	13.278	13.56
r78	0.19737	0.19737	0.19737	0.19737	0.19791	27.77	28.769	29.78
r79	0.19737	0.19737	0.19737	0.19737	0.19737	30.426	31.659	32.732
r80	0.19737	0.19737	0.19737	0.19737	0.19737	33.678	35.498	37.364
r81	0.19737	0.19737	0.19737	0.19737	0.19737	40.112	41.394	43.173
r82	0.19737	0.19737	0.19737	0.19737	0.19737	52.096	55.537	58.457

```
xxx TABLE:ec20_jaeemk XXXXXXXXXXXXXXXXXXXXXXXX
      c1          c2          c3          c4          c5          c526496    c526497    c526498
```

r1	0.033462	0.033996	0.037408	0.043215	0.048855	12.242	12.527	12.819
r2	0.033462	0.033996	0.037408	0.043883	0.049712	12.478	12.763	13.057
r3	0.033462	0.033996	0.037604	0.045059	0.050801	12.731	13.018	13.313
r4	0.034763	0.035298	0.038972	0.046376	0.052249	12.977	13.265	13.56
r5	0.036032	0.036566	0.040303	0.047654	0.053654	13.213	13.501	13.796
r79	0.19737	0.19791	0.20163	0.21175	0.23145	35.811	37.362	39.409
r80	0.19737	0.19791	0.20163	0.21175	0.23145	40.752	42.953	45.286
r81	0.19737	0.19791	0.20163	0.21175	0.23145	48.909	52.039	55.022
r82	0.19737	0.19791	0.20163	0.21175	0.23145	66.71	69.193	72.375
r83	0.19737	0.19791	0.20163	0.21175	0.23145	116.82	122.65	128.66

```
xxx TABLE:ev19_jaeemk xxxxxxxxxxxxxxxxxxxxxxxx
```

	c1	c2	c3	c4	c5	c526496	c526497	c526498
r1	-284.04	-284.04	-283.59	-279.25	-271.39	-4.3825	-4.288	-4.194
r2	-273.99	-273.99	-273.54	-269.79	-262.27	-4.2743	-4.1834	-4.093
r3	-263.81	-263.81	-263.65	-260.8	-253.57	-4.1639	-4.0766	-3.990
r4	-254.62	-254.62	-254.55	-251.83	-245.12	-4.05	-3.9664	-3.883
r5	-246.32	-246.32	-246.31	-243.7	-237.45	-3.9424	-3.8621	-3.782
r78	-13.649	-13.649	-13.649	-13.649	-13.635	-0.27318	-0.26108	-0.2497
r79	-12.29	-12.29	-12.29	-12.29	-12.29	-0.21858	-0.20783	-0.1987
r80	-10.611	-10.611	-10.611	-10.611	-10.611	-0.16128	-0.15409	-0.1473
r81	-8.3555	-8.3555	-8.3555	-8.3555	-8.3555	-0.10114	-0.097402	-0.09344
r82	-5.0715	-5.0715	-5.0715	-5.0715	-5.0715	-0.044205	-0.041465	-0.03941

```
xxx TABLE:ev20_jaeemk xxxxxxxxxxxxxxxxxxxxxxxx
```

	c1	c2	c3	c4	c5	c526496	c526497	c526498
r1	-297.16	-296.66	-293.58	-287.23	-277.75	-4.3618	-4.2675	-4.174
r2	-287.62	-287.12	-284.04	-277.74	-268.53	-4.2552	-4.1645	-4.074
r3	-278.06	-277.57	-274.51	-268.33	-259.57	-4.1462	-4.059	-3.972
r4	-268.3	-267.84	-264.99	-259.19	-250.96	-4.0343	-3.9508	-3.868
r5	-259.47	-259.05	-256.38	-250.92	-243.16	-3.9288	-3.8486	-3.769
r79	-13.642	-13.628	-13.535	-13.298	-12.896	-0.22092	-0.21058	-0.2008
r80	-12.283	-12.269	-12.176	-11.939	-11.537	-0.16979	-0.16182	-0.154
r81	-10.605	-10.591	-10.498	-10.261	-9.8589	-0.11712	-0.11163	-0.1064
r82	-8.3494	-8.3358	-8.2424	-8.0055	-7.6035	-0.065333	-0.062242	-0.0593
r83	-5.0665	-5.0529	-4.9595	-4.7226	-4.3206	-0.020968	-0.019972	-0.01903

% Call Function

```
welf_checks = 2;
[ev19_jaeemk_check2, ec19_jaeemk_check2, ev20_jaeemk_check2, ec20_jaeemk_check2] = snw_evuvw19_jaeemk(
    welf_checks, st_solu_type, mp_params, mp_controls, ...
    V_emp_2020, ap_ss, cons_emp_2020, V_unemp_2020, cons_unemp_2020, mp_precompute_res);
```

Completed SNW\_A4CHK\_WRK\_BISEC\_VEC;SNW\_MP\_PARAM=bidenchk;welf\_checks=2;TR=0.0015999;SNW\_MP\_PARAM=default\_docdense;SNW\_MP\_CONTRQL=default\_test;timeEUEC=7.96

Completed SNW\_EVUVW20\_JAEEMK;SNW\_MP\_PARAM=default\_docdense;SNW\_MP\_CONTRQL=default\_test;timeEUEC=7.96

Completed SNW\_EVUVW19\_JAEEMK\_FOC;st\_biden\_or\_trump=bidenchk;SNW\_MP\_PARAM=default\_docdense;SNW\_MP\_CONTRQL=default\_test;timeEUEC=7.96

```
xxxxxxxxxxxxxxxxxxxxxxxxxxxxxxxxxxxxxxxxxxxxxxxxxxxxxxxxxxxxxxxxxxxxxxxxxxxx
CONTAINER NAME: mp_outcomes ND Array (Matrix etc)
```

```
xxxxxxxxxxxxxxxxxxxxxxxxxxxxxxxxxxxxxxxxxxxxxxxxxxxxxxxxxxxxxxxxxxxxxxxxxxxx
```

i	idx	ndim	numel	rowN	colN	sum	mean
---	-----	------	-------	------	------	-----	------



	-	---	----	-----	----	-----	-----	-----
ec19_jaeemk	1	1	6	4.3173e+07	82	5.265e+05	1.9675e+08	4.5574
ec20_jaeemk	2	2	6	4.37e+07	83	5.265e+05	2.3261e+08	5.323
ev19_jaeemk	3	3	6	4.3173e+07	82	5.265e+05	-6.4916e+08	-15.036
ev20_jaeemk	4	4	6	4.37e+07	83	5.265e+05	-6.6772e+08	-15.28

xxx TABLE:ec19\_jaeemk xxxxxxxxxxxxxxxxxxxxxxx

	c1	c2	c3	c4	c5	c526496	c526497	c526498
r1	0.039371	0.039371	0.03984	0.043617	0.0497	12.017	12.289	12.569
r2	0.039522	0.039522	0.040022	0.043796	0.050541	12.261	12.534	12.815
r3	0.040961	0.040961	0.041164	0.044279	0.051563	12.496	12.77	13.052
r4	0.042361	0.042361	0.042463	0.045683	0.05298	12.753	13.028	13.311
r5	0.043704	0.043704	0.043709	0.04707	0.054441	13.002	13.278	13.561
r78	0.20057	0.20057	0.20057	0.20057	0.20111	27.771	28.77	29.781
r79	0.20057	0.20057	0.20057	0.20057	0.20057	30.427	31.66	32.733
r80	0.20057	0.20057	0.20057	0.20057	0.20057	33.68	35.5	37.365
r81	0.20057	0.20057	0.20057	0.20057	0.20057	40.114	41.396	43.176
r82	0.20057	0.20057	0.20057	0.20057	0.20057	52.099	55.54	58.46

xxx TABLE:ec20\_jaeemk xxxxxxxxxxxxxxxxxxxxxxx

	c1	c2	c3	c4	c5	c526496	c526497	c526498
r1	0.036428	0.036915	0.039238	0.044128	0.049481	12.243	12.527	12.82
r2	0.036428	0.036915	0.039449	0.044827	0.050406	12.478	12.763	13.057
r3	0.036567	0.037083	0.039954	0.045988	0.051564	12.732	13.018	13.313
r4	0.037916	0.038441	0.041306	0.047327	0.053041	12.977	13.265	13.56
r5	0.03923	0.039763	0.04262	0.048625	0.054472	13.213	13.502	13.797
r79	0.20057	0.20111	0.20483	0.21495	0.23328	35.812	37.363	39.41
r80	0.20057	0.20111	0.20483	0.21495	0.23328	40.753	42.954	45.288
r81	0.20057	0.20111	0.20483	0.21495	0.23328	48.911	52.041	55.024
r82	0.20057	0.20111	0.20483	0.21495	0.23352	66.711	69.194	72.378
r83	0.20057	0.20111	0.20483	0.21495	0.23465	116.83	122.65	128.67

xxx TABLE:ev19\_jaeemk xxxxxxxxxxxxxxxxxxxxxxx

	c1	c2	c3	c4	c5	c526496	c526497	c526498
r1	-281.59	-281.59	-281.18	-277.52	-270.11	-4.3824	-4.288	-4.194
r2	-271.55	-271.55	-271.16	-268.06	-261.04	-4.2742	-4.1833	-4.093
r3	-261.56	-261.56	-261.41	-259.11	-252.39	-4.1639	-4.0766	-3.990
r4	-252.52	-252.52	-252.45	-250.24	-244	-4.0499	-3.9663	-3.883
r5	-244.35	-244.35	-244.35	-242.21	-236.39	-3.9423	-3.8621	-3.782
r78	-13.568	-13.568	-13.568	-13.568	-13.555	-0.27317	-0.26107	-0.2497
r79	-12.209	-12.209	-12.209	-12.209	-12.209	-0.21857	-0.20783	-0.1987
r80	-10.531	-10.531	-10.531	-10.531	-10.531	-0.16127	-0.15408	-0.1473
r81	-8.2749	-8.2749	-8.2749	-8.2749	-8.2749	-0.10114	-0.097398	-0.0934
r82	-4.991	-4.991	-4.991	-4.991	-4.991	-0.044202	-0.041463	-0.03941

xxx TABLE:ev20\_jaeemk xxxxxxxxxxxxxxxxxxxxxxx

	c1	c2	c3	c4	c5	c526496	c526497	c526498
r1	-294.47	-294.03	-291.58	-285.7	-276.56	-4.3618	-4.2675	-4.174
r2	-284.93	-284.49	-282.06	-276.25	-267.39	-4.2552	-4.1644	-4.074

r3	-275.39	-274.95	-272.56	-266.91	-258.48	-4.1462	-4.059	-3.972
r4	-265.81	-265.4	-263.16	-257.86	-249.93	-4.0343	-3.9507	-3.868
r5	-257.15	-256.77	-254.66	-249.67	-242.18	-3.9287	-3.8486	-3.769
r79	-13.561	-13.548	-13.46	-13.233	-12.841	-0.22091	-0.21058	-0.2008
r80	-12.203	-12.189	-12.101	-11.874	-11.482	-0.16978	-0.16181	-0.154
r81	-10.524	-10.511	-10.423	-10.196	-9.8048	-0.11712	-0.11163	-0.1064
r82	-8.2689	-8.2556	-8.1674	-7.9402	-7.5499	-0.065331	-0.062241	-0.05935
r83	-4.9861	-4.9727	-4.8846	-4.6573	-4.2682	-0.020967	-0.019972	-0.01903

Differences between Checks in Expected Value and Expected Consumption

```
mn_V_U_gain_check = ev19_jaeemk_check2 - ev19_jaeemk_check0;
mn_MPC_U_gain_share_check = (ec19_jaeemk_check2 - ec19_jaeemk_check0)./(welf_checks*mp_params('TR'));
```

### 9.2.3 Param Results Define Frames

Define the matrix dimensions names and dimension vector values. Policy and Value Functions share the same ND dimensional structure.

```
% Grids:
age_grid = 18:99;
agrid = mp_params('agrid');
eta_H_grid = mp_params('eta_H_grid');
eta_S_grid = mp_params('eta_S_grid');
ar_st_eta_HS_grid = string(cellstr([num2str(eta_H_grid), 'hz=%3.2f;'], num2str(eta_S_grid), 'wz=%3.2f;'));
edu_grid = [0,1];
marry_grid = [0,1];
kids_grid = (1:1:mp_params('n_kidsgrid'))';
% NaN(n_jgrid,n_agrid,n_etagrid,n_educgrid,n_marriedgrid,n_kidsgrid);
cl_mp_datasetdesc = {};
cl_mp_datasetdesc{1} = containers.Map({'name', 'labval'}, {'age', age_grid});
cl_mp_datasetdesc{2} = containers.Map({'name', 'labval'}, {'savings', agrid});
cl_mp_datasetdesc{3} = containers.Map({'name', 'labval'}, {'eta', 1:length(eta_H_grid)});
cl_mp_datasetdesc{4} = containers.Map({'name', 'labval'}, {'edu', edu_grid});
cl_mp_datasetdesc{5} = containers.Map({'name', 'labval'}, {'marry', marry_grid});
cl_mp_datasetdesc{6} = containers.Map({'name', 'labval'}, {'kids', kids_grid});
```

### 9.2.4 Analyze Difference in V and C with Check

The difference between V and V with Check, marginal utility gain given the check.

```
% Generate some Data
mp_support_graph = containers.Map('KeyType', 'char', 'ValueType', 'any');
mp_support_graph('cl_st_xtitle') = {'Savings States', a};
mp_support_graph('st_legend_loc') = 'eastoutside';
mp_support_graph('bl_graph_logy') = true; % do not log
mp_support_graph('it_legend_select') = 21; % how many shock legends to show
mp_support_graph('cl_colors') = 'jet';
```

```
MEAN(MN_V_GAIN_CHECK(A,Z))
```

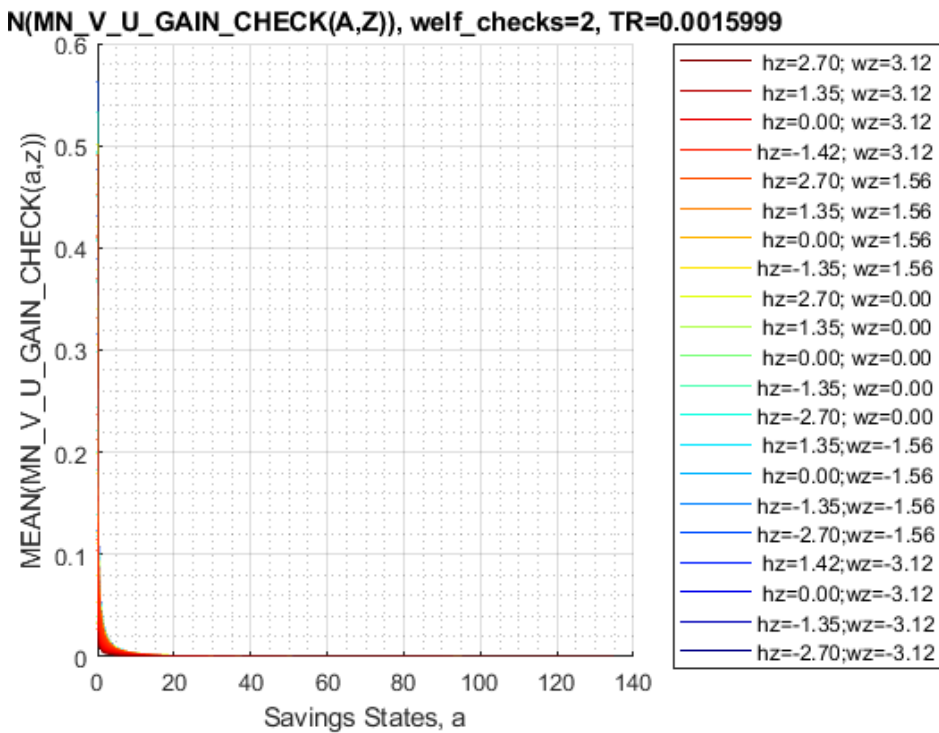
Tabulate value and policies along savings and shocks:

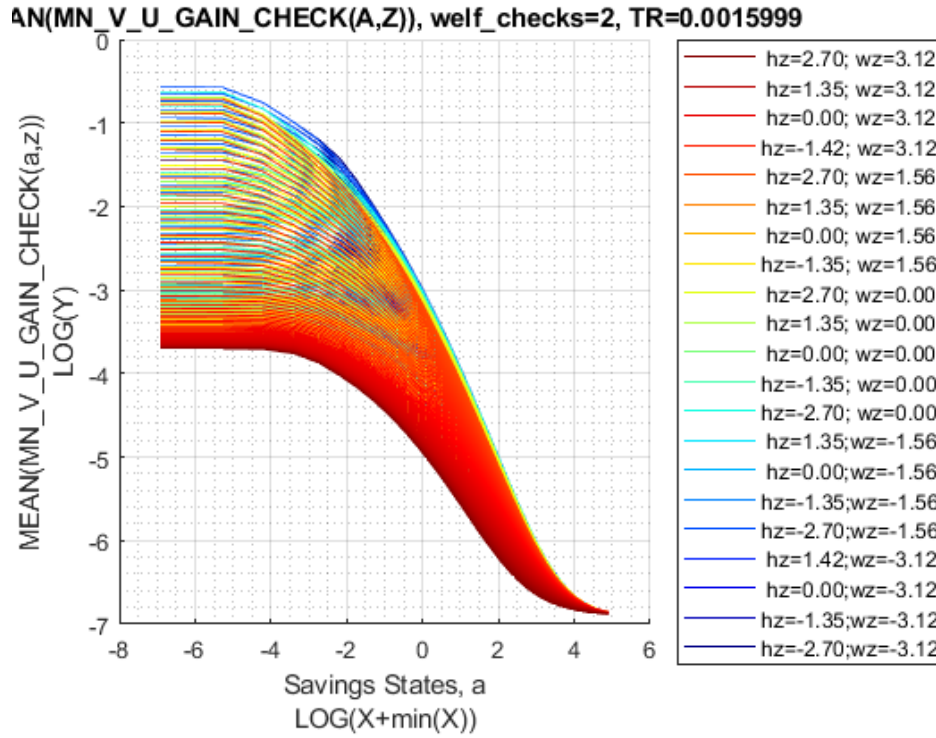
```
% Set
ar_permute = [1,4,5,6,3,2];
% Value Function
st_title = ['MEAN(MN_V_U_GAIN_CHECK(A,Z)), welf_checks=' num2str(welf_checks) ', TR=' num2str(mp_params('TR'))'];
tb_az_v = ff_summ_nd_array(st_title, mn_V_U_gain_check, true, ["mean"], 4, 1, cl_mp_datasetdesc, ar_permute);

xxx MEAN(MN_V_U_GAIN_CHECK(A,Z)), welf_checks=2, TR=0.0015999 xxxxxxxxxxxxxxxxxxxxxxxxxxxxxxxxxxxx
group savings mean_eta_1 mean_eta_2 mean_eta_3 mean_eta_4 mean_eta_5 mea
-----
```

1                    0                    0.56295                    0.52208                    0.47698                    0.43181                    0.38933

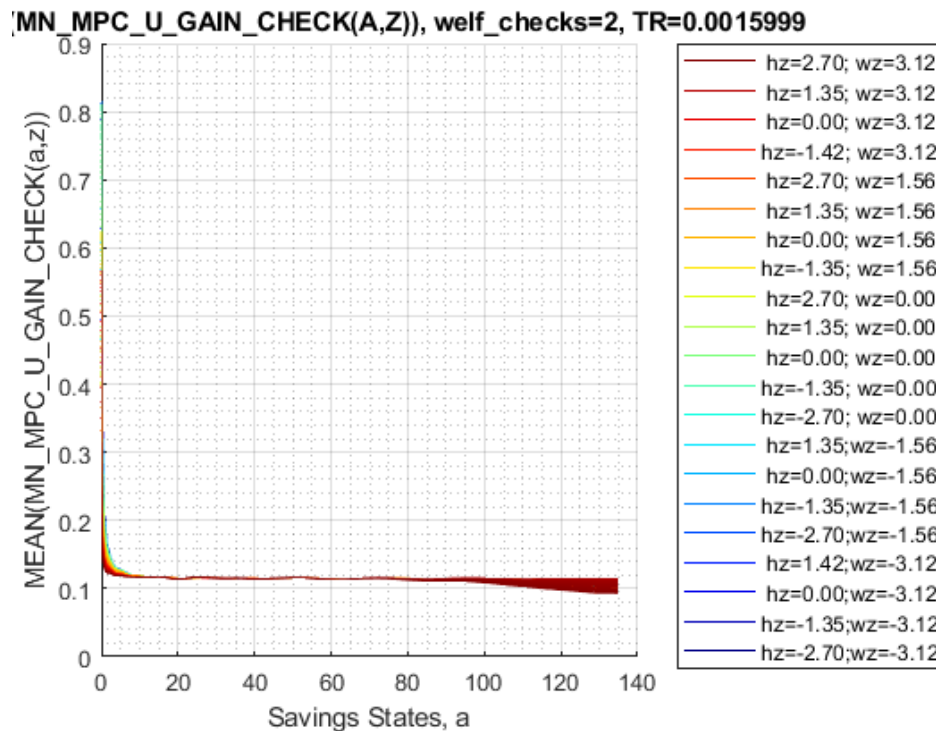
```
st_title = ['MEAN(MN\V\U\_GAIN\_CHECK(A,Z)), welf\_checks=' num2str(welf_checks) ', TR=' num2str(m
mp_support_graph('cl_st_graph_title') = {st_title};
mp_support_graph('cl_st_ytitle') = {'MEAN(MN\V\U\_GAIN\_CHECK(a,z))'};
ff_graph_grid((tb_az_v{1:end, 3:end})', ar_st_eta_HS_grid, agrid, mp_support_graph);
```

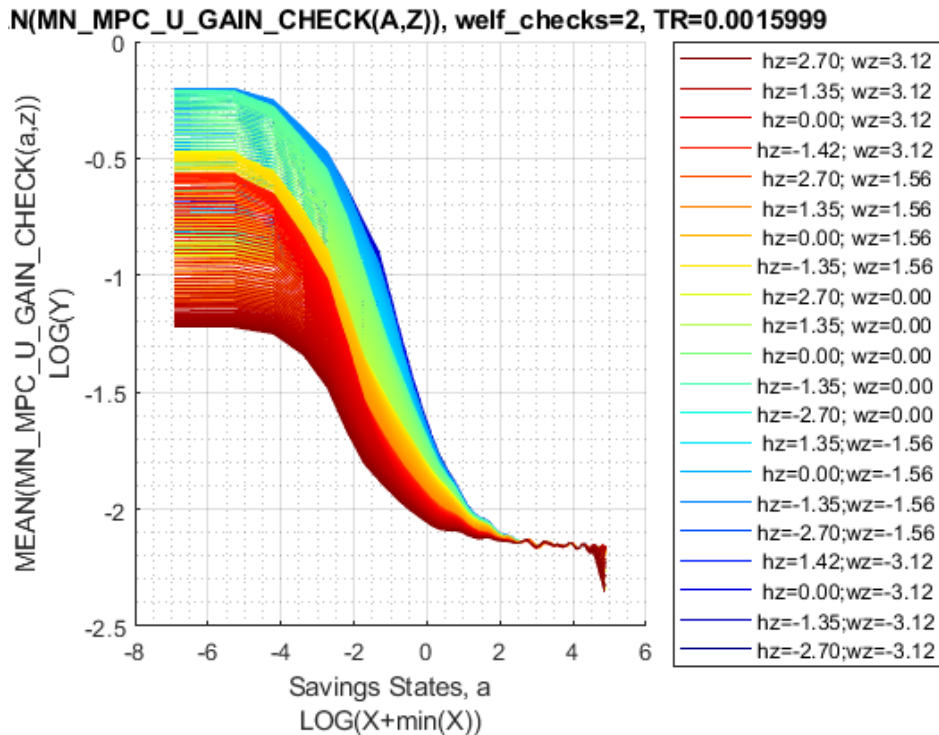




Graph Mean Consumption (*MPC: Share of Check Consumed*):

```
st_title = ['MEAN(MN\MPC\_U\_GAIN\_CHECK(A,Z)), welf\_checks=' num2str(welf_checks) ', TR=' num2str
mp_support_graph('cl_st_graph_title') = {st_title};
mp_support_graph('cl_st_ytitle') = {'MEAN(MN\MPC\_U\_GAIN\_CHECK(a,z))'};
ff_graph_grid((tb_az_c{1:end, 3:end}),' , ar_st_eta_HS_grid, agrid, mp_support_graph);
```





### 9.2.5 Analyze Marginal Value and MPC over $Y(a, \eta)$ , Conditional On Kids, Marry, Age, Education

Income is generated by savings and shocks, what are the income levels generated by all the shock and savings points conditional on kids, marital status, age and educational levels. Plot on the Y axis MPC, and plot on the X axis income levels, use colors to first distinguish between different  $a$  levels, then use colors to distinguish between different  $\eta$  levels.

Set Up date, Select Age 37vn

, unmarried, no kids, lower education:

```
% NaN(n_jgrid,n_agrid,n_etagrid,n_educgrid,n_marriedgrid,n_kidsgrid);
% 38 year old, unmarried, no kids, lower educated
% Only Household Head Shock Matters so select up to 'n_eta_H_grid'
mn_total_inc_jemk = total_inc_VFI(19, :, 1:mp_params('n_eta_H_grid'), 1, 1, 1);
mn_V_W_gain_check_use = ev19_jaeemk_check2 - ev19_jaeemk_check0;
mn_C_W_gain_check_use = ec19_jaeemk_check2 - ec19_jaeemk_check0;
```

Select Age, Education, Marital, Kids Count:s

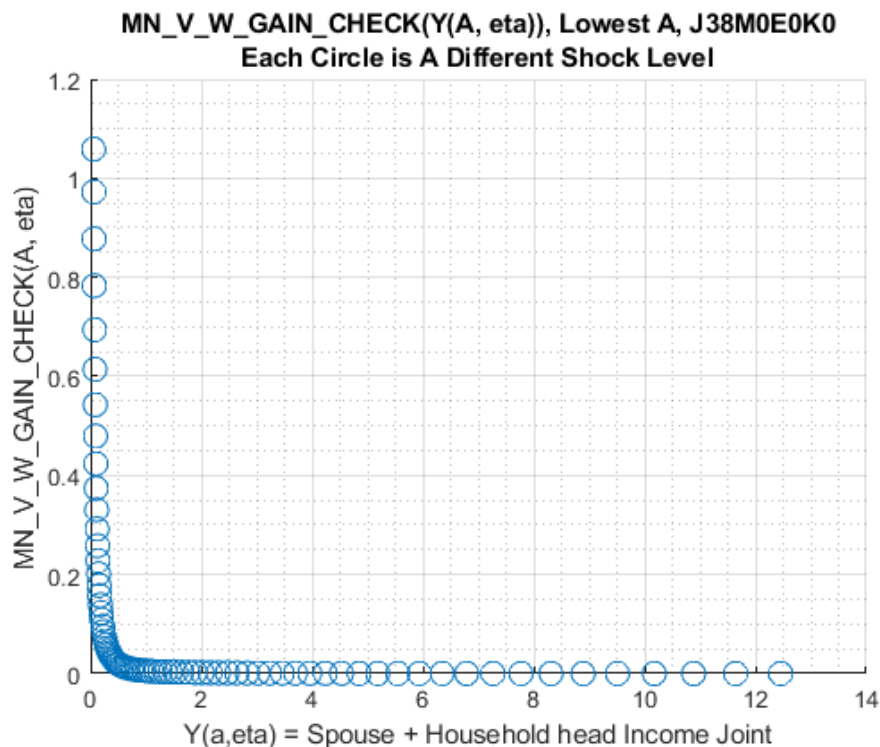
```
% Selections
it_age = 21; % +18
it_marital = 1; % 1 = unmarried
it_kids = 1; % 1 = kids is zero
it_educ = 1; % 1 = lower education
% Select: NaN(n_jgrid,n_agrid,n_etagrid,n_educgrid,n_marriedgrid,n_kidsgrid);
mn_C_W_gain_check_jemk = mn_C_W_gain_check_use(it_age, :, 1:mp_params('n_eta_H_grid'), it_educ, it_m
mn_V_W_gain_check_jemk = mn_V_W_gain_check_use(it_age, :, 1:mp_params('n_eta_H_grid'), it_educ, it_m
% Reshape, so shock is the first dim, a is the second
mt_total_inc_jemk = permute(mn_total_inc_jemk, [3, 2, 1]);
mt_C_W_gain_check_jemk = permute(mn_C_W_gain_check_jemk, [3, 2, 1]);
mt_C_W_gain_check_jemk(mt_C_W_gain_check_jemk <= 1e-10) = 1e-10;
mt_V_W_gain_check_jemk = permute(mn_V_W_gain_check_jemk, [3, 2, 1]);
mt_V_W_gain_check_jemk(mt_V_W_gain_check_jemk <= 1e-10) = 1e-10;
% Generate meshed a and shock grid
```

```
[mt_eta_H, mt_a] = ndgrid(eta_H_grid(1:mp_params('n_eta_H_grid')), agrid);
```

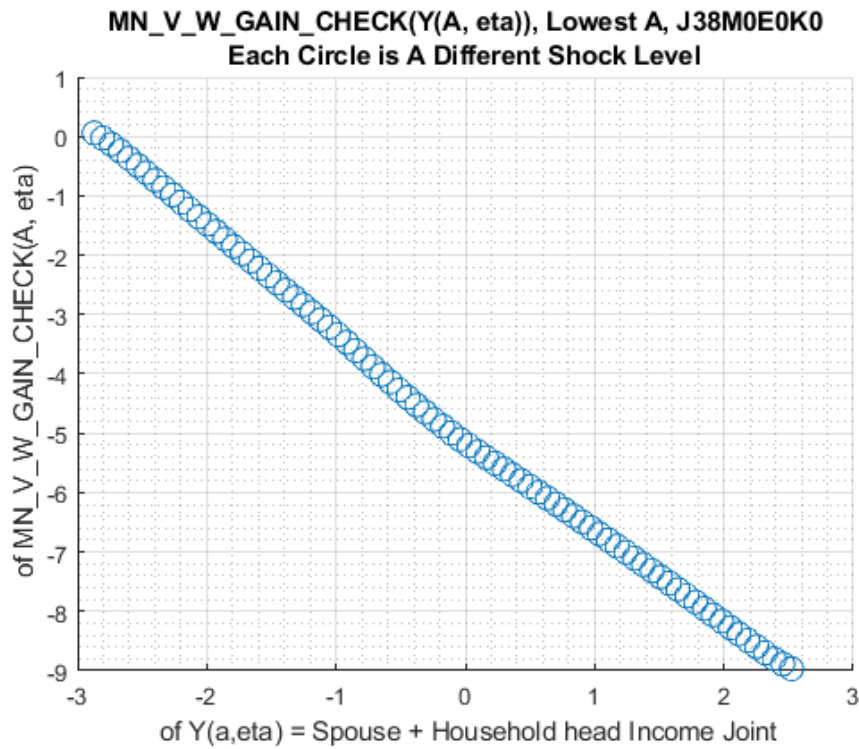
### 9.2.6 Marginal Value Gains, Color as Shock, Conditional on Age, Marital, Kids, and Education

How do shocks and  $a$  impact marginal value. First plot one asset level, variation comes only from increasingly higher shocks:

```
figure();
it_a = 1;
scatter((mt_total_inc_jemk(:,it_a)), (mt_V_W_gain_check_jemk(:,it_a)), 100);
title({'MN\V\W\GAIN\CHECK(Y(A, eta)), Lowest A, J38M0E0K0', ...
      'Each Circle is A Different Shock Level'});
xlabel('Y(a,eta) = Spouse + Household head Income Joint');
ylabel('MN\V\W\GAIN\CHECK(A, eta)');
grid on;
grid minor;
```

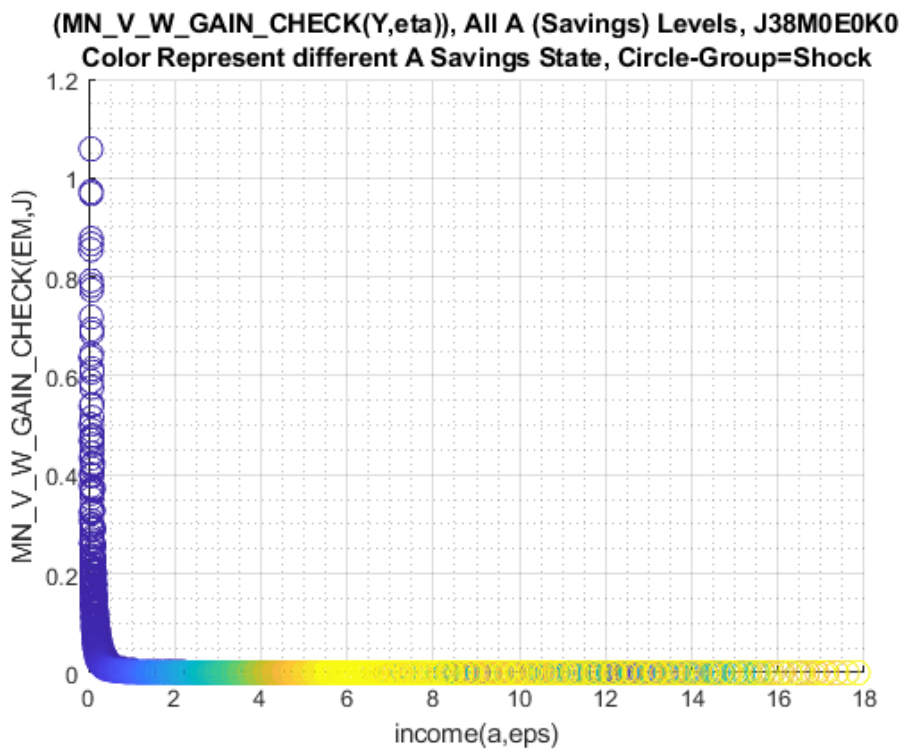


```
figure();
it_shock = 1;
scatter(log(mt_total_inc_jemk(:,it_a)), log(mt_V_W_gain_check_jemk(:,it_a)), 100);
title({'MN\V\W\GAIN\CHECK(Y(A, eta)), Lowest A, J38M0E0K0', ...
      'Each Circle is A Different Shock Level'});
xlabel(' of Y(a,eta) = Spouse + Household head Income Joint');
ylabel(' of MN\V\W\GAIN\CHECK(A, eta)');
grid on;
grid minor;
```



Plot all asset levels:

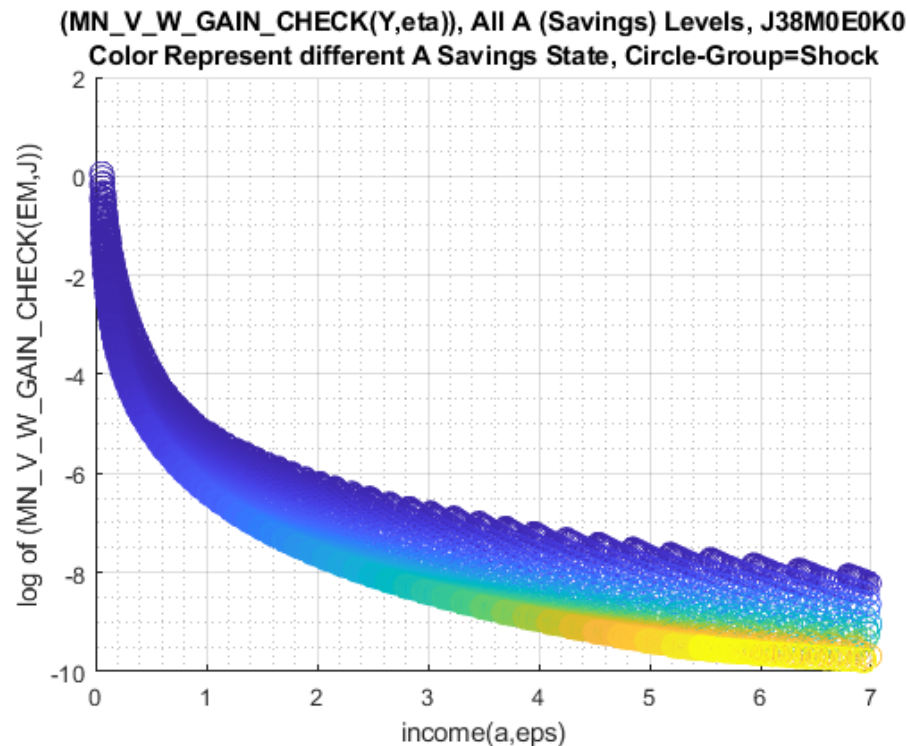
```
figure();
scatter((mt_total_inc_jemk(:)), (mt_V_W_gain_check_jemk(:)), 100, mt_a(:));
title({'(MN_V_W_GAIN_CHECK(Y,eta)), All A (Savings) Levels, J38M0E0K0', ...
      'Color Represent different A Savings State, Circle-Group=Shock'});
xlabel('income(a,eps)');
ylabel('MN_V_W_GAIN_CHECK(EM,J)');
grid on;
grid minor;
```



```

figure();
scatter(mt_total_inc_jemk(:), log(mt_V_W_gain_check_jemk(:)), 100, mt_a(:));
title({'(MN_V_W_GAIN_CHECK(Y,eta)), All A (Savings) Levels, J38MOEOK0', ...
      'Color Represent different A Savings State, Circle-Group=Shock'});
xlabel('income(a,eps)');
ylabel('log of (MN_V_W_GAIN_CHECK(EM,J))');
xlim([0,7]);
grid on;
grid minor;

```



### 9.2.7 Marginal Consumption Gains, Color as Shock, Conditional on Age, Marital, Kids, and Education

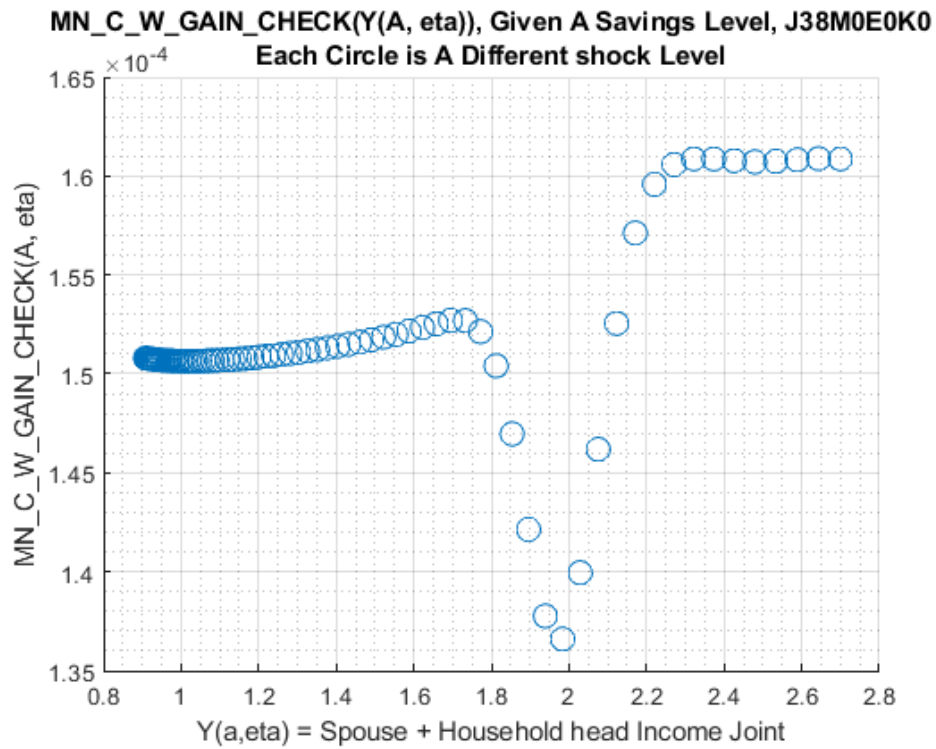
How do shocks and  $a$  impact marginal value. First plot one asset level, variation comes only from increasingly higher shocks:

```

figure();
it_a = 50;
scatter(log(mt_total_inc_jemk(:,it_a)), mt_C_W_gain_check_jemk(:,it_a), 100);
title({'MN_C_W_GAIN_CHECK(Y(A, eta)), Given A Savings Level, J38MOEOK0', ...
      'Each Circle is A Different shock Level'});
xlabel('Y(a,eta) = Spouse + Household head Income Joint');
ylabel('MN_C_W_GAIN_CHECK(A, eta)');
grid on;
grid minor;

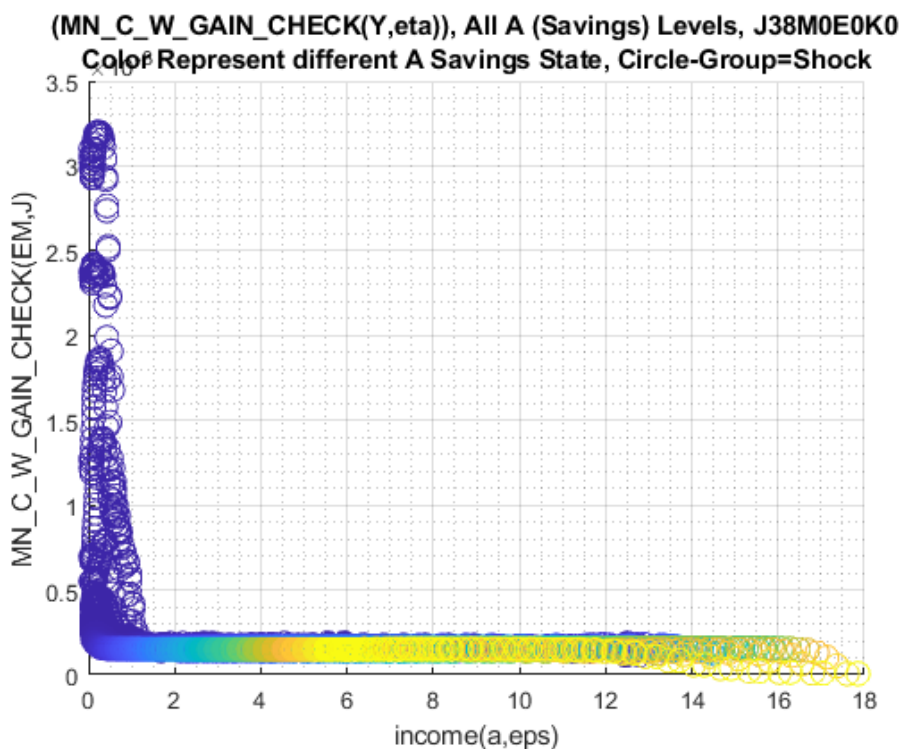
```





Plot all asset levels:

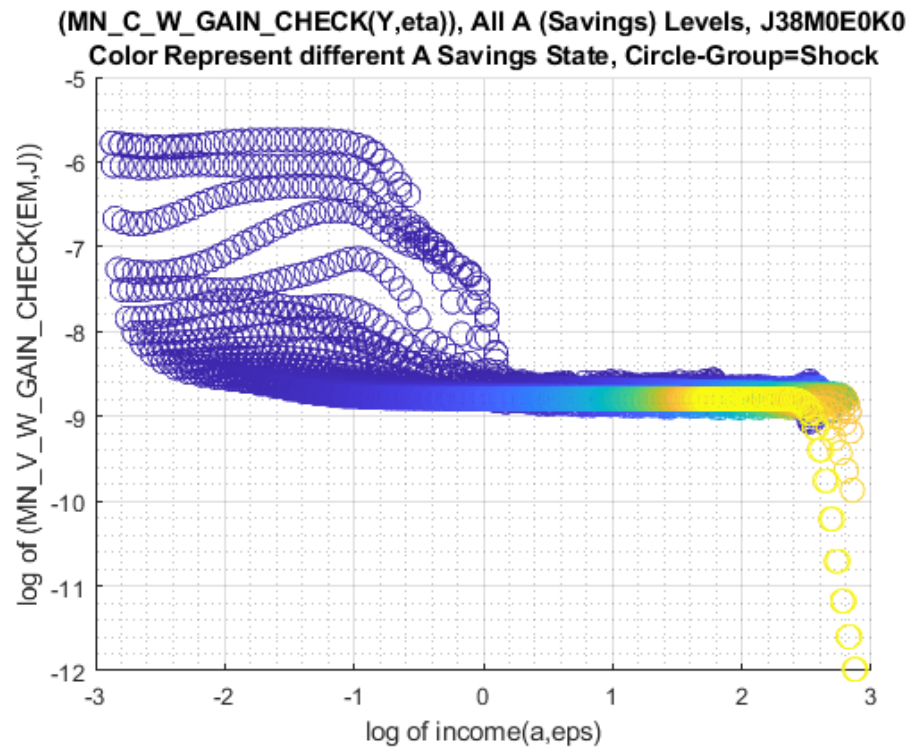
```
figure();
scatter((mt_total_inc_jemk(:)), (mt_C_W_gain_check_jemk(:)), 100, mt_a(:));
title({'(MN\C\W\GAIN\CHECK(Y,eta)), All A (Savings) Levels, J38M0E0K0', ...
      'Color Represent different A Savings State, Circle-Group=Shock'});
xlabel('income(a,eps)');
ylabel('MN\C\W\GAIN\CHECK(EM,J)');
grid on;
grid minor;
```



```

figure();
scatter(log(mt_total_inc_jemk(:)), log(mt_C_W_gain_check_jemk(:)), 100, mt_a(:));
title({'(MN\C\W\_GAIN\_CHECK(Y,eta)), All A (Savings) Levels, J38M0E0K0', ...
      'Color Represent different A Savings State, Circle-Group=Shock'});
xlabel('log of income(a,eps)');
ylabel('log of (MN\_V\_W\_GAIN\_CHECK(EM,J))');
grid on;
grid minor;

```



### 9.2.8 Analyze Kids and Marriage and Age

Aggregating over education, savings, and shocks, what are the differential effects of Marriage and Age.

```

% Generate some Data
mp_support_graph = containers.Map('KeyType', 'char', 'ValueType', 'any');
ar_row_grid = [...
    "k0M0", "k1M0", "k2M0", "k3M0", "k4M0", ...
    "k0M1", "k1M1", "k2M1", "k3M1", "k4M1"];
mp_support_graph('cl_st_xtitle') = {'Age'};
mp_support_graph('st_legend_loc') = 'best';
mp_support_graph('bl_graph_logy') = true; % do not log
mp_support_graph('st_rounding') = '6.2f'; % format shock legend
mp_support_graph('cl_scatter_shapes') = {...
    'o', 'd', 's', 'x', '*', ...
    'o', 'd', 's', 'x', '*'};
mp_support_graph('cl_colors') = {...
    'red', 'red', 'red', 'red', 'red'...
    'blue', 'blue', 'blue', 'blue', 'blue'};
MEAN(VAL(KM,J)), MEAN(AP(KM,J)), MEAN(C(KM,J))

Tabulate value and policies:

% Set
% NaN(n_jgrid,n_agrid,n_etagrid,n_educgrid,n_marriedgrid,n_kidsgrid);
ar_permute = [2,3,4,1,6,5];

```

% Value Function

```
st_title = ['MEAN(MN_V_U_GAIN_CHECK(KM,J)), welf_checks=' num2str(welf_checks) ', TR=' num2str(mp_pa
tb_az_v = ff_summ_nd_array(st_title, mn_V_U_gain_check, true, ["mean"], 3, 1, cl_mp_datasetdesc, ar_
```

```
xxx MEAN(MN_V_U_GAIN_CHECK(KM,J)), welf_checks=2, TR=0.0015999 xxxxxxxxxxxxxxxxxxxxxxxxxxxxxxx
```

group	kids	marry	mean_age_18	mean_age_19	mean_age_20	mean_age_21	mean_age_2
1	1	0	0.030027	0.029309	0.027141	0.024832	0.022901
2	2	0	0.04151	0.04055	0.037518	0.034247	0.031504
3	3	0	0.048832	0.047813	0.043942	0.040179	0.037025
4	4	0	0.055554	0.054443	0.050039	0.045784	0.042216
5	5	0	0.0609	0.05977	0.054981	0.05038	0.046522
6	1	1	0.0055093	0.0051081	0.0046334	0.0041967	0.0038272
7	2	1	0.0077846	0.0072287	0.0065562	0.0059314	0.0054057
8	3	1	0.0094266	0.008771	0.0079723	0.0072201	0.0065859
9	4	1	0.011763	0.010976	0.009988	0.0090498	0.0082597
10	5	1	0.014764	0.013879	0.012683	0.011539	0.010569

% Consumption Function

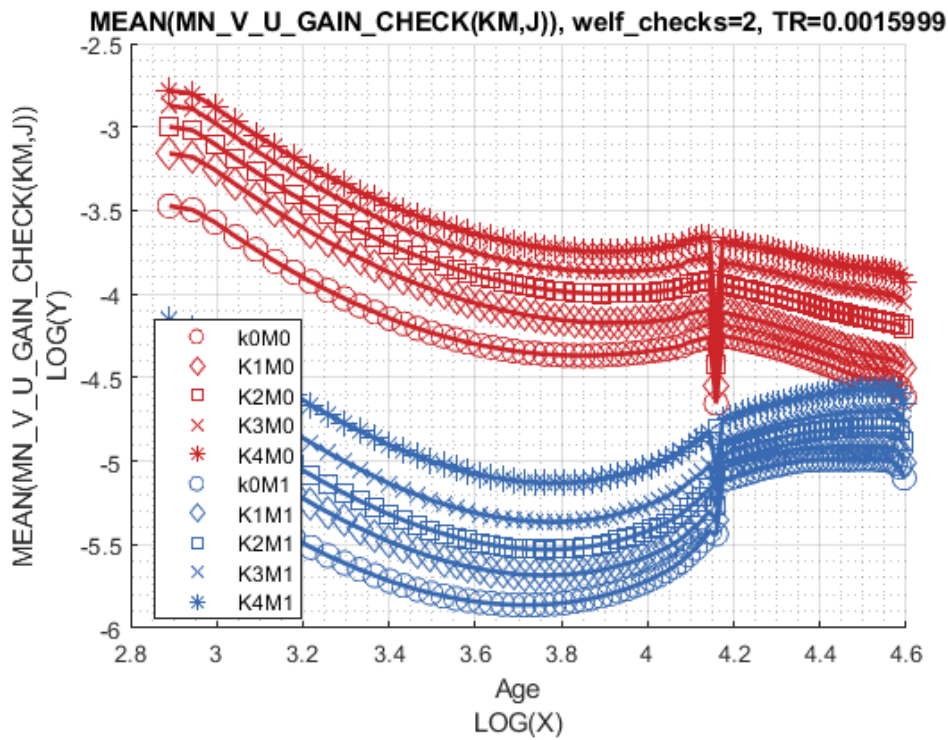
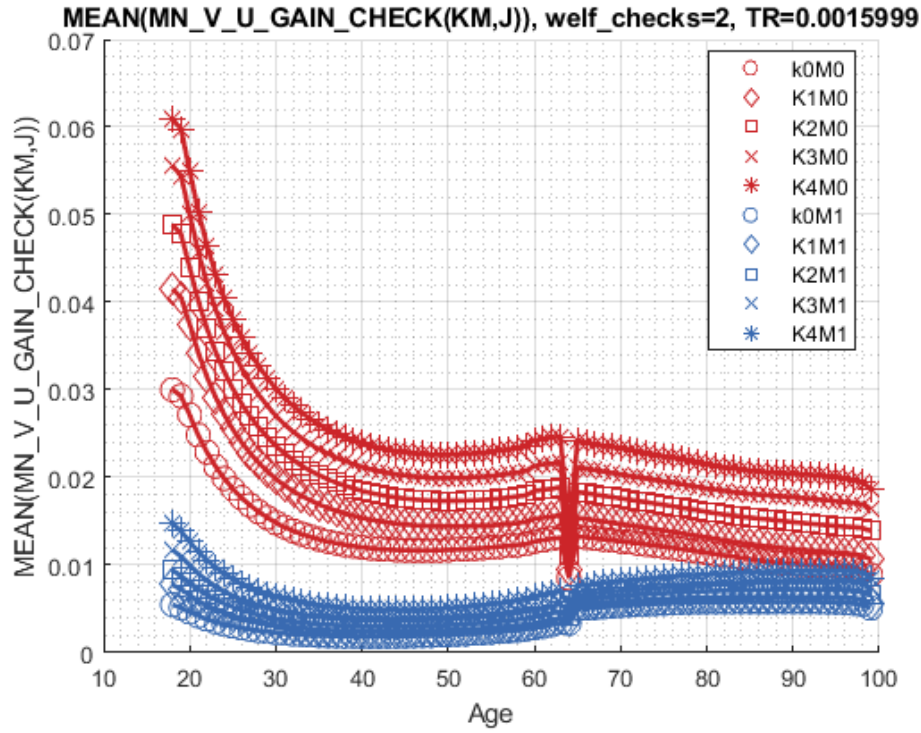
```
st_title = ['MEAN(MN_MPC_U_GAIN_CHECK(KM,J)), welf_checks=' num2str(welf_checks) ', TR=' num2str(mp_
tb_az_c = ff_summ_nd_array(st_title, mn_MPC_U_gain_share_check, true, ["mean"], 3, 1, cl_mp_datasetd
```

```
xxx MEAN(MN_MPC_U_GAIN_CHECK(KM,J)), welf_checks=2, TR=0.0015999 xxxxxxxxxxxxxxxxxxxxxxxxxxxxxxx
```

group	kids	marry	mean_age_18	mean_age_19	mean_age_20	mean_age_21	mean_age_2
1	1	0	0.08445	0.099691	0.10757	0.10468	0.10247
2	2	0	0.096015	0.11123	0.12103	0.11789	0.11535
3	3	0	0.10769	0.12614	0.13451	0.13081	0.12755
4	4	0	0.11389	0.13321	0.14167	0.1377	0.13399
5	5	0	0.1198	0.14051	0.14851	0.144	0.13992
6	1	1	0.096558	0.10433	0.1066	0.10427	0.1019
7	2	1	0.10023	0.10921	0.11152	0.10928	0.10824
8	3	1	0.10587	0.11747	0.1188	0.11732	0.11596
9	4	1	0.11202	0.12194	0.12444	0.1225	0.11996
10	5	1	0.12325	0.13304	0.13672	0.13148	0.12849

Graph Mean Values:

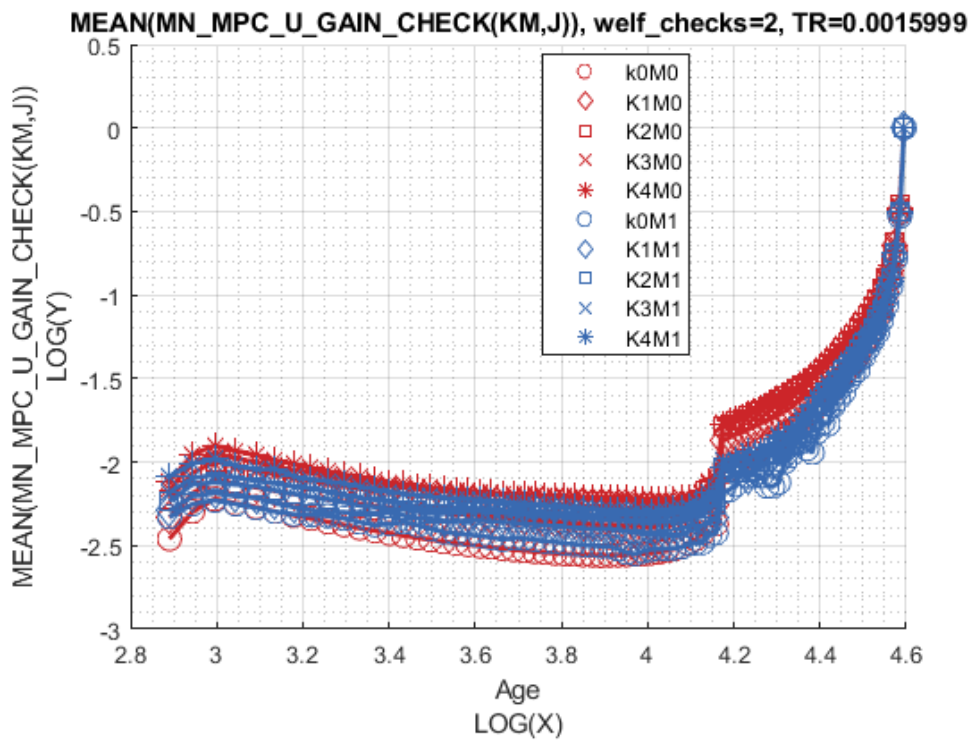
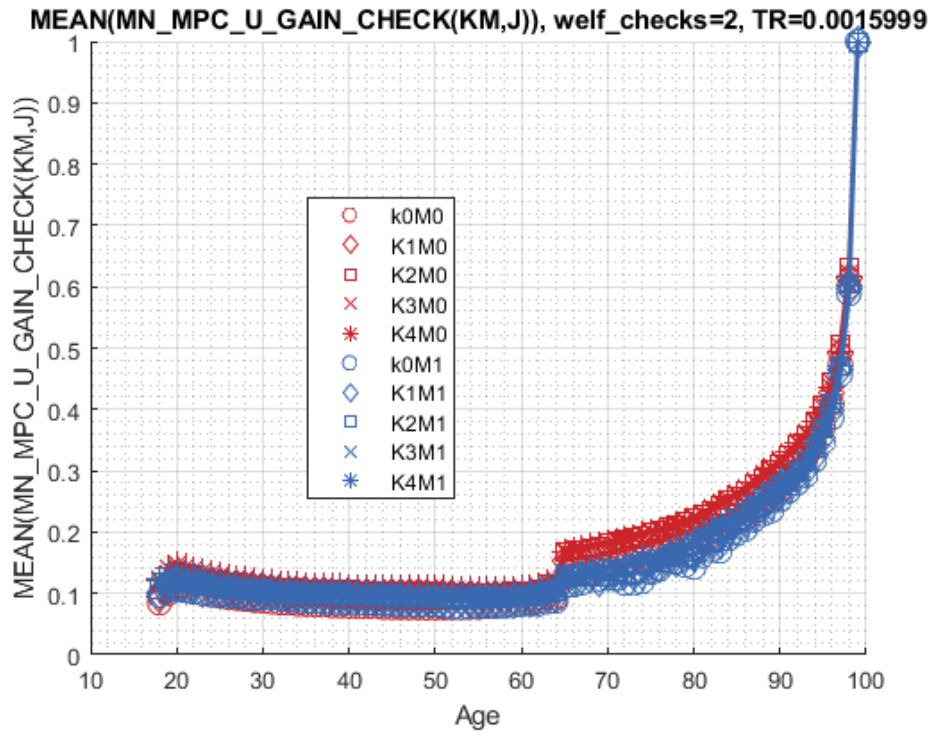
```
st_title = ['MEAN(MN\V\U\_GAIN\_CHECK(KM,J)), welf\_checks=' num2str(welf_checks) ', TR=' num2str(
mp_support_graph('cl_st_graph_title') = {st_title};
mp_support_graph('cl_st_ytitle') = {'MEAN(MN\V\U\_GAIN\_CHECK(KM,J))'};
ff_graph_grid((tb_az_v{1:end, 4:end}), ar_row_grid, age_grid, mp_support_graph);
```



Graph Mean Consumption (*MPC: Share of Check Consumed*):

```

st_title = ['MEAN(MN\MPC\U\_GAIN\_CHECK(KM,J)), welf_checks=' num2str(welf_checks) ', TR=' num2str
mp_support_graph('cl_st_graph_title') = {st_title};
mp_support_graph('cl_st_ytitle') = {'MEAN(MN\MPC\U\_GAIN\_CHECK(KM,J))'};
ff_graph_grid((tb_az_c{1:end, 4:end}), ar_row_grid, age_grid, mp_support_graph);
    
```



### 9.2.9 Analyze Education and Marriage

Aggregating over education, savings, and shocks, what are the differential effects of Marriage and Age.

```
% Generate some Data
mp_support_graph = containers.Map('KeyType', 'char', 'ValueType', 'any');
ar_row_grid = ["E0M0", "E1M0", "E0M1", "E1M1"];
mp_support_graph('cl_st_xtitle') = {'Age'};
mp_support_graph('st_legend_loc') = 'best';
mp_support_graph('bl_graph_logy') = true; % do not log
```

```

mp_support_graph('st_rounding') = '6.2f'; % format shock legend
mp_support_graph('cl_scatter_shapes') = {'*', 'p', '*', 'p' };
mp_support_graph('cl_colors') = {'red', 'red', 'blue', 'blue'};

```

```

MEAN(VAL(EM,J)), MEAN(AP(EM,J)), MEAN(C(EM,J))

```

Tabulate value and policies:

```

% Set
% NaN(n_jgrid,n_agrid,n_etagrid,n_educgrid,n_marriedgrid,n_kidsgrid);
ar_permute = [2,3,6,1,4,5];
% Value Function
st_title = ['MEAN(MN_V_U_GAIN_CHECK(EM,J)), welf_checks=' num2str(welf_checks) ', TR=' num2str(mp_pa
tb_az_v = ff_summ_nd_array(st_title, mn_V_U_gain_check, true, ["mean"], 3, 1, cl_mp_datasetdesc, ar_

```

```

xxx MEAN(MN_V_U_GAIN_CHECK(EM,J)), welf_checks=2, TR=0.0015999 xxxxxxxxxxxxxxxxxxxxxxxxxxxxxxx
  group   edu   marry   mean_age_18   mean_age_19   mean_age_20   mean_age_21   mean_age_22
  -----   ---   -----   -----
  1         0     0         0.04847       0.04767       0.045314      0.042735      0.040445
  2         1     0         0.04626       0.045083      0.040135      0.035433      0.031622
  3         0     1         0.010726      0.010058      0.0092963     0.0085699     0.0079386
  4         1     1         0.0089734     0.0083275     0.0074368     0.0066048     0.0059203

```

```

% Consumption
st_title = ['MEAN(MN_MPC_U_GAIN_CHECK(EM,J)), welf_checks=' num2str(welf_checks) ', TR=' num2str(mp_
tb_az_c = ff_summ_nd_array(st_title, mn_MPC_U_gain_share_check, true, ["mean"], 3, 1, cl_mp_datasetd

```

```

xxx MEAN(MN_MPC_U_GAIN_CHECK(EM,J)), welf_checks=2, TR=0.0015999 xxxxxxxxxxxxxxxxxxxxxxxxxxxxxxx
  group   edu   marry   mean_age_18   mean_age_19   mean_age_20   mean_age_21   mean_age_22
  -----   ---   -----   -----
  1         0     0         0.092366      0.10262       0.1087        0.10789       0.10721
  2         1     0         0.11637       0.1417        0.15261       0.14614       0.1405
  3         0     1         0.098134      0.10328       0.1058        0.10505       0.10409
  4         1     1         0.11704       0.13112       0.13343       0.12889       0.12573

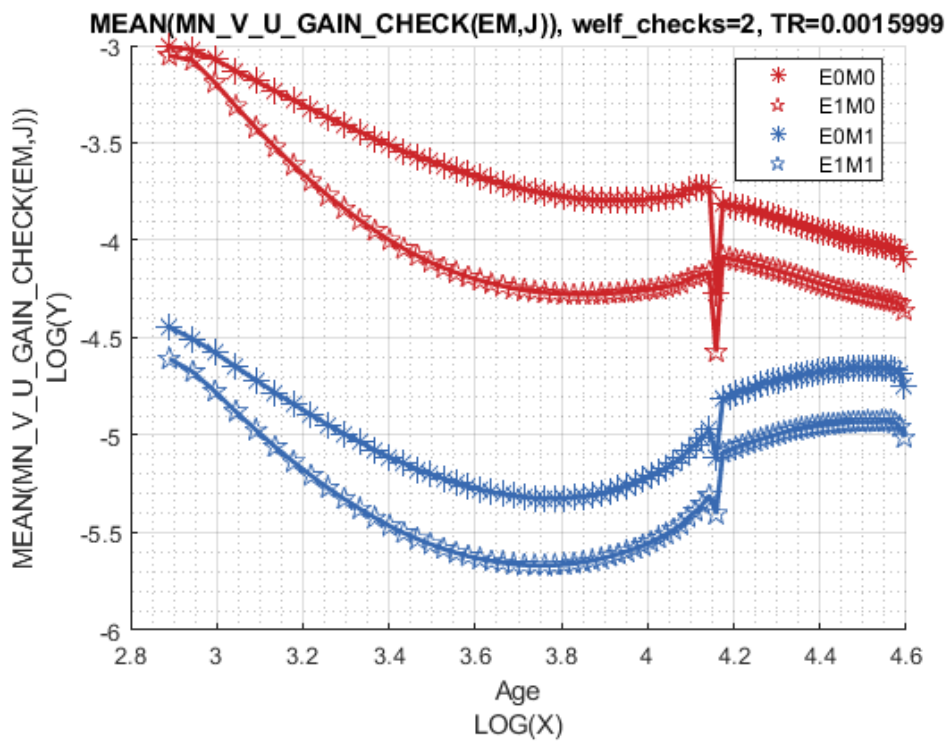
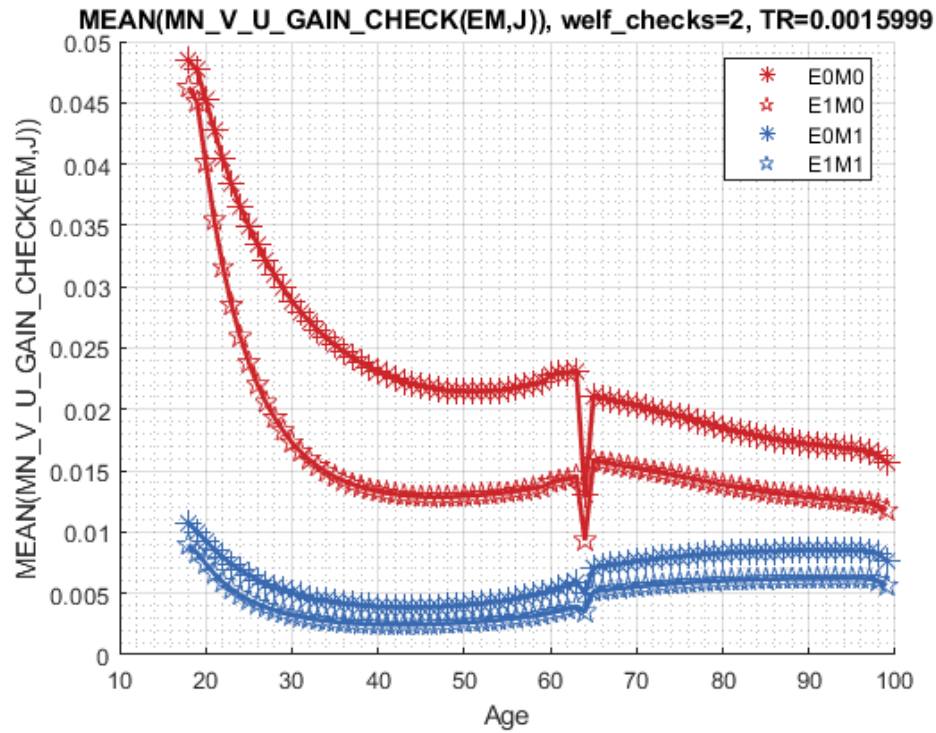
```

Graph Mean Values:

```

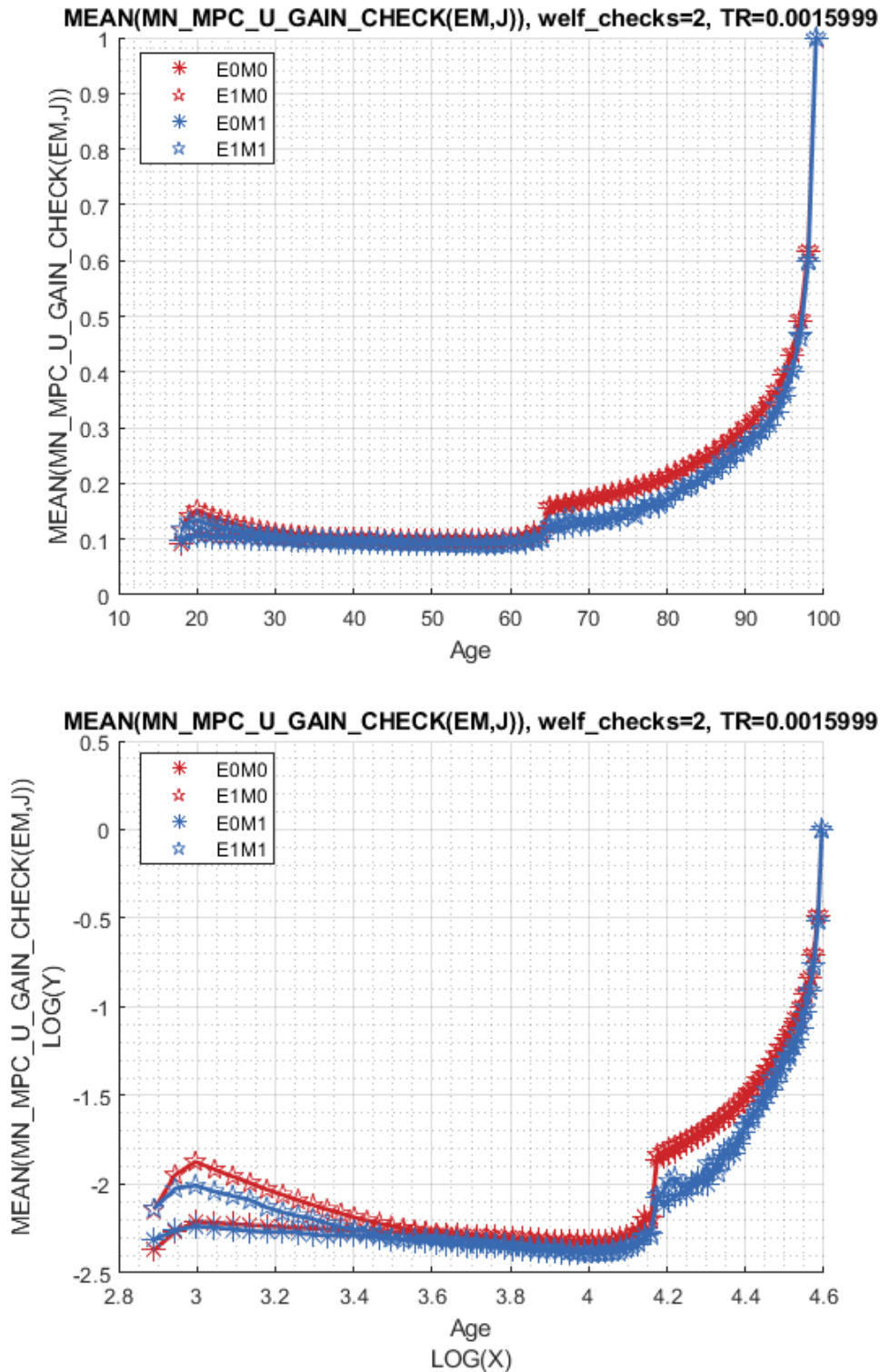
st_title = ['MEAN(MN_V_U_GAIN_CHECK(EM,J)), welf_checks=' num2str(welf_checks) ', TR=' num2str(
mp_support_graph('cl_st_graph_title') = {st_title};
mp_support_graph('cl_st_ytitle') = {'MEAN(MN_V_U_GAIN_CHECK(EM,J))'};
ff_graph_grid((tb_az_v{1:end, 4:end}), ar_row_grid, age_grid, mp_support_graph);

```



Graph Mean Consumption (*MPC: Share of Check Consumed*):

```
st_title = ['MEAN(MN\MPC\U\_GAIN\_CHECK(EM,J)), welf_checks=' num2str(welf_checks) ', TR=' num2str(
mp_support_graph('cl_st_graph_title') = {st_title};
mp_support_graph('cl_st_ytitle') = {'MEAN(MN\MPC\U\_GAIN\_CHECK(EM,J))'};
ff_graph_grid((tb_az_c{1:end, 4:end}), ar_row_grid, age_grid, mp_support_graph);
```



### 9.3 2008 Value and Optimal Savings and Consumption Given Stimulus

This is the example vignette for function: `snw_v08_jaeemk` from the `PrjOptiSNW Package`. This is similar to `snw_evuvw20_jaeemk`, but for the 2008 Bush stimulus. `snw_v08p08_jaeemk` already solved for optimal policy and value functions in 2008, given expected unemployment shock in 2009. In this function, given some stimulus amount, we use `snw_a4chk_wrk_bisec_vec` to compute the updated optimal  $V$  and  $C$  in 2008 given the stimulus amount, based on the values for  $V$  and  $C$  without stimulus



computed by [snw\\_v08p08\\_jaeemk](#).

Note that [snw\\_a4chk\\_wrk\\_bisec\\_vec](#) computes the adjustment in the savings state that would be equivalent to the increase in stimulus amount (which is not a state variable) to current resources, this is faster than resolving 2008 optimal V and C at specific stimulus check amount levels.

Note [snw\\_evuvw20\\_jaeemk](#) has EVUVW, but here, we only have V08, because in the 2020 problem, households receive checks ex-post of the COVID MIT shocks in 2020 and the EVUVW is the weighted average in V between the MIT unemployed and non-shock employed state. In 2008, however, there are no shocks yet, the state-space is the same as normal, the only difference is that households might receive stimulus checks from Bush. The Bush stimulus is provided ex-ante of the shock realization. The 2009 shocks due to the great recession is not a MIT shock, but expected shock. The effect of the 2009 shock on consumption, savings is solved by [snw\\_v08p08\\_jaeemk](#). The expectation over shock, in another word, for the [snw\\_v08\\_jaeemk](#) is already included in EV' in 2008 for 2009.

### 9.3.1 Solve 2008 Value and Policy Function with SNW\_V08p08\_JAEEMK

Solve for the Value and Policy functions in 2008 given expected unemployment shock that is specific to age and education group in 2009, no stimulus amounts.

First, set various parameters

```
% 1. Paramters
% Parameters
mp_more_inputs = containers.Map('KeyType','char', 'ValueType','any');
mp_more_inputs('fl_ss_non_college') = 0.225;
mp_more_inputs('fl_ss_college') = 0.271;
fl_p50_hh_income_07 = 54831;
mp_more_inputs('fl_scaleconvertor') = fl_p50_hh_income_07;

% st_param_group = 'default_small';
% st_param_group = 'default_dense';
st_param_group = 'default_docdense';
mp_params = snw_mp_param(st_param_group, false, 'tauchen', false, 8, 8, mp_more_inputs);
mp_params('beta') = 0.95;

% Control parameters
mp_controls = snw_mp_control('default_test');
mp_controls('bl_print_a4chk') = false;
mp_controls('bl_print_a4chk_verbose') = false;
mp_controls('bl_print_vfi') = false;
mp_controls('bl_print_vfi_verbose') = false;
mp_controls('bl_print_ds') = false;
mp_controls('bl_print_ds_verbose') = false;
mp_controls('bl_print_v08p08_jaeemk') = false;
mp_controls('bl_print_v08p08_jaeemk_verbose') = false;
mp_controls('bl_print_v08_jaeemk') = true;
mp_controls('bl_print_v08_jaeemk_verbose') = true;
```

Second, solve the steady-state problem, same as employed results in 2009.

```
% 2. Solve value steady state (2009 employed)
[V_VFI_ss, ap_VFI_ss, cons_VFI_ss, mp_valpol_more_ss] = snw_vfi_main_bisec_vec(mp_params, mp_control

Completed SNW_VFI_MAIN_BISEC_VEC;SNW_MP_PARAM=default_docdense;SNW_MP_CONTROL=default_test;time=530.

inc_VFI = mp_valpol_more_ss('inc_VFI');
spouse_inc_VFI = mp_valpol_more_ss('spouse_inc_VFI');
total_inc_VFI = inc_VFI + spouse_inc_VFI;
V_emp_2009 = V_VFI_ss;
% Solve for probability mass, needed for pre-compute
```

```
[Phi_true] = snw_ds_main_vec(mp_params, mp_controls, ap_VFI_ss, cons_VFI_ss, mp_valpol_more_ss);
```

```
Completed SNW_DS_MAIN_VEC;SNW_MP_PARAM=default_docdense;SNW_MP_CONTROL=default_test;time=1271.649
```

```
% Solve for household head and spouse income and sum to total income.
```

```
inc_VFI = mp_valpol_more_ss('inc_VFI');
spouse_inc_VFI = mp_valpol_more_ss('spouse_inc_VFI');
total_inc_VFI = inc_VFI + spouse_inc_VFI;
```

Third, solve the unemployment problem in 2009. With 2009 specific unemployment parameters calibrated and found from data. Using  $b$  calibrated by [snw\\_calibrate\\_2009\\_b](#).

```
% 3. Solve value unemployed 2009
```

```
% Set Unemployment Related Variables
```

```
mp_params('xi') = 0.532;
```

```
% Calibrated by snw_calibrate_2009_b
```

```
mp_params('b') = 0.37992;
```

```
mp_params('a2_covidyr') = mp_params('a2_greatrecession_2009');
```

```
mp_params('TR') = 100/fl_p50_hh_income_07; % Value of a stimulus check (can receive multiple checks)
```

```
[V_unemp_2009] = snw_vfi_main_bisec_vec(mp_params, mp_controls, V_VFI_ss);
```

```
Completed SNW_VFI_MAIN_BISEC_VEC 1 Period Unemp Shock;SNW_MP_PARAM=default_docdense;SNW_MP_CONTROL=d
```

Fourth, solve the 2008 problem, with 2008-specific value and policy functions.

```
% 4. Value and Optimal choice in 2009
```

```
[V_2008, ap_2008, cons_2008, ev_empshk_2009] = ...
```

```
    snw_v08p08_jaeemk(mp_params, mp_controls, V_emp_2009, V_unemp_2009);
```

```
Completed SNW_VFI_MAIN_BISEC_VEC 1 Period Unemp Shock;SNW_MP_PARAM=default_docdense;SNW_MP_CONTROL=d
```

```
Completed SNW_V08P08_JAEEMK;SNW_MP_PARAM=default_docdense;SNW_MP_CONTROL=default_test;time=522.6257
```

```
% 5. pre-compute
```

```
cl_st_precompute_list = {'a', ...
```

```
    'inc', 'inc_unemp', 'spouse_inc', 'spouse_inc_unemp', 'ref_earn_wageind_grid'};
```

```
mp_controls('bl_print_precompute_verbos') = false;
```

```
[mp_precompute_res] = snw_hh_precompute(mp_params, mp_controls, cl_st_precompute_list, ap_VFI_ss, Ph
```

```
Wage quintile cutoffs=0.4645    0.71528    1.0335    1.5632
SNW_HH_PRECOMPUTE: Finished Age Group:1 of 82, time-this-age:3.2746
SNW_HH_PRECOMPUTE: Finished Age Group:2 of 82, time-this-age:3.2852
SNW_HH_PRECOMPUTE: Finished Age Group:3 of 82, time-this-age:3.3869
SNW_HH_PRECOMPUTE: Finished Age Group:4 of 82, time-this-age:3.4589
SNW_HH_PRECOMPUTE: Finished Age Group:5 of 82, time-this-age:3.254
SNW_HH_PRECOMPUTE: Finished Age Group:6 of 82, time-this-age:3.3465
SNW_HH_PRECOMPUTE: Finished Age Group:7 of 82, time-this-age:3.4109
SNW_HH_PRECOMPUTE: Finished Age Group:8 of 82, time-this-age:3.4221
SNW_HH_PRECOMPUTE: Finished Age Group:9 of 82, time-this-age:3.4152
SNW_HH_PRECOMPUTE: Finished Age Group:10 of 82, time-this-age:3.4065
SNW_HH_PRECOMPUTE: Finished Age Group:11 of 82, time-this-age:3.1869
SNW_HH_PRECOMPUTE: Finished Age Group:12 of 82, time-this-age:3.3572
SNW_HH_PRECOMPUTE: Finished Age Group:13 of 82, time-this-age:3.4748
SNW_HH_PRECOMPUTE: Finished Age Group:14 of 82, time-this-age:3.3824
SNW_HH_PRECOMPUTE: Finished Age Group:15 of 82, time-this-age:3.4573
SNW_HH_PRECOMPUTE: Finished Age Group:16 of 82, time-this-age:3.3233
SNW_HH_PRECOMPUTE: Finished Age Group:17 of 82, time-this-age:3.3965
SNW_HH_PRECOMPUTE: Finished Age Group:18 of 82, time-this-age:3.3613
SNW_HH_PRECOMPUTE: Finished Age Group:19 of 82, time-this-age:3.3402
SNW_HH_PRECOMPUTE: Finished Age Group:20 of 82, time-this-age:3.479
SNW_HH_PRECOMPUTE: Finished Age Group:21 of 82, time-this-age:3.2899
```

SNW\_HH\_PRECOMPUTE: Finished Age Group:22 of 82, time-this-age:3.3222  
SNW\_HH\_PRECOMPUTE: Finished Age Group:23 of 82, time-this-age:3.3025  
SNW\_HH\_PRECOMPUTE: Finished Age Group:24 of 82, time-this-age:3.3682  
SNW\_HH\_PRECOMPUTE: Finished Age Group:25 of 82, time-this-age:3.3555  
SNW\_HH\_PRECOMPUTE: Finished Age Group:26 of 82, time-this-age:3.3701  
SNW\_HH\_PRECOMPUTE: Finished Age Group:27 of 82, time-this-age:3.5453  
SNW\_HH\_PRECOMPUTE: Finished Age Group:28 of 82, time-this-age:3.2218  
SNW\_HH\_PRECOMPUTE: Finished Age Group:29 of 82, time-this-age:3.3947  
SNW\_HH\_PRECOMPUTE: Finished Age Group:30 of 82, time-this-age:3.3024  
SNW\_HH\_PRECOMPUTE: Finished Age Group:31 of 82, time-this-age:3.3699  
SNW\_HH\_PRECOMPUTE: Finished Age Group:32 of 82, time-this-age:3.4931  
SNW\_HH\_PRECOMPUTE: Finished Age Group:33 of 82, time-this-age:3.3584  
SNW\_HH\_PRECOMPUTE: Finished Age Group:34 of 82, time-this-age:3.4127  
SNW\_HH\_PRECOMPUTE: Finished Age Group:35 of 82, time-this-age:3.4113  
SNW\_HH\_PRECOMPUTE: Finished Age Group:36 of 82, time-this-age:3.2095  
SNW\_HH\_PRECOMPUTE: Finished Age Group:37 of 82, time-this-age:3.4244  
SNW\_HH\_PRECOMPUTE: Finished Age Group:38 of 82, time-this-age:3.5012  
SNW\_HH\_PRECOMPUTE: Finished Age Group:39 of 82, time-this-age:3.2675  
SNW\_HH\_PRECOMPUTE: Finished Age Group:40 of 82, time-this-age:3.2625  
SNW\_HH\_PRECOMPUTE: Finished Age Group:41 of 82, time-this-age:3.4011  
SNW\_HH\_PRECOMPUTE: Finished Age Group:42 of 82, time-this-age:3.2533  
SNW\_HH\_PRECOMPUTE: Finished Age Group:43 of 82, time-this-age:3.5132  
SNW\_HH\_PRECOMPUTE: Finished Age Group:44 of 82, time-this-age:3.4771  
SNW\_HH\_PRECOMPUTE: Finished Age Group:45 of 82, time-this-age:3.3133  
SNW\_HH\_PRECOMPUTE: Finished Age Group:46 of 82, time-this-age:3.4673  
SNW\_HH\_PRECOMPUTE: Finished Age Group:47 of 82, time-this-age:3.1794  
SNW\_HH\_PRECOMPUTE: Finished Age Group:48 of 82, time-this-age:3.1958  
SNW\_HH\_PRECOMPUTE: Finished Age Group:49 of 82, time-this-age:3.4545  
SNW\_HH\_PRECOMPUTE: Finished Age Group:50 of 82, time-this-age:3.355  
SNW\_HH\_PRECOMPUTE: Finished Age Group:51 of 82, time-this-age:3.2059  
SNW\_HH\_PRECOMPUTE: Finished Age Group:52 of 82, time-this-age:3.2882  
SNW\_HH\_PRECOMPUTE: Finished Age Group:53 of 82, time-this-age:3.3772  
SNW\_HH\_PRECOMPUTE: Finished Age Group:54 of 82, time-this-age:3.3279  
SNW\_HH\_PRECOMPUTE: Finished Age Group:55 of 82, time-this-age:3.5412  
SNW\_HH\_PRECOMPUTE: Finished Age Group:56 of 82, time-this-age:3.504  
SNW\_HH\_PRECOMPUTE: Finished Age Group:57 of 82, time-this-age:3.4961  
SNW\_HH\_PRECOMPUTE: Finished Age Group:58 of 82, time-this-age:3.3629  
SNW\_HH\_PRECOMPUTE: Finished Age Group:59 of 82, time-this-age:3.4105  
SNW\_HH\_PRECOMPUTE: Finished Age Group:60 of 82, time-this-age:3.3755  
SNW\_HH\_PRECOMPUTE: Finished Age Group:61 of 82, time-this-age:3.4102  
SNW\_HH\_PRECOMPUTE: Finished Age Group:62 of 82, time-this-age:3.4844  
SNW\_HH\_PRECOMPUTE: Finished Age Group:63 of 82, time-this-age:3.3864  
SNW\_HH\_PRECOMPUTE: Finished Age Group:64 of 82, time-this-age:3.6674  
SNW\_HH\_PRECOMPUTE: Finished Age Group:65 of 82, time-this-age:3.3549  
SNW\_HH\_PRECOMPUTE: Finished Age Group:66 of 82, time-this-age:3.3543  
SNW\_HH\_PRECOMPUTE: Finished Age Group:67 of 82, time-this-age:3.3775  
SNW\_HH\_PRECOMPUTE: Finished Age Group:68 of 82, time-this-age:3.3574  
SNW\_HH\_PRECOMPUTE: Finished Age Group:69 of 82, time-this-age:3.3706  
SNW\_HH\_PRECOMPUTE: Finished Age Group:70 of 82, time-this-age:3.4841  
SNW\_HH\_PRECOMPUTE: Finished Age Group:71 of 82, time-this-age:3.361  
SNW\_HH\_PRECOMPUTE: Finished Age Group:72 of 82, time-this-age:3.3692  
SNW\_HH\_PRECOMPUTE: Finished Age Group:73 of 82, time-this-age:3.4296  
SNW\_HH\_PRECOMPUTE: Finished Age Group:74 of 82, time-this-age:3.4363  
SNW\_HH\_PRECOMPUTE: Finished Age Group:75 of 82, time-this-age:3.391  
SNW\_HH\_PRECOMPUTE: Finished Age Group:76 of 82, time-this-age:3.4927  
SNW\_HH\_PRECOMPUTE: Finished Age Group:77 of 82, time-this-age:3.4073  
SNW\_HH\_PRECOMPUTE: Finished Age Group:78 of 82, time-this-age:3.3416  
SNW\_HH\_PRECOMPUTE: Finished Age Group:79 of 82, time-this-age:3.4042

```
SNW_HH_PRECOMPUTE: Finished Age Group:80 of 82, time-this-age:3.4844
SNW_HH_PRECOMPUTE: Finished Age Group:81 of 82, time-this-age:3.4572
SNW_HH_PRECOMPUTE: Finished Age Group:82 of 82, time-this-age:3.2411
SNW_HH_PRECOMPUTE: Finished Age Group:83 of 82, time-this-age:3.3428
Completed SNW_HH_PRECOMPUTE;SNW_MP_PARAM=default_docdense;SNW_MP_CONTROL=default_test;time cost=284.
```

### 9.3.2 Solve for 2008 Value and Consumption with 0 and 2 Checks

Now we use the `snw_v08_jaeemk` function, which takes as inputs the 2008-specific value and policy we have already found, to compute the 2008 value and consumption based on different stimulus amounts via asset-equivalent transformation given stimulus amounts.

First, obtain V and C with zero stimulus.

```
% Call Function
welf_checks = 0;
[V_2008_check0, C_2008_check0] = snw_v08_jaeemk(...
    welf_checks, mp_params, mp_controls, V_2008, cons_2008, mp_precompute_res);

Solve for V_2008_check for 0 stimulus checks
Completed SNW_A4CHK_WRK_BISEC_VEC;SNW_MP_PARAM=st_biden_or_trump_undefined;welf_checks=0;TR=0.001823
Completed SNW_V08_JAEEMK;SNW_MP_PARAM=default_docdense;SNW_MP_CONTROL=default_test;timeEUEC=3e-05
-----
XXXXXXXXXXXXXXXXXXXXXXXXXXXXXXXXXXXXXXXXXXXXXXXXXXXX
CONTAINER NAME: mp_outcomes ND Array (Matrix etc)
XXXXXXXXXXXXXXXXXXXXXXXXXXXXXXXXXXXXXXXXXXXXXXXXXXXX
          i      idx      ndim      numel      rowN      colN      sum      mean
          -      ---      ----      -
C_2008_check  1      1      6      4.37e+07      83      5.265e+05      2.3277e+08      5.3267
V_2008_check  2      2      6      4.37e+07      83      5.265e+05      -6.6426e+08      -15.201

xxx TABLE:C_2008_check XXXXXXXXXXXXXXXXXXXXXXXX
          c1      c2      c3      c4      c5      c526496      c526497      c526498
          -----
r1      0.036218      0.036736      0.038184      0.042735      0.048545      12.256      12.541      12.835
r2      0.036271      0.036736      0.038385      0.043404      0.049852      12.491      12.778      13.072
r3      0.036717      0.037251      0.039845      0.044907      0.051515      12.744      13.032      13.327
r4      0.038144      0.038678      0.041269      0.046371      0.053128      12.989      13.277      13.573
r5      0.039534      0.040068      0.042653      0.047793      0.054687      13.224      13.513      13.809
r79     0.2016      0.20214      0.20586      0.21598      0.23568      35.82      37.367      39.414
r80     0.2016      0.20214      0.20586      0.21598      0.23568      40.755      42.955      45.289
r81     0.2016      0.20214      0.20586      0.21598      0.23568      48.912      52.041      55.022
r82     0.2016      0.20214      0.20586      0.21598      0.23568      66.719      69.201      72.373
r83     0.2016      0.20214      0.20586      0.21598      0.23568      116.83      122.65      128.67

xxx TABLE:V_2008_check XXXXXXXXXXXXXXXXXXXXXXXX
          c1      c2      c3      c4      c5      c526496      c526497      c526498
          -----
r1      -295.66      -295.26      -292.66      -286.62      -277.22      -4.3615      -4.2673      -4.174
r2      -286.11      -285.71      -283.12      -277.16      -268.03      -4.2548      -4.1641      -4.074
r3      -276.49      -276.09      -273.59      -267.84      -259.11      -4.1461      -4.0589      -3.972
r4      -266.77      -266.41      -264.08      -258.7      -250.49      -4.0342      -3.9507      -3.86
r5      -257.99      -257.65      -255.48      -250.43      -242.69      -3.9287      -3.8485      -3.76
r79     -13.356      -13.343      -13.253      -13.025      -12.638      -0.22088      -0.21055      -0.2008
r80     -12.025      -12.012      -11.923      -11.695      -11.308      -0.16977      -0.1618      -0.1542
r81     -10.382      -10.369      -10.28      -10.052      -9.6651      -0.11711      -0.11162      -0.1064
```

```
r82    -8.1742    -8.1611    -8.0716    -7.844     -7.457     -0.065329   -0.062239   -0.05935
r83    -4.9602    -4.9471    -4.8576    -4.6301    -4.2431    -0.020966   -0.019971   -0.01903
```

% Call Function

Second, obtain V and C with two stimulus checks.

```
welf_checks = 2;
[V_2008_check2, C_2008_check2] = snw_v08_jaeemk(...
    welf_checks, mp_params, mp_controls, V_2008, cons_2008, mp_precompute_res);
```

Solve for V\_2008\_check for 2 stimulus checks  
 Completed SNW\_A4CHK\_WRK\_BISEC\_VEC;SNW\_MP\_PARAM=st\_biden\_or\_trump\_undefined;welf\_checks=2;TR=0.001823  
 Completed SNW\_V08\_JAEEMK;SNW\_MP\_PARAM=default\_docdense;SNW\_MP\_CONTROL=default\_test;timeEUEC=2.16e-05

```
-----
XXXXXXXXXXXXXXXXXXXXXXXXXXXXXXXXXXXXXXXXXXXXXXXXXXXX
CONTAINER NAME: mp_outcomes ND Array (Matrix etc)
XXXXXXXXXXXXXXXXXXXXXXXXXXXXXXXXXXXXXXXXXXXXXXXXXXXX
```

	i	idx	ndim	numel	rowN	colN	sum	mean
C_2008_check	1	1	6	4.37e+07	83	5.265e+05	2.328e+08	5.3273
V_2008_check	2	2	6	4.37e+07	83	5.265e+05	-6.6365e+08	-15.187

```
xxx TABLE:C_2008_check XXXXXXXXXXXXXXXXXXXXXXXX
```

	c1	c2	c3	c4	c5	c526496	c526497	c526498
r1	0.037941	0.038148	0.039819	0.043807	0.049244	12.256	12.541	12.835
r2	0.038108	0.038344	0.040188	0.044594	0.050571	12.492	12.778	13.073
r3	0.03941	0.039781	0.041664	0.046126	0.052244	12.745	13.032	13.327
r4	0.040834	0.041205	0.043102	0.047618	0.053867	12.989	13.278	13.573
r5	0.04222	0.042589	0.0445	0.049065	0.055435	13.224	13.513	13.809
r79	0.20525	0.20579	0.20951	0.21963	0.23776	35.821	37.368	39.415
r80	0.20525	0.20579	0.20951	0.21963	0.23776	40.756	42.957	45.29
r81	0.20525	0.20579	0.20951	0.21963	0.2378	48.914	52.043	55.024
r82	0.20525	0.20579	0.20951	0.21963	0.23814	66.72	69.203	72.375
r83	0.20525	0.20579	0.20951	0.21963	0.23933	116.84	122.66	128.68

```
xxx TABLE:V_2008_check XXXXXXXXXXXXXXXXXXXXXXXX
```

	c1	c2	c3	c4	c5	c526496	c526497	c526498
r1	-293.09	-292.72	-290.49	-284.88	-275.86	-4.3615	-4.2672	-4.174
r2	-283.55	-283.18	-280.98	-275.47	-266.73	-4.2548	-4.164	-4.074
r3	-274.01	-273.65	-271.52	-266.23	-257.88	-4.146	-4.0589	-3.972
r4	-264.47	-264.13	-262.14	-257.19	-249.33	-4.0341	-3.9506	-3.867
r5	-255.84	-255.53	-253.66	-249	-241.59	-3.9286	-3.8484	-3.76
r79	-13.268	-13.255	-13.171	-12.954	-12.578	-0.22088	-0.21054	-0.2008
r80	-11.937	-11.924	-11.841	-11.623	-11.248	-0.16976	-0.16179	-0.1542
r81	-10.294	-10.281	-10.198	-9.9804	-9.6057	-0.11711	-0.11162	-0.1064
r82	-8.0862	-8.0735	-7.9895	-7.7724	-7.3981	-0.065327	-0.062237	-0.05935
r83	-4.8723	-4.8595	-4.7755	-4.5584	-4.1854	-0.020965	-0.01997	-0.01903

Differences between Checks in Expected Value and Expected Consumption

```
mn_V_U_gain_check = V_2008_check2 - V_2008_check0;
mn_MPC_U_gain_share_check = (C_2008_check2 - C_2008_check0)./(welf_checks*mp_params('TR'));
```

### 9.3.3 Param Results Define Frames

Define the matrix dimensions names and dimension vector values. Policy and Value Functions share the same ND dimensional structure.

```
% Grids:
age_grid = 18:100;
agrid = mp_params('agrid');
eta_H_grid = mp_params('eta_H_grid');
eta_S_grid = mp_params('eta_S_grid');
ar_st_eta_HS_grid = string(cellstr([num2str(eta_H_grid', 'hz=%3.2f;'), num2str(eta_S_grid', 'wz=%3.2f;')]);
edu_grid = [0,1];
marry_grid = [0,1];
kids_grid = (1:1:mp_params('n_kidsgrid'))';
% NaN(n_jgrid,n_agrid,n_etagrid,n_educgrid,n_marriedgrid,n_kidsgrid);
cl_mp_datasetdesc = {};
cl_mp_datasetdesc{1} = containers.Map({'name', 'labval'}, {'age', age_grid});
cl_mp_datasetdesc{2} = containers.Map({'name', 'labval'}, {'savings', agrid});
cl_mp_datasetdesc{3} = containers.Map({'name', 'labval'}, {'eta', 1:length(eta_H_grid)});
cl_mp_datasetdesc{4} = containers.Map({'name', 'labval'}, {'edu', edu_grid});
cl_mp_datasetdesc{5} = containers.Map({'name', 'labval'}, {'marry', marry_grid});
cl_mp_datasetdesc{6} = containers.Map({'name', 'labval'}, {'kids', kids_grid});
```

### 9.3.4 Analyze Difference in V and C with Check

The difference between V and V with Check, marginal utility gain given the check.

```
% Generate some Data
mp_support_graph = containers.Map('KeyType', 'char', 'ValueType', 'any');
mp_support_graph('cl_st_xtitle') = {'Savings States', 'a'};
mp_support_graph('st_legend_loc') = 'eastoutside';
mp_support_graph('bl_graph_logy') = true; % do not log
mp_support_graph('it_legend_select') = 21; % how many shock legends to show
mp_support_graph('cl_colors') = 'jet';
```

```
MEAN(MN_V_GAIN_CHECK(A,Z))
```

Tabulate value and policies along savings and shocks:

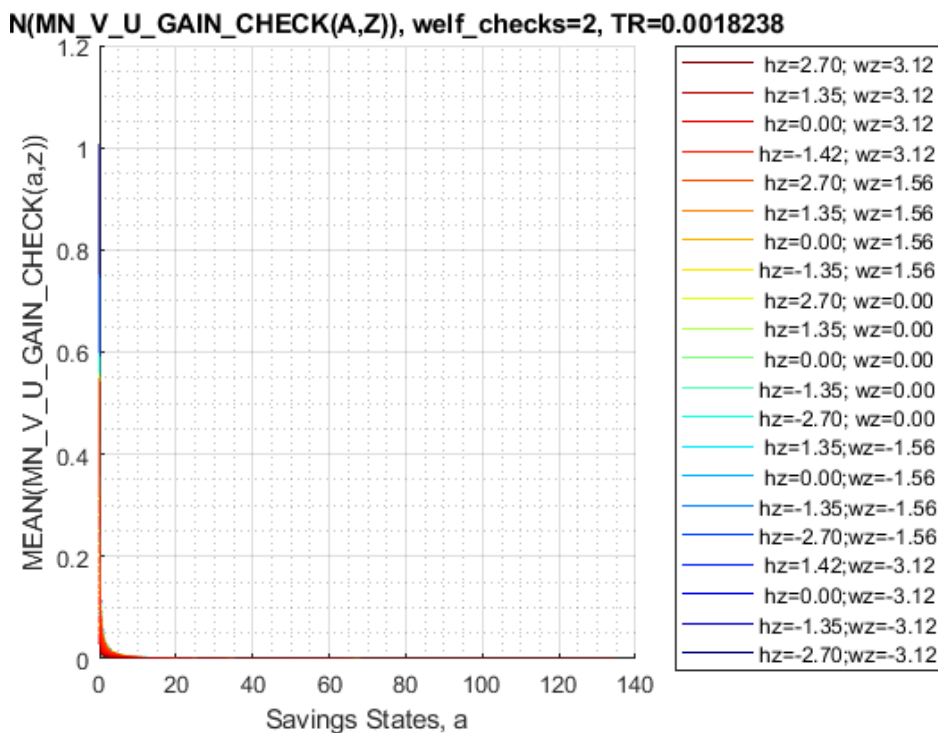
```
% Set
ar_permute = [1,4,5,6,3,2];
% Value Function
st_title = ['MEAN(MN_V_U_GAIN_CHECK(A,Z)), welf_checks=' num2str(welf_checks) ', TR=' num2str(mp_par
tb_az_v = ff_summ_nd_array(st_title, mn_V_U_gain_check, true, ["mean"], 4, 1, cl_mp_datasetdesc, ar_
```

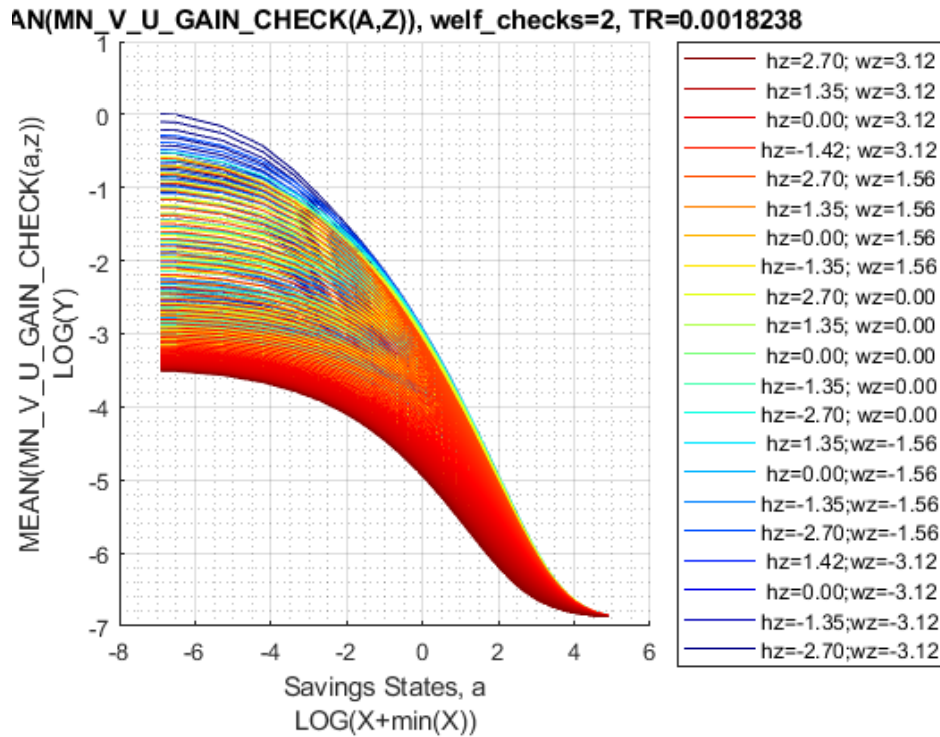
```
xxx MEAN(MN_V_U_GAIN_CHECK(A,Z)), welf_checks=2, TR=0.0018238 xxxxxxxxxxxxxxxxxxxxxxxxxxxxxxxx
  group      savings      mean_eta_1      mean_eta_2      mean_eta_3      mean_eta_4      mean_eta_5      mea
  -----      -
  1            0            1.0061            0.90365            0.8116            0.72825            0.65329
```

group	savings	mean_eta_1	mean_eta_2	mean_eta_3	mean_eta_4	mean_eta_5	mea
1	0	0.96418	0.92776	0.90436	0.88966	0.87994	0.

```

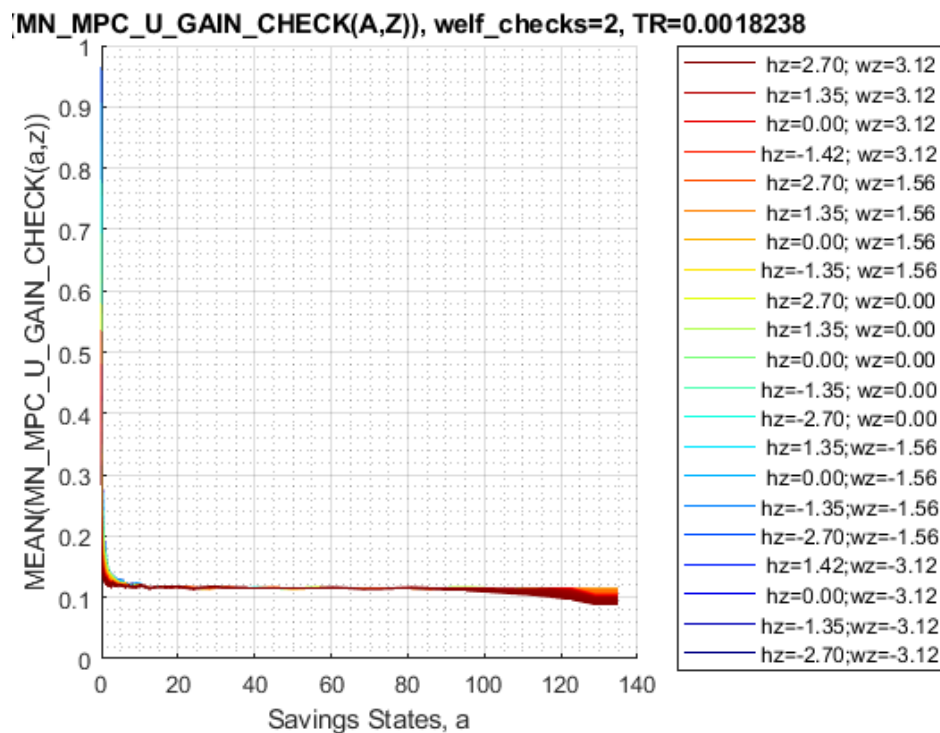
st_title = ['MEAN(MN\V_U_GAIN_CHECK(A,Z)), welf_checks=' num2str(welf_checks) ', TR=' num2str(m
mp_support_graph('cl_st_graph_title') = {st_title};
mp_support_graph('cl_st_ytitle') = {'MEAN(MN\V_U_GAIN_CHECK(a,z))'};
ff_graph_grid((tb_az_v{1:end, 3:end}),' ar_st_eta_HS_grid, agrid, mp_support_graph);
    
```



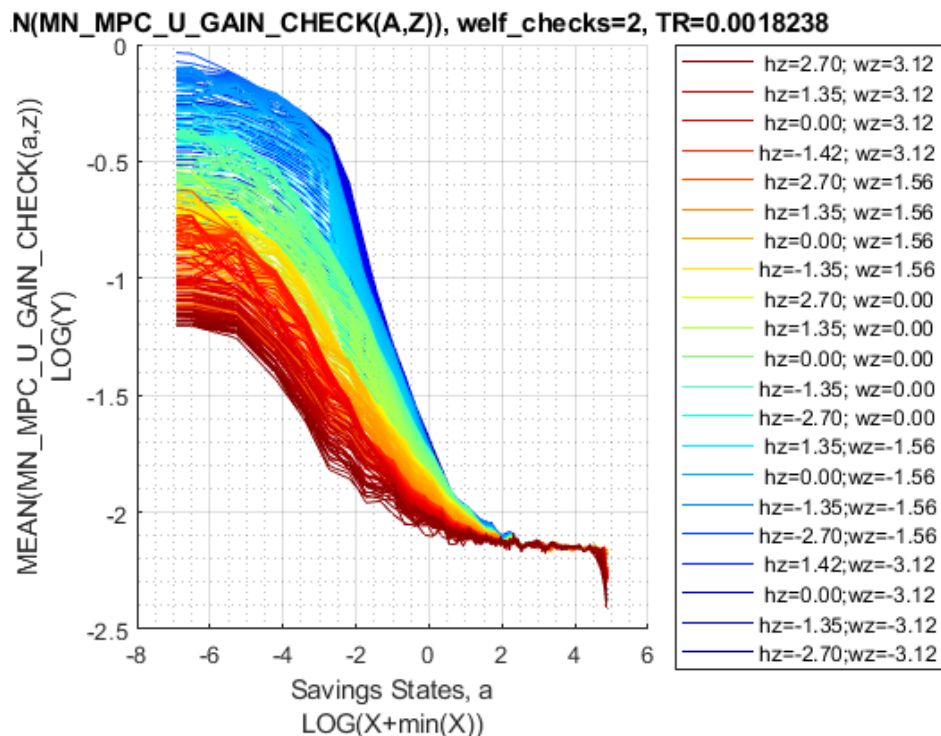


Graph Mean Consumption (*MPC: Share of Check Consumed*):

```
st_title = ['MEAN(MN_MPC_U_GAIN_CHECK(A,Z)), welf_checks=' num2str(welf_checks) ', TR=' num2str
mp_support_graph('cl_st_graph_title') = {st_title};
mp_support_graph('cl_st_ytitle') = {'MEAN(MN_MPC_U_GAIN_CHECK(a,z))'};
ff_graph_grid((tb_az_c{1:end, 3:end}'), ar_st_eta_HS_grid, agrid, mp_support_graph);
```







### 9.3.5 Analyze Marginal Value and MPC over $Y(a,\eta)$ , Conditional On Kids, Marry, Age, Education

Income is generated by savings and shocks, what are the income levels generated by all the shock and savings points conditional on kids, marital status, age and educational levels. Plot on the Y axis MPC, and plot on the X axis income levels, use colors to first distinguish between different  $a$  levels, then use colors to distinguish between different  $\eta$  levels.

Set Up date, Select Age, unmarried, no kids, lower education:

```
% NaN(n_jgrid,n_agrid,n_etagrid,n_eduagrid,n_marriedgrid,n_kidsgrid);
% 38 year old, unmarried, no kids, lower educated
% Only Household Head Shock Matters so select up to 'n_eta_H_grid'
mn_total_inc_jemk = total_inc_VFI(19, :, 1:mp_params('n_eta_H_grid'), 1, 1, 1);
mn_V_W_gain_check_use = V_2008_check2 - V_2008_check0;
mn_C_W_gain_check_use = C_2008_check2 - C_2008_check0;
```

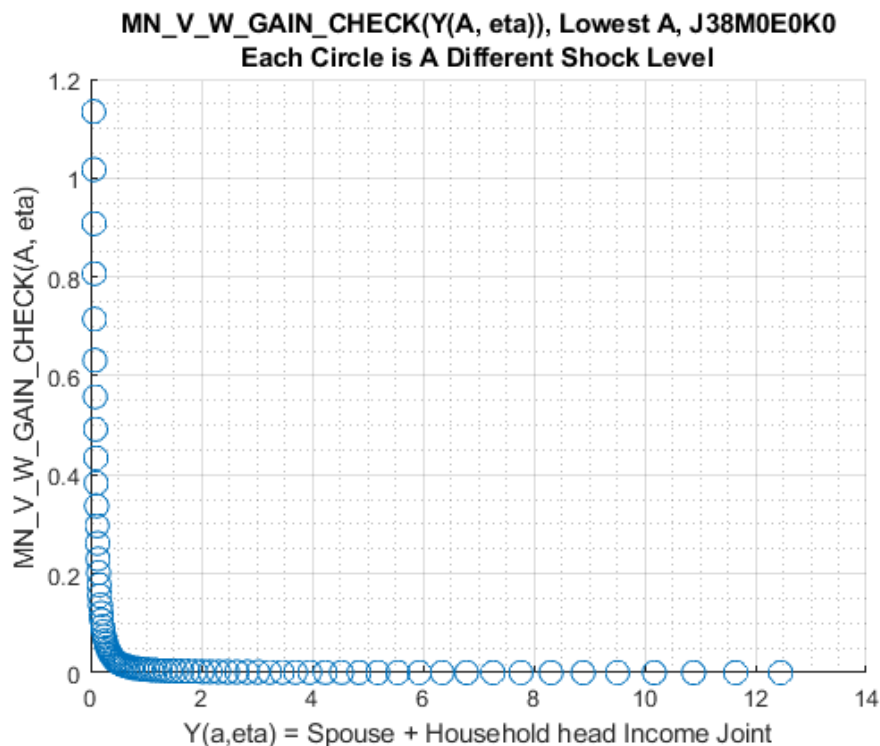
Select Age, Education, Marital, Kids Count:s

```
% Selections
it_age = 21; % +18
it_marital = 1; % 1 = unmarried
it_kids = 1; % 1 = kids is zero
it_educ = 1; % 1 = lower education
% Select: NaN(n_jgrid,n_agrid,n_etagrid,n_eduagrid,n_marriedgrid,n_kidsgrid);
mn_C_W_gain_check_jemk = mn_C_W_gain_check_use(it_age, :, 1:mp_params('n_eta_H_grid'), it_educ, it_m
mn_V_W_gain_check_jemk = mn_V_W_gain_check_use(it_age, :, 1:mp_params('n_eta_H_grid'), it_educ, it_m
% Reshape, so shock is the first dim, a is the second
mt_total_inc_jemk = permute(mn_total_inc_jemk, [3, 2, 1]);
mt_C_W_gain_check_jemk = permute(mn_C_W_gain_check_jemk, [3, 2, 1]);
mt_C_W_gain_check_jemk(mt_C_W_gain_check_jemk <= 1e-10) = 1e-10;
mt_V_W_gain_check_jemk = permute(mn_V_W_gain_check_jemk, [3, 2, 1]);
mt_V_W_gain_check_jemk(mt_V_W_gain_check_jemk <= 1e-10) = 1e-10;
% Generate meshed a and shock grid
[mt_eta_H, mt_a] = ndgrid(eta_H_grid(1:mp_params('n_eta_H_grid')), agrid);
```

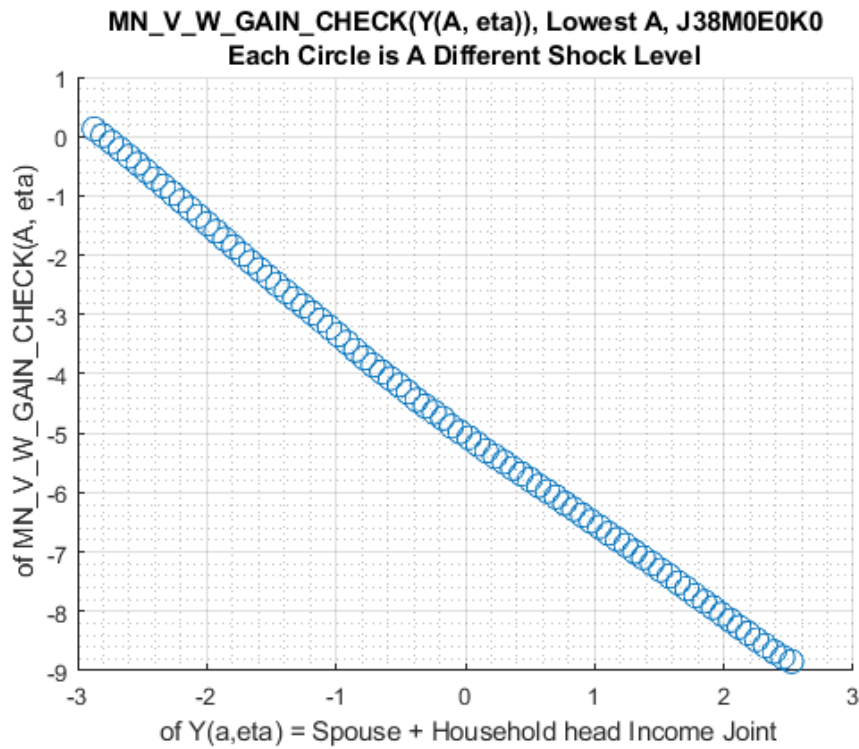
### 9.3.6 Marginal Value Gains, Color as Shock, Conditional on Age, Marital, Kids, and Education

How do shocks and a impact marginal value. First plot one asset level, variation comes only from increasingly higher shocks:

```
figure();
it_a = 1;
scatter(mt_total_inc_jemk(:,it_a)), (mt_V_W_gain_check_jemk(:,it_a)), 100);
title({'MN\V\W\GAIN\CHECK(Y(A, eta)), Lowest A, J38M0E0K0', ...
      'Each Circle is A Different Shock Level'});
xlabel('Y(a,eta) = Spouse + Household head Income Joint');
ylabel('MN\V\W\GAIN\CHECK(A, eta)');
grid on;
grid minor;
```

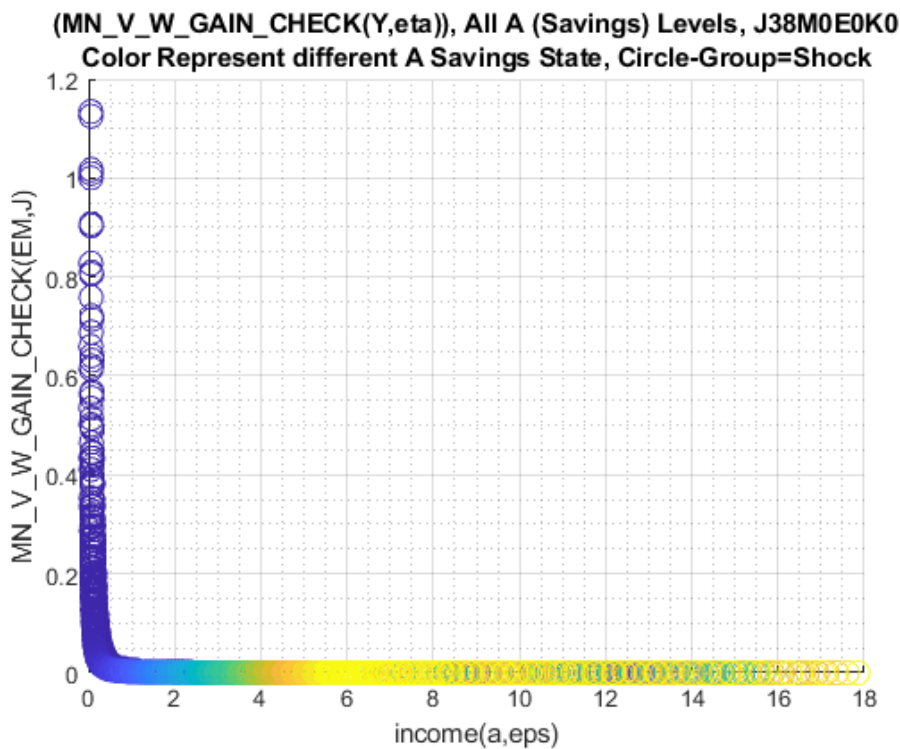


```
figure();
it_shock = 1;
scatter(log(mt_total_inc_jemk(:,it_a)), log(mt_V_W_gain_check_jemk(:,it_a)), 100);
title({'MN\V\W\GAIN\CHECK(Y(A, eta)), Lowest A, J38M0E0K0', ...
      'Each Circle is A Different Shock Level'});
xlabel(' of Y(a,eta) = Spouse + Household head Income Joint');
ylabel(' of MN\V\W\GAIN\CHECK(A, eta)');
grid on;
grid minor;
```



Plot all asset levels:

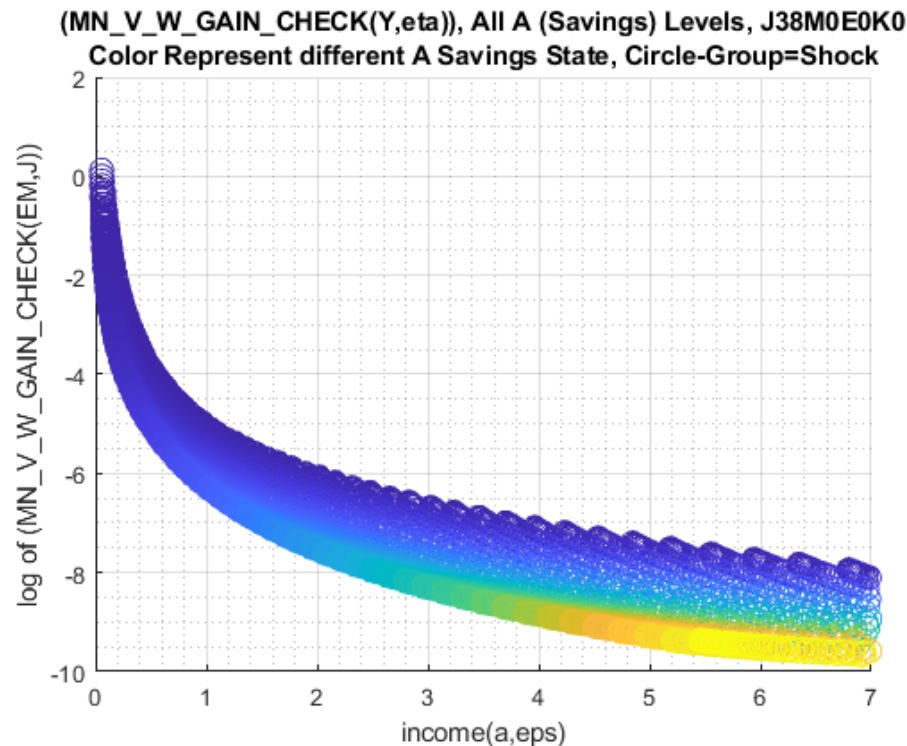
```
figure();
scatter((mt_total_inc_jemk(:)), (mt_V_W_gain_check_jemk(:)), 100, mt_a(:));
title({'(MN_V_W_GAIN_CHECK(Y,eta)), All A (Savings) Levels, J38M0E0K0', ...
      'Color Represent different A Savings State, Circle-Group=Shock'});
xlabel('income(a,eps)');
ylabel('MN_V_W_GAIN_CHECK(EM,J)');
grid on;
grid minor;
```



```

figure();
scatter(mt_total_inc_jemk(:), log(mt_V_W_gain_check_jemk(:), 100, mt_a(:));
title({'(MN_V_W_GAIN_CHECK(Y,eta)), All A (Savings) Levels, J38MOEOK0', ...
      'Color Represent different A Savings State, Circle-Group=Shock'});
xlabel('income(a,eps)');
ylabel('log of (MN_V_W_GAIN_CHECK(EM,J))');
xlim([0,7]);
grid on;
grid minor;

```



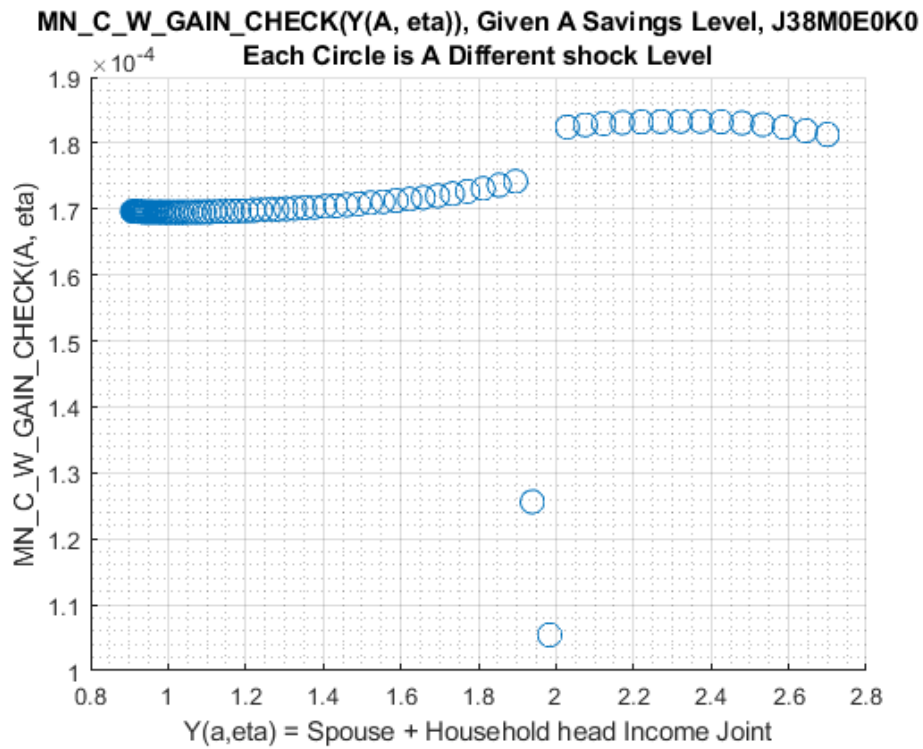
### 9.3.7 Marginal Consumption Gains, Color as Shock, Conditional on Age, Marital, Kids, and Education

How do shocks and  $a$  impact marginal value. First plot one asset level, variation comes only from increasingly higher shocks:

```

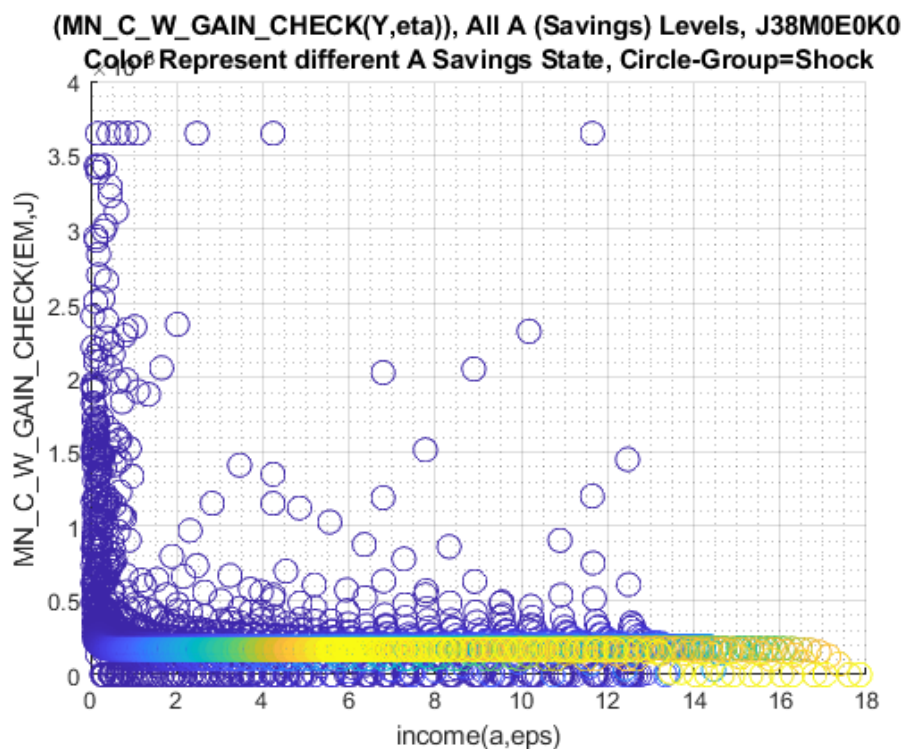
figure();
it_a = 50;
scatter(log(mt_total_inc_jemk(:,it_a)), mt_C_W_gain_check_jemk(:,it_a), 100);
title({'MN_C_W_GAIN_CHECK(Y(A, eta)), Given A Savings Level, J38MOEOK0', ...
      'Each Circle is A Different shock Level'});
xlabel('Y(a,eta) = Spouse + Household head Income Joint');
ylabel('MN_C_W_GAIN_CHECK(A, eta)');
grid on;
grid minor;

```



Plot all asset levels:

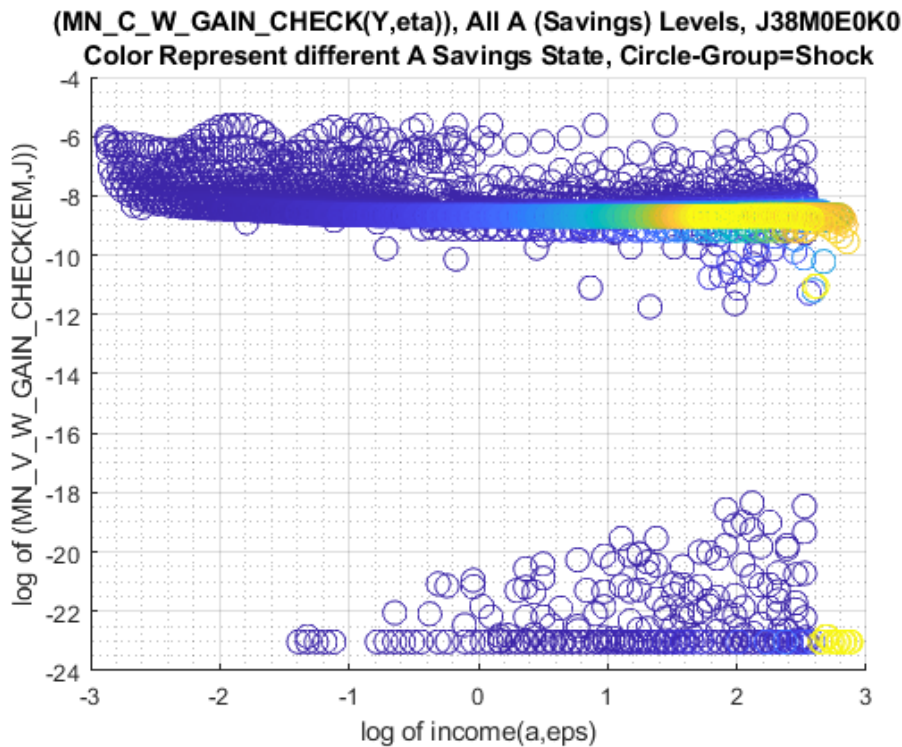
```
figure();
scatter((mt_total_inc_jemk(:)), (mt_C_W_gain_check_jemk(:)), 100, mt_a(:));
title({'(MN\C\W\_GAIN\_CHECK(Y,eta)), All A (Savings) Levels, J38M0E0K0', ...
      'Color Represent different A Savings State, Circle-Group=Shock'});
xlabel('income(a,eps)');
ylabel('MN\C\W\_GAIN\_CHECK(EM,J)');
grid on;
grid minor;
```



```

figure();
scatter(log(mt_total_inc_jemk(:)), log(mt_C_W_gain_check_jemk(:)), 100, mt_a(:));
title({'(MN\C\W\GAIN\CHECK(Y,eta)), All A (Savings) Levels, J38M0E0K0', ...
      'Color Represent different A Savings State, Circle-Group=Shock'});
xlabel('log of income(a,eps)');
ylabel('log of (MN\V\W\GAIN\CHECK(EM,J))');
grid on;
grid minor;

```



### 9.3.8 Analyze Kids and Marriage and Age

Aggregating over education, savings, and shocks, what are the differential effects of Marriage and Age.

```

% Generate some Data
mp_support_graph = containers.Map('KeyType', 'char', 'ValueType', 'any');
ar_row_grid = [...
    "k0M0", "k1M0", "k2M0", "k3M0", "k4M0", ...
    "k0M1", "k1M1", "k2M1", "k3M1", "k4M1"];
mp_support_graph('cl_st_xtitle') = {'Age'};
mp_support_graph('st_legend_loc') = 'best';
mp_support_graph('bl_graph_logy') = true; % do not log
mp_support_graph('st_rounding') = '6.2f'; % format shock legend
mp_support_graph('cl_scatter_shapes') = {...
    'o', 'd', 's', 'x', '*', ...
    'o', 'd', 's', 'x', '*'};
mp_support_graph('cl_colors') = {...
    'red', 'red', 'red', 'red', 'red'...
    'blue', 'blue', 'blue', 'blue', 'blue'};
MEAN(VAL(KM,J)), MEAN(AP(KM,J)), MEAN(C(KM,J))

```

Tabulate value and policies:

```

% Set
% NaN(n_jgrid,n_agrid,n_etagrid,n_educgrid,n_marriedgrid,n_kidsgrid);
ar_permute = [2,3,4,1,6,5];

```

% Value Function

```
st_title = ['MEAN(MN_V_U_GAIN_CHECK(KM,J)), welf_checks=' num2str(welf_checks) ', TR=' num2str(mp_pa
tb_az_v = ff_summ_nd_array(st_title, mn_V_U_gain_check, true, ["mean"], 3, 1, cl_mp_datasetdesc, ar
```

```
xxx MEAN(MN_V_U_GAIN_CHECK(KM,J)), welf_checks=2, TR=0.0018238 xxxxxxxxxxxxxxxxxxxxxxxxxxxxxxxx
  group  kids  marry  mean_age_18  mean_age_19  mean_age_20  mean_age_21  mean_age_2
-----  ----  -----  -
1      1      0      0.03116      0.030004      0.028268      0.025846      0.023825
2      2      0      0.042925      0.041372      0.038951      0.035539      0.032682
3      3      0      0.050042      0.048477      0.045918      0.041935      0.038603
4      4      0      0.056814      0.055153      0.05234       0.047822      0.044043
5      5      0      0.06224       0.060592      0.057683      0.052755      0.048636
6      1      1      0.0089468     0.0085141     0.0080936     0.0073219     0.006674
7      2      1      0.012008      0.011426      0.01086       0.0098202     0.0089462
8      3      1      0.014485      0.01381       0.013144      0.011882      0.010826
9      4      1      0.017392      0.016611      0.015824      0.014325      0.013061
10     5      1      0.021156      0.020287      0.019385      0.017573      0.016058
```

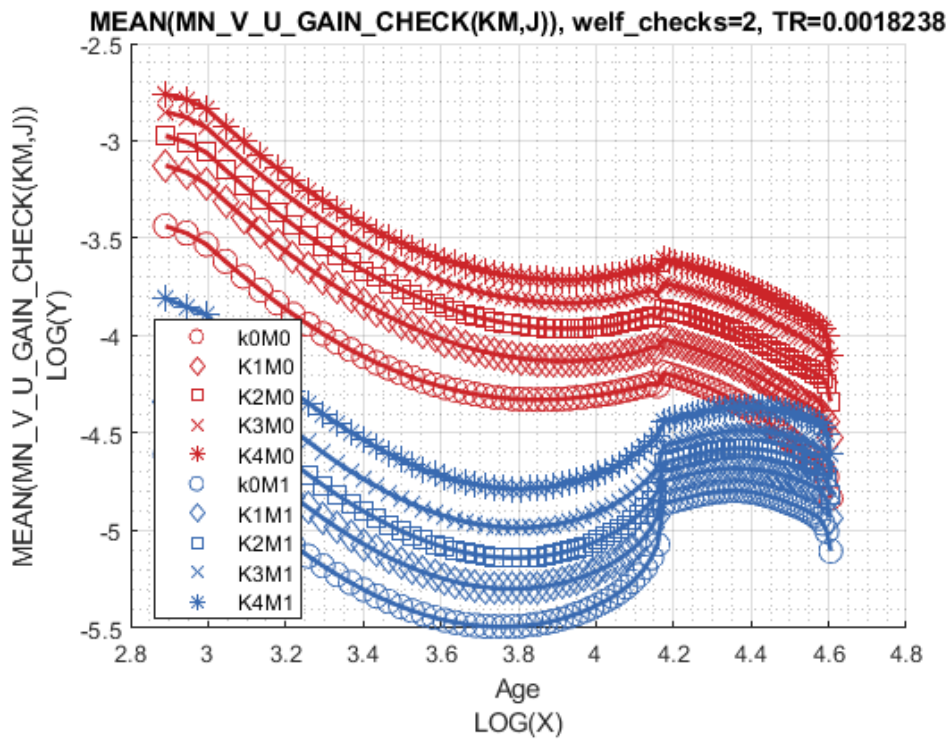
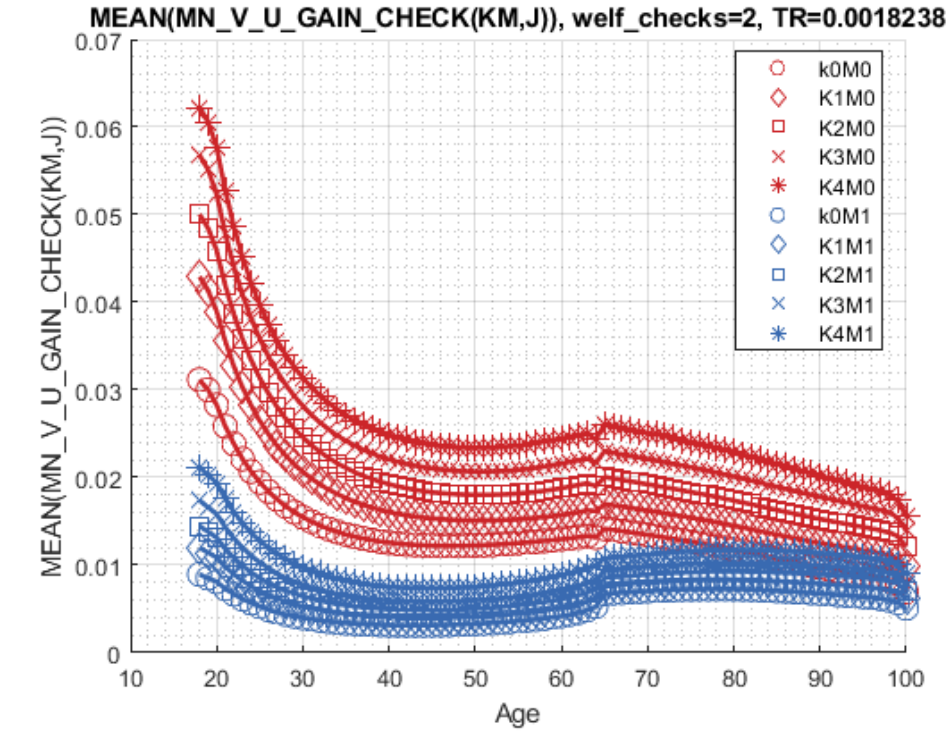
% Consumption Function

```
st_title = ['MEAN(MN_MPC_U_GAIN_CHECK(KM,J)), welf_checks=' num2str(welf_checks) ', TR=' num2str(mp_
tb_az_c = ff_summ_nd_array(st_title, mn_MPC_U_gain_share_check, true, ["mean"], 3, 1, cl_mp_datasetd
```

```
xxx MEAN(MN_MPC_U_GAIN_CHECK(KM,J)), welf_checks=2, TR=0.0018238 xxxxxxxxxxxxxxxxxxxxxxxxxxxxxxxx
  group  kids  marry  mean_age_18  mean_age_19  mean_age_20  mean_age_21  mean_age_2
-----  ----  -----  -
1      1      0      0.071209      0.076265      0.082919      0.080484      0.079666
2      2      0      0.08025       0.085444      0.092048      0.090298      0.089234
3      3      0      0.087972      0.095508      0.10343       0.10119       0.099548
4      4      0      0.092255      0.099859      0.10923       0.10651       0.10388
5      5      0      0.09665       0.1041       0.11456       0.11152       0.10814
6      1      1      0.101         0.10439      0.10978       0.10855       0.10822
7      2      1      0.10297      0.10717      0.11242       0.11166       0.10915
8      3      1      0.10827      0.11355      0.11922       0.11713       0.11645
9      4      1      0.10932      0.11394      0.12031       0.11884       0.11867
10     5      1      0.11555      0.12093      0.1289        0.12462       0.12328
```

Graph Mean Values:

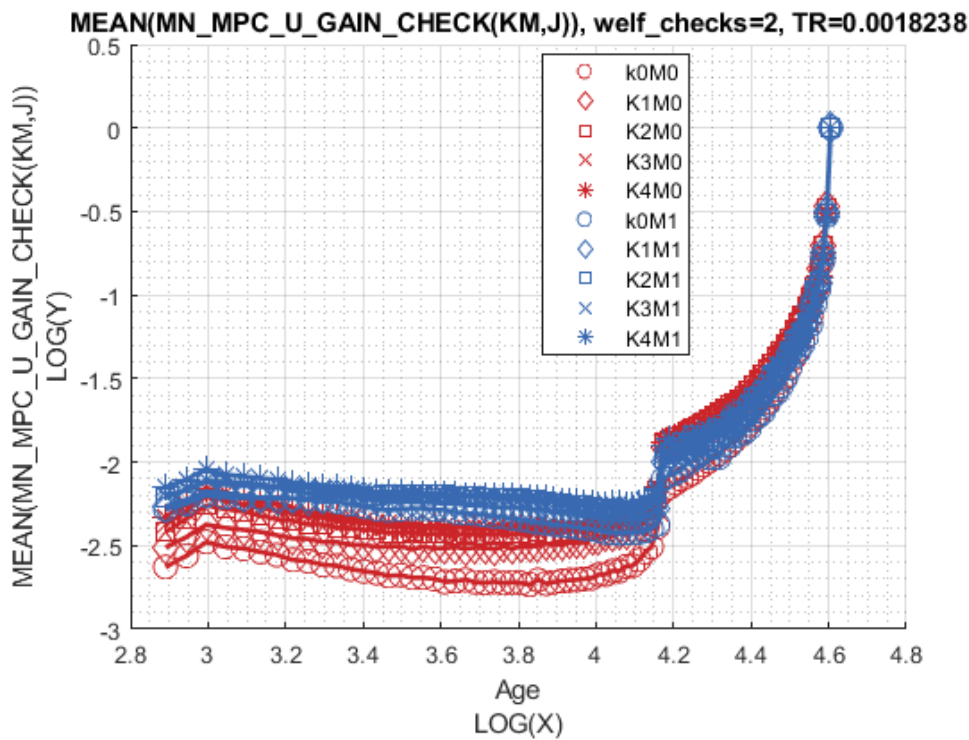
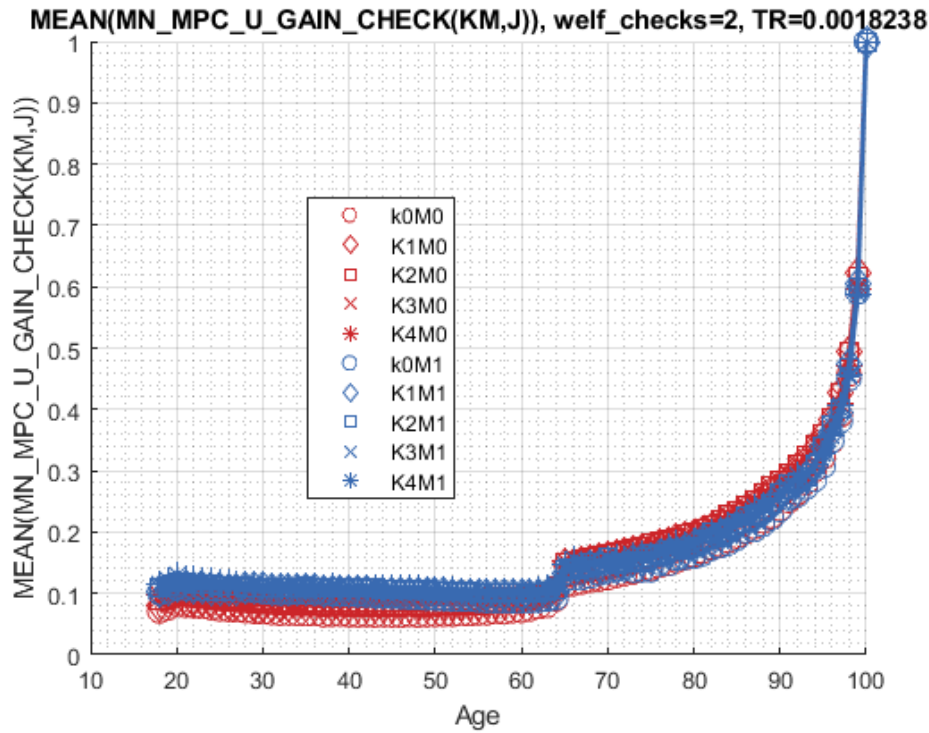
```
st_title = ['MEAN(MN_V_U_GAIN_CHECK(KM,J)), welf_checks=' num2str(welf_checks) ', TR=' num2str(
mp_support_graph('cl_st_graph_title') = {st_title};
mp_support_graph('cl_st_ytitle') = {'MEAN(MN_V_U_GAIN_CHECK(KM,J))'};
ff_graph_grid((tb_az_v{1:end, 4:end}), ar_row_grid, age_grid, mp_support_graph);
```



Graph Mean Consumption (*MPC: Share of Check Consumed*):

```
st_title = ['MEAN(MN\MPC\U\_GAIN\_CHECK(KM,J))', welf_checks=' num2str(welf_checks) ', TR=' num2str(
mp_support_graph('cl_st_graph_title') = {st_title};
mp_support_graph('cl_st_ytitle') = {'MEAN(MN\MPC\U\_GAIN\_CHECK(KM,J))'};
ff_graph_grid((tb_az_c{1:end, 4:end}), ar_row_grid, age_grid, mp_support_graph);
```





### 9.3.9 Analyze Education and Marriage

Aggregating over education, savings, and shocks, what are the differential effects of Marriage and Age.

```
% Generate some Data
mp_support_graph = containers.Map('KeyType', 'char', 'ValueType', 'any');
ar_row_grid = ["E0M0", "E1M0", "E0M1", "E1M1"];
mp_support_graph('cl_st_xtitle') = {'Age'};
mp_support_graph('st_legend_loc') = 'best';
mp_support_graph('bl_graph_logy') = true; % do not log
```

```
mp_support_graph('st_rounding') = '6.2f'; % format shock legend
mp_support_graph('cl_scatter_shapes') = {'*', 'p', '*', 'p' };
mp_support_graph('cl_colors') = {'red', 'red', 'blue', 'blue'};
```

```
MEAN(VAL(EM,J)), MEAN(AP(EM,J)), MEAN(C(EM,J))
```

Tabulate value and policies:

```
% Set
% NaN(n_jgrid,n_agrid,n_etagrid,n_educgrid,n_marriedgrid,n_kidsgrid);
ar_permute = [2,3,6,1,4,5];
% Value Function
st_title = ['MEAN(MN_V_U_GAIN_CHECK(EM,J)), welf_checks=' num2str(welf_checks) ', TR=' num2str(mp_pa
tb_az_v = ff_summ_nd_array(st_title, mn_V_U_gain_check, true, ["mean"], 3, 1, cl_mp_datasetdesc, ar_
```

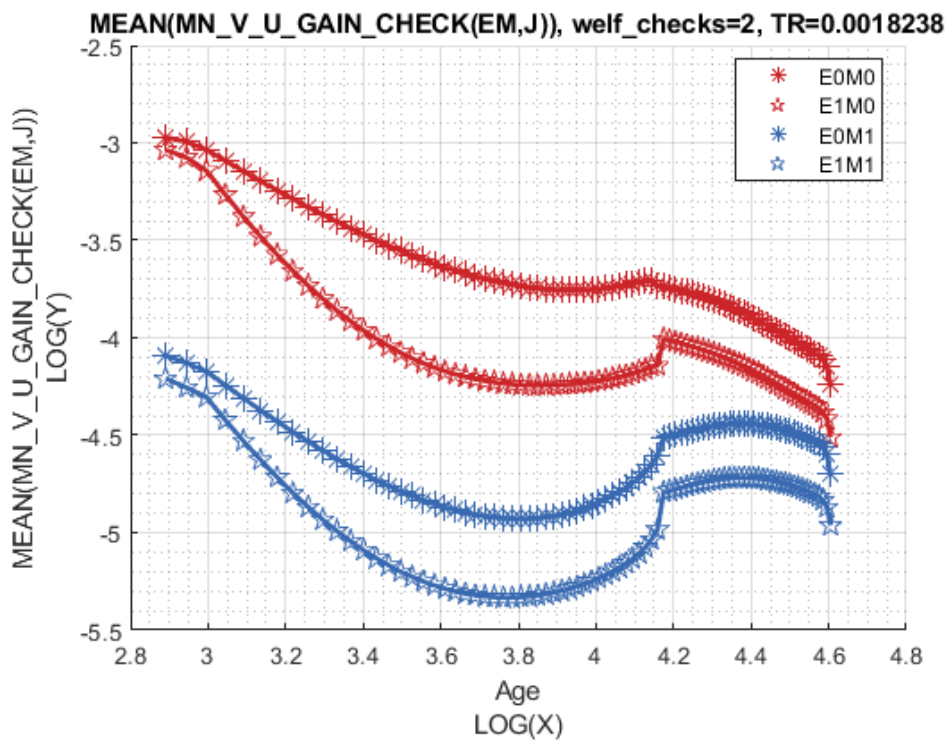
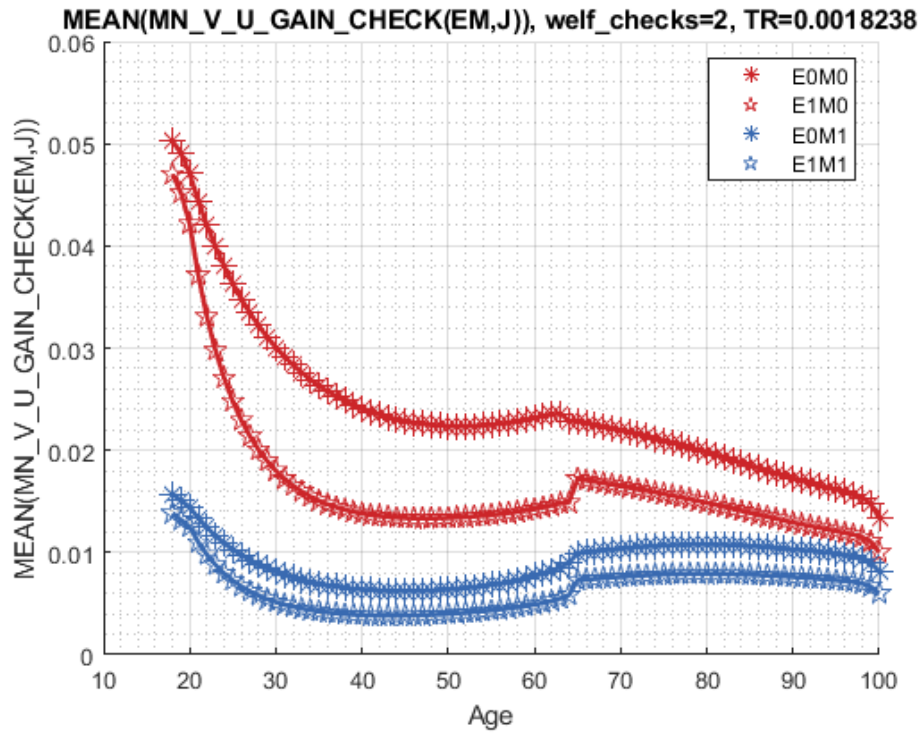
```
xxx MEAN(MN_V_U_GAIN_CHECK(EM,J)), welf_checks=2, TR=0.0018238 xxxxxxxxxxxxxxxxxxxxxxxxxxxxxxx
  group   edu   marry   mean_age_18   mean_age_19   mean_age_20   mean_age_21   mean_age_22
  -----   ---   -----   -----
  1         0     0     0.050249     0.049057     0.04709      0.044412     0.042032
  2         1     0     0.047023     0.045182     0.042174     0.037147     0.033084
  3         0     1     0.015742     0.015072     0.014412     0.01336      0.012437
  4         1     1     0.013853     0.013188     0.012511     0.011009     0.0097884
```

```
% Consumption
st_title = ['MEAN(MN_MPC_U_GAIN_CHECK(EM,J)), welf_checks=' num2str(welf_checks) ', TR=' num2str(mp_
tb_az_c = ff_summ_nd_array(st_title, mn_MPC_U_gain_share_check, true, ["mean"], 3, 1, cl_mp_datasetd
```

```
xxx MEAN(MN_MPC_U_GAIN_CHECK(EM,J)), welf_checks=2, TR=0.0018238 xxxxxxxxxxxxxxxxxxxxxxxxxxxxxxx
  group   edu   marry   mean_age_18   mean_age_19   mean_age_20   mean_age_21   mean_age_22
  -----   ---   -----   -----
  1         0     0     0.07766      0.081478     0.084248     0.083711     0.083393
  2         1     0     0.093675     0.10299      0.11663      0.11229      0.10879
  3         0     1     0.099571     0.10294      0.10634      0.10623      0.10602
  4         1     1     0.11528      0.12105      0.12991      0.12609      0.12429
```

Graph Mean Values:

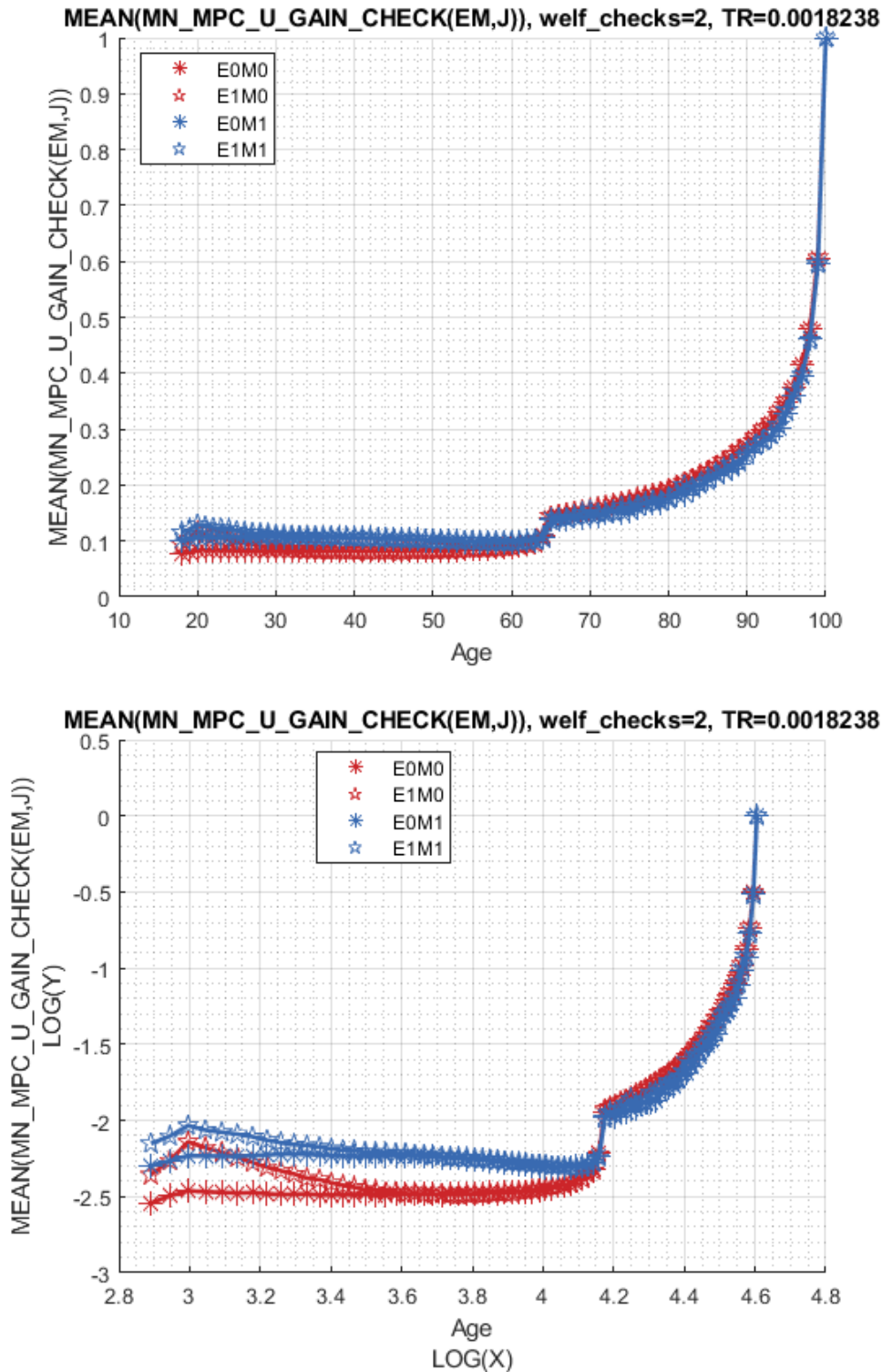
```
st_title = ['MEAN(MN_V_U_GAIN_CHECK(EM,J)), welf_checks=' num2str(welf_checks) ', TR=' num2str(
mp_support_graph('cl_st_graph_title') = {st_title};
mp_support_graph('cl_st_ytitle') = {'MEAN(MN_V_U_GAIN_CHECK(EM,J))'};
ff_graph_grid((tb_az_v{1:end, 4:end}), ar_row_grid, age_grid, mp_support_graph);
```



Graph Mean Consumption (*MPC: Share of Check Consumed*):

```

st_title = ['MEAN(MN\MPC\U\_GAIN\_CHECK(EM,J)), welf_checks=' num2str(welf_checks) ', TR=' num2str
mp_support_graph('cl_st_graph_title') = {st_title};
mp_support_graph('cl_st_ytitle') = {'MEAN(MN\MPC\U\_GAIN\_CHECK(EM,J))'};
ff_graph_grid((tb_az_c{1:end, 4:end}), ar_row_grid, age_grid, mp_support_graph);
    
```



## 9.4 2007 (Bush 2008 Stimulus) Full States EV and EC of Two Checks

This is the example vignette for function: [snw\\_evuvw19\\_jaeemk\\_foc](#) from the [PrjOptiSNW Package](#). 2008 integrated over VU and VW, given optimal savings choices, unemployment shocks and various expectations.

Given 2008 policy and value functions (given expectation of 2009 crisis unemployment shocks), call `SNW_V08_JAEEMK` to solve for value and consumption given stimulus checks. And then integrate

over 08 JAEEMK states given 07 JAEEMK states (age, endogenous savings, education, income shock, marital status, kids count). The stimulus will be provisioned based on 07 JAEEMK states. Note that `snw_evuvw19_jaeemk` does not solve the 07/08 problem.

Despite the name, this function supports solving the 2019 looking into 2020 as well as the 2007 looking into 2008 problems. The idea is that the planner only has information from 2019 and from 2007, and must allocate using those information. Stimulus, however, is given in 2020 and in 2008. So the planner needs to consider expected values in consumption or welfare given the transition probabilities of states in 2007 to 2008 and in 2019 to 2020. The `snw_evuvw19_jmky` file then aggregates the full state-space results to just JMKY state-space, which is the extend of information available to the planner.

### 9.4.1 Test SNW\_EVUVW19\_JAEEMK Defaults for 2019

Call the function with defaults. First, set up some parameters.

```
clear all;
% Solution types
st_biden_or_trump = 'bushchck';

% Solve the VFI Problem and get Value Function
mp_controls = snw_mp_control('default_test');

% Solve for Unemployment Values
mp_controls('bl_print_a4chk') = false;
mp_controls('bl_print_a4chk_verbose') = false;
mp_controls('bl_print_vfi') = false;
mp_controls('bl_print_vfi_verbose') = false;
mp_controls('bl_print_ds') = false;
mp_controls('bl_print_ds_verbose') = false;
mp_controls('bl_print_precompute') = false;
mp_controls('bl_print_evuvw20_jaeemk') = false;
mp_controls('bl_print_evuvw20_jaeemk_verbose') = false;
mp_controls('bl_print_v08p08_jaeemk') = false;
mp_controls('bl_print_v08p08_jaeemk_verbose') = false;
mp_controls('bl_print_v08_jaeemk') = true;
mp_controls('bl_print_v08_jaeemk_verbose') = false;
```

Second, run initializing functions.

```
% 1. generate MP_PARAMS specific to 2008 stimulus
% Use non-default values for Bush Stimulus
mp_more_inputs = containers.Map('KeyType','char','ValueType','any');
mp_more_inputs('fl_ss_non_college') = 0.225;
mp_more_inputs('fl_ss_college') = 0.271;
fl_p50_hh_income_07 = 54831;
mp_more_inputs('fl_scaleconvertor') = fl_p50_hh_income_07;
% st_param_group = 'default_small';
st_param_group = 'default_dense';
st_param_group = 'default_docdense';
mp_params = snw_mp_param(st_param_group, false, 'tauchen', false, 8, 8, mp_more_inputs);
mp_params('st_biden_or_trump') = st_biden_or_trump;
mp_params('beta') = 0.95;
% 2. Solve value steady state (2009 employed)
[V_ss, ap_ss, cons_ss, mp_valpol_more_ss] = snw_vfi_main_bisec_vec(mp_params, mp_controls);
```

Completed SNW\_VFI\_MAIN\_BISEC\_VEC;SNW\_MP\_PARAM=default\_docdense;SNW\_MP\_CONTROL=default\_test;time=495.

```
V_emp_2009 = V_ss;
inc_ss = mp_valpol_more_ss('inc_VFI');
spouse_inc_ss = mp_valpol_more_ss('spouse_inc_VFI');
```

```

total_inc_ss = inc_ss + spouse_inc_ss;
% 3. Solve value unemployed 2009
mp_params('xi') = 0.532;
mp_params('b') = 0.37992;
mp_params('a2_covidyr') = mp_params('a2_greatrecession_2009');
mp_params('TR') = 100/fl_p50_hh_income_07;
[V_unemp_2009] = snw_vfi_main_bisec_vec(mp_params, mp_controls, V_ss);

Completed SNW_VFI_MAIN_BISEC_VEC 1 Period Unemp Shock;SNW_MP_PARAM=default_docdense;SNW_MP_CONTROL=d

% 4. Value and Optimal choice in 2008
[V_2008, ap_2008, cons_2008, ev_empshk_2009] = ...
    snw_v08p08_jaeemk(mp_params, mp_controls, V_emp_2009, V_unemp_2009);

Completed SNW_VFI_MAIN_BISEC_VEC 1 Period Unemp Shock;SNW_MP_PARAM=default_docdense;SNW_MP_CONTROL=d
Completed SNW_V08P08_JAEEMK;SNW_MP_PARAM=default_docdense;SNW_MP_CONTROL=default_test;time=497.3876

% 5. matrixes to pre-compute
% Only using the SNW_A4CHK_WRK_BISEC_VEC function, no unemployment
% related matrixes needed Also don't need REF_EARN_WAGEIND_GRID,
% become unemployment not conditional on wage in 2009.
cl_st_precompute_list = {'a', ...
    'inc', 'inc_unemp', 'spouse_inc',...
    'ar_z_ctr_amz'};
% Shared: Steady-State distribution
[Phi_true] = snw_ds_main(mp_params, mp_controls, ap_ss, cons_ss, mp_valpol_more_ss);

Completed SNW_DS_MAIN;SNW_MP_PARAM=default_docdense;SNW_MP_CONTROL=default_test;time=1775.4241

% Shared: precompute, get Matrixes
% note, the mp_params inputs are based on unemployed in 2020 (MIT) or unemployed in 2009 (Expected)
% note, however, for the 2008/9 problem, only will use inc, inc_unemp, spouse_inc
mp_controls('bl_print_precompute_verbose') = false;
[mp_precompute_res] = snw_hh_precompute(mp_params, mp_controls, cl_st_precompute_list, ap_ss, Phi_tr

Wage quintile cutoffs=0.4645    0.71528    1.0335    1.5632
Completed SNW_HH_PRECOMPUTE;SNW_MP_PARAM=default_docdense;SNW_MP_CONTROL=default_test;time cost=254.

```

### 9.4.2 Solve for 2019 Evuvw With 0 and 2 Checks

Solve for 0 and 2 checks, by finding the increase to asset state-space that is equivalent to the check increase, so that the problem can be solved without increasing the state-space.

```

% Call Function
welf_checks = 0;
[ev07_jaeemk_check0, ec07_jaeemk_check0, ev08_jaeemk_check0, ec08_jaeemk_check0] = snw_evuvw19_jaeemk(
    welf_checks, mp_params, mp_controls, ...
    ap_ss, V_2008, cons_2008, mp_precompute_res);

```

```

Solve for V_2008_check for 0 stimulus checks
Completed SNW_A4CHK_WRK_BISEC_VEC;SNW_MP_PARAM=bushchck;welf_checks=0;TR=0.0018238;SNW_MP_PARAM=defa
Completed SNW_V08_JAEEMK;SNW_MP_PARAM=default_docdense;SNW_MP_CONTROL=default_test;timeEUEC=6.99e-05
Completed SNW_EVUVW19_JAEEMK_FOC;st_biden_or_trump=bushchck;SNW_MP_PARAM=default_docdense;SNW_MP_CON

```

```

-----
XXXXXXXXXXXXXXXXXXXXXXXXXXXXXXXXXXXXXXXXXXXXXXXXXXXX

```

```

CONTAINER NAME: mp_outcomes ND Array (Matrix etc)

```

```

XXXXXXXXXXXXXXXXXXXXXXXXXXXXXXXXXXXXXXXXXXXXXXXXXXXX

```

i	idx	ndim	numel	rowN	colN	sum	mean
---	-----	------	-------	------	------	-----	------

	-	---	----	-----	----	-----	-----	-----
ec07_jaeemk	1	1	6	4.3173e+07	82	5.265e+05	1.9685e+08	4.5597
ec08_jaeemk	2	2	6	4.37e+07	83	5.265e+05	2.3277e+08	5.3267
ev07_jaeemk	3	3	6	4.3173e+07	82	5.265e+05	-6.4618e+08	-14.967
ev08_jaeemk	4	4	6	4.37e+07	83	5.265e+05	-6.6426e+08	-15.201

xxx TABLE:ec07\_jaeemk xxxxxxxxxxxxxxxxxxxxxxx

	c1	c2	c3	c4	c5	c526496	c526497	c526498
	-----	-----	-----	-----	-----	-----	-----	-----
r1	0.039543	0.039543	0.039978	0.042271	0.04854	12.009	12.281	12.561
r2	0.039889	0.039889	0.040323	0.043305	0.049735	12.251	12.524	12.806
r3	0.041432	0.041432	0.041608	0.043991	0.050734	12.485	12.759	13.042
r4	0.042935	0.042935	0.043023	0.045459	0.052199	12.742	13.017	13.3
r5	0.044395	0.044395	0.044399	0.046895	0.053615	12.99	13.266	13.548
r78	0.2016	0.2016	0.2016	0.2016	0.20214	27.775	28.774	29.785
r79	0.2016	0.2016	0.2016	0.2016	0.2016	30.43	31.663	32.736
r80	0.2016	0.2016	0.2016	0.2016	0.2016	33.68	35.501	37.368
r81	0.2016	0.2016	0.2016	0.2016	0.2016	40.118	41.397	43.175
r82	0.2016	0.2016	0.2016	0.2016	0.2016	52.1	55.541	58.464

xxx TABLE:ec08\_jaeemk xxxxxxxxxxxxxxxxxxxxxxx

	c1	c2	c3	c4	c5	c526496	c526497	c526498
	-----	-----	-----	-----	-----	-----	-----	-----
r1	0.036218	0.036736	0.038184	0.042735	0.048545	12.256	12.541	12.835
r2	0.036271	0.036736	0.038385	0.043404	0.049852	12.491	12.778	13.072
r3	0.036717	0.037251	0.039845	0.044907	0.051515	12.744	13.032	13.327
r4	0.038144	0.038678	0.041269	0.046371	0.053128	12.989	13.277	13.573
r5	0.039534	0.040068	0.042653	0.047793	0.054687	13.224	13.513	13.809
r79	0.2016	0.20214	0.20586	0.21598	0.23568	35.82	37.367	39.414
r80	0.2016	0.20214	0.20586	0.21598	0.23568	40.755	42.955	45.289
r81	0.2016	0.20214	0.20586	0.21598	0.23568	48.912	52.041	55.022
r82	0.2016	0.20214	0.20586	0.21598	0.23568	66.719	69.201	72.373
r83	0.2016	0.20214	0.20586	0.21598	0.23568	116.83	122.65	128.67

xxx TABLE:ev07\_jaeemk xxxxxxxxxxxxxxxxxxxxxxx

	c1	c2	c3	c4	c5	c526496	c526497	c526498
	-----	-----	-----	-----	-----	-----	-----	-----
r1	-282.59	-282.59	-282.23	-278.38	-270.8	-4.3833	-4.2888	-4.195
r2	-272.49	-272.49	-272.13	-268.93	-261.76	-4.2754	-4.1844	-4.094
r3	-262.36	-262.36	-262.23	-259.89	-253.05	-4.1651	-4.0777	-3.991
r4	-253.22	-253.22	-253.16	-250.92	-244.6	-4.0512	-3.9675	-3.884
r5	-244.95	-244.95	-244.95	-242.81	-236.93	-3.9436	-3.8633	-3.783
r78	-13.362	-13.362	-13.362	-13.362	-13.349	-0.27313	-0.26104	-0.2497
r79	-12.032	-12.032	-12.032	-12.032	-12.032	-0.21855	-0.20781	-0.1987
r80	-10.388	-10.388	-10.388	-10.388	-10.388	-0.16126	-0.15407	-0.1473
r81	-8.1801	-8.1801	-8.1801	-8.1801	-8.1801	-0.10114	-0.097396	-0.09343
r82	-4.9651	-4.9651	-4.9651	-4.9651	-4.9651	-0.044201	-0.041462	-0.03941

xxx TABLE:ev08\_jaeemk xxxxxxxxxxxxxxxxxxxxxxx

	c1	c2	c3	c4	c5	c526496	c526497	c526498
	-----	-----	-----	-----	-----	-----	-----	-----
r1	-295.66	-295.26	-292.66	-286.62	-277.22	-4.3615	-4.2673	-4.174
r2	-286.11	-285.71	-283.12	-277.16	-268.03	-4.2548	-4.1641	-4.074

r3	-276.49	-276.09	-273.59	-267.84	-259.11	-4.1461	-4.0589	-3.972
r4	-266.77	-266.41	-264.08	-258.7	-250.49	-4.0342	-3.9507	-3.86
r5	-257.99	-257.65	-255.48	-250.43	-242.69	-3.9287	-3.8485	-3.76
r79	-13.356	-13.343	-13.253	-13.025	-12.638	-0.22088	-0.21055	-0.2008
r80	-12.025	-12.012	-11.923	-11.695	-11.308	-0.16977	-0.1618	-0.1542
r81	-10.382	-10.369	-10.28	-10.052	-9.6651	-0.11711	-0.11162	-0.1064
r82	-8.1742	-8.1611	-8.0716	-7.844	-7.457	-0.065329	-0.062239	-0.05935
r83	-4.9602	-4.9471	-4.8576	-4.6301	-4.2431	-0.020966	-0.019971	-0.01903

% Call Function

```
welf_checks = 2;
[ev07_jaeemk_check2, ec07_jaeemk_check2, ev08_jaeemk_check2, ec08_jaeemk_check2] = snw_evuvw19_jaeemk(
    welf_checks, mp_params, mp_controls, ...
    ap_ss, V_2008, cons_2008, mp_precompute_res);
```

Solve for V\_2008\_check for 2 stimulus checks

```
Completed SNW_A4CHK_WRK_BISEC_VEC;SNW_MP_PARAM=bushchck;welf_checks=2;TR=0.0018238;SNW_MP_PARAM=default
Completed SNW_V08_JAEEMK;SNW_MP_PARAM=default_docdense;SNW_MP_CONTROL=default_test;timeEUEC=2.82e-05
Completed SNW_EVUVW19_JAEEMK_FOC;st_biden_or_trump=bushchck;SNW_MP_PARAM=default_docdense;SNW_MP_CON
```

```
-----
XXXXXXXXXXXXXXXXXXXXXXXXXXXXXXXXXXXXXXXXXXXXXXXXXXXX
CONTAINER NAME: mp_outcomes ND Array (Matrix etc)
XXXXXXXXXXXXXXXXXXXXXXXXXXXXXXXXXXXXXXXXXXXXXXXXXXXX
```

	i	idx	ndim	numel	rowN	colN	sum	mean
	-	---	----	-----	----	-----	-----	-----
ec07_jaeemk	1	1	6	4.3173e+07	82	5.265e+05	1.9688e+08	4.5603
ec08_jaeemk	2	2	6	4.37e+07	83	5.265e+05	2.328e+08	5.3273
ev07_jaeemk	3	3	6	4.3173e+07	82	5.265e+05	-6.4561e+08	-14.954
ev08_jaeemk	4	4	6	4.37e+07	83	5.265e+05	-6.6365e+08	-15.187

```
xxx TABLE:ec07_jaeemk XXXXXXXXXXXXXXXXXXXXXXXX
```

	c1	c2	c3	c4	c5	c526496	c526497	c526498
	-----	-----	-----	-----	-----	-----	-----	-----
r1	0.040827	0.040827	0.040972	0.04389	0.049551	12.009	12.281	12.561
r2	0.042096	0.042096	0.0424	0.045024	0.050802	12.251	12.524	12.806
r3	0.043624	0.043624	0.043746	0.045821	0.051869	12.485	12.76	13.042
r4	0.04511	0.04511	0.04517	0.047304	0.053361	12.742	13.017	13.3
r5	0.04655	0.04655	0.046553	0.048751	0.054802	12.99	13.266	13.549
r78	0.20525	0.20525	0.20525	0.20525	0.20579	27.775	28.775	29.786
r79	0.20525	0.20525	0.20525	0.20525	0.20525	30.431	31.664	32.737
r80	0.20525	0.20525	0.20525	0.20525	0.20525	33.681	35.503	37.369
r81	0.20525	0.20525	0.20525	0.20525	0.20525	40.119	41.4	43.178
r82	0.20525	0.20525	0.20525	0.20525	0.20525	52.103	55.545	58.468

```
xxx TABLE:ec08_jaeemk XXXXXXXXXXXXXXXXXXXXXXXX
```

	c1	c2	c3	c4	c5	c526496	c526497	c526498
	-----	-----	-----	-----	-----	-----	-----	-----
r1	0.037941	0.038148	0.039819	0.043807	0.049244	12.256	12.541	12.835
r2	0.038108	0.038344	0.040188	0.044594	0.050571	12.492	12.778	13.073
r3	0.03941	0.039781	0.041664	0.046126	0.052244	12.745	13.032	13.327
r4	0.040834	0.041205	0.043102	0.047618	0.053867	12.989	13.278	13.573
r5	0.04222	0.042589	0.0445	0.049065	0.055435	13.224	13.513	13.809
r79	0.20525	0.20579	0.20951	0.21963	0.23776	35.821	37.368	39.415
r80	0.20525	0.20579	0.20951	0.21963	0.23776	40.756	42.957	45.29
r81	0.20525	0.20579	0.20951	0.21963	0.2378	48.914	52.043	55.024



r82	0.20525	0.20579	0.20951	0.21963	0.23814	66.72	69.203	72.375
r83	0.20525	0.20579	0.20951	0.21963	0.23933	116.84	122.66	128.68

```
xxx TABLE:ev07_jaeemk xxxxxxxxxxxxxxxxxxxxxx
```

	c1	c2	c3	c4	c5	c526496	c526497	c526498
	-----	-----	-----	-----	-----	-----	-----	-----
r1	-280.23	-280.23	-279.88	-276.5	-269.35	-4.3833	-4.2887	-4.195
r2	-270.21	-270.21	-269.89	-267.08	-260.35	-4.2753	-4.1844	-4.094
r3	-260.26	-260.26	-260.13	-258.1	-251.71	-4.165	-4.0777	-3.991
r4	-251.26	-251.26	-251.2	-249.25	-243.33	-4.0511	-3.9674	-3.884
r5	-243.12	-243.12	-243.12	-241.24	-235.73	-3.9436	-3.8633	-3.783
r78	-13.274	-13.274	-13.274	-13.274	-13.262	-0.27312	-0.26103	-0.249
r79	-11.944	-11.944	-11.944	-11.944	-11.944	-0.21854	-0.2078	-0.1987
r80	-10.3	-10.3	-10.3	-10.3	-10.3	-0.16125	-0.15406	-0.1473
r81	-8.0921	-8.0921	-8.0921	-8.0921	-8.0921	-0.10113	-0.097391	-0.09343
r82	-4.8771	-4.8771	-4.8771	-4.8771	-4.8771	-0.044198	-0.04146	-0.0394

```
xxx TABLE:ev08_jaeemk xxxxxxxxxxxxxxxxxxxxxx
```

	c1	c2	c3	c4	c5	c526496	c526497	c526498
	-----	-----	-----	-----	-----	-----	-----	-----
r1	-293.09	-292.72	-290.49	-284.88	-275.86	-4.3615	-4.2672	-4.174
r2	-283.55	-283.18	-280.98	-275.47	-266.73	-4.2548	-4.164	-4.074
r3	-274.01	-273.65	-271.52	-266.23	-257.88	-4.146	-4.0589	-3.972
r4	-264.47	-264.13	-262.14	-257.19	-249.33	-4.0341	-3.9506	-3.867
r5	-255.84	-255.53	-253.66	-249	-241.59	-3.9286	-3.8484	-3.76
r79	-13.268	-13.255	-13.171	-12.954	-12.578	-0.22088	-0.21054	-0.2008
r80	-11.937	-11.924	-11.841	-11.623	-11.248	-0.16976	-0.16179	-0.1542
r81	-10.294	-10.281	-10.198	-9.9804	-9.6057	-0.11711	-0.11162	-0.1064
r82	-8.0862	-8.0735	-7.9895	-7.7724	-7.3981	-0.065327	-0.062237	-0.05935
r83	-4.8723	-4.8595	-4.7755	-4.5584	-4.1854	-0.020965	-0.01997	-0.01903

Differences between Checks in Expected Value and Expected Consumption

```
mn_V_U_gain_check_07 = ev07_jaeemk_check2 - ev07_jaeemk_check0;
```

```
mn_MPC_U_gain_share_check_07 = (ec07_jaeemk_check2 - ec07_jaeemk_check0)./(welf_checks*mp_params('TR
```

### 9.4.3 Param Results Define Frames

Define the matrix dimensions names and dimension vector values. Policy and Value Functions share the same ND dimensional structure.

```
% Grids:
age_grid = 18:99;
agrid = mp_params('agrid');
eta_H_grid = mp_params('eta_H_grid');
eta_S_grid = mp_params('eta_S_grid');
ar_st_eta_HS_grid = string(cellstr([num2str(eta_H_grid', 'hz=%3.2f;'), num2str(eta_S_grid', 'wz=%3.2
edu_grid = [0,1];
marry_grid = [0,1];
kids_grid = (1:1:mp_params('n_kidsgrid'))';
% NaN(n_jgrid,n_agrid,n_etagrid,n_educgrid,n_marriedgrid,n_kidsgrid);
cl_mp_datasetdesc = {};
cl_mp_datasetdesc{1} = containers.Map({'name', 'labval'}, {'age', age_grid});
cl_mp_datasetdesc{2} = containers.Map({'name', 'labval'}, {'savings', agrid});
cl_mp_datasetdesc{3} = containers.Map({'name', 'labval'}, {'eta', 1:length(eta_H_grid)});
cl_mp_datasetdesc{4} = containers.Map({'name', 'labval'}, {'edu', edu_grid});
cl_mp_datasetdesc{5} = containers.Map({'name', 'labval'}, {'marry', marry_grid});
cl_mp_datasetdesc{6} = containers.Map({'name', 'labval'}, {'kids', kids_grid});
```

### 9.4.4 Analyze Difference in V and C with Check

The difference between V and V with Check, marginal utility gain given the check.

```
% Generate some Data
mp_support_graph = containers.Map('KeyType', 'char', 'ValueType', 'any');
mp_support_graph('cl_st_xtitle') = {'Savings States, a'};
mp_support_graph('st_legend_loc') = 'eastoutside';
mp_support_graph('bl_graph_logy') = true; % do not log
mp_support_graph('it_legend_select') = 21; % how many shock legends to show
mp_support_graph('cl_colors') = 'jet';
```

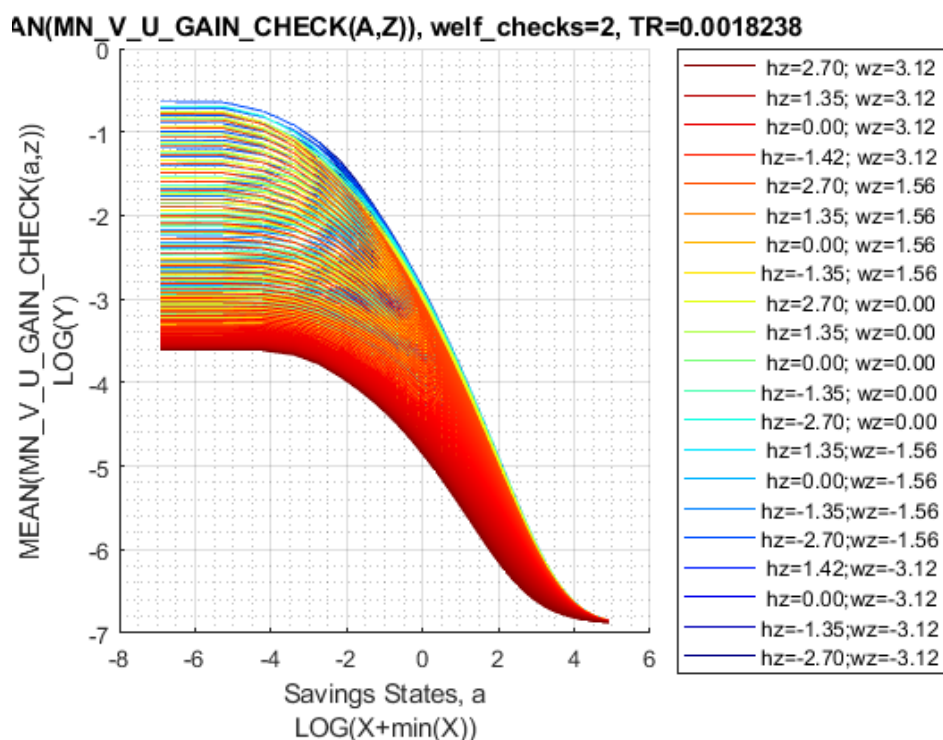
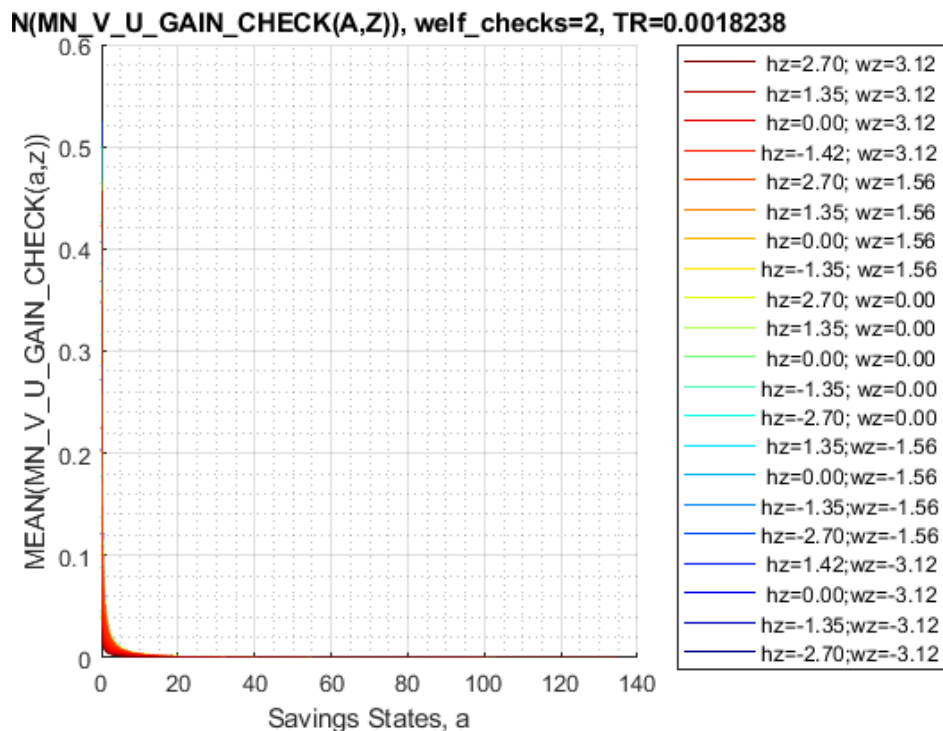
```
MEAN(MN_V_GAIN_CHECK(A,Z))
```

Tabulate value and policies along savings and shocks:

```
% Set
ar_permute = [1,4,5,6,3,2];
% Value Function
st_title = ['MEAN(MN_V_U_GAIN_CHECK(A,Z)), welf_checks=' num2str(welf_checks) ', TR=' num2str(mp_par
tb_az_v = ff_summ_nd_array(st_title, mn_V_U_gain_check_07, true, ["mean"], 4, 1, cl_mp_datasetdesc,
```

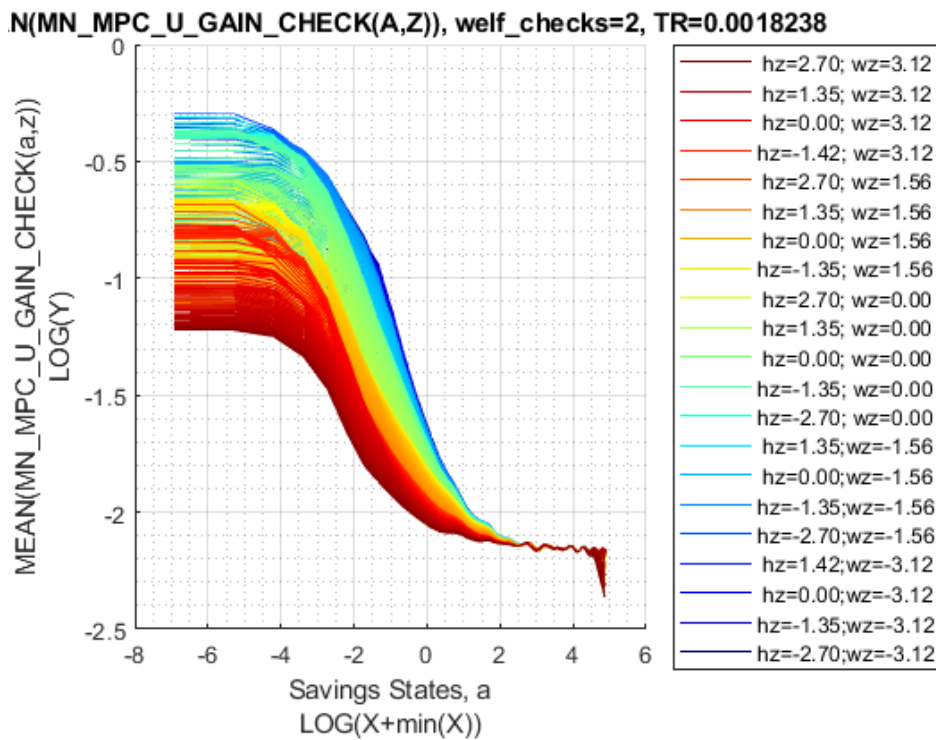
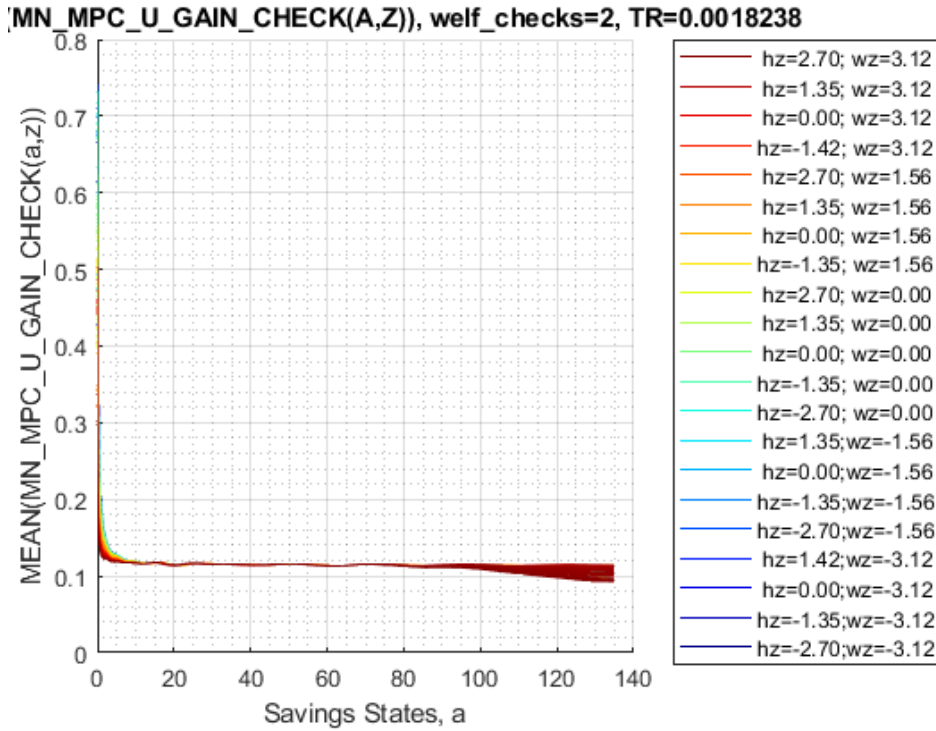
```
xxx MEAN(MN_V_U_GAIN_CHECK(A,Z)), welf_checks=2, TR=0.0018238 xxxxxxxxxxxxxxxxxxxxxxxxxxxxxxxx
  group      savings      mean_eta_1      mean_eta_2      mean_eta_3      mean_eta_4      mean_eta_5      mea
-----
  1          0          0.52526          0.48873          0.44813          0.40715          0.3683
```

```
st_title = ['MEAN(MN\V\U\_GAIN\_CHECK(A,Z)), welf\_checks=' num2str(welf_checks) ', TR=' num2str(m
mp_support_graph('cl_st_graph_title') = {st_title};
mp_support_graph('cl_st_ytitle') = {'MEAN(MN\V\U\_GAIN\_CHECK(a,z))'};
ff_graph_grid((tb_az_v{1:end, 3:end}'), ar_st_eta_HS_grid, agrid, mp_support_graph);
```



Graph Mean Consumption (*MPC: Share of Check Consumed*):

```
st_title = ['MEAN(MN\MPC\U\_GAIN\_CHECK(A,Z)), welf_checks=' num2str(welf_checks) ', TR=' num2str
mp_support_graph('cl_st_graph_title') = {st_title};
mp_support_graph('cl_st_ytitle') = {'MEAN(MN\MPC\U\_GAIN\_CHECK(a,z))'};
ff_graph_grid((tb_az_c{1:end, 3:end}),' , ar_st_eta_HS_grid, agrid, mp_support_graph);
```



### 9.4.5 Analyze Marginal Value and MPC over $Y(a, \eta)$ , Conditional On Kids, Marry, Age, Education

Income is generated by savings and shocks, what are the income levels generated by all the shock and savings points conditional on kids, marital status, age and educational levels. Plot on the Y axis MPC, and plot on the X axis income levels, use colors to first distinguish between different  $a$  levels, then use colors to distinguish between different  $\eta$  levels.

Set Up date, Select Age 37vn

, unmarried, no kids, lower education:

```
% NaN(n_jgrid,n_agrid,n_etagrid,n_educgrid,n_marriedgrid,n_kidsgrid);
% 38 year old, unmarried, no kids, lower educated
% Only Household Head Shock Matters so select up to 'n_eta_H_grid'
mn_total_inc_jemk_ss = total_inc_ss(19, :, 1:mp_params('n_eta_H_grid'), 1, 1, 1);
mn_V_W_gain_check_use_07 = ev07_jaeemk_check2 - ev07_jaeemk_check0;
mn_C_W_gain_check_use_07 = ec07_jaeemk_check2 - ec07_jaeemk_check0;
```

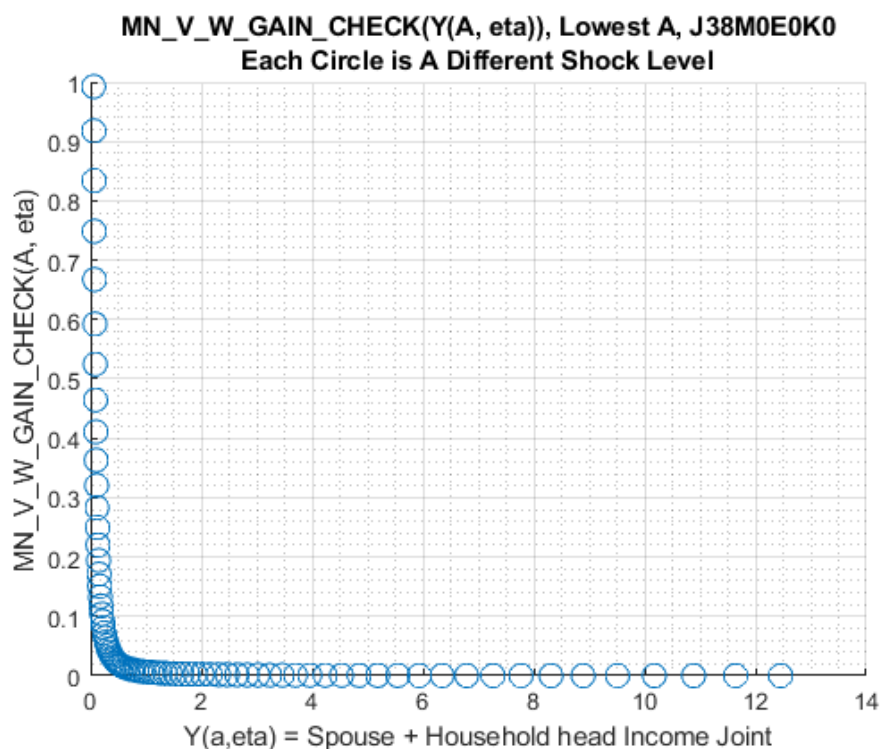
Select Age, Education, Marital, Kids Count:s

```
% Selections
it_age = 21; % +18
it_marital = 1; % 1 = unmarried
it_kids = 1; % 1 = kids is zero
it_educ = 1; % 1 = lower education
% Select: NaN(n_jgrid,n_agrid,n_etagrid,n_educgrid,n_marriedgrid,n_kidsgrid);
mn_C_W_gain_check_jemk_07 = mn_C_W_gain_check_use_07(it_age, :, 1:mp_params('n_eta_H_grid'), it_educ);
mn_V_W_gain_check_jemk_07 = mn_V_W_gain_check_use_07(it_age, :, 1:mp_params('n_eta_H_grid'), it_educ);
% Reshape, so shock is the first dim, a is the second
mt_total_inc_jemk = permute(mn_total_inc_jemk_ss, [3, 2, 1]);
mt_C_W_gain_check_jemk_07 = permute(mn_C_W_gain_check_jemk_07, [3, 2, 1]);
mt_C_W_gain_check_jemk_07(mt_C_W_gain_check_jemk_07 <= 1e-10) = 1e-10;
mt_V_W_gain_check_jemk_07 = permute(mn_V_W_gain_check_jemk_07, [3, 2, 1]);
mt_V_W_gain_check_jemk_07(mt_V_W_gain_check_jemk_07 <= 1e-10) = 1e-10;
% Generate meshed a and shock grid
[mt_eta_H, mt_a] = ndgrid(eta_H_grid(1:mp_params('n_eta_H_grid')), agrid);
```

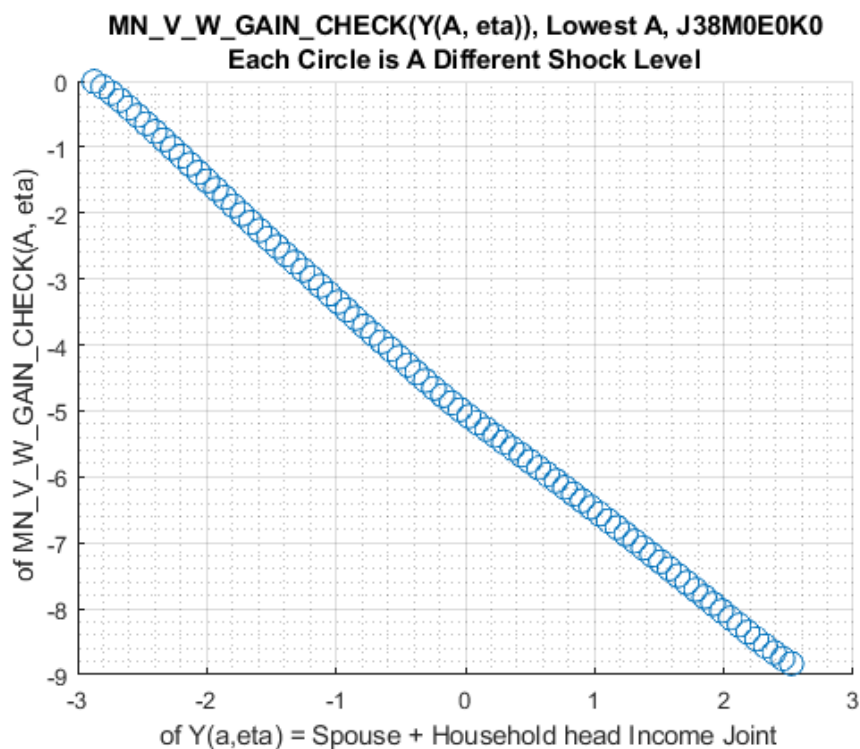
#### 9.4.6 Marginal Value Gains, Color as Shock, Conditional on Age, Marital, Kids, and Education

How do shocks and a impact marginal value. First plot one asset level, variation comes only from increasingly higher shocks:

```
figure();
it_a = 1;
scatter(mt_total_inc_jemk(:, it_a), (mt_V_W_gain_check_jemk_07(:, it_a)), 100);
title({'MN\_V\_W\_GAIN\_CHECK(Y(A, eta)), Lowest A, J38MOEOKO', ...
      'Each Circle is A Different Shock Level'});
xlabel('Y(a, eta) = Spouse + Household head Income Joint');
ylabel('MN\_V\_W\_GAIN\_CHECK(A, eta)');
grid on;
grid minor;
```

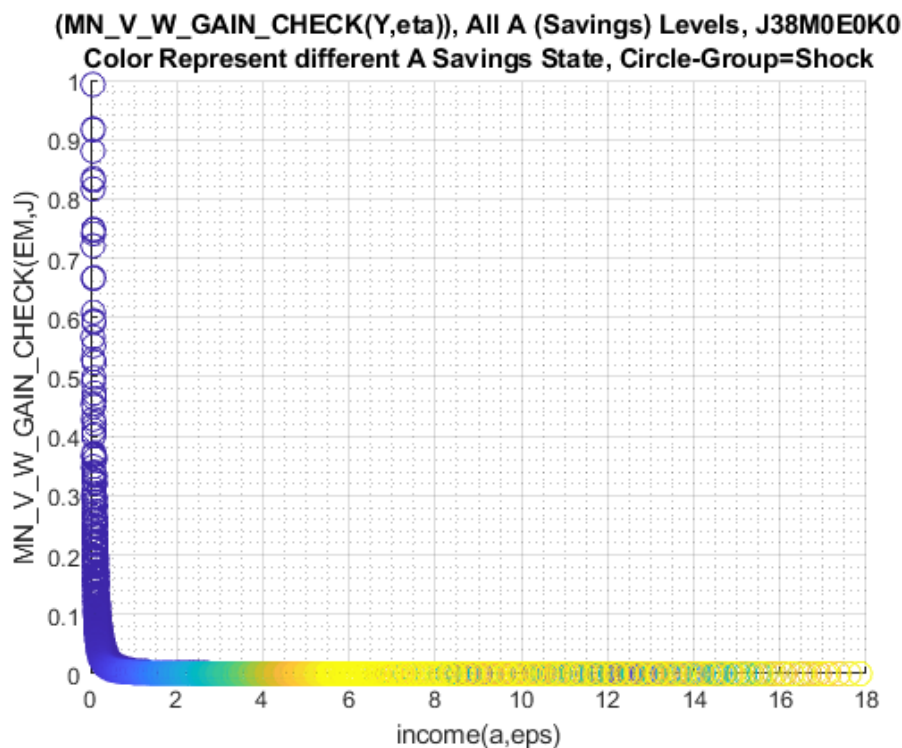


```
figure();
it_shock = 1;
scatter(log(mt_total_inc_jemk(:,it_a)), log(mt_V_W_gain_check_jemk_07(:,it_a)), 100);
title({'MN_V_W_GAIN_CHECK(Y(A, eta)), Lowest A, J38M0E0K0', ...
      'Each Circle is A Different Shock Level'});
xlabel(' of Y(a,eta) = Spouse + Household head Income Joint');
ylabel(' of MN_V_W_GAIN_CHECK(A, eta)');
grid on;
grid minor;
```

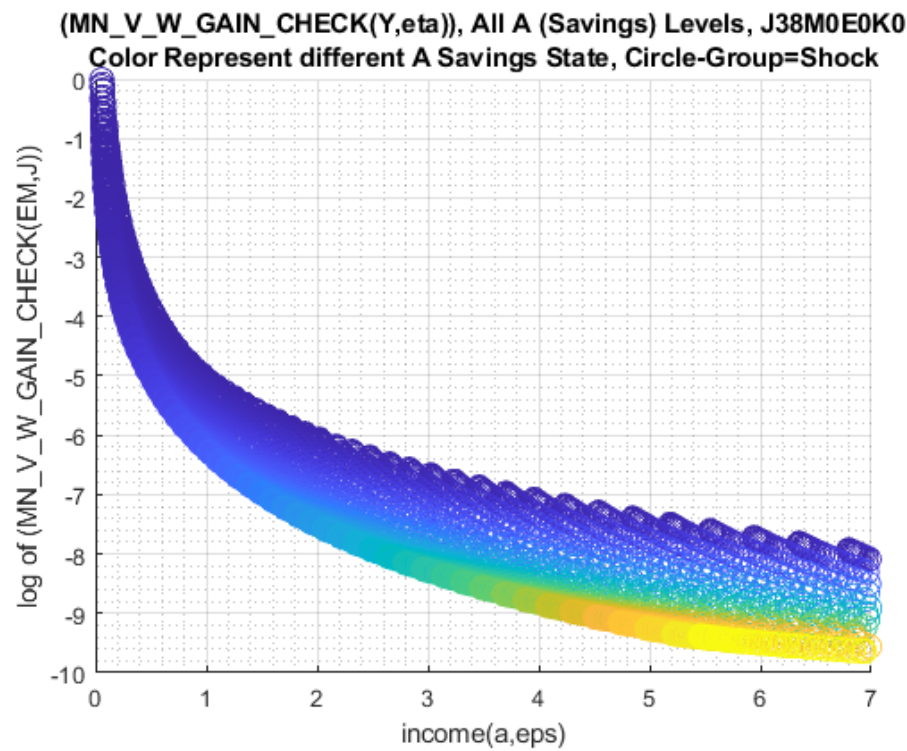


Plot all asset levels:

```
figure();
scatter(mt_total_inc_jemk(:), (mt_V_W_gain_check_jemk_07(:)), 100, mt_a(:));
title({'(MN_V_W_GAIN_CHECK(Y,eta)), All A (Savings) Levels, J38M0E0K0', ...
      'Color Represent different A Savings State, Circle-Group=Shock'});
xlabel('income(a,eps)');
ylabel('MN_V_W_GAIN_CHECK(EM,J)');
grid on;
grid minor;
```



```
figure();
scatter(mt_total_inc_jemk(:), log(mt_V_W_gain_check_jemk_07(:)), 100, mt_a(:));
title({'(MN_V_W_GAIN_CHECK(Y,eta)), All A (Savings) Levels, J38M0E0K0', ...
      'Color Represent different A Savings State, Circle-Group=Shock'});
xlabel('income(a,eps)');
ylabel('log of (MN_V_W_GAIN_CHECK(EM,J))');
xlim([0,7]);
grid on;
grid minor;
```

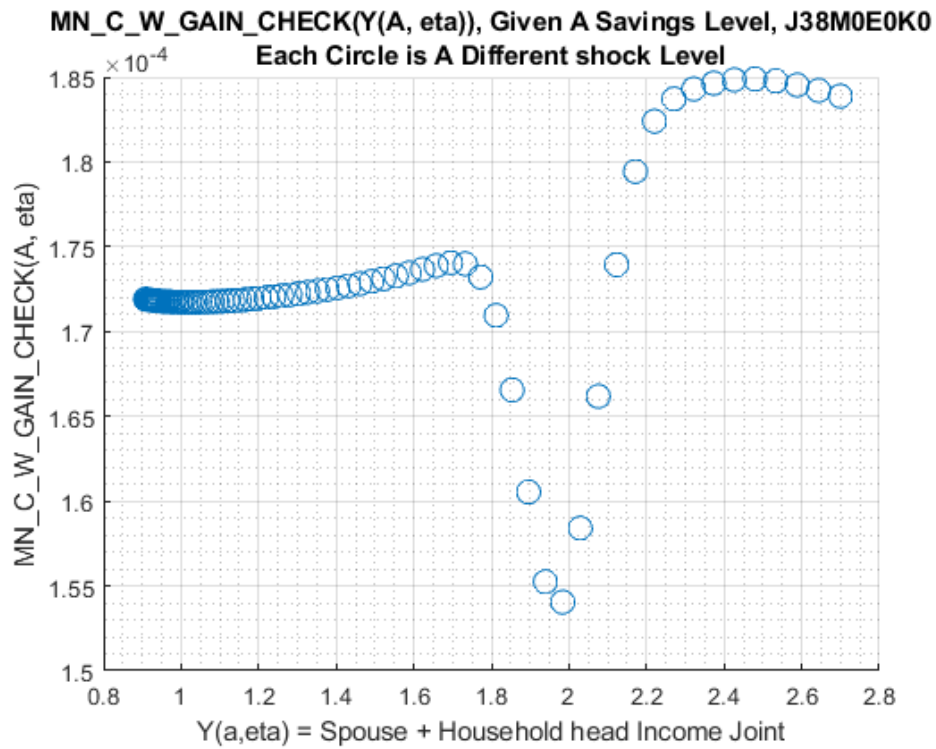


#### 9.4.7 Marginal Consumption Gains, Color as Shock, Conditional on Age, Marital, Kids, and Education

How do shocks and  $a$  impact marginal value. First plot one asset level, variation comes only from increasingly higher shocks:

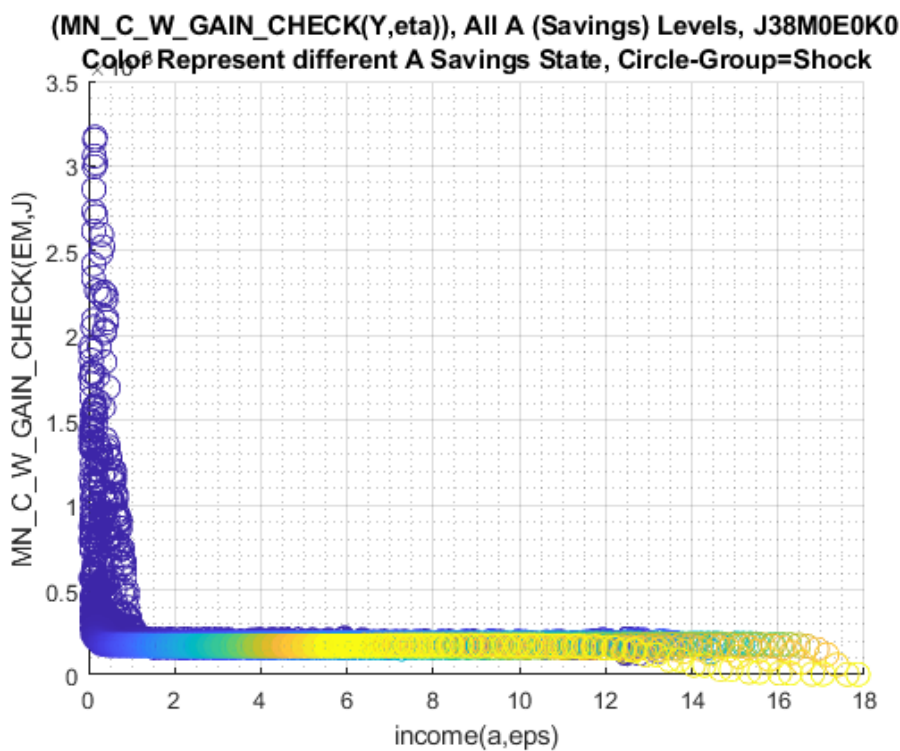
```
figure();
it_a = 50;
scatter(log(mt_total_inc_jemk(:,it_a)), mt_C_W_gain_check_jemk_07(:,it_a), 100);
title({'MN\C\W\GAIN\CHECK(Y(A, eta)), Given A Savings Level, J38MOE0K0', ...
      'Each Circle is A Different shock Level'});
xlabel('Y(a,eta) = Spouse + Household head Income Joint');
ylabel('MN\C\W\GAIN\CHECK(A, eta)');
grid on;
grid minor;
```





Plot all asset levels:

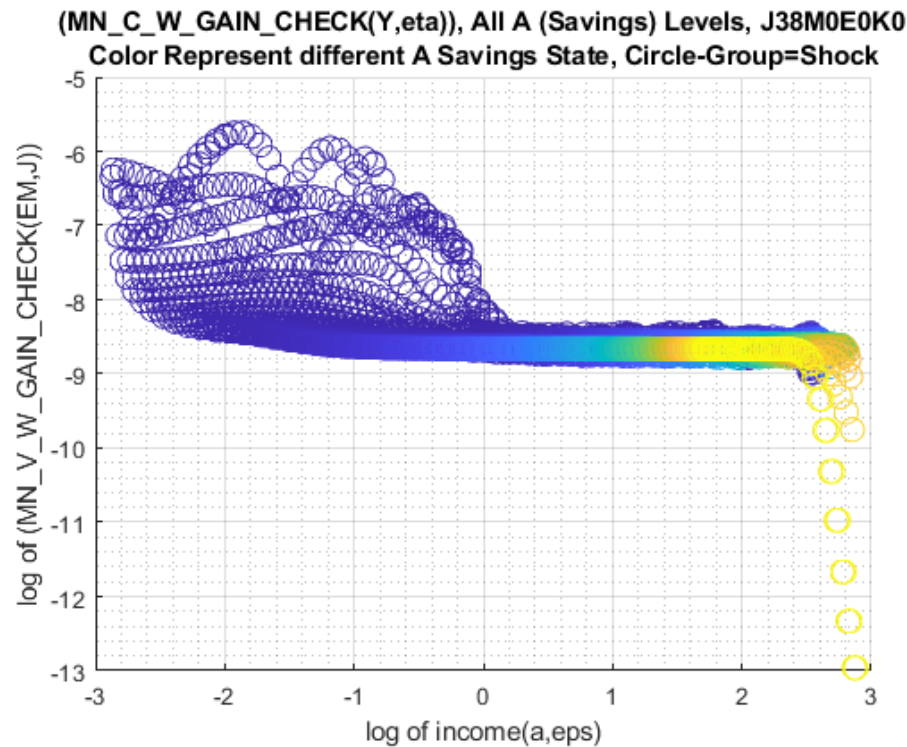
```
figure();
scatter((mt_total_inc_jemk(:)), (mt_C_W_gain_check_jemk_07(:)), 100, mt_a(:));
title({'(MN_C_W_GAIN_CHECK(Y,eta)), All A (Savings) Levels, J38M0E0K0', ...
      'Color Represent different A Savings State, Circle-Group=Shock'});
xlabel('income(a,eps)');
ylabel('MN_C_W_GAIN_CHECK(EM,J)');
grid on;
grid minor;
```



```

figure();
scatter(log(mt_total_inc_jemk(:)), log(mt_C_W_gain_check_jemk_07(:)), 100, mt_a(:));
title({'(MN\C\W\_GAIN\_CHECK(Y,eta)), All A (Savings) Levels, J38M0E0K0', ...
      'Color Represent different A Savings State, Circle-Group=Shock'});
xlabel('log of income(a,eps)');
ylabel('log of (MN\_V\_W\_GAIN\_CHECK(EM,J))');
grid on;
grid minor;

```



#### 9.4.8 Analyze Kids and Marriage and Age

Aggregating over education, savings, and shocks, what are the differential effects of Marriage and Age.

```

% Generate some Data
mp_support_graph = containers.Map('KeyType', 'char', 'ValueType', 'any');
ar_row_grid = [...
    "k0M0", "k1M0", "k2M0", "k3M0", "k4M0", ...
    "k0M1", "k1M1", "k2M1", "k3M1", "k4M1"];
mp_support_graph('cl_st_xtitle') = {'Age'};
mp_support_graph('st_legend_loc') = 'best';
mp_support_graph('bl_graph_logy') = true; % do not log
mp_support_graph('st_rounding') = '6.2f'; % format shock legend
mp_support_graph('cl_scatter_shapes') = {...
    'o', 'd', 's', 'x', '*'}, ...
    'o', 'd', 's', 'x', '*'};
mp_support_graph('cl_colors') = {...
    'red', 'red', 'red', 'red', 'red'...
    'blue', 'blue', 'blue', 'blue', 'blue'};

MEAN(VAL(KM,J)), MEAN(AP(KM,J)), MEAN(C(KM,J))

Tabulate value and policies:

% Set
% NaN(n_jgrid,n_agrid,n_etagrid,n_educgrid,n_marriedgrid,n_kidsgrid);
ar_permute = [2,3,4,1,6,5];

```

% Value Function

```
st_title = ['MEAN(MN_V_U_GAIN_CHECK(KM,J)), welf_checks=' num2str(welf_checks) ', TR=' num2str(mp_pa
tb_az_v = ff_summ_nd_array(st_title, mn_V_U_gain_check_07, true, ["mean"], 3, 1, cl_mp_datasetdesc,
```

```
xxx MEAN(MN_V_U_GAIN_CHECK(KM,J)), welf_checks=2, TR=0.0018238 xxxxxxxxxxxxxxxxxxxxxxxxxxxxxxx
```

group	kids	marry	mean_age_18	mean_age_19	mean_age_20	mean_age_21	mean_age_2
1	1	0	0.031908	0.030377	0.028045	0.025708	0.023751
2	2	0	0.043916	0.04186	0.038596	0.035292	0.032514
3	3	0	0.051104	0.04891	0.044943	0.04117	0.038001
4	4	0	0.057927	0.055555	0.051064	0.046812	0.043241
5	5	0	0.06325	0.060842	0.055977	0.051401	0.047557
6	1	1	0.005762	0.0053279	0.0048412	0.0043955	0.0040141
7	2	1	0.0081705	0.0075587	0.0068473	0.0061989	0.005658
8	3	1	0.0099025	0.0091765	0.0083275	0.0075396	0.0068765
9	4	1	0.012339	0.011465	0.01043	0.0094589	0.008631
10	5	1	0.015374	0.014388	0.013133	0.01196	0.010966

% Consumption Function

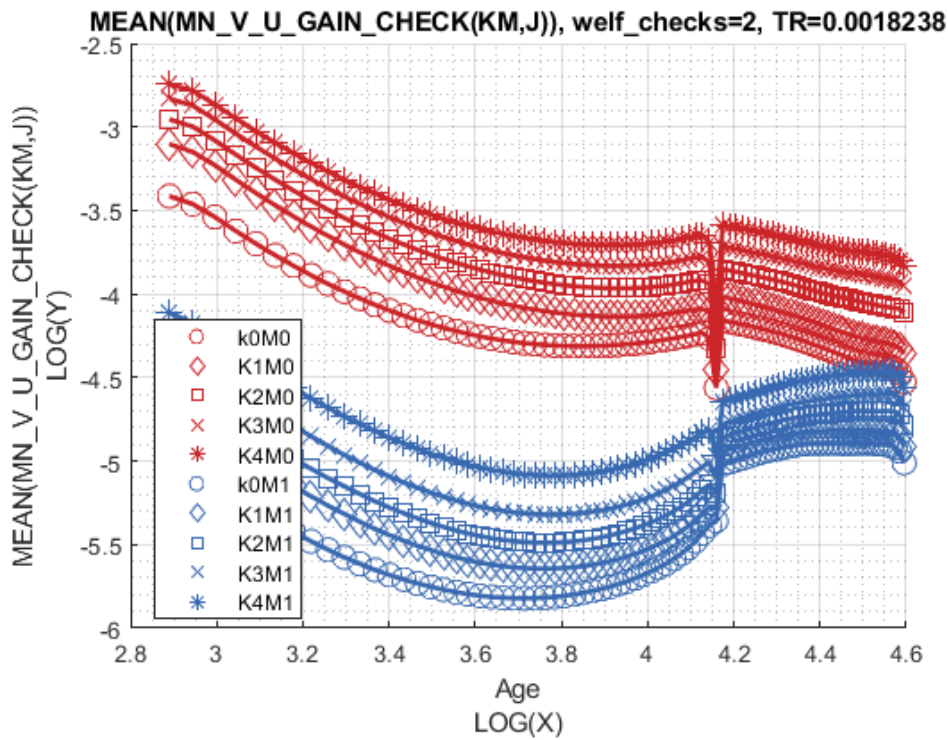
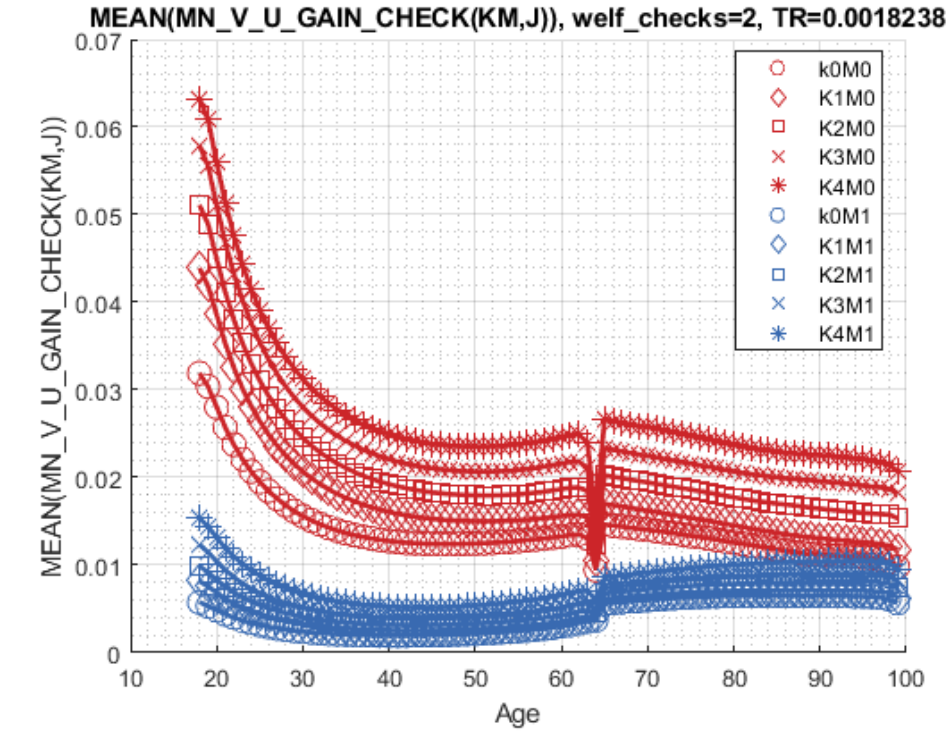
```
st_title = ['MEAN(MN_MPC_U_GAIN_CHECK(KM,J)), welf_checks=' num2str(welf_checks) ', TR=' num2str(mp_
tb_az_c = ff_summ_nd_array(st_title, mn_MPC_U_gain_share_check_07, true, ["mean"], 3, 1, cl_mp_datas
```

```
xxx MEAN(MN_MPC_U_GAIN_CHECK(KM,J)), welf_checks=2, TR=0.0018238 xxxxxxxxxxxxxxxxxxxxxxxxxxxxxxx
```

group	kids	marry	mean_age_18	mean_age_19	mean_age_20	mean_age_21	mean_age_2
1	1	0	0.078069	0.086102	0.087377	0.085109	0.082559
2	2	0	0.088091	0.096475	0.099705	0.096801	0.094582
3	3	0	0.096309	0.10647	0.11111	0.10818	0.10451
4	4	0	0.10137	0.11245	0.11806	0.11424	0.11063
5	5	0	0.10569	0.11834	0.12441	0.11996	0.11559
6	1	1	0.091639	0.097614	0.095796	0.09274	0.094336
7	2	1	0.098891	0.10394	0.10413	0.10026	0.097592
8	3	1	0.10228	0.10811	0.10782	0.10839	0.10652
9	4	1	0.10459	0.11283	0.11208	0.11053	0.10913
10	5	1	0.11468	0.12506	0.12335	0.12035	0.11807

Graph Mean Values:

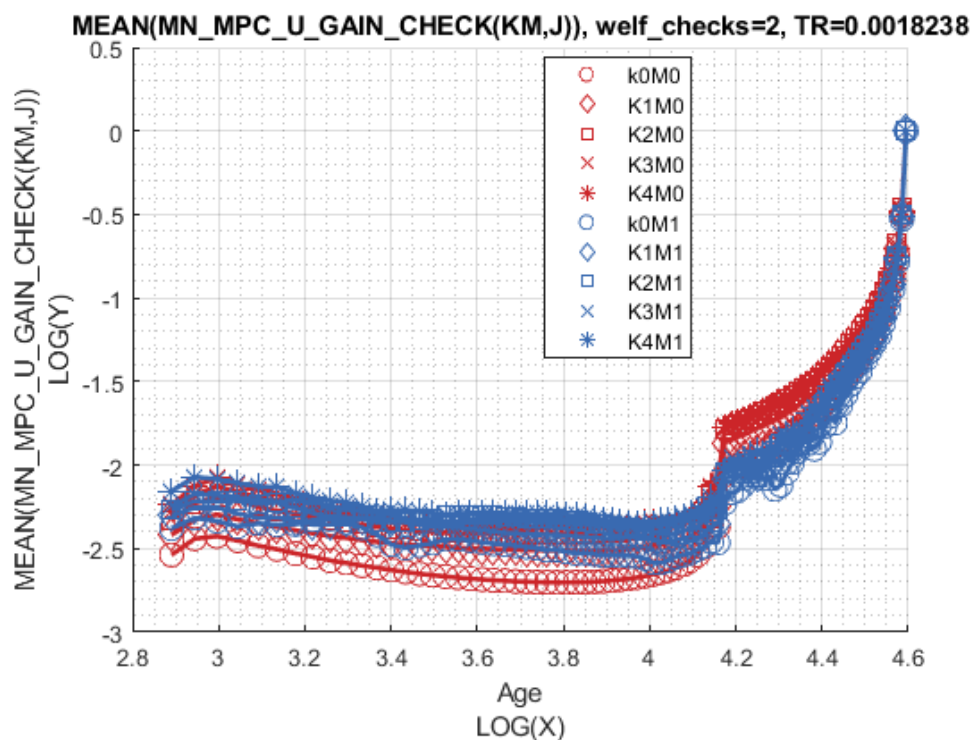
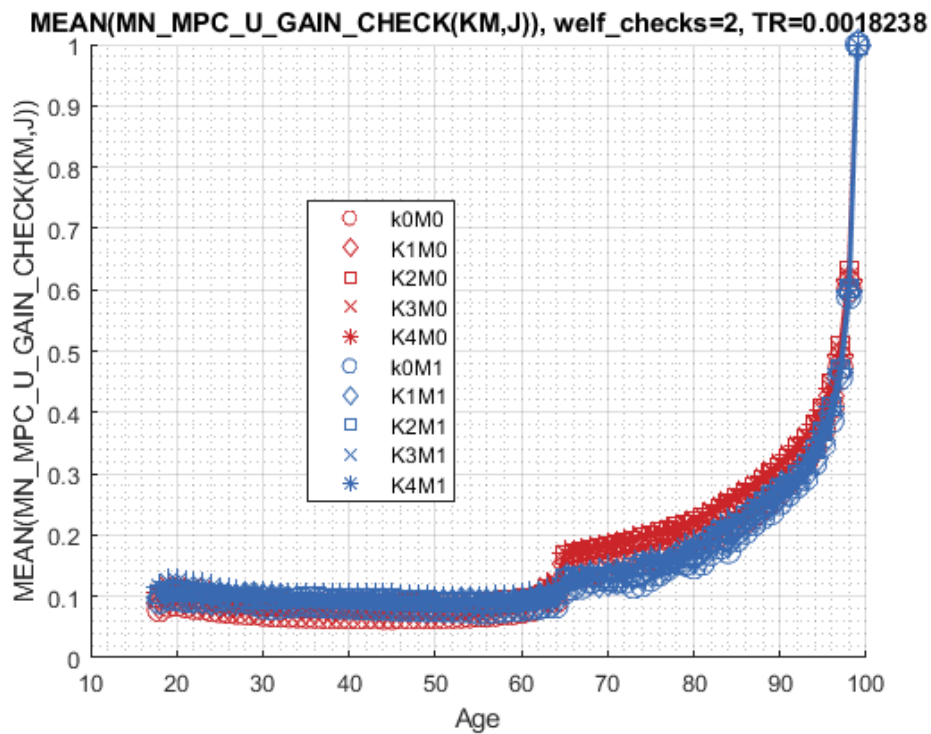
```
st_title = ['MEAN(MN\V_U_GAIN_CHECK(KM,J)), welf_checks=' num2str(welf_checks) ', TR=' num2str(
mp_support_graph('cl_st_graph_title') = {st_title};
mp_support_graph('cl_st_ytitle') = {'MEAN(MN\V_U_GAIN_CHECK(KM,J))'};
ff_graph_grid((tb_az_v{1:end, 4:end}), ar_row_grid, age_grid, mp_support_graph);
```



Graph Mean Consumption (*MPC: Share of Check Consumed*):

```

st_title = ['MEAN(MN\MPC\U\_GAIN\_CHECK(KM,J)), welf_checks=' num2str(welf_checks) ', TR=' num2str
mp_support_graph('cl_st_graph_title') = {st_title};
mp_support_graph('cl_st_ytitle') = {'MEAN(MN\MPC\U\_GAIN\_CHECK(KM,J))'};
ff_graph_grid((tb_az_c{1:end}, 4:end}), ar_row_grid, age_grid, mp_support_graph);
    
```



### 9.4.9 Analyze Education and Marriage

Aggregating over education, savings, and shocks, what are the differential effects of Marriage and Age.

```
% Generate some Data
mp_support_graph = containers.Map('KeyType', 'char', 'ValueType', 'any');
ar_row_grid = ["E0M0", "E1M0", "E0M1", "E1M1"];
mp_support_graph('cl_st_xtitle') = {'Age'};
mp_support_graph('st_legend_loc') = 'best';
mp_support_graph('bl_graph_logy') = true; % do not log
```

```
mp_support_graph('st_rounding') = '6.2f'; % format shock legend
mp_support_graph('cl_scatter_shapes') = {'*', 'p', '*', 'p' };
mp_support_graph('cl_colors') = {'red', 'red', 'blue', 'blue'};
```

```
MEAN(VAL(EM,J)), MEAN(AP(EM,J)), MEAN(C(EM,J))
```

Tabulate value and policies:

```
% Set
% NaN(n_jgrid,n_agrid,n_etagrid,n_educgrid,n_marriedgrid,n_kidsgrid);
ar_permute = [2,3,6,1,4,5];
% Value Function
st_title = ['MEAN(MN_V_U_GAIN_CHECK(EM,J)), welf_checks=' num2str(welf_checks) ', TR=' num2str(mp_pa
tb_az_v = ff_summ_nd_array(st_title, mn_V_U_gain_check_07, true, ["mean"], 3, 1, cl_mp_datasetdesc,
```

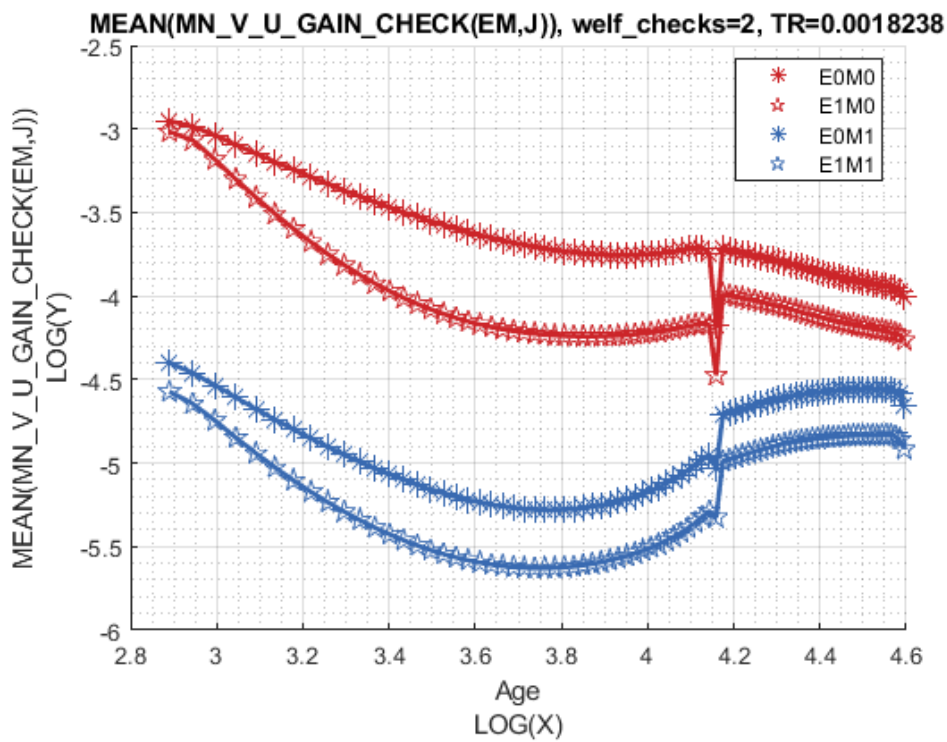
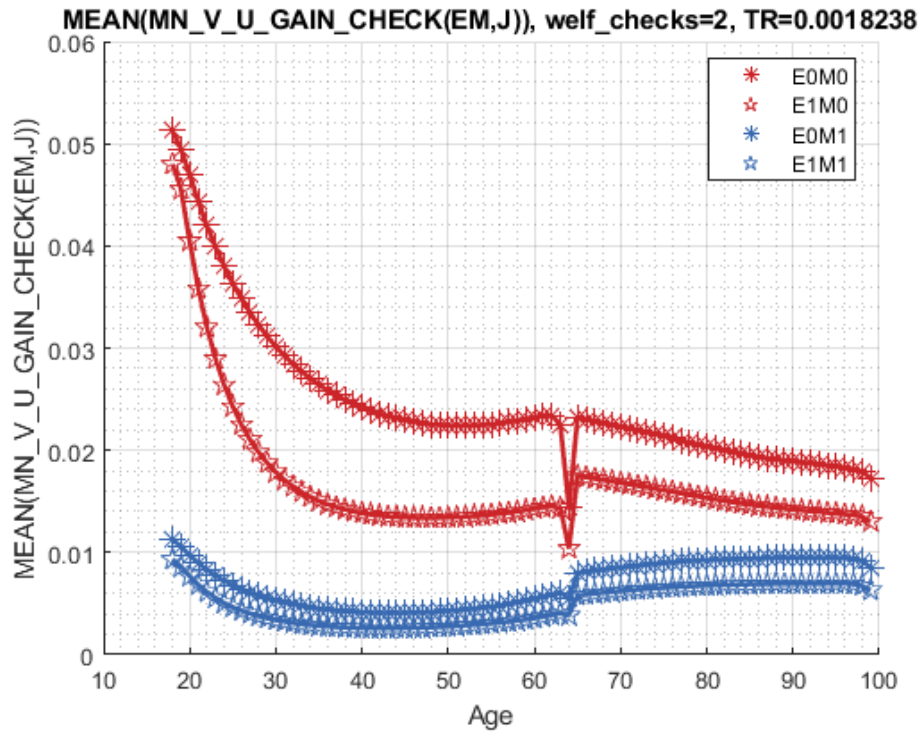
```
xxx MEAN(MN_V_U_GAIN_CHECK(EM,J)), welf_checks=2, TR=0.0018238 xxxxxxxxxxxxxxxxxxxxxxxxxxxxxxx
  group   edu   marry   mean_age_18   mean_age_19   mean_age_20   mean_age_21   mean_age_22
  -----   ---   -----   -----
  1         0     0         0.051256     0.049485     0.046969     0.044331     0.041985
  2         1     0         0.047986     0.045532     0.040481     0.035822     0.032041
  3         0     1         0.01129      0.010552     0.0097415    0.0089796    0.0083154
  4         1     1         0.0093296    0.0086141    0.0076904    0.0068414    0.0061429
```

```
% Consumption
st_title = ['MEAN(MN_MPC_U_GAIN_CHECK(EM,J)), welf_checks=' num2str(welf_checks) ', TR=' num2str(mp_
tb_az_c = ff_summ_nd_array(st_title, mn_MPC_U_gain_share_check_07, true, ["mean"], 3, 1, cl_mp_datas
```

```
xxx MEAN(MN_MPC_U_GAIN_CHECK(EM,J)), welf_checks=2, TR=0.0018238 xxxxxxxxxxxxxxxxxxxxxxxxxxxxxxx
  group   edu   marry   mean_age_18   mean_age_19   mean_age_20   mean_age_21   mean_age_22
  -----   ---   -----   -----
  1         0     0         0.081794     0.085652     0.08723      0.08665      0.085947
  2         1     0         0.10602      0.12228      0.12903      0.12307      0.1172
  3         0     1         0.093649     0.097104     0.096702     0.095946     0.095996
  4         1     1         0.11118      0.12192      0.12057      0.11696      0.11426
```

Graph Mean Values:

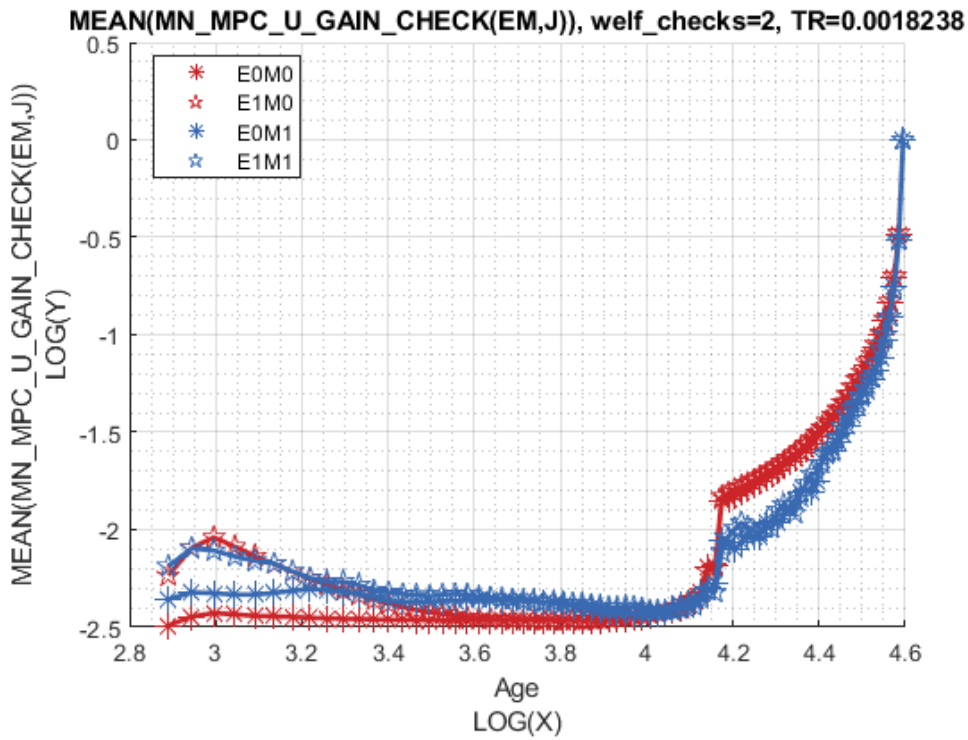
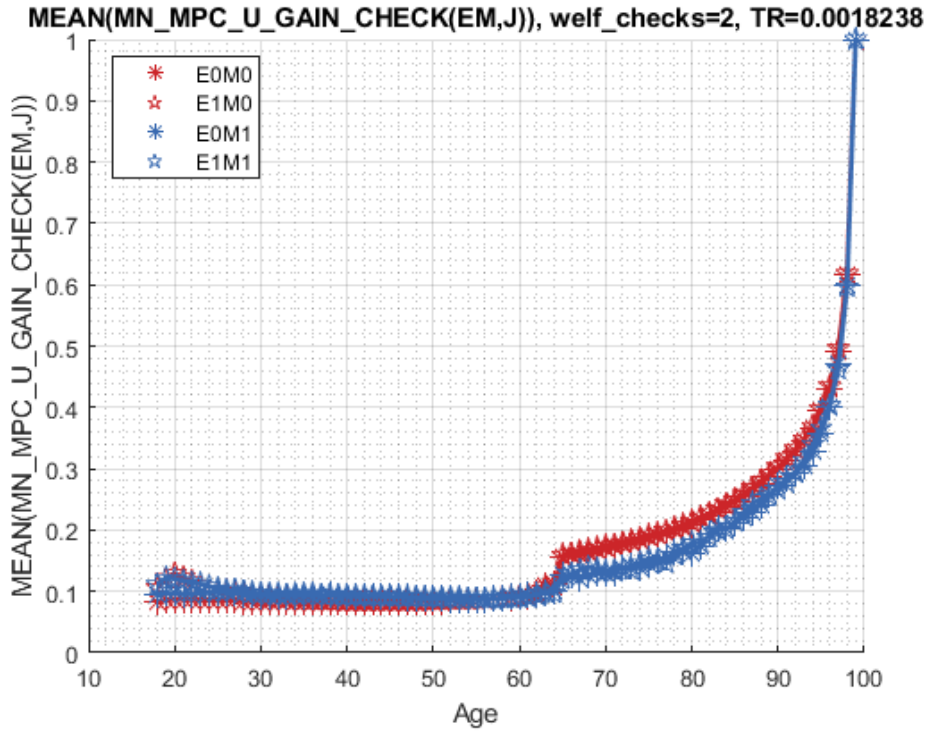
```
st_title = ['MEAN(MN\V\U\_GAIN\_CHECK(EM,J)), welf\_checks=' num2str(welf_checks) ', TR=' num2str(
mp_support_graph('cl_st_graph_title') = {st_title};
mp_support_graph('cl_st_ytitle') = {'MEAN(MN\V\U\_GAIN\_CHECK(EM,J))'};
ff_graph_grid((tb_az_v{1:end, 4:end}), ar_row_grid, age_grid, mp_support_graph);
```



Graph Mean Consumption (*MPC: Share of Check Consumed*):

```

st_title = ['MEAN(MN\MPC\U\_GAIN\_CHECK(EM,J)), welf_checks=' num2str(welf_checks) ', TR=' num2str
mp_support_graph('cl_st_graph_title') = {st_title};
mp_support_graph('cl_st_ytitle') = {'MEAN(MN\MPC\U\_GAIN\_CHECK(EM,J))'};
ff_graph_grid((tb_az_c{1:end, 4:end}), ar_row_grid, age_grid, mp_support_graph);
    
```





## Chapter 10

# 2019 Expectations Given Income, Age, Kids and Marital Status

### 10.1 2019 Age, Income, Kids, Marry EV and EC of One Check

This is the example vignette for function: `snw_evuvw19_jmky` from the [PrjOptiSNW Package](#). 2019 integrated over VU and VW

#### 10.1.1 Test SNW\_EVUVW19\_JMKY Defaults Dense

Set Parameters

Call the function with defaults.

```
clear all;
st_solu_type = 'bisec_vec';

% Solve the VFI Problem and get Value Function
% mp_params = snw_mp_param('default_tiny');
% mp_params = snw_mp_param('default_dense');
mp_params = snw_mp_param('default_docdense');
mp_params('beta') = 0.95;
mp_controls = snw_mp_control('default_test');

% set Unemployment Related Variables
xi=0.5; % Proportional reduction in income due to unemployment (xi=0 refers to 0 labor income; xi=1
b=0; % Unemployment insurance replacement rate (b=0 refers to no UI benefits; b=1 refers to 100 perc
TR=100/58056; % Value of a welfare check (can receive multiple checks). TO DO: Update with alternati

mp_params('xi') = xi;
mp_params('b') = b;
mp_params('TR') = TR;

% Check Numbers
% n_incgrid=201; % Number of income groups
% n_incgrid_aux=round(0.75*n_incgrid);
% inc_grid1=linspace(0,4,n_incgrid_aux)'; % 4 refers to 4*58056=232224 dollars in 2012USD
% inc_grid=[inc_grid1;linspace(4+((7-4)/(n_incgrid-n_incgrid_aux)),7,n_incgrid-n_incgrid_aux)']; % 7
n_incgrid=201; % Number of income groups
inc_grid=linspace(0,7,n_incgrid)';
mp_params('n_incgrid') = n_incgrid;
mp_params('inc_grid') = inc_grid;
```

```

% Solve for Unemployment Values
mp_controls('bl_print_vfi') = false;
mp_controls('bl_print_vfi_verbose') = false;
mp_controls('bl_print_ds') = false;
mp_controls('bl_print_ds_verbose') = false;
mp_controls('bl_print_precompute') = false;
mp_controls('bl_print_precompute_verbose') = false;
mp_controls('bl_print_a4chk') = false;
mp_controls('bl_print_a4chk_verbose') = false;
mp_controls('bl_print_evuvw20_jaeemk') = false;
mp_controls('bl_print_evuvw20_jaeemk_verbose') = false;
mp_controls('bl_print_evuvw19_jaeemk') = false;
mp_controls('bl_print_evuvw19_jaeemk_verbose') = false;
mp_controls('bl_print_evuvw19_jmky') = false;

```

### 10.1.2 Solve VFI and Distributon

```

% Solve the Model to get V working and unemployed
[V_ss,ap_ss,cons_ss,mp_valpol_more_ss] = snw_vfi_main_bisec_vec(mp_params, mp_controls);

Completed SNW_VFI_MAIN_BISEC_VEC;SNW_MP_PARAM=default_docdense;SNW_MP_CONTROL=default_test;time=533.

inc_VFI = mp_valpol_more_ss('inc_VFI');
spouse_inc_VFI = mp_valpol_more_ss('spouse_inc_VFI');
total_inc_VFI = inc_VFI + spouse_inc_VFI;

% COVID year tax
mp_params('a2_covidyr') = mp_params('a2_covidyr_manna_heaven');
% 2020 V and C same as V_SS and cons_ss if tax the same
if (mp_params('a2_covidyr') == mp_params('a2'))
    % mana from heaven
    V_ss_2020 = V_ss;
    cons_ss_2020 = cons_ss;
else
    % change xi and b to for people without unemployment shock
    % solving for employed but 2020 tax results
    % a2_covidyr > a2, we increased tax in 2020 to pay for covid and other
    % costs resolve for both employed and unemployed
    xi = mp_params('xi');
    b = mp_params('b');
    mp_params('xi') = 1;
    mp_params('b') = 0;
    [V_ss_2020,~,cons_ss_2020,~] = snw_vfi_main_bisec_vec(mp_params, mp_controls, V_ss);
    mp_params('xi') = xi;
    mp_params('b') = b;
end

% Solve unemployment
[V_unemp_2020,~,cons_unemp_2020] = snw_vfi_main_bisec_vec(mp_params, mp_controls, V_ss);

Completed SNW_VFI_MAIN_BISEC_VEC 1 Period Unemp Shock;SNW_MP_PARAM=default_docdense;SNW_MP_CONTROL=d

[Phi_true] = snw_ds_main(mp_params, mp_controls, ap_ss, cons_ss, mp_valpol_more_ss);

Completed SNW_DS_MAIN;SNW_MP_PARAM=default_docdense;SNW_MP_CONTROL=default_test;time=1486.9836

% Get Matrixes
cl_st_precompute_list = {'a', ...
    'inc', 'inc_unemp', 'spouse_inc', 'spouse_inc_unemp', 'ref_earn_wageind_grid', ...

```

```
'ap_idx_lower_ss', 'ap_idx_higher_ss', 'ap_idx_lower_weight_ss', ...
'inc_tot_ygroup_grid'};
mp_controls('bl_print_precompute_verbose') = false;
```

### 10.1.3 Pre-Compute Matrixes and YMKY Mass

```
% Pre-compute
[mp_precompute_res] = snw_hh_precompute(mp_params, mp_controls, cl_st_precompute_list, ap_ss, Phi_tr

Wage quintile cutoffs=0.4645    0.71528    1.0335    1.5632
Completed SNW_HH_PRECOMPUTE;SNW_MP_PARAM=default_docdense;SNW_MP_CONTROL=default_test;time cost=405.

inc_tot_ygroup_grid = mp_precompute_res('inc_tot_ygroup_grid');
% YMKY Mass
[Phi_true_jmky] = snw_evuvw19_jmky_mass(mp_params, mp_controls, Phi_true, inc_tot_ygroup_grid);
```

```
SNW_EVUVW19_JMKY_MASS Start
Completed SNW_EVUVW19_JMKY_MASS;SNW_MP_PARAM=default_docdense;SNW_MP_CONTROL=default_test;time=12.07
```

```
-----
XXXXXXXXXXXXXXXXXXXXXXXXXXXXXXXXXXXXXXXXXXXXXXXXXXXX
CONTAINER NAME: mp_outcomes ND Array (Matrix etc)
XXXXXXXXXXXXXXXXXXXXXXXXXXXXXXXXXXXXXXXXXXXXXXXXXXXX
```

	i	idx	ndim	numel	rowN	colN	sum	mean
	-	---	----	-----	----	-----	-----	-----
Phi_true	1	1	6	4.37e+07	83	5.265e+05	45.793	1.0479e-06
Phi_true_jmky	2	2	4	1.6482e+05	82	2010	45.787	0.0002778

### 10.1.4 Solve for 2019 Evuvw With 0 and 2 Checks

Zero checks:

```
% Solve ev 19 JAEEMK
welf_checks = 0;
[ev19_jaeemk_check0, ec19_jaeemk_check0, ev20_jaeemk_check0, ec20_jaeemk_check0] = ...
    snw_evuvw19_jaeemk(...
    welf_checks, st_solu_type, mp_params, mp_controls, ...
    V_ss_2020, cons_ss_2020, V_unemp_2020, cons_unemp_2020, mp_precompute_res);
```

```
Completed SNW_A4CHK_WRK_BISEC_VEC;SNW_MP_PARAM=st_biden_or_trump_undefined;welf_checks=0;TR=0.001722
Completed SNW_A4CHK_UNEMP_BISEC_VEC;welf_checks=0;TR=0.0017225;xi=0.5;b=0;SNW_MP_PARAM=default_docde
Completed SNW_EVUVW20_JAEEMK;SNW_MP_PARAM=default_docdense;SNW_MP_CONTROL=default_test;timeEUEC=8.03
Completed SNW_EVUVW19_JAEEMK;SNW_MP_PARAM=default_docdense;SNW_MP_CONTROL=default_test;time=4262.196
```

```
% Solve ev 19 JMKY
[ev19_jmky_check0, ec19_jmky_check0] = snw_evuvw19_jmky(...
    mp_params, mp_controls, ...
    ev19_jaeemk_check0, ec19_jaeemk_check0, ...
    Phi_true, Phi_true_jmky, inc_tot_ygroup_grid);
```

```
Completed SNW_EVUVW19_JMKY;SNW_MP_PARAM=default_docdense;SNW_MP_CONTROL=default_test;time=18.7645
```

```
-----
XXXXXXXXXXXXXXXXXXXXXXXXXXXXXXXXXXXXXXXXXXXXXXXXXXXX
CONTAINER NAME: mp_outcomes ND Array (Matrix etc)
XXXXXXXXXXXXXXXXXXXXXXXXXXXXXXXXXXXXXXXXXXXXXXXXXXXX
```

	i	idx	ndim	numel	rowN	colN	sum	mean
	-	---	----	-----	----	-----	-----	-----
Phi_true	1	1	6	4.37e+07	83	5.265e+05	45.793	1.0479e-06

Phi_true_jmky	2	2	4	1.6482e+05	82	2010	45.787	0.000277
ec19_jaeemk	3	3	6	4.3173e+07	82	5.265e+05	1.9659e+08	4.553
ec19_jmky	4	4	4	1.6482e+05	82	2010	3.4206e+05	2.075
ev19_jaeemk	5	5	6	4.3173e+07	82	5.265e+05	-6.521e+08	-15.10
ev19_jmky	6	6	4	1.6482e+05	82	2010	-2.1785e+06	-13.21

Two checks:

```
% Solve ev 19 JAEEMK
welf_checks = 1;
[ev19_jaeemk_check2, ec19_jaeemk_check2, ev20_jaeemk_check2, ec20_jaeemk_check2] = ...
    snw_evuvw19_jaeemk(...
    welf_checks, st_solu_type, mp_params, mp_controls, ...
    V_ss_2020, cons_ss_2020, V_unemp_2020, cons_unemp_2020, mp_precompute_res);
```

```
Completed SNW_A4CHK_WRK_BISEC_VEC;SNW_MP_PARAM=st_biden_or_trump_undefined;welf_checks=1;TR=0.001722
Completed SNW_A4CHK_UNEMP_BISEC_VEC;welf_checks=1;TR=0.0017225;xi=0.5;b=0;SNW_MP_PARAM=default_docde
Completed SNW_EVUVW20_JAEEMK;SNW_MP_PARAM=default_docdense;SNW_MP_CONTROL=default_test;timeEUEC=7.84
Completed SNW_EVUVW19_JAEEMK;SNW_MP_PARAM=default_docdense;SNW_MP_CONTROL=default_test;time=4279.329
```

```
% Solve ev 19 JMKY
[ev19_jmky_check2, ec19_jmky_check2] = snw_evuvw19_jmky(...
    mp_params, mp_controls, ...
    ev19_jaeemk_check2, ec19_jaeemk_check2, ...
    Phi_true, Phi_true_jmky, inc_tot_ygroup_grid);
```

```
Completed SNW_EVUVW19_JMKY;SNW_MP_PARAM=default_docdense;SNW_MP_CONTROL=default_test;time=19.3794
```

```
-----
XXXXXXXXXXXXXXXXXXXXXXXXXXXXXXXXXXXXXXXXXXXXXXXXXXXX
CONTAINER NAME: mp_outcomes ND Array (Matrix etc)
XXXXXXXXXXXXXXXXXXXXXXXXXXXXXXXXXXXXXXXXXXXXXXXXXXXX
```

	i	idx	ndim	numel	rowN	colN	sum	mean
	-	---	----	-----	----	-----	-----	-----
Phi_true	1	1	6	4.37e+07	83	5.265e+05	45.793	1.0479e-0
Phi_true_jmky	2	2	4	1.6482e+05	82	2010	45.787	0.000277
ec19_jaeemk	3	3	6	4.3173e+07	82	5.265e+05	1.966e+08	4.553
ec19_jmky	4	4	4	1.6482e+05	82	2010	3.421e+05	2.075
ev19_jaeemk	5	5	6	4.3173e+07	82	5.265e+05	-6.5176e+08	-15.09
ev19_jmky	6	6	4	1.6482e+05	82	2010	-2.1774e+06	-13.21

Differences between Checks in Expected Value and Expected Consumption

```
mn_V_U_gain_check = ev19_jmky_check2 - ev19_jmky_check0;
mn_MPC_U_gain_share_check = (ec19_jmky_check2 - ec19_jmky_check0)./(welf_checks*mp_params('TR'));
```

### 10.1.5 Dense Param Results Define Frames

Define the matrix dimensions names and dimension vector values. Policy and Value Functions share the same ND dimensional structure.

```
% Grids:
age_grid = 18:99;
marry_grid = [0,1];
kids_grid = (1:1:mp_params('n_kidsgrid'))';
inc_grid = mp_params('inc_grid');
cl_mp_datasetdesc = {};
cl_mp_datasetdesc{1} = containers.Map({'name', 'labval'}, {'age', age_grid});
cl_mp_datasetdesc{2} = containers.Map({'name', 'labval'}, {'marry', marry_grid});
cl_mp_datasetdesc{3} = containers.Map({'name', 'labval'}, {'kids', kids_grid});
cl_mp_datasetdesc{4} = containers.Map({'name', 'labval'}, {'ylower', inc_grid});
```

### 10.1.6 Analyze Marginal Value and MPC over $Y(a, \eta)$ , Conditional On Kids, Marry, Age, Education

Income is generated by savings and shocks, what are the income levels generated by all the shock and savings points conditional on kids, marital status, age and educational levels. Plot on the Y axis MPC, and plot on the X axis income levels, use colors to first distinguish between different  $a$  levels, then use colors to distinguish between different  $\eta$  levels.

Set Up date, Select Age 37, unmarried, no kids, lower education:

```
% NaN(n_jgrid,n_agrid,n_etagrid,n_eduagrid,n_marriedgrid,n_kidsgrid);
% 38 year old, unmarried, no kids, lower educated
% Only Household Head Shock Matters so select up to 'n_eta_H_grid'
mn_V_W_gain_check_use = ev19_jmky_check2 - ev19_jmky_check0;
mn_C_W_gain_check_use = ec19_jmky_check2 - ec19_jmky_check0;
```

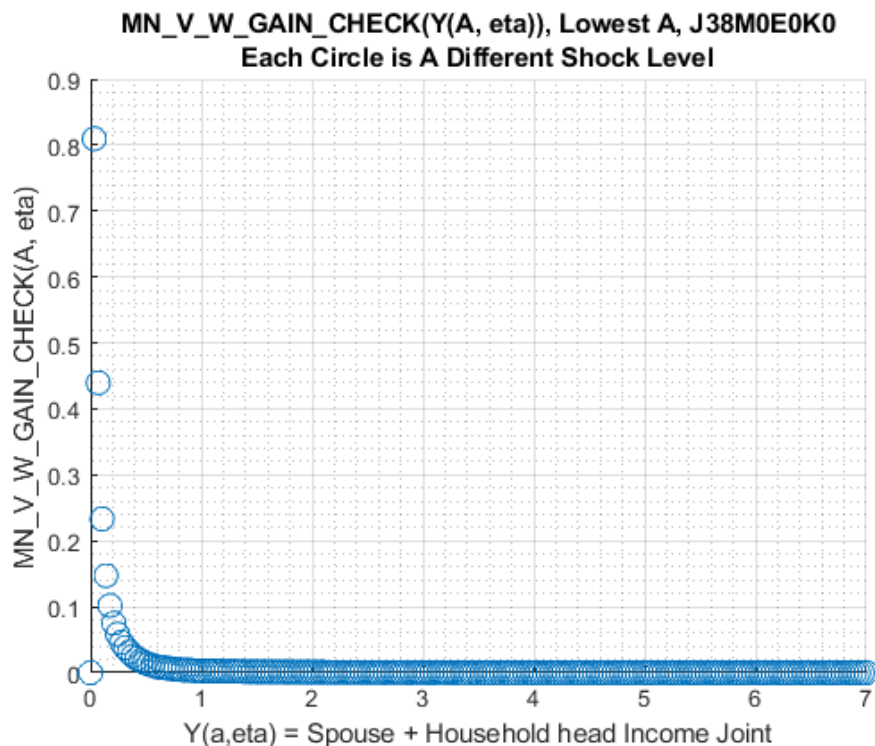
Select Age, Education, Marital, Kids Count:s

```
% Selections
it_age = 21; % +18
it_marital = 1; % 1 = unmarried
it_kids = 1; % 1 = kids is zero
% Select: NaN(n_jgrid-1,n_marriedgrid,n_kidsgrid,n_incgrid);
mn_C_W_gain_check_jemk = mn_C_W_gain_check_use(it_age, it_marital, it_kids, :);
mn_V_W_gain_check_jemk = mn_V_W_gain_check_use(it_age, it_marital, it_kids, :);
% Reshape, so shock is the first dim, a is the second
ar_C_W_gain_check_jemk = mn_C_W_gain_check_jemk(:);
ar_V_W_gain_check_jemk = mn_V_W_gain_check_jemk(:);
```

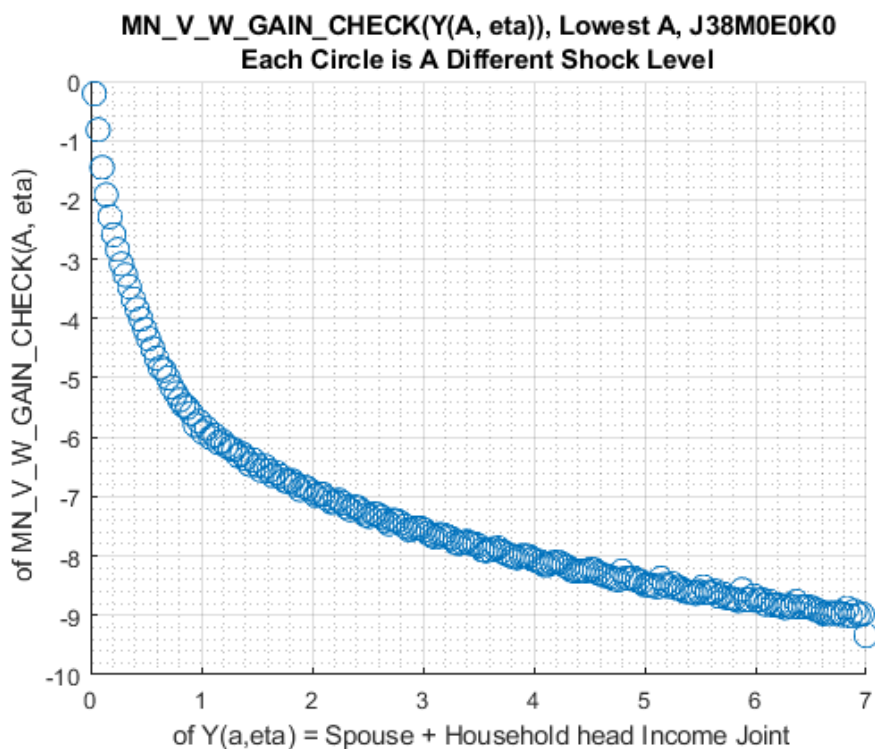
Marginal Value Gains, Color as Shock, Conditional on Age, Marital, Kids, and Education

How do shocks and  $a$  impact marginal value. First plot one asset level, variation comes only from increasingly higher shocks:

```
figure();
scatter(inc_grid, ar_V_W_gain_check_jemk, 100);
title({'MN\_V\_W\_GAIN\_CHECK(Y(A, eta)), Lowest A, J38MOEOKO', ...
      'Each Circle is A Different Shock Level'});
xlabel('Y(a,eta) = Spouse + Household head Income Joint');
ylabel('MN\_V\_W\_GAIN\_CHECK(A, eta)');
grid on;
grid minor;
```



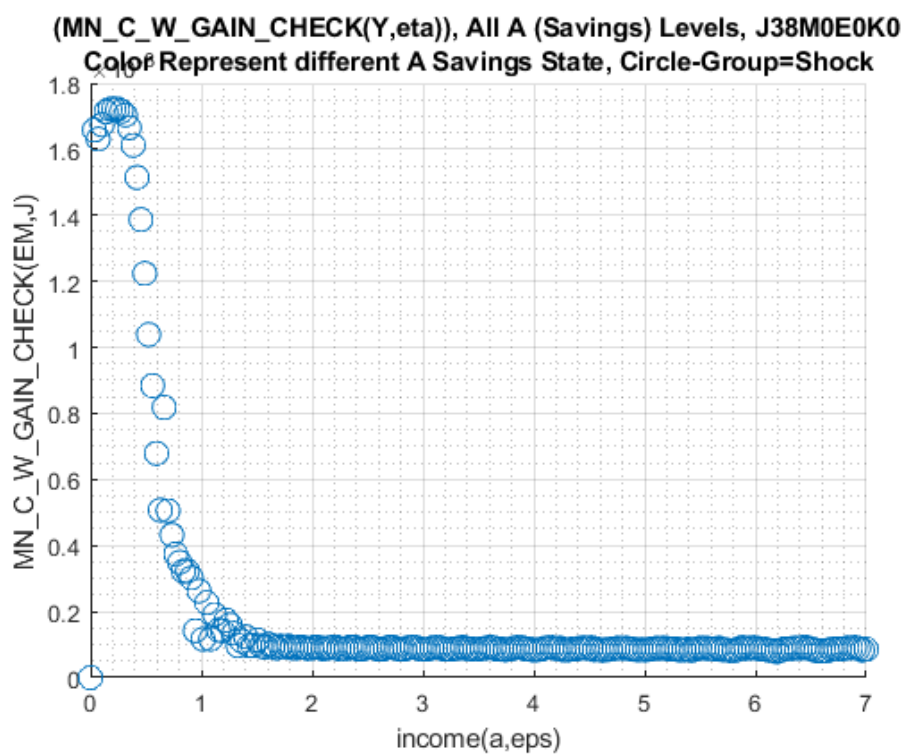
```
figure();
it_shock = 1;
scatter((inc_grid), log(ar_V_W_gain_check_jemk), 100);
title({'MN_V_W_GAIN_CHECK(Y(A, eta)), Lowest A, J38M0E0K0', ...
      'Each Circle is A Different Shock Level'});
xlabel(' of Y(a,eta) = Spouse + Household head Income Joint');
ylabel(' of MN_V_W_GAIN_CHECK(A, eta)');
grid on;
grid minor;
```



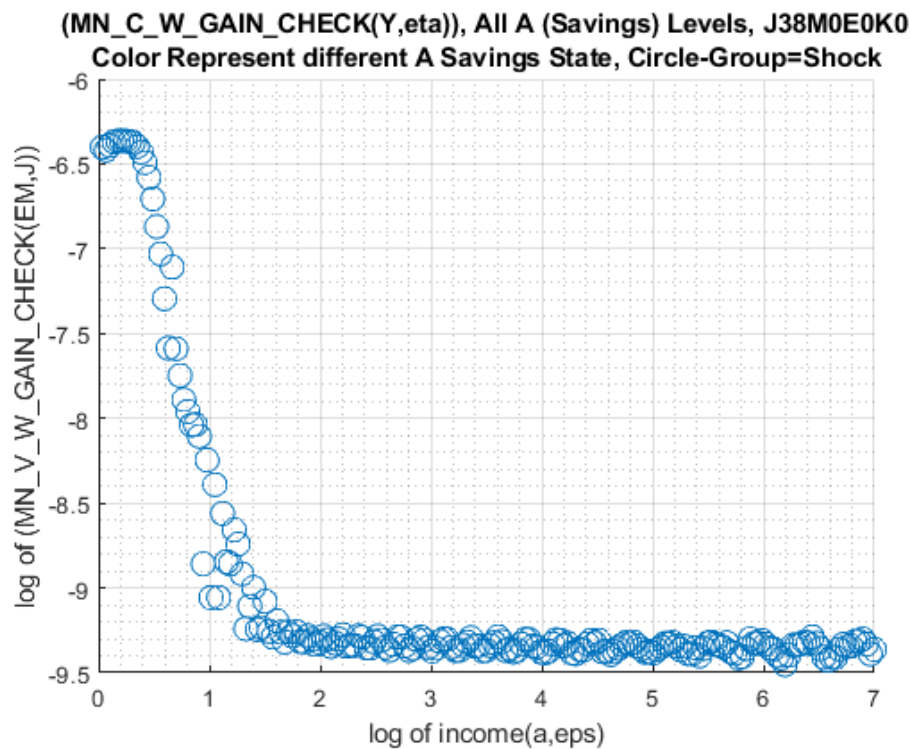
Marginal Consumption Gains, Color as Shock, Conditional on Age, Marital, Kids, and Education

Plot all asset levels:

```
figure();
scatter(inc_grid, ar_C_W_gain_check_jemk, 100);
title({'(MN\C_W_GAIN_CHECK(Y,eta)), All A (Savings) Levels, J38M0E0K0', ...
      'Color Represent different A Savings State, Circle-Group=Shock'});
xlabel('income(a,eps)');
ylabel('MN\C_W_GAIN_CHECK(EM,J)');
grid on;
grid minor;
```



```
figure();
scatter((inc_grid), log(ar_C_W_gain_check_jemk), 100);
title({'(MN\C_W_GAIN_CHECK(Y,eta)), All A (Savings) Levels, J38M0E0K0', ...
      'Color Represent different A Savings State, Circle-Group=Shock'});
xlabel('log of income(a,eps)');
ylabel('log of (MN\C_W_GAIN_CHECK(EM,J))');
grid on;
grid minor;
```



## 10.2 2019/2020 Age, Income, Kids, Marry EV and EC All Checks (Biden Checks)

This is the example vignette for function: [snw\\_evuvw19\\_jmky\\_allchecks](#) from the [PrjOptiSNW Package](#). 2019 integrated over VU and VW

The key features of the Biden stimulus check are: i) determined based on 2020 information; ii) checks received in 2021, ex-post the realization of the second one-time MIT shock, which similar to the first MIT shock, is conditional on income and age groups; iii) state of the economy returns to steady-state in 2022; iv) trump checks were provided in 2020, which changes saves and consumption and distributions in 2020, and appropriate adjustments are made so that the biden check is conditional on the distributional changes in endogenous savings due to the Trump checks.

### 10.2.1 Test SNW\_EVUVW19\_JMKY\_ALLCHECKS Parameters for Biden Checks

Save a result that is low in memory cost so that it can be loaded quickly for various allocation tests. Turn off Various Printing Controls. Call function with wide income bins to reduce memory storage and retrieval costs

```
clear all;
% Start mp contorls
mp_controls = snw_mp_control('default_test');
% Solve for Unemployment Values
mp_controls('bl_timer') = true;
mp_controls('bl_print_vfi') = false;
mp_controls('bl_print_vfi_verbose') = false;
mp_controls('bl_print_ds') = false;
mp_controls('bl_print_ds_verbose') = true;
mp_controls('bl_print_precompute') = false;
mp_controls('bl_print_precompute_verbose') = false;
mp_controls('bl_print_a4chk') = false;
mp_controls('bl_print_a4chk_verbose') = false;
```



```

mp_controls('bl_print_evuvw20_jaeemk') = false;
mp_controls('bl_print_evuvw20_jaeemk_verbose') = false;
mp_controls('bl_print_evuvw19_jaeemk') = false;
mp_controls('bl_print_evuvw19_jaeemk_verbose') = false;
mp_controls('bl_print_evuvw19_jmky') = false;
mp_controls('bl_print_evuvw19_jmky_verbose') = false;

```

Dense default, and unemployment parameters:

```

% default dense load
% mp_params = snw_mp_param('default_dense');
mp_params = snw_mp_param('default_docdense')

```

```
mp_params =
```

```
  Map with properties:
```

```

    Count: 64
    KeyType: char
    ValueType: any

```

```

mp_params('beta') = 0.95;
fl_scaleconvertor = 62502;
mp_more_inputs('fl_scaleconvertor') = fl_scaleconvertor;
% Unemployment
xi = 0.651; % Proportional reduction in income due to unemployment (xi=0 refers to 0 labor income; x
b=1; % Unemployment insurance replacement rate (b=0 refers to no UI benefits; b=1 refers to 100 perc
TR=100/fl_scaleconvertor; % Value of a wezlfare check (can receive multiple checks). TO DO: Update w
mp_params('pi_unemp') = mp_params('pi_unemp_2020_juneadj');
mp_params('xi') = xi;
mp_params('b') = b;
mp_params('TR') = TR;
% Check Count: 89 checks to allow for both the first and the second round
n_welfchecksgrid = 3;
mp_params('n_welfchecksgrid') = n_welfchecksgrid;
mp_params('a2_covidyr') = mp_params('a2_covidyr_manna_heaven');

```

Income bins:

```

% Income Grid
% 4 refers to 4*58056=232224 dollars in 2012USD
% max 7 refers to 7*58056=406392 dollars in 2012USD
% all phase out = (4400/5)*100 + 150000 = 238000
% if 500 dollar interval, need 476 inc groups before 238000
% if have 85 percent of points between 238000,
fl_max_phaseout = 238000;
fl_multiple = fl_scaleconvertor;
it_bin_dollar_before_phaseout = 5000;
it_bin_dollar_after_phaseout = 25000;
fl_thres = fl_max_phaseout/fl_multiple;
inc_grid1 = linspace(0,fl_thres,(fl_max_phaseout)/it_bin_dollar_before_phaseout);
inc_grid2 = linspace(fl_thres, 7, (7*fl_multiple-fl_max_phaseout)/it_bin_dollar_after_phaseout);
inc_grid=sort(unique([inc_grid1 inc_grid2]'));
mp_params('n_incgrid') = length(inc_grid);
mp_params('inc_grid') = inc_grid;

```

### 10.2.2 SNW\_EVUVW19\_JMKY\_ALLCHECKS Low Storage Invoke for Biden Checks

The simulation here (dense) requires less than 10 GB of memory with 8 workers (8 threads needed), simulating over 88 checks takes with 8 workers

```

st_biden_or_trump = 'bidenchk';
st_solu_type = 'bisech_vec';
bl_parfor = false;
it_workers = 1;
bl_export = false;
bl_load_mat = false;
snm_suffix = ['_test_ybin' num2str(it_bin_dollar_before_phaseout)];
[ev19_jmky_allchecks, ec19_jmky_allchecks, output] = ...
    snw_evuvw19_jmky_allchecks(mp_params, mp_controls, ...
    st_biden_or_trump, st_solu_type, ...
    bl_parfor, it_workers, ...
    bl_export, bl_load_mat, snm_suffix);

```

```

Completed SNW_VFI_MAIN_BISEC_VEC;SNW_MP_PARAM=default_docdense;SNW_MP_CONTROL=default_test;time=338.
Completed SNW_VFI_MAIN_BISEC_VEC 1 Period Unemp Shock;SNW_MP_PARAM=default_docdense;SNW_MP_CONTROL=d
sum of Phi_adj:83
sum of Phi_true:45.7931
sum of Phiss:83
summ of diff of Phiss and Phi_adj:-3.4939e-12
summ of diff of Phiss and Phi_true:37.2069
Completed SNW_DS_MAIN_VEC;SNW_MP_PARAM=default_docdense;SNW_MP_CONTROL=default_test;time=951.9985
Biden Check, resolve for distributions given Trump check
Completed SNW_VFI_MAIN_BISEC_VEC 1 Period Unemp Shock;SNW_MP_PARAM=default_docdense;SNW_MP_CONTROL=d
sum of Phi_adj:83
sum of Phi_true:45.7931
sum of Phiss:83
summ of diff of Phiss and Phi_adj:-1.0845e-13
summ of diff of Phiss and Phi_true:37.2069
summ of diff of Phi_adj_base and Phiss:1.0838e-13
Completed SNW_DS_MAIN_VEC;SNW_MP_PARAM=default_docdense;SNW_MP_CONTROL=default_test;time=1016.4233
Wage quintile cutoffs=0.4645    0.71528    1.0335    1.5632
Completed SNW_HH_PRECOMPUTE;SNW_MP_PARAM=default_docdense;SNW_MP_CONTROL=default_test;time cost=300.
SNW_EVUVW19_JMKY_MASS Start
Completed SNW_EVUVW19_JMKY_MASS;SNW_MP_PARAM=default_docdense;SNW_MP_CONTROL=default_test;time=5.304

```

```

-----
XXXXXXXXXXXXXXXXXXXXXXXXXXXXXXXXXXXXXXXXXXXXXXXXXXXX
CONTAINER NAME: mp_outcomes ND Array (Matrix etc)
XXXXXXXXXXXXXXXXXXXXXXXXXXXXXXXXXXXXXXXXXXXXXXXXXXXX

```

	i	idx	ndim	numel	rowN	colN	sum	mean	
Phi_true	1	1	6	4.37e+07	83	5.265e+05	45.793	1.0479e-06	1
Phi_true_jmky	2	2	4	43460	82	530	45.787	0.0010535	0

```

SNW_EVUVW19_JMKY_ALLCHECKS Start
XXXXXXXXXXXXXXXXXXXXXXXXXXXXXXXXXXXXXXXXXXXXXXXXXXXX
Completed SNW_A4CHK_WRK_BISEC_VEC;SNW_MP_PARAM=bidenchk;welf_checks=0;TR=0.0015999;SNW_MP_PARAM=defa
Completed SNW_A4CHK_UNEMP_BISEC_VEC;welf_checks=0;TR=0.0015999;xi=0.651;b=1;SNW_MP_PARAM=default_doc
Completed SNW_EVUVW20_JAEEMK;SNW_MP_PARAM=default_docdense;SNW_MP_CONTROL=default_test;timeEUEC=8.32
Completed SNW_EVUVW19_JAEEMK_FOC;st_biden_or_trump=bidenchk;SNW_MP_PARAM=default_docdense;SNW_MP_CON
Completed SNW_EVUVW19_JMKY;SNW_MP_PARAM=default_docdense;SNW_MP_CONTROL=default_test;time=9.5927
SNW_EVUVW19_JMKY_ALLCHECKS: Finished Check 0 of 2, time=190.7959
XXXXXXXXXXXXXXXXXXXXXXXXXXXXXXXXXXXXXXXXXXXXXXXXXXXX
Completed SNW_A4CHK_WRK_BISEC_VEC;SNW_MP_PARAM=bidenchk;welf_checks=1;TR=0.0015999;SNW_MP_PARAM=defa
Completed SNW_A4CHK_UNEMP_BISEC_VEC;welf_checks=1;TR=0.0015999;xi=0.651;b=1;SNW_MP_PARAM=default_doc
Completed SNW_EVUVW20_JAEEMK;SNW_MP_PARAM=default_docdense;SNW_MP_CONTROL=default_test;timeEUEC=7.75
Completed SNW_EVUVW19_JAEEMK_FOC;st_biden_or_trump=bidenchk;SNW_MP_PARAM=default_docdense;SNW_MP_CON
Completed SNW_EVUVW19_JMKY;SNW_MP_PARAM=default_docdense;SNW_MP_CONTROL=default_test;time=9.57

```

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SNW\_EVUVW19\_JMKY\_ALLCHECKS: Finished Check 1 of 2, time=190.7479

XX

Completed SNW\_A4CHK\_WRK\_BISEC\_VEC;SNW\_MP\_PARAM=bidenchk;welf\_checks=2;TR=0.0015999;SNW\_MP\_PARAM=defa

Completed SNW\_A4CHK\_UNEMP\_BISEC\_VEC;welf\_checks=2;TR=0.0015999;xi=0.651;b=1;SNW\_MP\_PARAM=default\_doc

Completed SNW\_EVUVW20\_JAEEMK;SNW\_MP\_PARAM=default\_docdense;SNW\_MP\_CONTROL=default\_test;timeEUEC=7.98

Completed SNW\_EVUVW19\_JAEEMK\_FOC;st\_biden\_or\_trump=bidenchk;SNW\_MP\_PARAM=default\_docdense;SNW\_MP\_CON

Completed SNW\_EVUVW19\_JMKY;SNW\_MP\_PARAM=default\_docdense;SNW\_MP\_CONTROL=default\_test;time=9.4891

SNW\_EVUVW19\_JMKY\_ALLCHECKS: Finished Check 2 of 2, time=191.4103

Completed SNW\_EVUVW19\_JMKY\_ALLCHECKS;ST\_BIDEN\_OR\_TRUMP=bidenchk;SNW\_MP\_PARAM=default\_docdense;SNW\_MP

XX

CONTAINER NAME: mp\_outcomes ND Array (Matrix etc)

XX

	i	idx	ndim	numel	rowN	colN	sum
Output	1	1	2	1.0453e+06	1.1615e+05	9	7.7287e
ec19_jmky_allchecks	2	2	5	1.3038e+05	3	43460	2.7167e
ec19_jmky_allchecks_posmass	3	3	2	1.1615e+05	1.1615e+05	1	2.7167e
ev19_jmky_allchecks	4	4	5	1.3038e+05	3	43460	-2.3026e
ev19_jmky_allchecks_posmass	5	5	2	1.1615e+05	1.1615e+05	1	17

xxx TABLE:Output xxxxxxxxxxxxxxxxxxxxxxx

	c1	c2	c3	c4	c6	c7	c8	c9
r1	18	0	0	0	2.1599e-05	-0.57722	0.0053864	0.068495
r2	18	0	0	1	2.1599e-05	-0.57722	0.0053978	0.069683
r3	18	0	0	2	2.1599e-05	-0.57722	0.005409	0.070689
r4	19	0	0	0	1.9002e-05	0.42278	0.0056805	0.075684
r5	19	0	0	1	1.9002e-05	0.42278	0.0056903	0.07644
r116141	86	1	4	1	3.9923e-49	4.2268	0.97814	13.904
r116142	86	1	4	2	3.9923e-49	4.2268	0.97816	13.904
r116143	87	1	4	0	7.923e-63	4.2413	1.071	14.588
r116144	87	1	4	1	7.923e-63	4.2413	1.071	14.588
r116145	87	1	4	2	7.923e-63	4.2413	1.0711	14.589

xxx TABLE:ec19\_jmky\_allchecks xxxxxxxxxxxxxxxxxxxxxxx

	c1	c2	c3	c4	c43457	c43458	c43459	c43460
r1	0.068495	0.075684	0.077039	0.075763	0	0	0	0
r2	0.069683	0.07644	0.077934	0.076696	0	0	0	0
r3	0.070689	0.077196	0.078828	0.077629	0	0	0	0

xxx TABLE:ec19\_jmky\_allchecks\_posmass xxxxxxxxxxxxxxxxxxxxxxx

	c1
r1	0.068495
r2	0.069683
r3	0.070689
r4	0.075684
r5	0.07644
r116141	13.904
r116142	13.904
r116143	14.588
r116144	14.588

```

r116145      14.589

xxx TABLE:ev19_jmky_allchecks xxxxxxxxxxxxxxxxxxxxxxxx
      c1      c2      c3      c4      c43457      c43458      c43459      c43460
      -----      -----      -----      -----      -----      -----      -----      -----
r1      -185.65      -176.04      -169.67      -170.69      0      0      0      0
r2      -185.26      -175.74      -169.37      -170.39      0      0      0      0
r3      -184.88      -175.43      -169.08      -170.09      0      0      0      0

xxx TABLE:ev19_jmky_allchecks_posmass xxxxxxxxxxxxxxxxxxxxxxxx
      c1
      -----
r1      0.0053864
r2      0.0053978
r3      0.005409
r4      0.0056805
r5      0.0056903
r116141      0.97814
r116142      0.97816
r116143      1.071
r116144      1.071
r116145      1.0711

```

### 10.3 2007 Age, Income, Kids, Marry EV and EC All Checks (Bush Checks)

This is the example vignette for function: [snw\\_evuvw19\\_jmky\\_allchecks](#) from the [PrjOptiSNW Package](#). 2019 integrated over VU and VW

The function [snw\\_evuvw19\\_jmky\\_allchecks](#) was initiall designed to handle the COVID problem, the revised version of the program handles both the 2007/8/9 Bush stimulus check problem, and the 2019/20/21 Trump and Biden stimulus check problems.

The key features of the Bush stimulus checks are: i) determined based on 2007 information; ii) checks received in 2008, when the great recession has not arrived yet, but all expect it to in 2009; iii) the Great Recession hits in 2009, putting some people, based on education and age, into unemployment state with a shared unemployment duration and lost income and also UI benefits (calibrated to match overall UI share of wages); iv) the economy returns to steady-state in 2010.

#### 10.3.1 Test SNW\_EVUVW19\_JMKY\_ALLCHECKS Parameters for Bush Checks

Save a result that is low in memory cost so that it can be loaded quickly for various allocation tests. Turn off Various Printing Controls. Call function with wide income bins to reduce memory storage and retrieval costs

```

clear all;
% Start mp contorls
mp_controls = snw_mp_control('default_test');
% Solve for Unemployment Values
mp_controls('bl_timer') = true;
mp_controls('bl_print_vfi') = false;
mp_controls('bl_print_vfi_verbose') = false;
mp_controls('bl_print_ds') = false;
mp_controls('bl_print_ds_verbose') = true;
mp_controls('bl_print_precompute') = false;
mp_controls('bl_print_precompute_verbose') = false;

```

```

mp_controls('bl_print_a4chk') = false;
mp_controls('bl_print_a4chk_verbose') = false;
mp_controls('bl_print_v08p08_jaeemk') = false;
mp_controls('bl_print_v08p08_jaeemk_verbose') = false;
mp_controls('bl_print_v08_jaeemk') = false;
mp_controls('bl_print_v08_jaeemk_verbose') = false;
mp_controls('bl_print_evuvw20_jaeemk') = false;
mp_controls('bl_print_evuvw20_jaeemk_verbose') = false;
mp_controls('bl_print_evuvw19_jaeemk') = false;
mp_controls('bl_print_evuvw19_jaeemk_verbose') = false;
mp_controls('bl_print_evuvw19_jmky') = false;
mp_controls('bl_print_evuvw19_jmky_verbose') = false;

```

Dense default, and unemployment parameters:

```

% default dense load
% 1. generate MP_PARAMS specific to 2008 stimulus
% Use non-default values for Bush Stimulus
mp_more_inputs = containers.Map('KeyType','char', 'ValueType','any');
mp_more_inputs('fl_ss_non_college') = 0.225;
mp_more_inputs('fl_ss_college') = 0.271;
fl_p50_hh_income_07 = 54831;
mp_more_inputs('fl_scaleconvertor') = fl_p50_hh_income_07;
% st_param_group = 'default_small';
% st_param_group = 'default_dense';
st_param_group = 'default_docdense';
mp_params = snw_mp_param(st_param_group, false, 'tauchen', false, 8, 8, mp_more_inputs);
% mp_params = snw_mp_param('default_docdense')
mp_params('beta') = 0.95;
fl_scaleconvertor = 62502;
mp_more_inputs('fl_scaleconvertor') = fl_scaleconvertor;
% Unemployment
mp_params('xi') = 0.532;
mp_params('b') = 0.37992;
mp_params('a2_covidyr') = mp_params('a2_greatrecession_2009');
mp_params('TR') = 100/fl_p50_hh_income_07;
% Check Count: 89 checks to allow for both the first and the second round
n_welfchecksgrid = 3;
mp_params('n_welfchecksgrid') = n_welfchecksgrid;
mp_params('a2_covidyr') = mp_params('a2_greatrecession_2009');

```

Income bins:

```

% Income Grid
% 4 refers to 4*58056=232224 dollars in 2012USD
% max 7 refers to 7*58056=406392 dollars in 2012USD
% all phase out = (4400/5)*100 + 150000 = 238000
% if 500 dollar interval, need 476 inc groups before 238000
% if have 85 percent of points between 238000,
fl_max_phaseout = 238000;
fl_multiple = fl_scaleconvertor;
it_bin_dollar_before_phaseout = 5000;
it_bin_dollar_after_phaseout = 25000;
fl_thres = fl_max_phaseout/fl_multiple;
inc_grid1 = linspace(0,fl_thres,(fl_max_phaseout)/it_bin_dollar_before_phaseout);
inc_grid2 = linspace(fl_thres, 7, (7*fl_multiple-fl_max_phaseout)/it_bin_dollar_after_phaseout);
inc_grid=sort(unique([inc_grid1 inc_grid2]'));
mp_params('n_incgrid') = length(inc_grid);
mp_params('inc_grid') = inc_grid;

```

### 10.3.2 SNW\_EVUVW19\_JMKY\_ALLCHECKS Low Storage Invoke for Bush Checks

The simulation here (dense) requires less than 10 GB of memory with 8 workers (8 threads needed), simulating over 88 checks takes with 8 workers

```
st_biden_or_trump = 'bushchck';
st_solu_type = 'bisec_vec';
bl_parfor = false;
it_workers = 1;
bl_export = false;
bl_load_mat = false;
snm_suffix = ['_test_ybin' num2str(it_bin_dollar_before_phaseout)];
[ev19_jmky_allchecks, ec19_jmky_allchecks, output] = ...
    snw_evuvw19_jmky_allchecks(mp_params, mp_controls, ...
    st_biden_or_trump, st_solu_type, ...
    bl_parfor, it_workers, ...
    bl_export, bl_load_mat, snm_suffix);
```

```
Completed SNW_VFI_MAIN_BISEC_VEC;SNW_MP_PARAM=default_docdense;SNW_MP_CONTROL=default_test;time=330.
Completed SNW_VFI_MAIN_BISEC_VEC 1 Period Unemp Shock;SNW_MP_PARAM=default_docdense;SNW_MP_CONTROL=d
Completed SNW_VFI_MAIN_BISEC_VEC 1 Period Unemp Shock;SNW_MP_PARAM=default_docdense;SNW_MP_CONTROL=d
Completed SNW_V08P08_JAEEMK;SNW_MP_PARAM=default_docdense;SNW_MP_CONTROL=default_test;time=524.1155
sum of Phi_adj:83
sum of Phi_true:45.7931
sum of Phiss:83
summ of diff of Phiss and Phi_adj:-3.4775e-12
summ of diff of Phiss and Phi_true:37.2069
Completed SNW_DS_MAIN_VEC;SNW_MP_PARAM=default_docdense;SNW_MP_CONTROL=default_test;time=1254.4898
Trump Check, do not need to resolve distribution
Wage quintile cutoffs=0.4645    0.71528    1.0335    1.5632
Completed SNW_HH_PRECOMPUTE;SNW_MP_PARAM=default_docdense;SNW_MP_CONTROL=default_test;time cost=265.
SNW_EVUVW19_JMKY_MASS Start
Completed SNW_EVUVW19_JMKY_MASS;SNW_MP_PARAM=default_docdense;SNW_MP_CONTROL=default_test;time=5.264
```

```
-----
XXXXXXXXXXXXXXXXXXXXXXXXXXXXXXXXXXXXXXXXXXXXXXXXXXXX
CONTAINER NAME: mp_outcomes ND Array (Matrix etc)
XXXXXXXXXXXXXXXXXXXXXXXXXXXXXXXXXXXXXXXXXXXXXXXXXXXX
```

	i	idx	ndim	numel	rowN	colN	sum	mean	
Phi_true	1	1	6	4.37e+07	83	5.265e+05	45.793	1.0479e-06	1.
Phi_true_jmky	2	2	4	43460	82	530	45.787	0.0010535	0

```
SNW_EVUVW19_JMKY_ALLCHECKS Start
```

```
XXXXXXXXXXXXXXXXXXXXXXXXXXXXXXXXXXXXXXXXXXXXXXXXXXXX
```

```
Completed SNW_A4CHK_WRK_BISEC_VEC;SNW_MP_PARAM=bushchck;welf_checks=0;TR=0.0018238;SNW_MP_PARAM=defa
Completed SNW_V08_JAEEMK;SNW_MP_PARAM=default_docdense;SNW_MP_CONTROL=default_test;timeEUEC=2.81e-05
Completed SNW_EVUVW19_JAEEMK_FOC;st_biden_or_trump=bushchck;SNW_MP_PARAM=default_docdense;SNW_MP_CON
Completed SNW_EVUVW19_JMKY;SNW_MP_PARAM=default_docdense;SNW_MP_CONTROL=default_test;time=10.3545
SNW_EVUVW19_JMKY_ALLCHECKS: Finished Check 0 of 2, time=106.2974
```

```
XXXXXXXXXXXXXXXXXXXXXXXXXXXXXXXXXXXXXXXXXXXXXXXXXXXX
```

```
Completed SNW_A4CHK_WRK_BISEC_VEC;SNW_MP_PARAM=bushchck;welf_checks=1;TR=0.0018238;SNW_MP_PARAM=defa
Completed SNW_V08_JAEEMK;SNW_MP_PARAM=default_docdense;SNW_MP_CONTROL=default_test;timeEUEC=2.94e-05
Completed SNW_EVUVW19_JAEEMK_FOC;st_biden_or_trump=bushchck;SNW_MP_PARAM=default_docdense;SNW_MP_CON
Completed SNW_EVUVW19_JMKY;SNW_MP_PARAM=default_docdense;SNW_MP_CONTROL=default_test;time=10.0897
SNW_EVUVW19_JMKY_ALLCHECKS: Finished Check 1 of 2, time=106.6849
```

```
XXXXXXXXXXXXXXXXXXXXXXXXXXXXXXXXXXXXXXXXXXXXXXXXXXXX
```

```
Completed SNW_A4CHK_WRK_BISEC_VEC;SNW_MP_PARAM=bushchck;welf_checks=2;TR=0.0018238;SNW_MP_PARAM=defa
```

Completed SNW\_V08\_JAEEMK;SNW\_MP\_PARAM=default\_docdense;SNW\_MP\_CONTROL=default\_test;timeEUEC=2.1e-05  
 Completed SNW\_EVUVW19\_JAEEMK\_FOC;st\_biden\_or\_trump=bushchck;SNW\_MP\_PARAM=default\_docdense;SNW\_MP\_CON  
 Completed SNW\_EVUVW19\_JMKY;SNW\_MP\_PARAM=default\_docdense;SNW\_MP\_CONTROL=default\_test;time=10.1555  
 SNW\_EVUVW19\_JMKY\_ALLCHECKS: Finished Check 2 of 2, time=106.7998  
 Completed SNW\_EVUVW19\_JMKY\_ALLCHECKS;ST\_BIDEN\_OR\_TRUMP=bushchck;SNW\_MP\_PARAM=default\_docdense;SNW\_MP

CONTAINER NAME: mp\_outcomes ND Array (Matrix etc)

	i	idx	ndim	numel	rowN	colN	sum
Output	1	1	2	1.0483e+06	1.1648e+05	9	7.7619e
ec19_jmky_allchecks	2	2	5	1.3038e+05	3	43460	2.737e
ec19_jmky_allchecks_posmass	3	3	2	1.1648e+05	1.1648e+05	1	2.737e
ev19_jmky_allchecks	4	4	5	1.3038e+05	3	43460	-2.3148e
ev19_jmky_allchecks_posmass	5	5	2	1.1648e+05	1.1648e+05	1	17

xxx TABLE:Output xxxxxxxxxxxxxxxxxxxxxxx

	c1	c2	c3	c4	c6	c7	c8	c9
r1	18	0	0	0	2.1599e-05	-0.57722	0.0053606	0.066639
r2	18	0	0	1	2.1599e-05	-0.57722	0.0053744	0.067396
r3	18	0	0	2	2.1599e-05	-0.57722	0.0053882	0.068355
r4	19	0	0	0	1.9002e-05	0.42278	0.0055828	0.068128
r5	19	0	0	1	1.9002e-05	0.42278	0.0055969	0.069089
r116474	86	1	4	1	3.937e-49	4.2268	0.97866	13.912
r116475	86	1	4	2	3.937e-49	4.2268	0.97868	13.912
r116476	87	1	4	0	1.0014e-58	4.2413	1.0716	14.596
r116477	87	1	4	1	1.0014e-58	4.2413	1.0716	14.597
r116478	87	1	4	2	1.0014e-58	4.2413	1.0716	14.597

xxx TABLE:ec19\_jmky\_allchecks xxxxxxxxxxxxxxxxxxxxxxx

	c1	c2	c3	c4	c43457	c43458	c43459	c43460
r1	0.066639	0.068128	0.071766	0.071091	0	0	0	0
r2	0.067396	0.069089	0.072695	0.072031	0	0	0	0
r3	0.068355	0.069782	0.073378	0.07271	0	0	0	0

xxx TABLE:ec19\_jmky\_allchecks\_posmass xxxxxxxxxxxxxxxxxxxxxxx

	c1
r1	0.066639
r2	0.067396
r3	0.068355
r4	0.068128
r5	0.069089
r116474	13.912
r116475	13.912
r116476	14.596
r116477	14.597
r116478	14.597

xxx TABLE:ev19\_jmky\_allchecks xxxxxxxxxxxxxxxxxxxxxxx

	c1	c2	c3	c4	c43457	c43458	c43459	c43460
--	----	----	----	----	--------	--------	--------	--------

	-----	-----	-----	-----	-----	-----	-----	-----
r1	-186.55	-179.12	-171.74	-172.54	0	0	0	0
r2	-186.07	-178.67	-171.33	-172.13	0	0	0	0
r3	-185.59	-178.22	-170.92	-171.72	0	0	0	0

xxx TABLE:ev19\_jmky\_allchecks\_posmass xxxxxxxxxxxxxxxxxxxxxx  
c1

	-----
r1	0.0053606
r2	0.0053744
r3	0.0053882
r4	0.0055828
r5	0.0055969
r116474	0.97866
r116475	0.97868
r116476	1.0716
r116477	1.0716
r116478	1.0716



# Chapter 11

## Taxes and Stimulus

### 11.1 Compute for Equilibrium Tax

Taking advantage of `snw_find_tax_rate` from the [PrjOptiSNW Package](#), this function solves for equilibrium tax rate.

#### 11.1.1 Parameter Controls

```
clear all;
mp_params = snw_mp_param('default_docdense');
% mp_params = snw_mp_param('default_dense');
% mp_params = snw_mp_param('default_base');
% mp_params = snw_mp_param('default_small');
mp_params('beta') = 0.95;
xi=0.651; % Proportional reduction in income due to unemployment (xi=0 refers to 0 labor income; xi=
b=1; % Unemployment insurance replacement rate (b=0 refers to no UI benefits; b=1 refers to 100 perc
mp_params('xi') = xi;
mp_params('b') = b;
mp_controls = snw_mp_control('default_test');
```

Parameters for COVID related Costs:

```
% Average check per household, given COVID actual policy payment schedule
% And given distribution. The number is from averaging over the actual
% allocations given distribution.
Covid_checks_per_capita = 18.7255856*100/62502;
% Covid_checks_per_capita = 0;
% which tax parameter to change a2 is the default, a0 shifts max tax rate
bl_adjust_a0 = false;
bl_load_existing = false;
```

Graph Controls etc:

```
mp_controls('bl_timer') = true;
mp_controls('bl_print_vfi') = false;
mp_controls('bl_print_vfi_verbose') = false;
mp_controls('bl_print_ds') = false;
mp_controls('bl_print_ds_verbose') = false;
mp_controls('bl_print_find_tax_rate') = true;
mp_controls('bl_print_find_tax_rate_verbose') = true;
```

#### 11.1.2 Solve for New Tax Rate

Solve for Equilibrium Tax rate that clears government costs and income. In the extreme bounding exercise, we assume the government will pay COVID costs all in one year. This is to test whether an

extreme tax scenario will lead to changes in allocation results.

Given the checks that the government hands out and the taxes imposed, individual resources post-tax are different in 2020. Households' savings decisions in 2020 vary with taxes and checks. However, the policy function post 2020 shifts back to the previous non-COVID world's policy function because the COVID shock is an one period surprise shock.

```
a2 = snw_find_tax_rate(mp_params, mp_controls, Covid_checks_per_capita, bl_adjust_a0, bl_load_existi
```

```
Completed SNW_VFI_MAIN_BISEC_VEC;SNW_MP_PARAM=default_docdense;SNW_MP_CONTROL=default_test;time=315.
```

```
Completed SNW_DS_MAIN_VEC;SNW_MP_PARAM=default_docdense;SNW_MP_CONTROL=default_test;time=1056.1907
```

```
Wage quintile cutoffs=0.4645      0.71528      1.0335      1.5632
```

```
Y_inc_agg=61.7582
```

```
A_agg=119.2022
```

```
Y_inc_agg_per_capita_1=1.3486
```

```
A_per_capita=2.6031
```

```
Gov_cons_per_capita=0.23703
```

```
Covid_checks_share_of_GDP=0.022215
```

```
SNW_FIND_TAX_RATE: Aggregation, Finished Age Group:1 of 83, time-this-age:0.40805
SNW_FIND_TAX_RATE: Aggregation, Finished Age Group:2 of 83, time-this-age:0.33319
SNW_FIND_TAX_RATE: Aggregation, Finished Age Group:3 of 83, time-this-age:0.41771
SNW_FIND_TAX_RATE: Aggregation, Finished Age Group:4 of 83, time-this-age:0.34531
SNW_FIND_TAX_RATE: Aggregation, Finished Age Group:5 of 83, time-this-age:0.33489
SNW_FIND_TAX_RATE: Aggregation, Finished Age Group:6 of 83, time-this-age:0.35842
SNW_FIND_TAX_RATE: Aggregation, Finished Age Group:7 of 83, time-this-age:0.35655
SNW_FIND_TAX_RATE: Aggregation, Finished Age Group:8 of 83, time-this-age:0.35122
SNW_FIND_TAX_RATE: Aggregation, Finished Age Group:9 of 83, time-this-age:0.33076
SNW_FIND_TAX_RATE: Aggregation, Finished Age Group:10 of 83, time-this-age:0.33222
SNW_FIND_TAX_RATE: Aggregation, Finished Age Group:11 of 83, time-this-age:0.32783
SNW_FIND_TAX_RATE: Aggregation, Finished Age Group:12 of 83, time-this-age:0.32957
SNW_FIND_TAX_RATE: Aggregation, Finished Age Group:13 of 83, time-this-age:0.33172
SNW_FIND_TAX_RATE: Aggregation, Finished Age Group:14 of 83, time-this-age:0.37079
SNW_FIND_TAX_RATE: Aggregation, Finished Age Group:15 of 83, time-this-age:0.36121
SNW_FIND_TAX_RATE: Aggregation, Finished Age Group:16 of 83, time-this-age:0.34383
SNW_FIND_TAX_RATE: Aggregation, Finished Age Group:17 of 83, time-this-age:0.32866
SNW_FIND_TAX_RATE: Aggregation, Finished Age Group:18 of 83, time-this-age:0.31896
SNW_FIND_TAX_RATE: Aggregation, Finished Age Group:19 of 83, time-this-age:0.32354
SNW_FIND_TAX_RATE: Aggregation, Finished Age Group:20 of 83, time-this-age:0.35757
SNW_FIND_TAX_RATE: Aggregation, Finished Age Group:21 of 83, time-this-age:0.35162
SNW_FIND_TAX_RATE: Aggregation, Finished Age Group:22 of 83, time-this-age:0.33998
SNW_FIND_TAX_RATE: Aggregation, Finished Age Group:23 of 83, time-this-age:0.32237
SNW_FIND_TAX_RATE: Aggregation, Finished Age Group:24 of 83, time-this-age:0.32174
SNW_FIND_TAX_RATE: Aggregation, Finished Age Group:25 of 83, time-this-age:0.38317
SNW_FIND_TAX_RATE: Aggregation, Finished Age Group:26 of 83, time-this-age:0.342
SNW_FIND_TAX_RATE: Aggregation, Finished Age Group:27 of 83, time-this-age:0.32267
SNW_FIND_TAX_RATE: Aggregation, Finished Age Group:28 of 83, time-this-age:0.34224
SNW_FIND_TAX_RATE: Aggregation, Finished Age Group:29 of 83, time-this-age:0.34442
SNW_FIND_TAX_RATE: Aggregation, Finished Age Group:30 of 83, time-this-age:0.35185
SNW_FIND_TAX_RATE: Aggregation, Finished Age Group:31 of 83, time-this-age:0.32489
SNW_FIND_TAX_RATE: Aggregation, Finished Age Group:32 of 83, time-this-age:0.32887
SNW_FIND_TAX_RATE: Aggregation, Finished Age Group:33 of 83, time-this-age:0.33332
SNW_FIND_TAX_RATE: Aggregation, Finished Age Group:34 of 83, time-this-age:0.32678
SNW_FIND_TAX_RATE: Aggregation, Finished Age Group:35 of 83, time-this-age:0.37362
SNW_FIND_TAX_RATE: Aggregation, Finished Age Group:36 of 83, time-this-age:0.38589
SNW_FIND_TAX_RATE: Aggregation, Finished Age Group:37 of 83, time-this-age:0.35322
SNW_FIND_TAX_RATE: Aggregation, Finished Age Group:38 of 83, time-this-age:0.32684
SNW_FIND_TAX_RATE: Aggregation, Finished Age Group:39 of 83, time-this-age:0.34446
SNW_FIND_TAX_RATE: Aggregation, Finished Age Group:40 of 83, time-this-age:0.40304
SNW_FIND_TAX_RATE: Aggregation, Finished Age Group:41 of 83, time-this-age:0.36362
```

SNW\_FIND\_TAX\_RATE: Aggregation, Finished Age Group:42 of 83, time-this-age:0.32294  
SNW\_FIND\_TAX\_RATE: Aggregation, Finished Age Group:43 of 83, time-this-age:0.34509  
SNW\_FIND\_TAX\_RATE: Aggregation, Finished Age Group:44 of 83, time-this-age:0.32763  
SNW\_FIND\_TAX\_RATE: Aggregation, Finished Age Group:45 of 83, time-this-age:0.32328  
SNW\_FIND\_TAX\_RATE: Aggregation, Finished Age Group:46 of 83, time-this-age:0.3229  
SNW\_FIND\_TAX\_RATE: Aggregation, Finished Age Group:47 of 83, time-this-age:0.32421  
SNW\_FIND\_TAX\_RATE: Aggregation, Finished Age Group:48 of 83, time-this-age:0.36399  
SNW\_FIND\_TAX\_RATE: Aggregation, Finished Age Group:49 of 83, time-this-age:0.37545  
SNW\_FIND\_TAX\_RATE: Aggregation, Finished Age Group:50 of 83, time-this-age:0.37864  
SNW\_FIND\_TAX\_RATE: Aggregation, Finished Age Group:51 of 83, time-this-age:0.3443  
SNW\_FIND\_TAX\_RATE: Aggregation, Finished Age Group:52 of 83, time-this-age:0.3398  
SNW\_FIND\_TAX\_RATE: Aggregation, Finished Age Group:53 of 83, time-this-age:0.34794  
SNW\_FIND\_TAX\_RATE: Aggregation, Finished Age Group:54 of 83, time-this-age:0.36094  
SNW\_FIND\_TAX\_RATE: Aggregation, Finished Age Group:55 of 83, time-this-age:0.34198  
SNW\_FIND\_TAX\_RATE: Aggregation, Finished Age Group:56 of 83, time-this-age:0.36405  
SNW\_FIND\_TAX\_RATE: Aggregation, Finished Age Group:57 of 83, time-this-age:0.34572  
SNW\_FIND\_TAX\_RATE: Aggregation, Finished Age Group:58 of 83, time-this-age:0.34234  
SNW\_FIND\_TAX\_RATE: Aggregation, Finished Age Group:59 of 83, time-this-age:0.34115  
SNW\_FIND\_TAX\_RATE: Aggregation, Finished Age Group:60 of 83, time-this-age:0.36025  
SNW\_FIND\_TAX\_RATE: Aggregation, Finished Age Group:61 of 83, time-this-age:0.34223  
SNW\_FIND\_TAX\_RATE: Aggregation, Finished Age Group:62 of 83, time-this-age:0.34256  
SNW\_FIND\_TAX\_RATE: Aggregation, Finished Age Group:63 of 83, time-this-age:0.34432  
SNW\_FIND\_TAX\_RATE: Aggregation, Finished Age Group:64 of 83, time-this-age:0.34369  
SNW\_FIND\_TAX\_RATE: Aggregation, Finished Age Group:65 of 83, time-this-age:0.34474  
SNW\_FIND\_TAX\_RATE: Aggregation, Finished Age Group:66 of 83, time-this-age:0.36666  
SNW\_FIND\_TAX\_RATE: Aggregation, Finished Age Group:67 of 83, time-this-age:0.34095  
SNW\_FIND\_TAX\_RATE: Aggregation, Finished Age Group:68 of 83, time-this-age:0.34424  
SNW\_FIND\_TAX\_RATE: Aggregation, Finished Age Group:69 of 83, time-this-age:0.34722  
SNW\_FIND\_TAX\_RATE: Aggregation, Finished Age Group:70 of 83, time-this-age:0.34031  
SNW\_FIND\_TAX\_RATE: Aggregation, Finished Age Group:71 of 83, time-this-age:0.35799  
SNW\_FIND\_TAX\_RATE: Aggregation, Finished Age Group:72 of 83, time-this-age:0.34436  
SNW\_FIND\_TAX\_RATE: Aggregation, Finished Age Group:73 of 83, time-this-age:0.34066  
SNW\_FIND\_TAX\_RATE: Aggregation, Finished Age Group:74 of 83, time-this-age:0.34077  
SNW\_FIND\_TAX\_RATE: Aggregation, Finished Age Group:75 of 83, time-this-age:0.34236  
SNW\_FIND\_TAX\_RATE: Aggregation, Finished Age Group:76 of 83, time-this-age:0.34346  
SNW\_FIND\_TAX\_RATE: Aggregation, Finished Age Group:77 of 83, time-this-age:0.37815  
SNW\_FIND\_TAX\_RATE: Aggregation, Finished Age Group:78 of 83, time-this-age:0.3403  
SNW\_FIND\_TAX\_RATE: Aggregation, Finished Age Group:79 of 83, time-this-age:0.34125  
SNW\_FIND\_TAX\_RATE: Aggregation, Finished Age Group:80 of 83, time-this-age:0.34101  
SNW\_FIND\_TAX\_RATE: Aggregation, Finished Age Group:81 of 83, time-this-age:0.33996  
SNW\_FIND\_TAX\_RATE: Aggregation, Finished Age Group:82 of 83, time-this-age:0.3415  
SNW\_FIND\_TAX\_RATE: Aggregation, Finished Age Group:83 of 83, time-this-age:0.36096  
SNW\_FIND\_TAX\_RATE tax a2 or a0 adjustments;a2=1.8141;a0=0.258;err=0.20414;fl\_total\_costs=16.3562;Tax  
SNW\_FIND\_TAX\_RATE tax a2 or a0 adjustments;a2=2.0964;a0=0.258;err=0.17541;fl\_total\_costs=16.3562;Tax  
SNW\_FIND\_TAX\_RATE tax a2 or a0 adjustments;a2=2.3751;a0=0.258;err=0.15331;fl\_total\_costs=16.3562;Tax  
SNW\_FIND\_TAX\_RATE tax a2 or a0 adjustments;a2=2.65;a0=0.258;err=0.13583;fl\_total\_costs=16.3562;Tax\_r  
SNW\_FIND\_TAX\_RATE tax a2 or a0 adjustments;a2=2.9208;a0=0.258;err=0.12169;fl\_total\_costs=16.3562;Tax  
SNW\_FIND\_TAX\_RATE tax a2 or a0 adjustments;a2=3.1877;a0=0.258;err=0.11003;fl\_total\_costs=16.3562;Tax  
SNW\_FIND\_TAX\_RATE tax a2 or a0 adjustments;a2=3.4506;a0=0.258;err=0.10028;fl\_total\_costs=16.3562;Tax  
SNW\_FIND\_TAX\_RATE tax a2 or a0 adjustments;a2=3.7096;a0=0.258;err=0.091993;fl\_total\_costs=16.3562;Ta  
SNW\_FIND\_TAX\_RATE tax a2 or a0 adjustments;a2=3.9648;a0=0.258;err=0.084884;fl\_total\_costs=16.3562;Ta  
SNW\_FIND\_TAX\_RATE tax a2 or a0 adjustments;a2=4.2162;a0=0.258;err=0.078718;fl\_total\_costs=16.3562;Ta  
SNW\_FIND\_TAX\_RATE tax a2 or a0 adjustments;a2=4.464;a0=0.258;err=0.073324;fl\_total\_costs=16.3562;Tax  
SNW\_FIND\_TAX\_RATE tax a2 or a0 adjustments;a2=4.7083;a0=0.258;err=0.068568;fl\_total\_costs=16.3562;Ta  
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SNW\_FIND\_TAX\_RATE tax a2 or a0 adjustments;a2=5.1866;a0=0.258;err=0.060571;fl\_total\_costs=16.3562;Ta  
SNW\_FIND\_TAX\_RATE tax a2 or a0 adjustments;a2=5.4207;a0=0.258;err=0.05718;fl\_total\_costs=16.3562;Tax  
SNW\_FIND\_TAX\_RATE tax a2 or a0 adjustments;a2=5.6517;a0=0.258;err=0.054118;fl\_total\_costs=16.3562;Ta

SNW\_FIND\_TAX\_RATE tax a2 or a0 adjustments;a2=5.8796;a0=0.258;err=0.051339;fl\_total\_costs=16.3562;Ta  
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 SNW\_FIND\_TAX\_RATE tax a2 or a0 adjustments;a2=6.3263;a0=0.258;err=0.046491;fl\_total\_costs=16.3562;Ta  
 SNW\_FIND\_TAX\_RATE tax a2 or a0 adjustments;a2=6.5454;a0=0.258;err=0.044365;fl\_total\_costs=16.3562;Ta  
 SNW\_FIND\_TAX\_RATE tax a2 or a0 adjustments;a2=6.7616;a0=0.258;err=0.042406;fl\_total\_costs=16.3562;Ta  
 SNW\_FIND\_TAX\_RATE tax a2 or a0 adjustments;a2=6.975;a0=0.258;err=0.040597;fl\_total\_costs=16.3562;Tax  
 SNW\_FIND\_TAX\_RATE tax a2 or a0 adjustments;a2=7.1858;a0=0.258;err=0.03892;fl\_total\_costs=16.3562;Tax  
 SNW\_FIND\_TAX\_RATE tax a2 or a0 adjustments;a2=7.394;a0=0.258;err=0.037362;fl\_total\_costs=16.3562;Tax  
 SNW\_FIND\_TAX\_RATE tax a2 or a0 adjustments;a2=7.5996;a0=0.258;err=0.035911;fl\_total\_costs=16.3562;Ta  
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 SNW\_FIND\_TAX\_RATE tax a2 or a0 adjustments;a2=9.1588;a0=0.258;err=0.027132;fl\_total\_costs=16.3562;Ta  
 SNW\_FIND\_TAX\_RATE tax a2 or a0 adjustments;a2=9.3437;a0=0.258;err=0.026296;fl\_total\_costs=16.3562;Ta  
 SNW\_FIND\_TAX\_RATE tax a2 or a0 adjustments;a2=9.5265;a0=0.258;err=0.025504;fl\_total\_costs=16.3562;Ta  
 SNW\_FIND\_TAX\_RATE tax a2 or a0 adjustments;a2=9.7073;a0=0.258;err=0.024751;fl\_total\_costs=16.3562;Ta  
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 SNW\_FIND\_TAX\_RATE tax a2 or a0 adjustments;a2=10.4106;a0=0.258;err=0.022089;fl\_total\_costs=16.3562;T  
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 SNW\_FIND\_TAX\_RATE tax a2 or a0 adjustments;a2=11.2479;a0=0.258;err=0.019382;fl\_total\_costs=16.3562;T  
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 SNW\_FIND\_TAX\_RATE tax a2 or a0 adjustments;a2=12.7965;a0=0.258;err=0.015373;fl\_total\_costs=16.3562;T  
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 SNW\_FIND\_TAX\_RATE tax a2 or a0 adjustments;a2=13.3732;a0=0.258;err=0.014135;fl\_total\_costs=16.3562;T  
 SNW\_FIND\_TAX\_RATE tax a2 or a0 adjustments;a2=13.5139;a0=0.258;err=0.013851;fl\_total\_costs=16.3562;T  
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 SNW\_FIND\_TAX\_RATE tax a2 or a0 adjustments;a2=14.0628;a0=0.258;err=0.0128;fl\_total\_costs=16.3562;Tax  
 SNW\_FIND\_TAX\_RATE tax a2 or a0 adjustments;a2=14.1967;a0=0.258;err=0.012557;fl\_total\_costs=16.3562;T  
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 SNW\_FIND\_TAX\_RATE tax a2 or a0 adjustments;a2=14.8472;a0=0.258;err=0.011444;fl\_total\_costs=16.3562;T  
 SNW\_FIND\_TAX\_RATE tax a2 or a0 adjustments;a2=14.9736;a0=0.258;err=0.01124;fl\_total\_costs=16.3562;Ta  
 SNW\_FIND\_TAX\_RATE tax a2 or a0 adjustments;a2=15.0988;a0=0.258;err=0.011041;fl\_total\_costs=16.3562;T  
 SNW\_FIND\_TAX\_RATE tax a2 or a0 adjustments;a2=15.2228;a0=0.258;err=0.010848;fl\_total\_costs=16.3562;T  
 SNW\_FIND\_TAX\_RATE tax a2 or a0 adjustments;a2=15.3456;a0=0.258;err=0.01066;fl\_total\_costs=16.3562;Ta

```

SNW_FIND_TAX_RATE tax a2 or a0 adjustments;a2=15.4673;a0=0.258;err=0.010477;fl_total_costs=16.3562;T
SNW_FIND_TAX_RATE tax a2 or a0 adjustments;a2=15.5879;a0=0.258;err=0.010299;fl_total_costs=16.3562;T
SNW_FIND_TAX_RATE tax a2 or a0 adjustments;a2=15.7073;a0=0.258;err=0.010126;fl_total_costs=16.3562;T
SNW_FIND_TAX_RATE tax a2 or a0 adjustments;a2=15.8257;a0=0.258;err=0.0099566;fl_total_costs=16.3562;T
SNW_FIND_TAX_RATE tax a2 or a0 adjustments;a2=15.9429;a0=0.258;err=0.0097918;fl_total_costs=16.3562;T
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SNW_FIND_TAX_RATE tax a2 or a0 adjustments;a2=16.1741;a0=0.258;err=0.0094744;fl_total_costs=16.3562;T
SNW_FIND_TAX_RATE tax a2 or a0 adjustments;a2=16.2881;a0=0.258;err=0.0093215;fl_total_costs=16.3562;T
SNW_FIND_TAX_RATE tax a2 or a0 adjustments;a2=16.4011;a0=0.258;err=0.0091723;fl_total_costs=16.3562;T
SNW_FIND_TAX_RATE tax a2 or a0 adjustments;a2=16.513;a0=0.258;err=0.0090267;fl_total_costs=16.3562;T
SNW_FIND_TAX_RATE tax a2 or a0 adjustments;a2=16.6239;a0=0.258;err=0.0088845;fl_total_costs=16.3562;T
SNW_FIND_TAX_RATE tax a2 or a0 adjustments;a2=16.7338;a0=0.258;err=0.0087457;fl_total_costs=16.3562;T
SNW_FIND_TAX_RATE tax a2 or a0 adjustments;a2=16.8426;a0=0.258;err=0.0086101;fl_total_costs=16.3562;T
SNW_FIND_TAX_RATE tax a2 or a0 adjustments;a2=16.9505;a0=0.258;err=0.0084776;fl_total_costs=16.3562;T
SNW_FIND_TAX_RATE tax a2 or a0 adjustments;a2=17.0574;a0=0.258;err=0.0083482;fl_total_costs=16.3562;T
SNW_FIND_TAX_RATE tax a2 or a0 adjustments;a2=17.1634;a0=0.258;err=0.0082216;fl_total_costs=16.3562;T
SNW_FIND_TAX_RATE tax a2 or a0 adjustments;a2=17.2684;a0=0.258;err=0.0080979;fl_total_costs=16.3562;T
SNW_FIND_TAX_RATE tax a2 or a0 adjustments;a2=17.3724;a0=0.258;err=0.0079769;fl_total_costs=16.3562;T
SNW_FIND_TAX_RATE tax a2 or a0 adjustments;a2=17.4755;a0=0.258;err=0.0078586;fl_total_costs=16.3562;T
SNW_FIND_TAX_RATE tax a2 or a0 adjustments;a2=17.5777;a0=0.258;err=0.0077428;fl_total_costs=16.3562;T
SNW_FIND_TAX_RATE tax a2 or a0 adjustments;a2=17.6789;a0=0.258;err=0.0076295;fl_total_costs=16.3562;T
SNW_FIND_TAX_RATE tax a2 or a0 adjustments;a2=17.7793;a0=0.258;err=0.0075186;fl_total_costs=16.3562;T
SNW_FIND_TAX_RATE tax a2 or a0 adjustments;a2=17.8787;a0=0.258;err=0.0074101;fl_total_costs=16.3562;T
SNW_FIND_TAX_RATE tax a2 or a0 adjustments;a2=17.9773;a0=0.258;err=0.0073038;fl_total_costs=16.3562;T
SNW_FIND_TAX_RATE tax a2 or a0 adjustments;a2=18.075;a0=0.258;err=0.0071997;fl_total_costs=16.3562;T
SNW_FIND_TAX_RATE tax a2 or a0 adjustments;a2=18.1718;a0=0.258;err=0.0070978;fl_total_costs=16.3562;T
SNW_FIND_TAX_RATE tax a2 or a0 adjustments;a2=18.2678;a0=0.258;err=0.006998;fl_total_costs=16.3562;T
-----
--- SNW_FIND_TAX_RATE finished -
xxxxxxxxxxxxxxxxxxxxxxxxxxxxxxxxxxxxxxxxxxxx
xxxxxxxxxxxxxxxxxxxxxxxxxxxxxxxxxxxxxxxxxxxx
xxxxxxxxxxxxxxxxxxxxxxxxxxxxxxxxxxxxxxxxxxxx
SNW_FIND_TAX_RATE: Number of a2-adjustments (for taxation) used to balance the government budget= 10
SNW_FIND_TAX_RATE info A;a2_new=18.2678;a2_guess_orig(mana-heaven)=1.5286;a0_new=0.258;a0_guess_orig
SNW_FIND_TAX_RATE info B;Y_inc_agg=61.7582;Y_inc_agg_COVID=58.8608;GPD_COVID_CHANGE=0.046915;Y_inc_a
SNW_FIND_TAX_RATE info C;Covid_checks_per_capita=0.02996;Covid_checks_share_of_GDP=0.022215
SNW_FIND_TAX_RATE info D;UI_benefits=1.9702;SS_spend=2.1597;Gov_cons=10.8544;Covid_checks=1.372;Tax_
xxxxxxxxxxxxxxxxxxxxxxxxxxxxxxxxxxxxxxxxxxxx
-----

```

## 11.2 Existing Stimulus as a Function of Income and Family Status

Taking advantage of [snw\\_stimulus\\_checks](#) from the [PrjOptiSNW Package](#), this function presents stimulus checks at different income levels for households with different children count and marital status. The function considers the first as well as the second stimulus check.

### 11.2.1 Trump Stimulus Checks for Unmarried Households

Check base amount per adult and per child for the first and second rounds.

```

[fl_stimulus_adult_first, fl_stimulus_child_first] = deal(1200, 500);
[fl_stimulus_adult_second, fl_stimulus_child_second] = deal(600, 600);
bl_visualize = true;

```

Visualize stimulus check amounts.

```

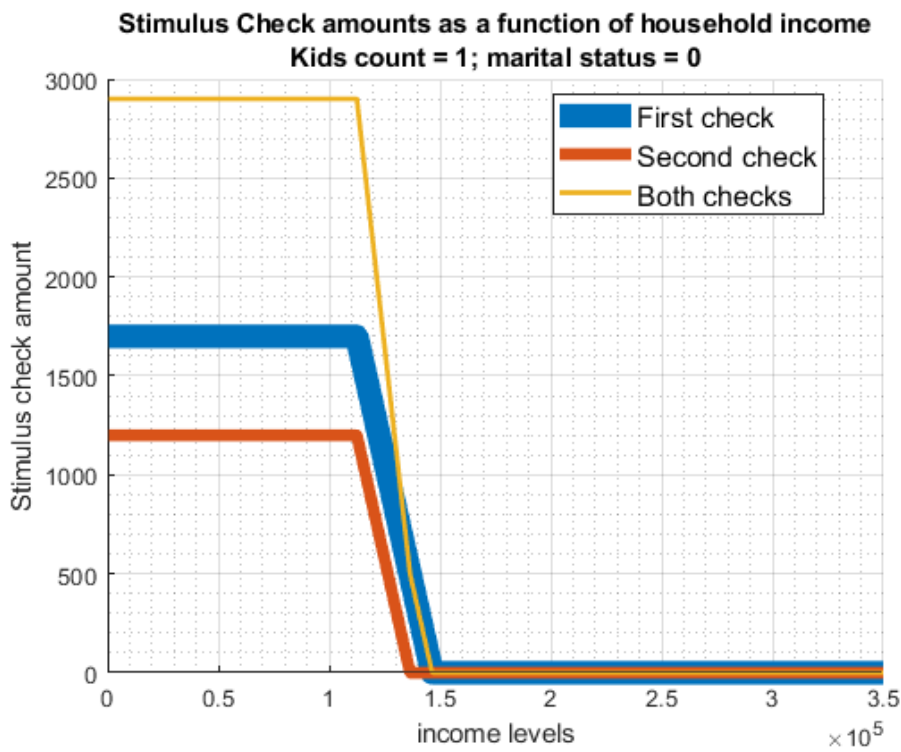
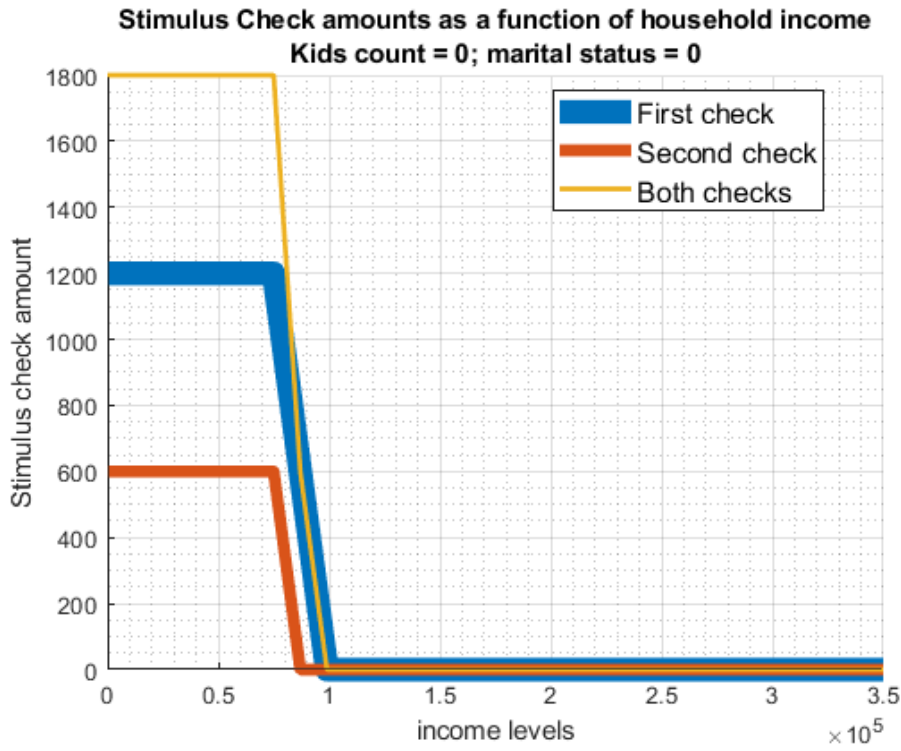
bl_marital = 0;
for it_kids=0:1:4

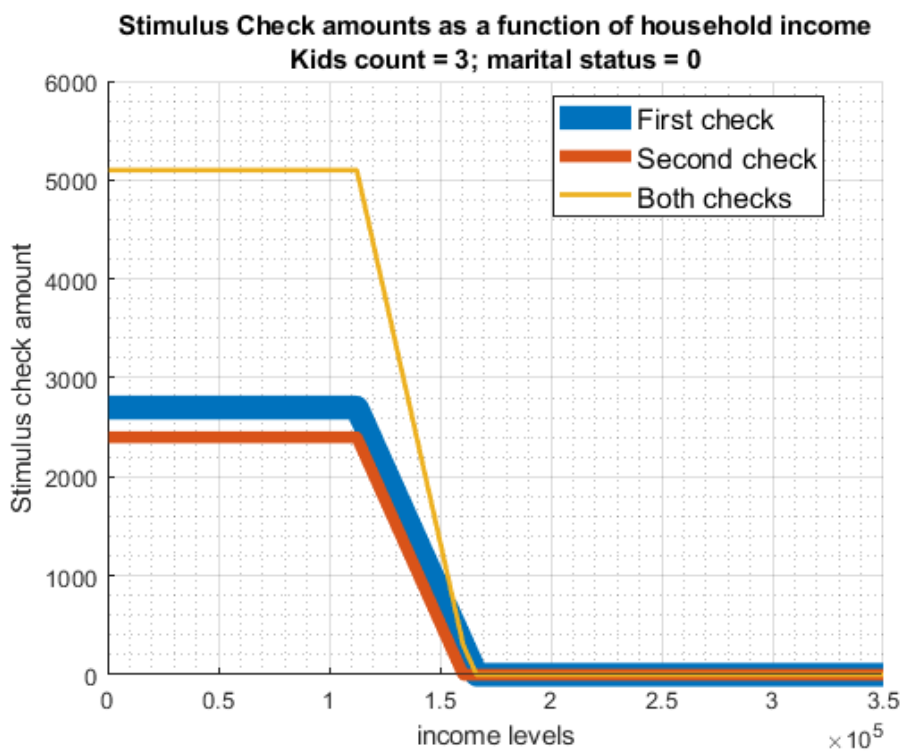
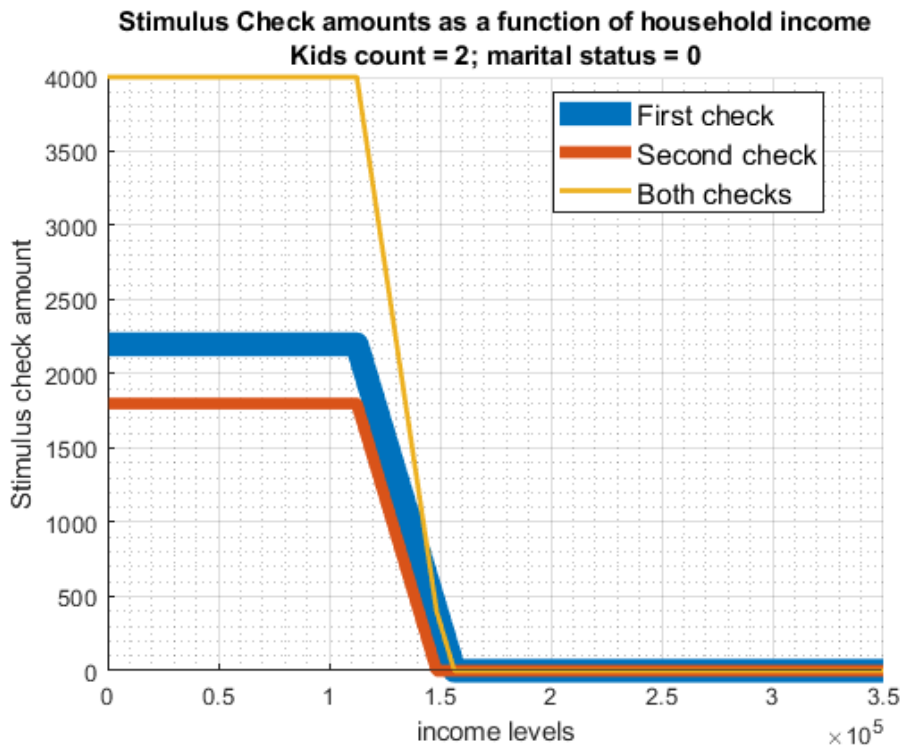
```

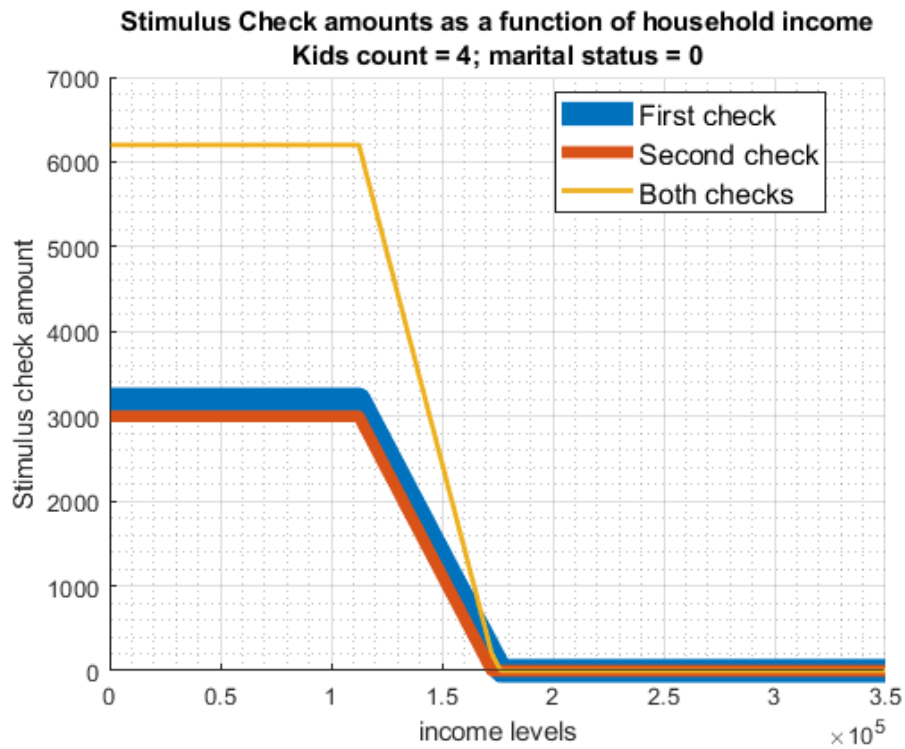
```

snw_stimulus_checks(it_kids, bl_marital, ...
    fl_stimulus_adult_first, fl_stimulus_child_first, ...
    fl_stimulus_adult_second, fl_stimulus_child_second, ...
    bl_visualize);
end

```





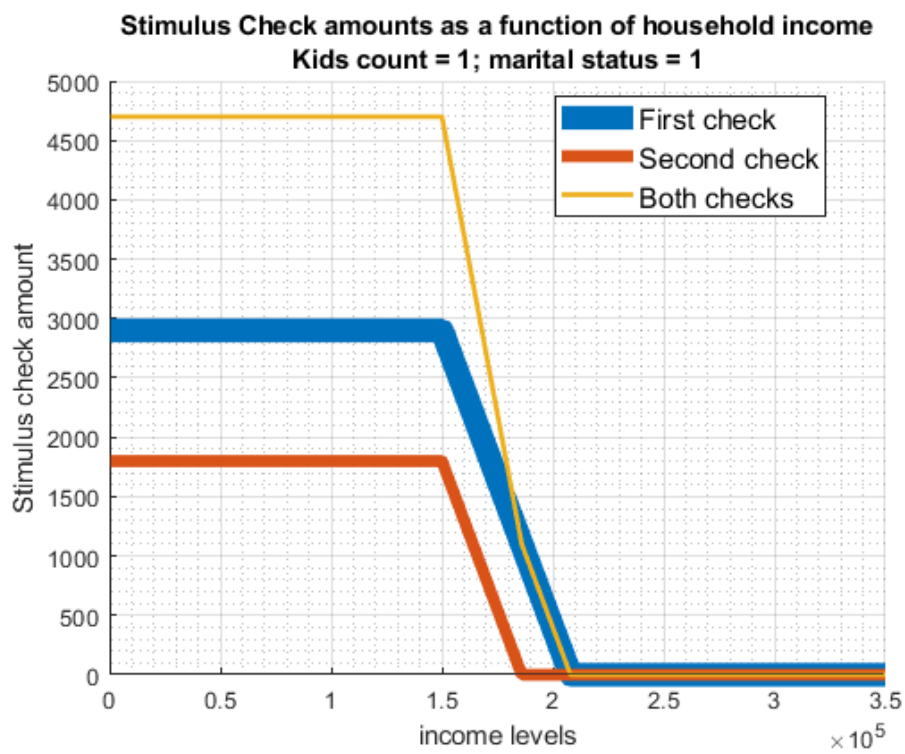
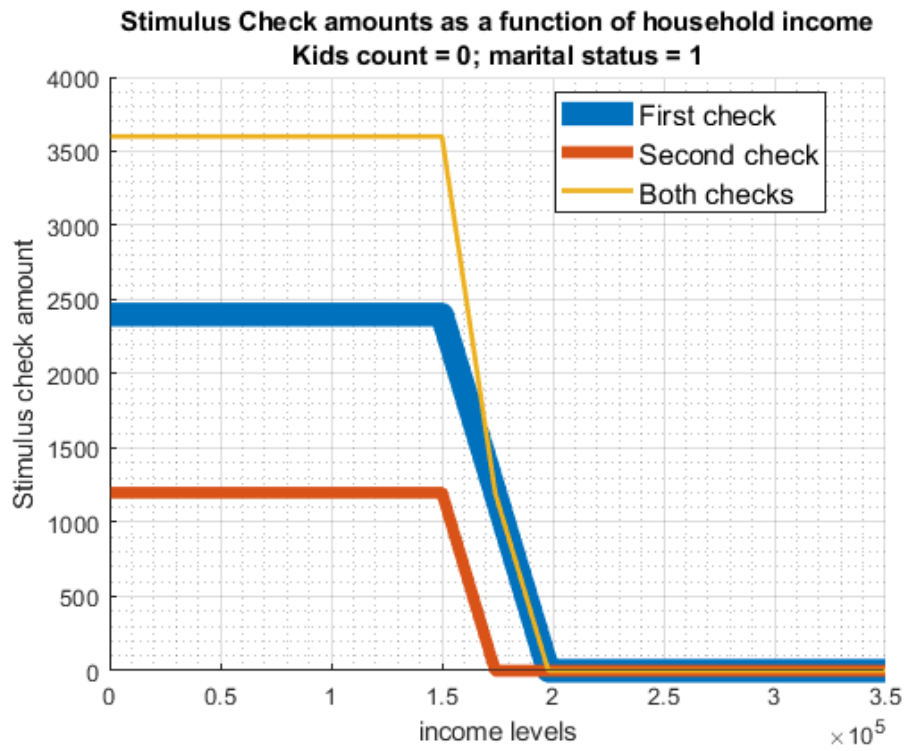


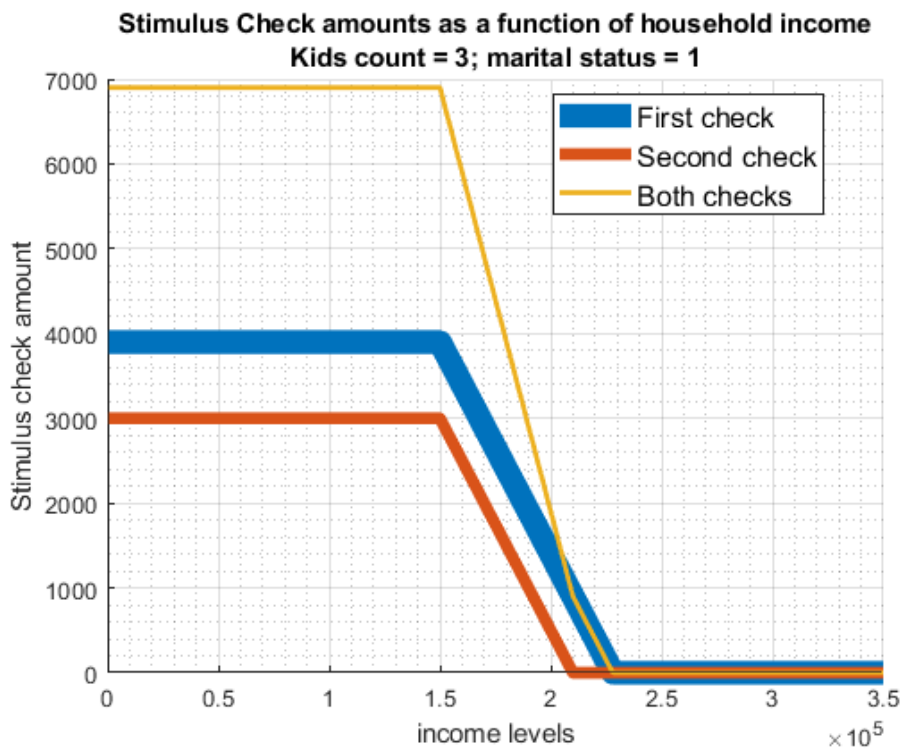
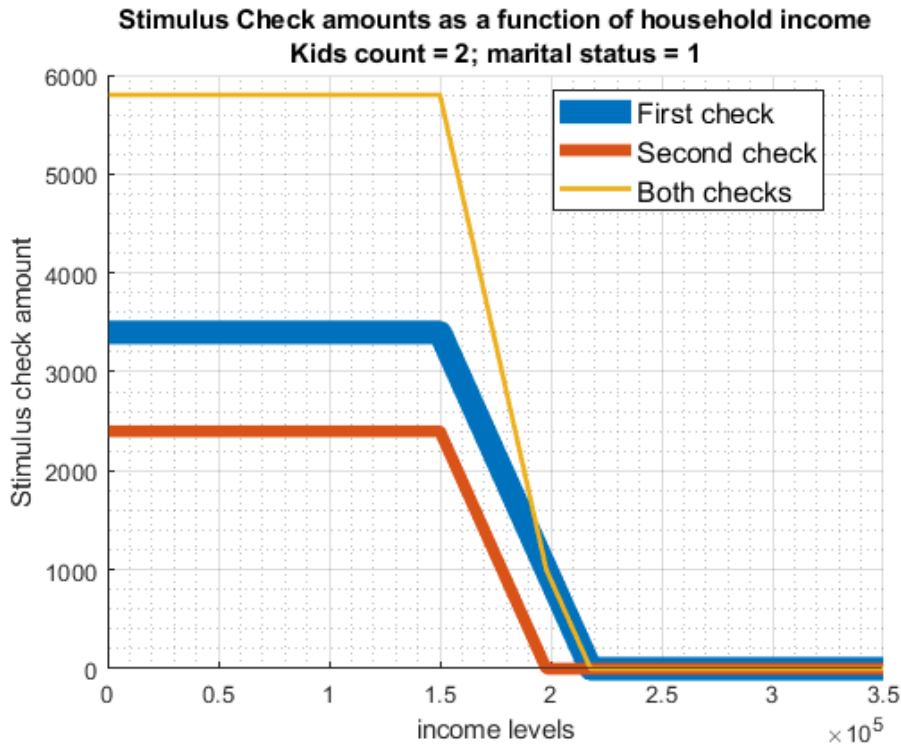
### 11.2.2 Trump Stimulus Checks for Married Households

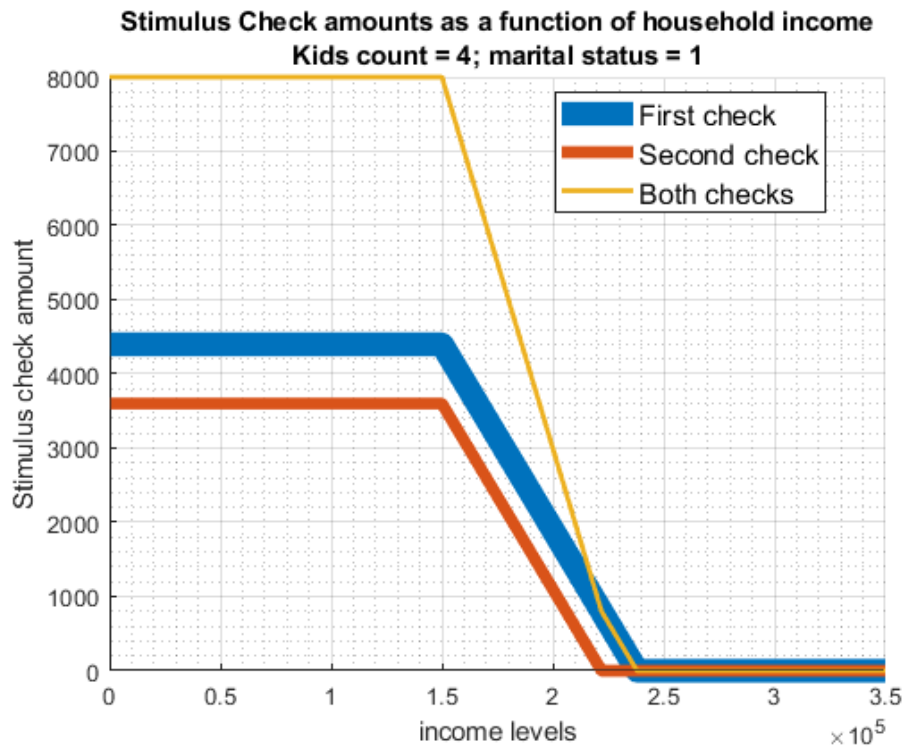
Visualize stimulus check amounts.

```
bl_marital = 1;
for it_kids=0:1:4
    snw_stimulus_checks(it_kids, bl_marital, ...
        fl_stimulus_adult_first, fl_stimulus_child_first, ...
        fl_stimulus_adult_second, fl_stimulus_child_second, ...
        bl_visualize);
end
```









## 11.3 Existing Stimulus as a Function of Income and Family Status

Taking advantage of `snw_stimulus_checks_biden` from the [PrjOptiSNW Package](#), this function presents stimulus checks at different income levels for households with different children count and marital status. This is for the Biden Stimulus under the [American Rescue Plan Act](#).

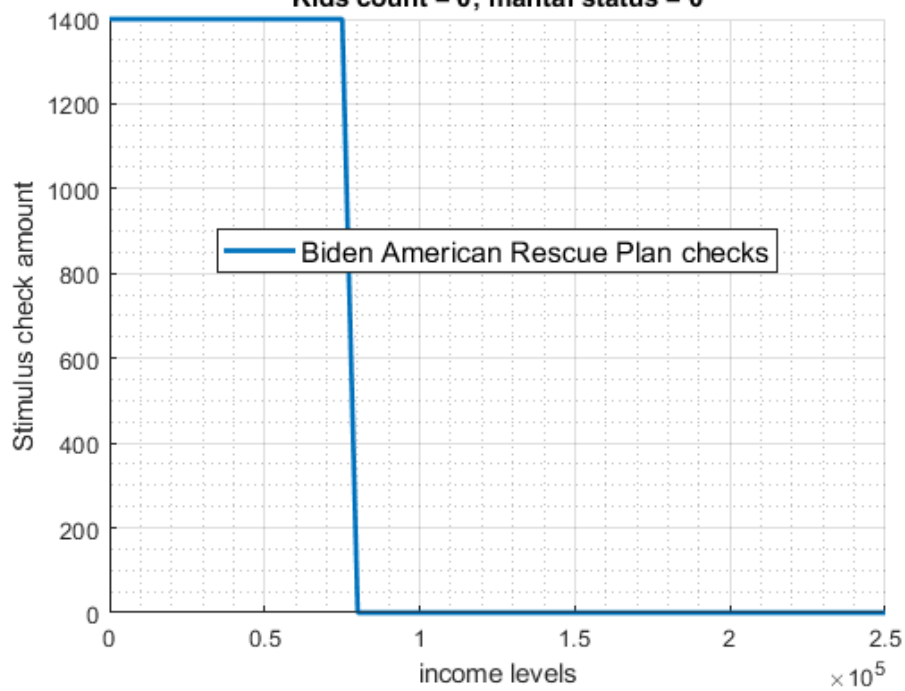
### 11.3.1 Biden Stimulus Checks for Unmarried Households

Check base amount per adult and per child for the first and second rounds.

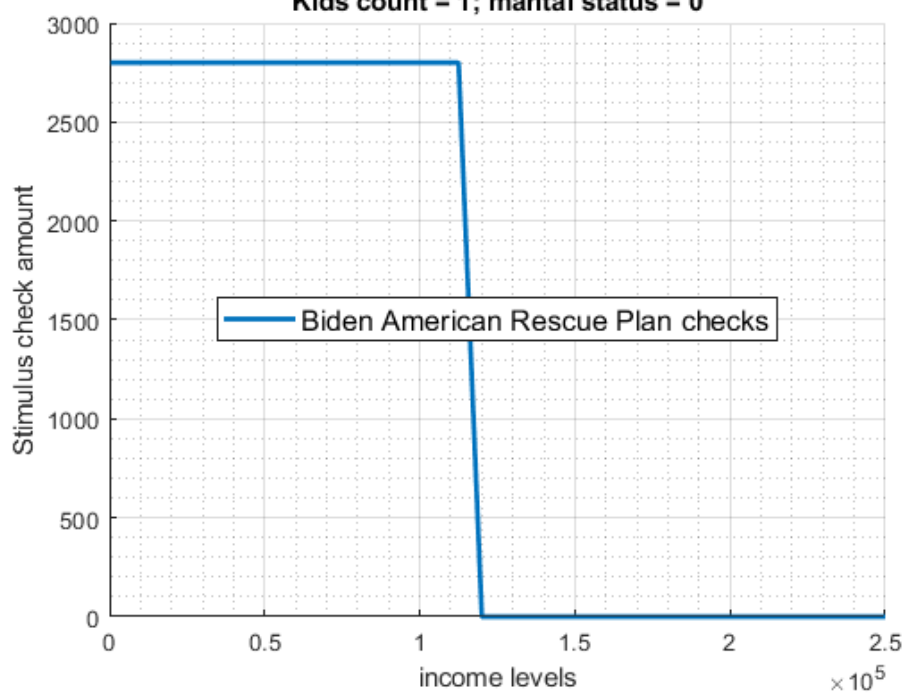
Visualize stimulus check amounts.

```
bl_visualize = true;
bl_marital = 0;
for it_kids=0:1:4
    snw_stimulus_checks_biden(it_kids, bl_marital, bl_visualize);
end
```

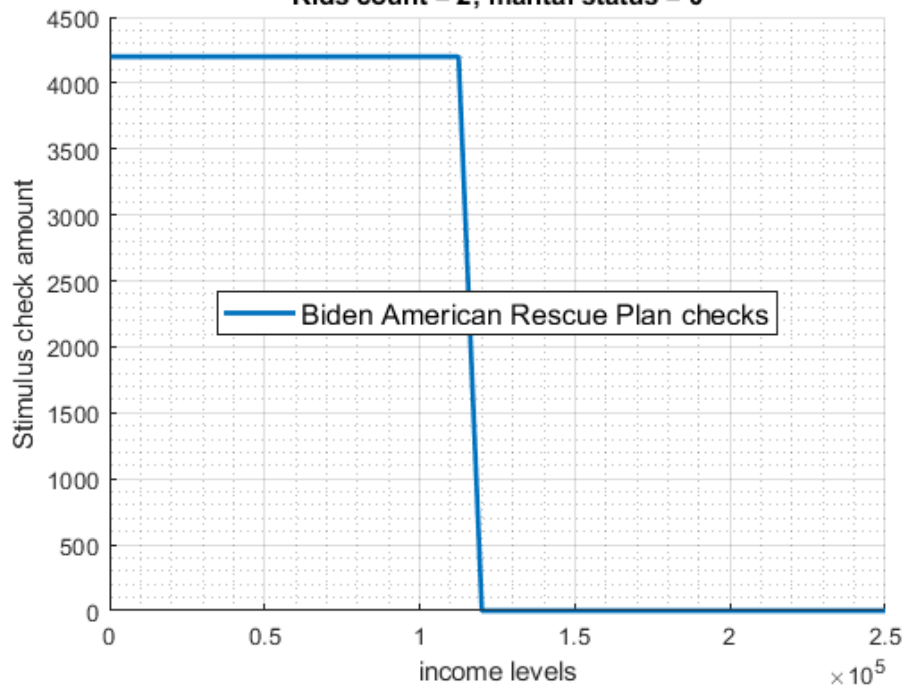
ten stimulus check amounts as a function of household income (under consideration):  
Kids count = 0; marital status = 0



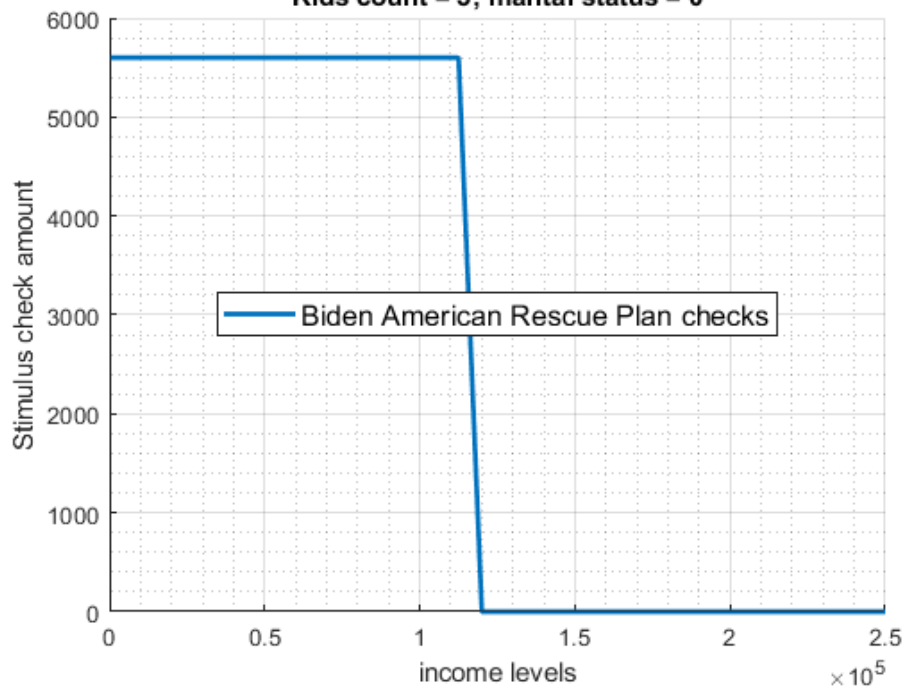
ten stimulus check amounts as a function of household income (under consideration):  
Kids count = 1; marital status = 0



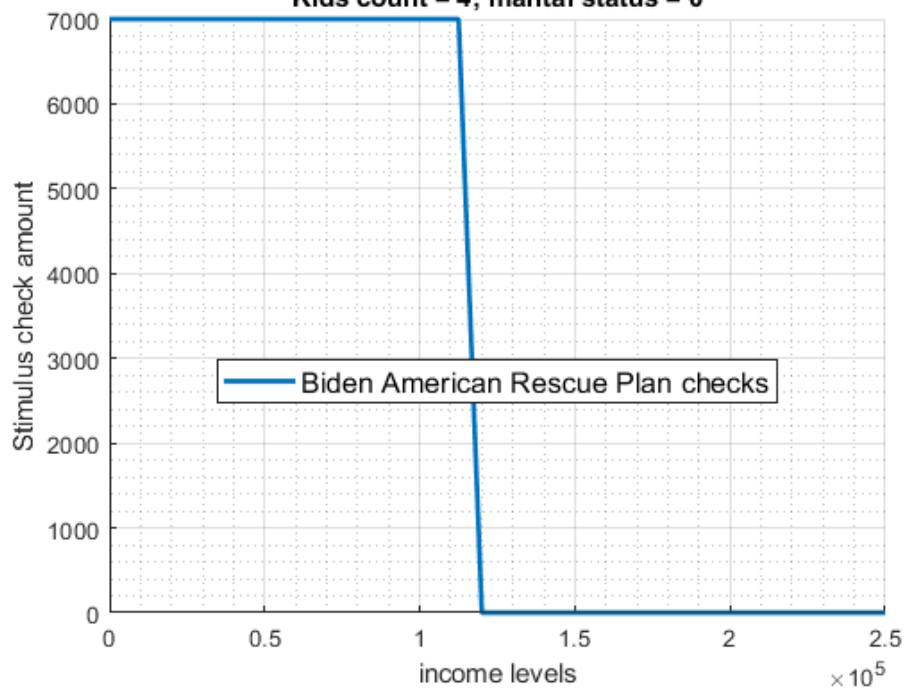
ten stimulus check amounts as a function of household income (under consider:  
Kids count = 2; marital status = 0



ten stimulus check amounts as a function of household income (under consider:  
Kids count = 3; marital status = 0



ten stimulus check amounts as a function of household income (under consider:  
Kids count = 4; marital status = 0

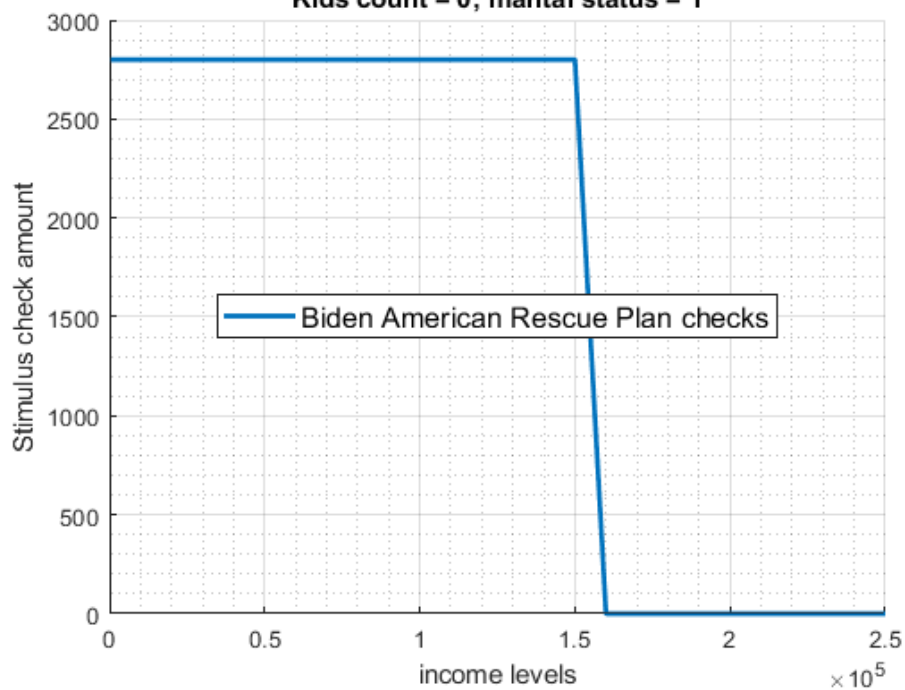


### 11.3.2 Biden Stimulus Checks for Married Households

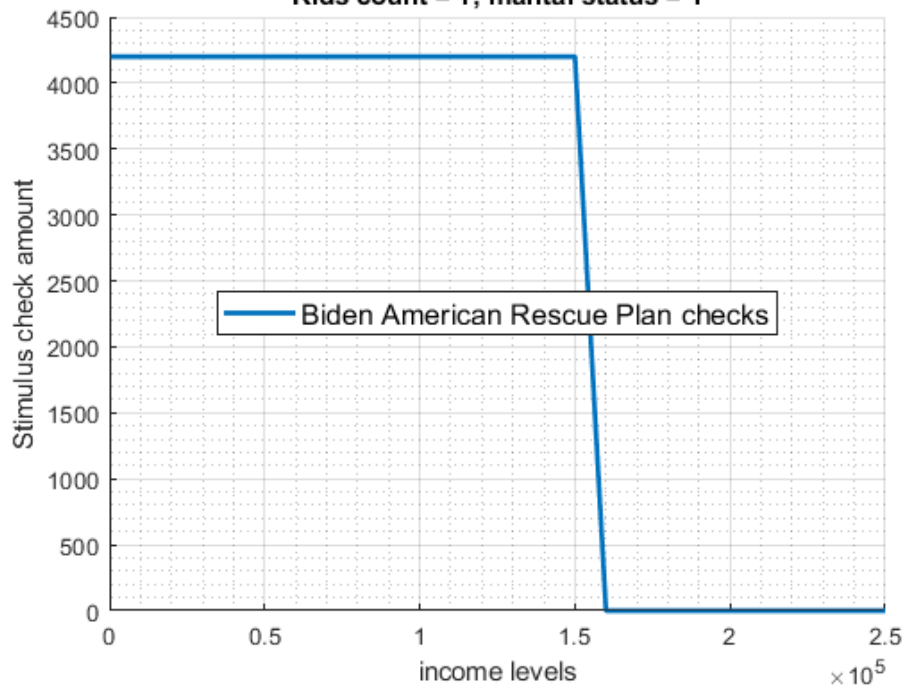
Visualize stimulus check amounts.

```
bl_marital = 1;
for it_kids=0:1:4
    snw_stimulus_checks_biden(it_kids, bl_marital, bl_visualize);
end
```

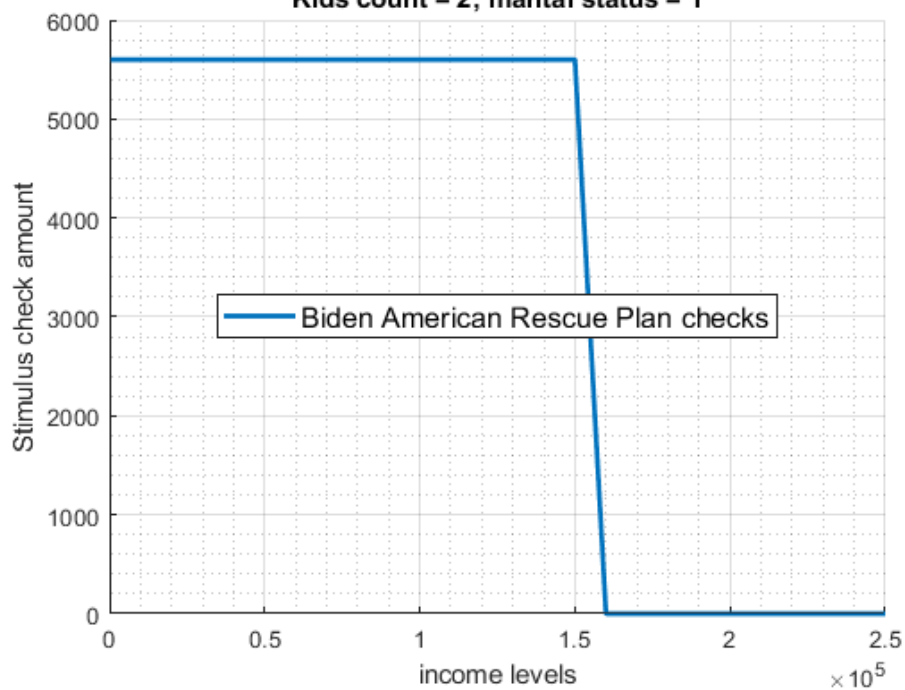
ten stimulus check amounts as a function of household income (under consider:  
Kids count = 0; marital status = 1



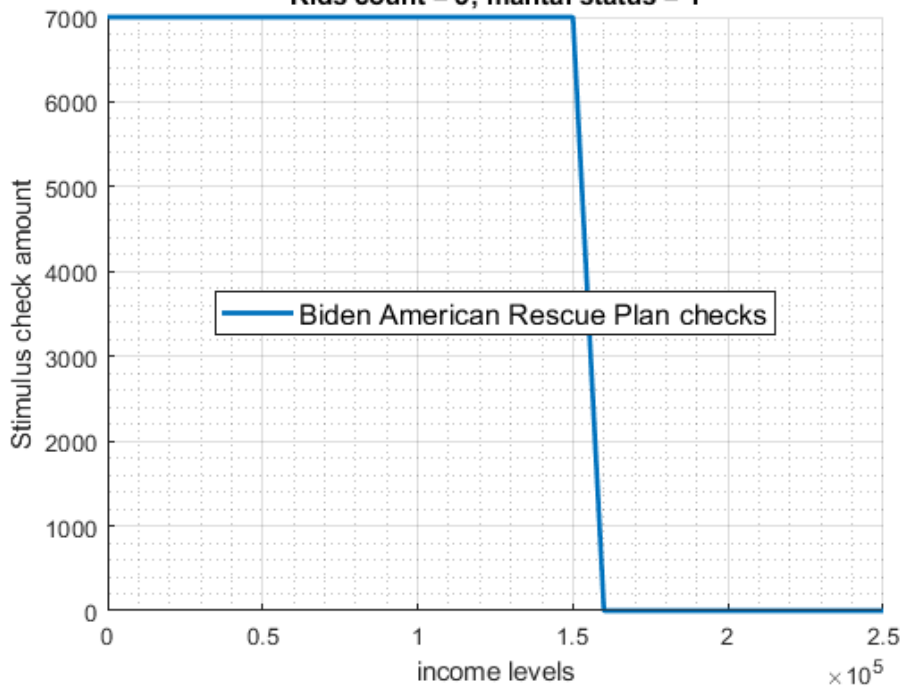
ten stimulus check amounts as a function of household income (under consider:  
Kids count = 1; marital status = 1



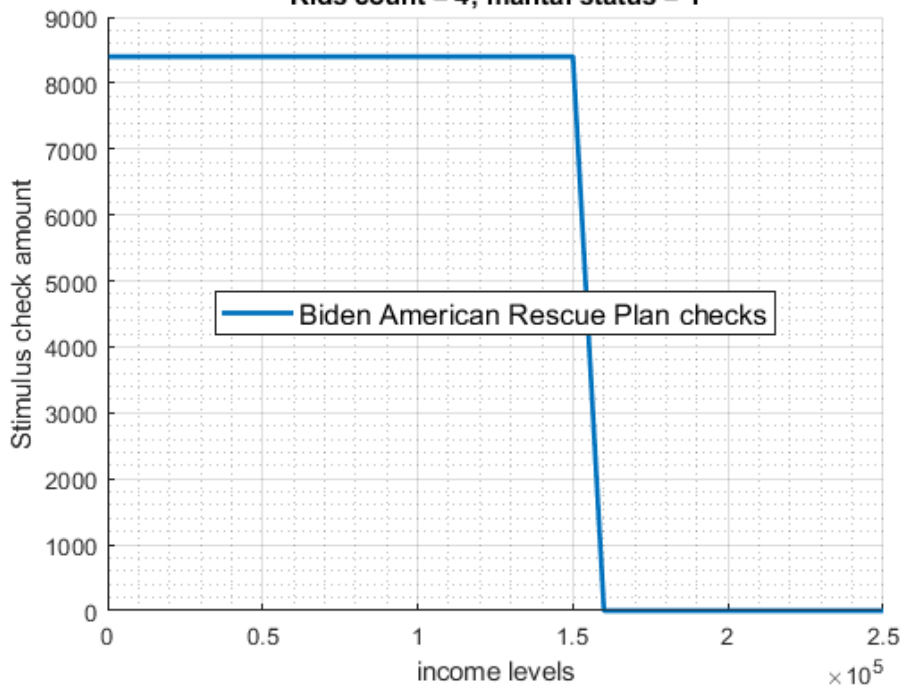
ten stimulus check amounts as a function of household income (under consider:  
Kids count = 2; marital status = 1



ten stimulus check amounts as a function of household income (under consideration: Kids count = 3; marital status = 1)



ten stimulus check amounts as a function of household income (under consideration: Kids count = 4; marital status = 1)



## 11.4 Taxable Income and Tax Liabilities in 2008

Taking advantage of `snw_tax_liability` from the [PrjOptiSNW Package](#), the function solves for tax liability.

We can study the effects of the 2008 Tax Rebate. The Tax rebate is a rebate based on how much tax was paid, so we need to know taxable income and tax liability. These differ by income, household marital status, and the count of children. Given an array of pre-tax income values, we compute for from 0 to 4 kids and both married and unmarried taxable-income and tax-liability at all points along the income

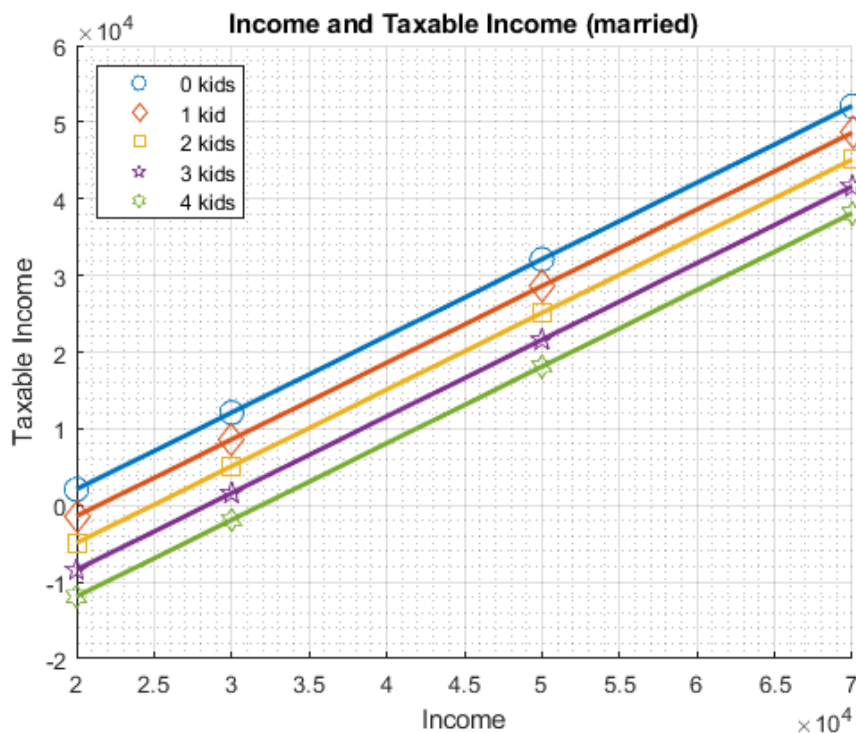
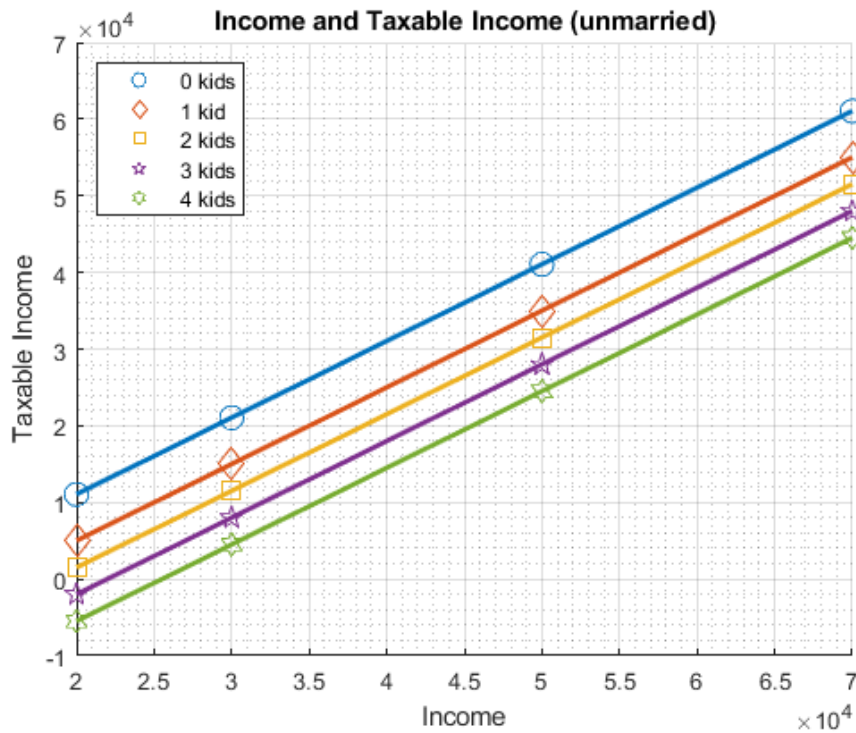


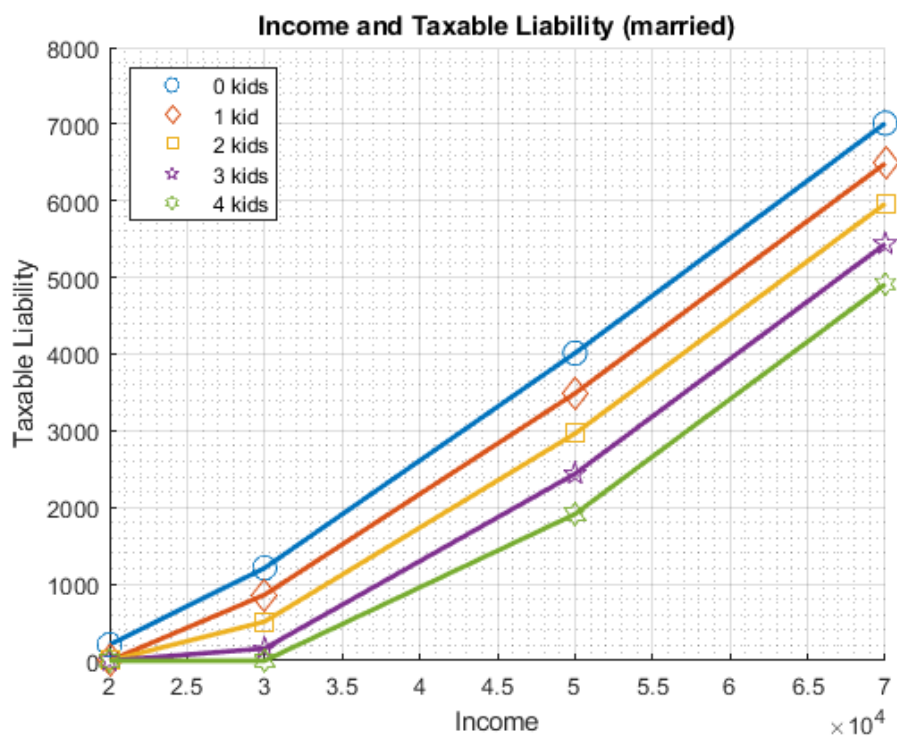
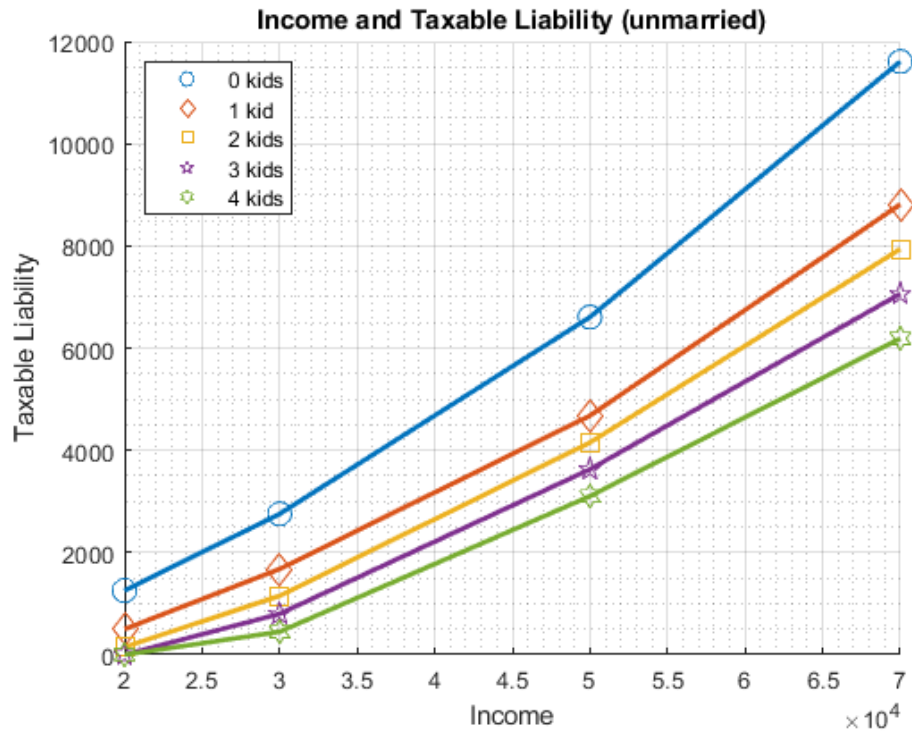
array. Deductions are from 2008 income (2008 IRS f1040). Tax brackets from 2008 are here (2008 IRS 1040tt).

### 11.4.1 Taxable Income and Tax Liabilities in 2008 for 4 Income Levels

Call the function at four income levels. Solve for different kids count and by marital status.

```
bl_visualize = true;
ar_income = [20000, 30000, 50000, 70000];
snw_tax_liability(ar_income, true);
```

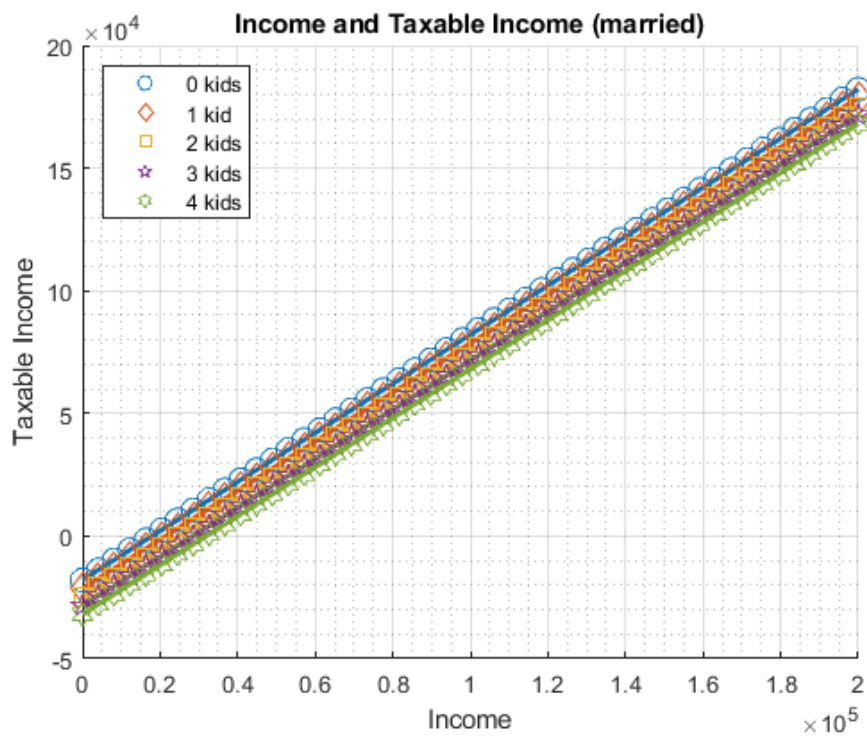
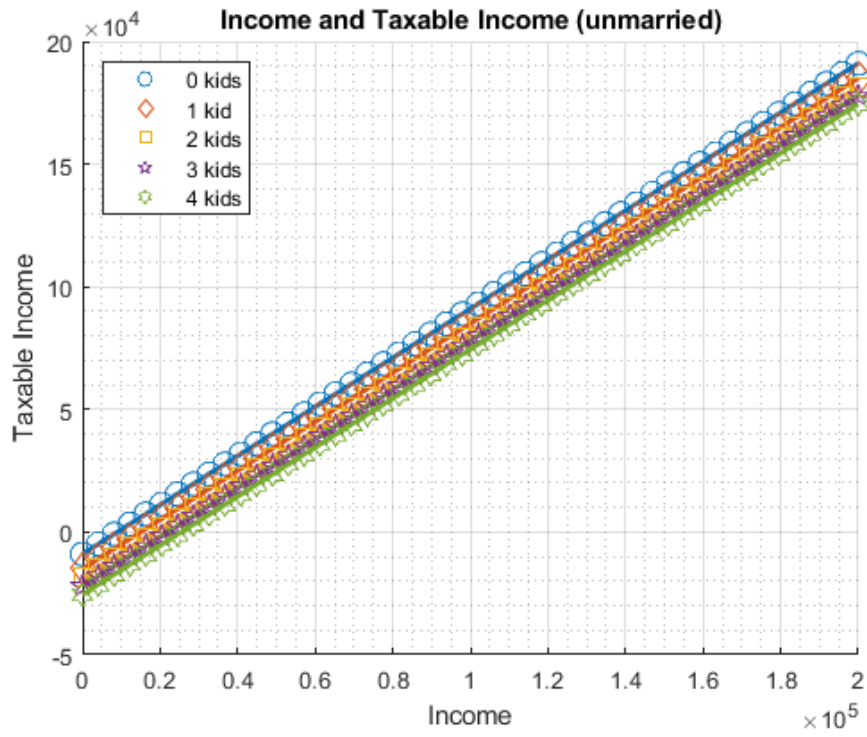


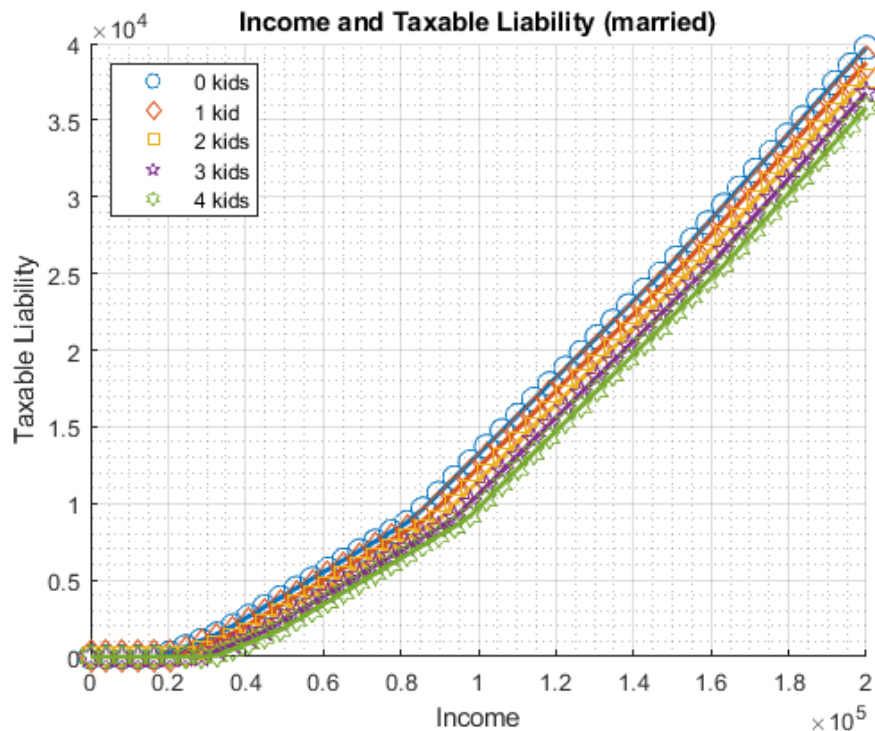
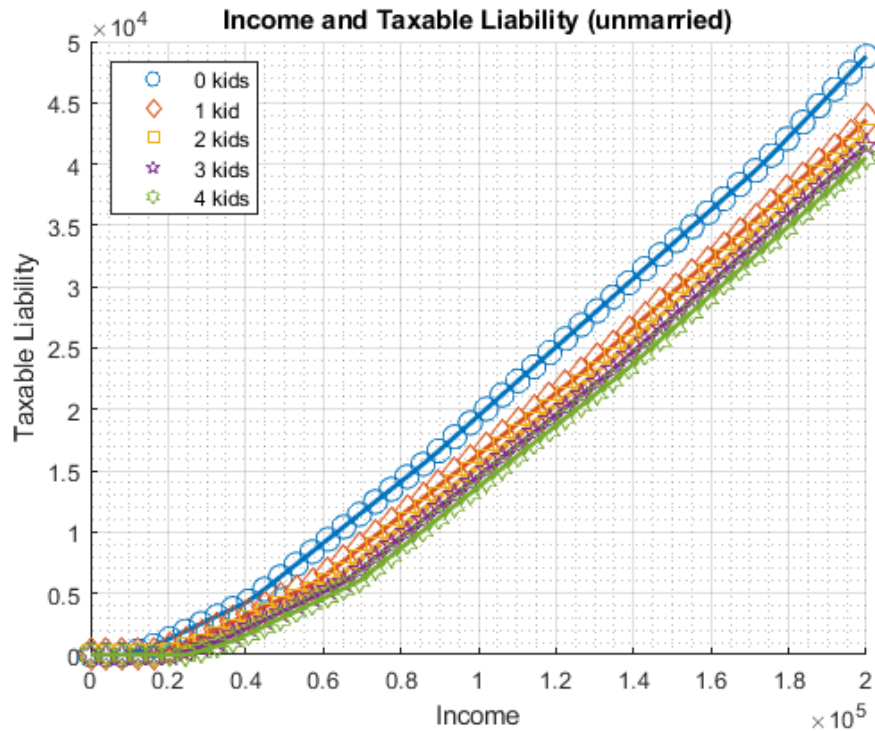


### 11.4.2 Taxable Income and Tax Liabilities in 2008 for 50 Income Levels

Call the function for incomes from 0 to 200k. Solve for different kids count and by marital status.

```
bl_visualize = true;
ar_income = linspace(0, 2e5, 50);
snw_tax_liability(ar_income, true);
```





## 11.5 Bush 2008 Stimulus as a Function of Income and Family Status

Taking advantage of `snw_stimulus_checks_bush` from the [PrjOptiSNW Package](#), this function presents stimulus checks at different income levels for households with different children count and marital status. The function considers the bush stimulus checks from the [Economic Stimulus Act of 2008](#). IRS information provides information at the [Economic Stimulus Payment Information Center](#).

Note that the Bush stimulus is a tax rebate, so we compute tax liability based on `snw_tax_liability`.

The Stimulus policy is expressed in the following formula, first four components ( $M$  is marital status, equals to 1 for married, 0 for unmarried,  $K$  is the number of kids,  $Y$  is pre-tax income) :

- $\text{MinChk}(M) = 300 \cdot (1 + M)$
- $\text{CappedRebate}(Y, K, M) = \min(\text{TaxLiability}(Y, K, M), 600 \cdot (1 + M))$
- $\text{PhaseOut}(Y, M) = \max(0, Y - 75000 \cdot (1 + M)) \cdot 0.05$
- $\text{KidsChk}(K) = 300 \cdot K$

Overall Tax-rebate Stimulus is:

$$\text{Bush08StimulusTaxRebate} = \max\left(\max\left(\text{MinChk}(M), \text{CappedRebate}(Y, K, M)\right) + \text{KidsChk}(K) - \text{PhaseOut}(Y, M), 0\right)$$

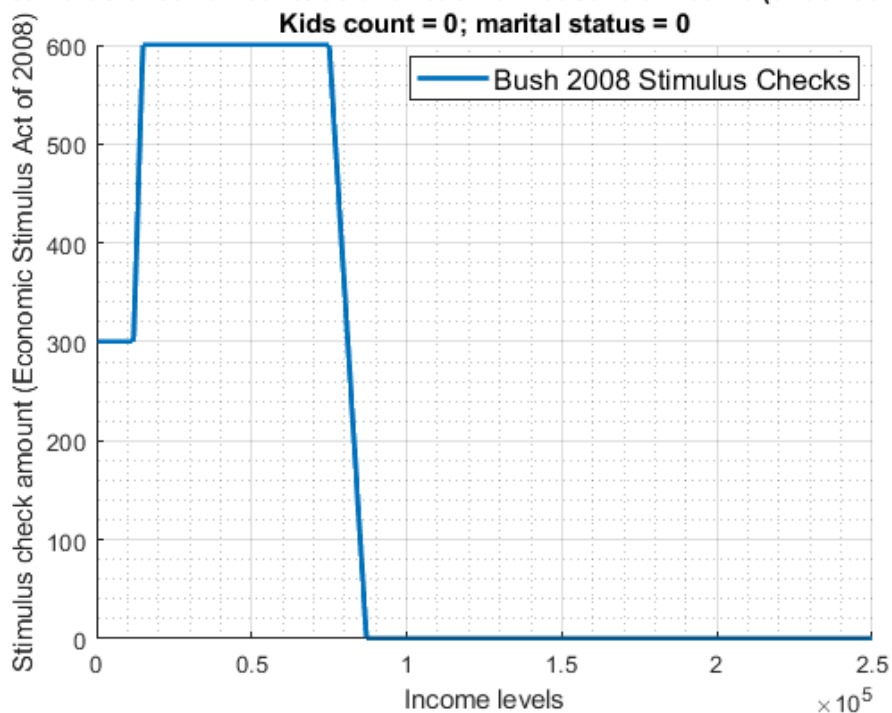
### 11.5.1 Bush Stimulus Checks for Unmarried Households

Check base amount per adult and per child for the first and second rounds.

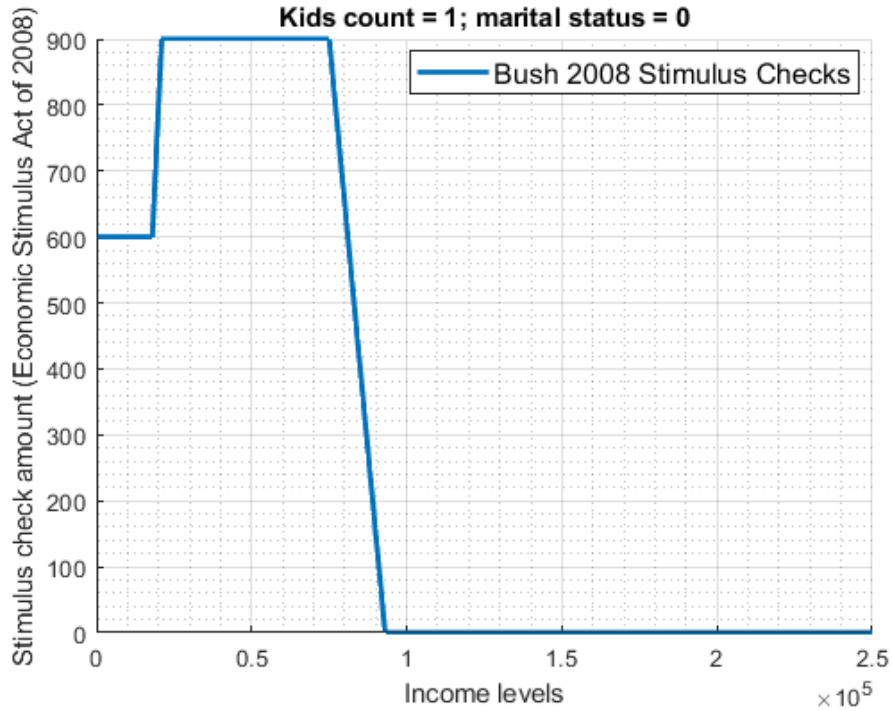
Visualize stimulus check amounts.

```
bl_visualize = true;
[fl_stimulus_adult, fl_stimulus_child] = deal(600, 300);
bl_marital = 0;
for it_kids=0:1:4
    snw_stimulus_checks_bush(it_kids, bl_marital, fl_stimulus_adult, fl_stimulus_child, bl_visualize)
end
```

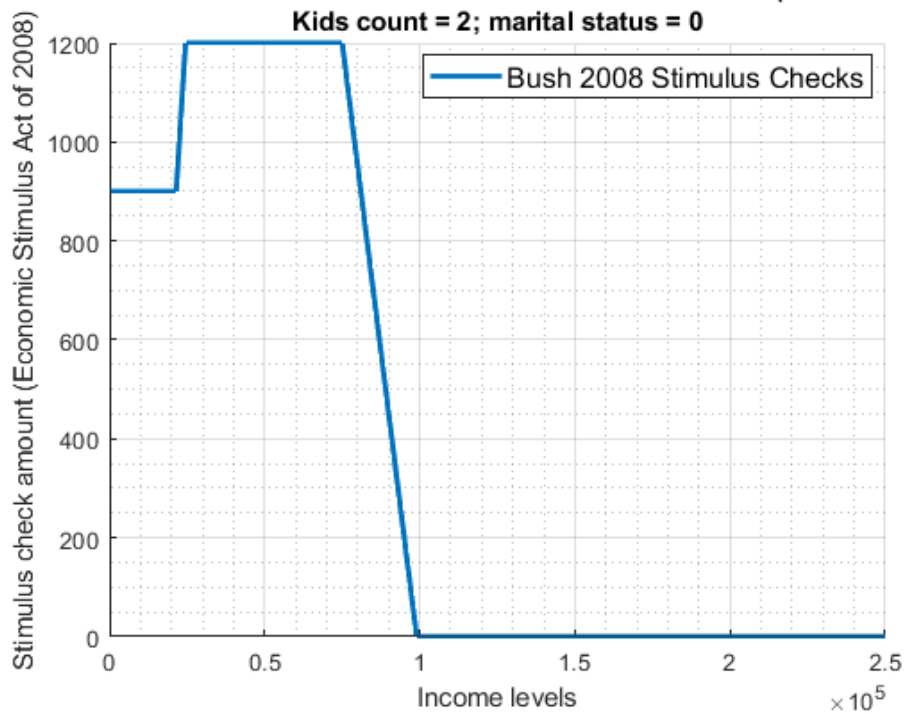
ish stimulus check amounts as a function of household income (under consider:



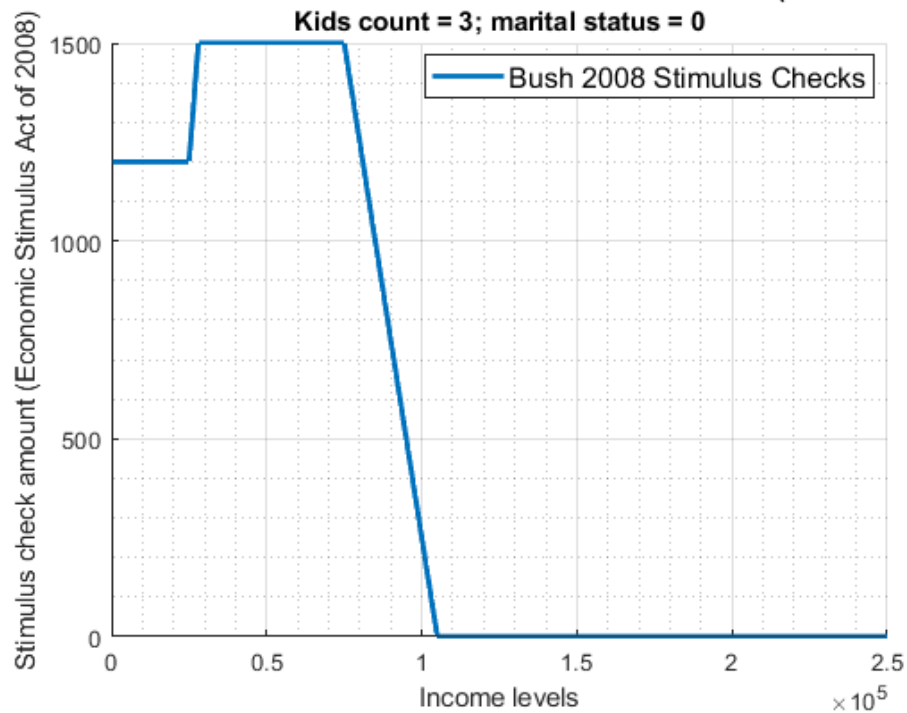
ish stimulus check amounts as a function of household income (under consider:  
Kids count = 1; marital status = 0



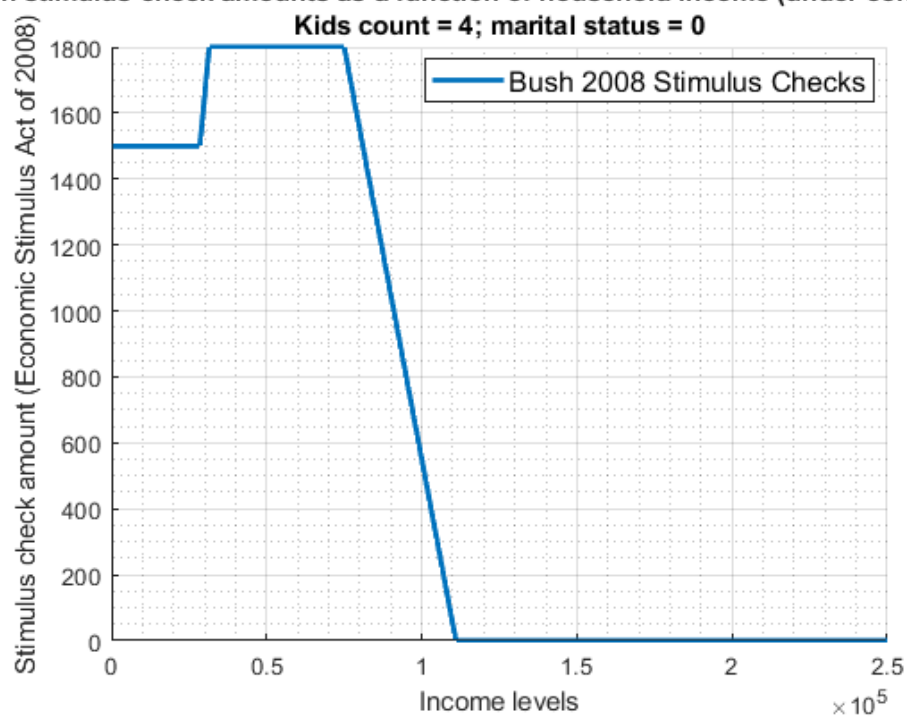
ish stimulus check amounts as a function of household income (under consider:  
Kids count = 2; marital status = 0



ish stimulus check amounts as a function of household income (under consider:



ish stimulus check amounts as a function of household income (under consider:



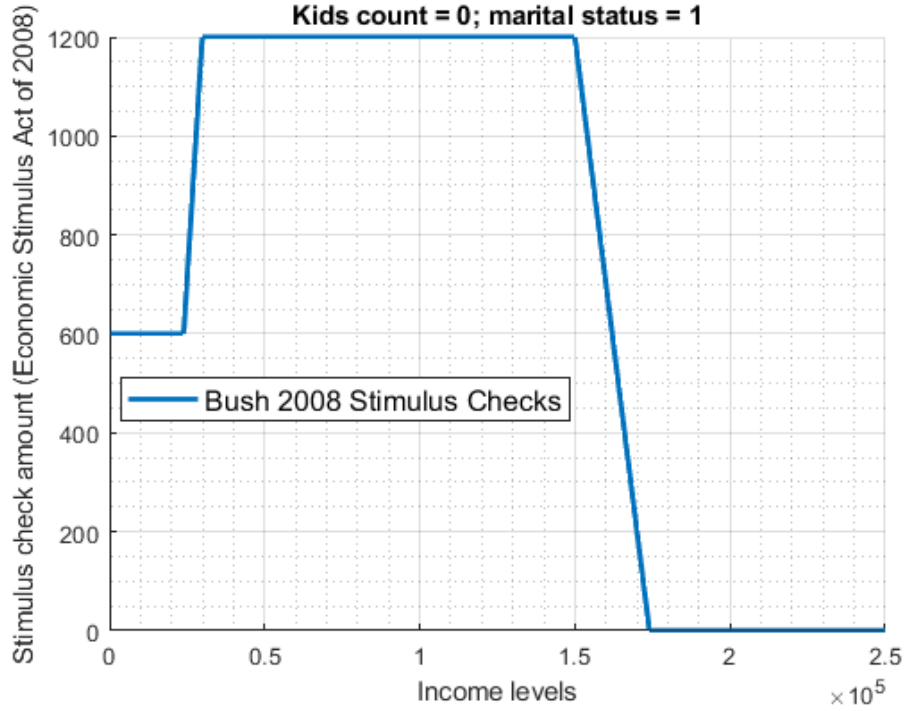
### 11.5.2 Bush Stimulus Checks for Married Households

Visualize stimulus check amounts.

```
[fl_stimulus_adult, fl_stimulus_child] = deal(600, 300);
bl_marital = 1;
for it_kids=0:1:4
    snw_stimulus_checks_bush(it_kids, bl_marital, fl_stimulus_adult, fl_stimulus_child, bl_visualize)
end
```

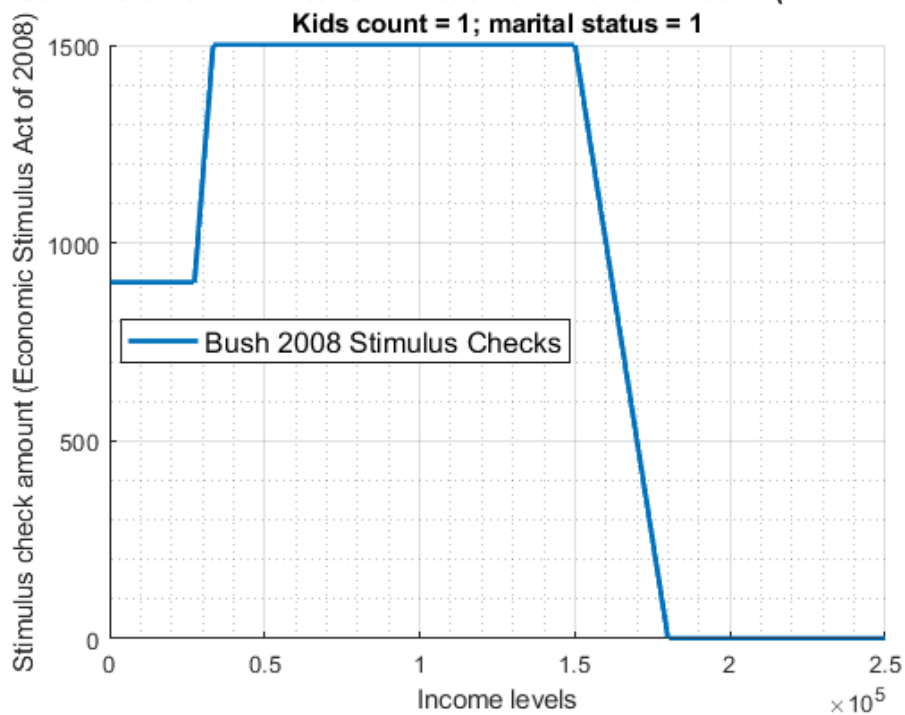
ish stimulus check amounts as a function of household income (under consider:

Kids count = 0; marital status = 1



ish stimulus check amounts as a function of household income (under consider:

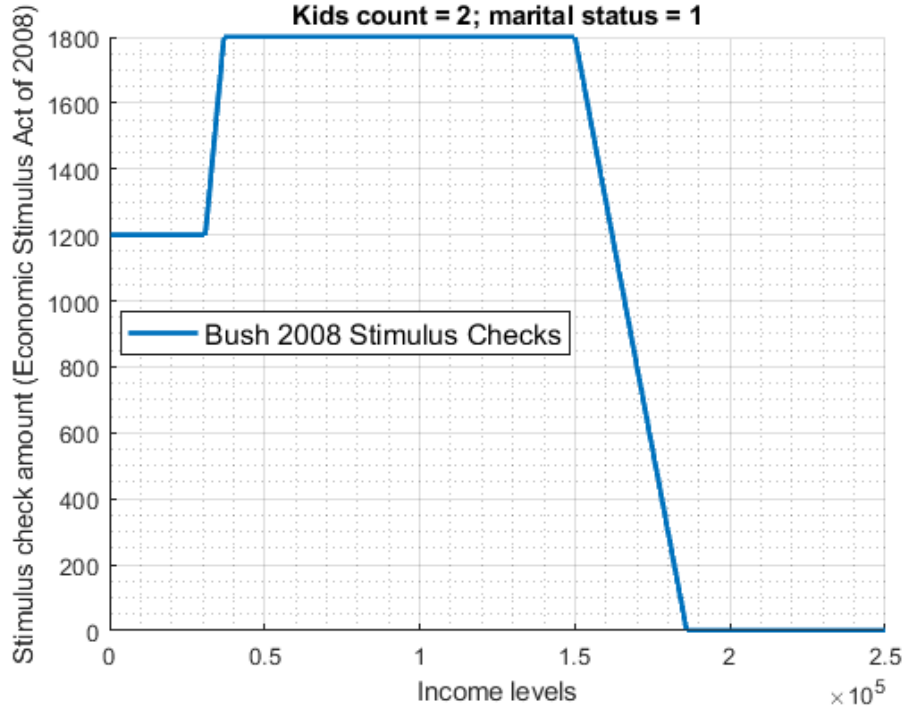
Kids count = 1; marital status = 1





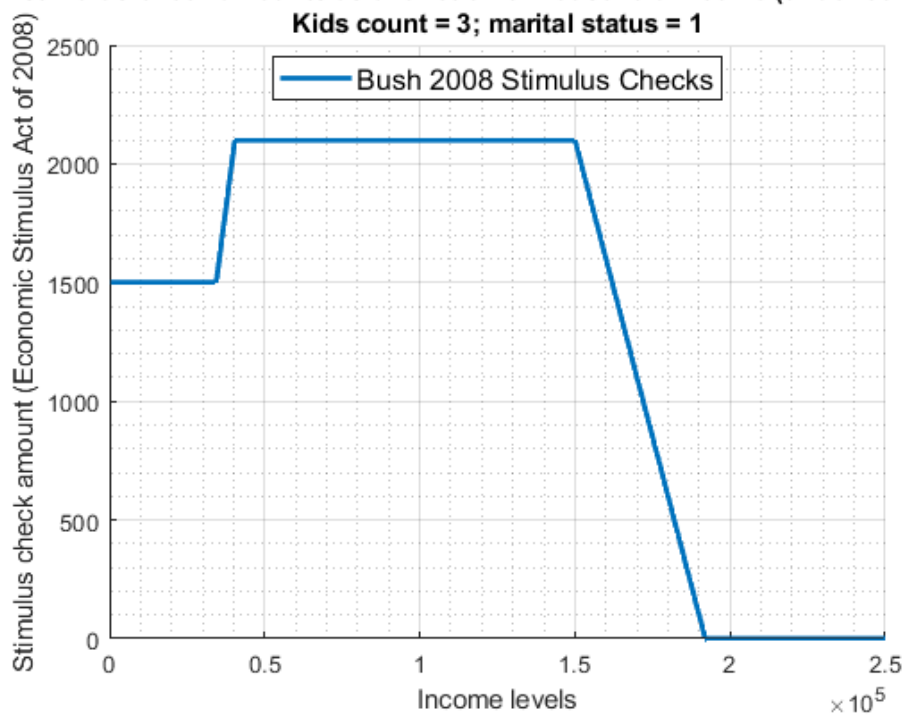
ish stimulus check amounts as a function of household income (under consider:

Kids count = 2; marital status = 1



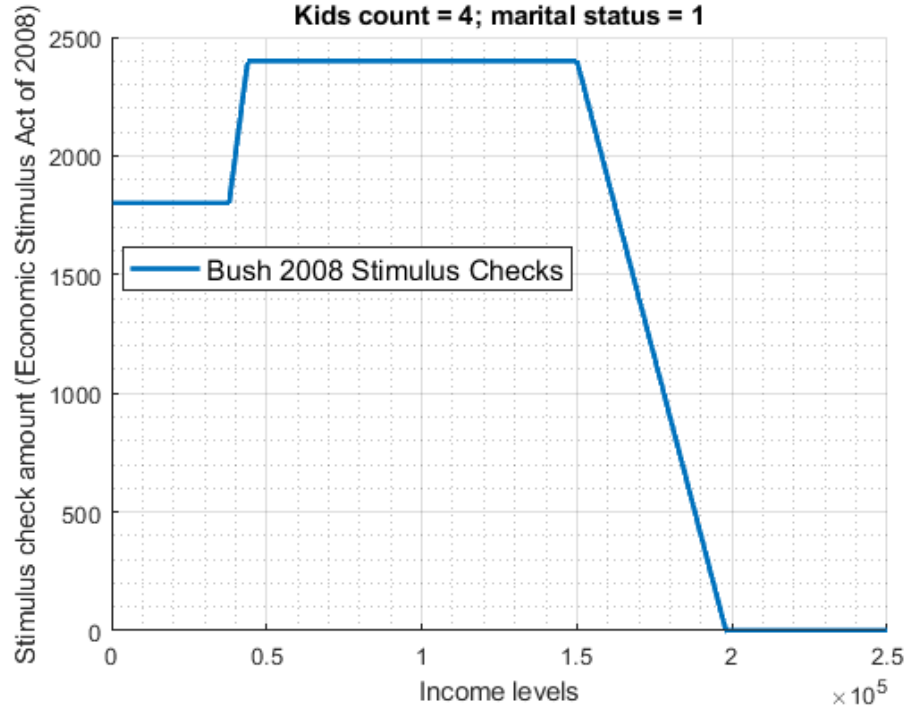
ish stimulus check amounts as a function of household income (under consider:

Kids count = 3; marital status = 1



ish stimulus check amounts as a function of household income (under consider:

Kids count = 4; marital status = 1



# Chapter 12

## Calibration

### 12.1 Model Calibration

Taking advantage of `snw_calibrate_beta_norm_gdp` from the [PrjOptiSNW Package](#), this function calibrates the discount factor and also solves for the normalizing constant.

#### 12.1.1 Calibrate Parameter Controls for SNW Functions

Set up controls for shock process and tiny/small/dense/densemoredense

```
clear all;
bl_print_mp_params = false;
% st_shock_method = 'rouwenhorst';
st_shock_method = 'tauchen';
% st_param_group = 'default_tiny';
% st_param_group = 'default_small';
% st_param_group = 'default_base';
% st_param_group = 'default_dense';
% st_param_group = 'default_moredense';
st_param_group = 'default_docdense';
mp_params = snw_mp_param(st_param_group, bl_print_mp_params, st_shock_method);
Pop = mp_params('Pop');
```

Set up print defaults

```
mp_controls = snw_mp_control('default_test');
mp_controls('bl_timer') = true;
mp_controls('bl_print_vfi') = false;
mp_controls('bl_print_vfi_verbose') = false;
mp_controls('bl_print_ds') = false;
mp_controls('bl_print_ds_verbose') = false;
```

#### 12.1.2 Calibrate Routine

Test this for 3 iterations

```
%% Calibration
err=1;
tol=0.005;
it_counter = 1;
while err>tol && it_counter <= 10
    disp('');
    it=1;

    while it>0
```

```

    % Solve optimization problem and get the distribution
    tm_start_a2 = tic;
    a2_old = mp_params('a2');
    [Phi_true,~,A_agg,Y_inc_agg,it,mp_dsvfi_results, a2] = snw_ds_main(mp_params, mp_controls);
    mp_params('a2') = a2;
    tm_end_a2 = toc(tm_start_a2);
    disp(['a2_old:' num2str(a2_old) ', a2_new:' num2str(a2) ', tm_end_a2:' num2str(tm_end_a2)])
end

% Get Stats
mp_cl_mt_xyz_of_s = mp_dsvfi_results('mp_cl_mt_xyz_of_s');
tb_outcomes = mp_cl_mt_xyz_of_s('tb_outcomes');
A_agg_alt = tb_outcomes{'a_ss', 'mean'}*sum(Pop);
Aprime_agg_alt = tb_outcomes{'ap_ss', 'mean'}*sum(Pop);
Y_inc_agg_alt = tb_outcomes{'y_all', 'mean'}*sum(Pop);
Y_inc_median = tb_outcomes{'y_all', 'p50'};

% Comparison
name='Median household income (target=1.0)=';
name2=[name,num2str(Y_inc_median)];
disp(name2);
name='Aggregate wealth to aggregate income (target=3.0)=';
name2=[name,num2str(A_agg/Y_inc_agg)];
disp(name2);

err1=abs(Y_inc_median-1.0); % Target: Median household income (normalized to 1 in the model)
err2=abs((A_agg/Y_inc_agg)-3.0); % Target: Annual capital/income ratio of 3

err=max(err1,err2);

% Beta and Theta
theta = mp_params('theta');
beta = mp_params('beta');
param_update=[theta;beta];

if err>tol

    theta=theta*((1.0/Y_inc_median)^0.2); % Normalize theta such that median household income eq
    beta=beta*((3.0/(A_agg/Y_inc_agg))^0.025); % Calibrate beta such that annual capital/income

end

mp_params('theta') = theta;
mp_params('beta') = beta;

param_update=[param_update(1,1),theta;param_update(2,1),beta];

it_counter = it_counter + 1;
name='Old/updated theta: ';
st_theta=[name, num2str(param_update(1,:))];
name='Old/updated beta: ';
st_beta=[name,num2str(param_update(2,:))];
disp(['counter=' num2str(it_counter) ...
      ';beta=' num2str(beta) ...
      ';theta=' num2str(theta)]);
end

Completed SNW_VFI_MAIN_BISEC_VEC;SNW_MP_PARAM=default_docdense;SNW_MP_CONTROL=default_test;time=489.

```

```

Completed SNW_DS_MAIN;SNW_MP_PARAM=default_docdense;SNW_MP_CONTROL=default_test;time=1835.3351
a2_old:1.5286, a2_new:1.4349, tm_end_a2:2440.3793
Completed SNW_VFI_MAIN_BISEC_VEC;SNW_MP_PARAM=default_docdense;SNW_MP_CONTROL=default_test;time=487.
Completed SNW_DS_MAIN;SNW_MP_PARAM=default_docdense;SNW_MP_CONTROL=default_test;time=1447.245
a2_old:1.4349, a2_new:1.4342, tm_end_a2:2051.784
Completed SNW_VFI_MAIN_BISEC_VEC;SNW_MP_PARAM=default_docdense;SNW_MP_CONTROL=default_test;time=483.
Completed SNW_DS_MAIN;SNW_MP_PARAM=default_docdense;SNW_MP_CONTROL=default_test;time=1352.0741
a2_old:1.4342, a2_new:1.4342, tm_end_a2:1951.1421
Median household income (target=1.0)=1.0024
Aggregate wealth to aggregate income (target=3.0)=3.0822
counter=2;beta=0.97051;theta=0.56495
Completed SNW_VFI_MAIN_BISEC_VEC;SNW_MP_PARAM=default_docdense;SNW_MP_CONTROL=default_test;time=493.
Completed SNW_DS_MAIN;SNW_MP_PARAM=default_docdense;SNW_MP_CONTROL=default_test;time=1570.3759
a2_old:1.4342, a2_new:1.4374, tm_end_a2:2178.0519
Completed SNW_VFI_MAIN_BISEC_VEC;SNW_MP_PARAM=default_docdense;SNW_MP_CONTROL=default_test;time=487.
Completed SNW_DS_MAIN;SNW_MP_PARAM=default_docdense;SNW_MP_CONTROL=default_test;time=1348.532
a2_old:1.4374, a2_new:1.4374, tm_end_a2:1948.8124
Median household income (target=1.0)=0.99971
Aggregate wealth to aggregate income (target=3.0)=3.0379
counter=3;beta=0.9702;theta=0.56499
Completed SNW_VFI_MAIN_BISEC_VEC;SNW_MP_PARAM=default_docdense;SNW_MP_CONTROL=default_test;time=486.
Completed SNW_DS_MAIN;SNW_MP_PARAM=default_docdense;SNW_MP_CONTROL=default_test;time=1503.2336
a2_old:1.4374, a2_new:1.439, tm_end_a2:2101.4027
Completed SNW_VFI_MAIN_BISEC_VEC;SNW_MP_PARAM=default_docdense;SNW_MP_CONTROL=default_test;time=485.
Completed SNW_DS_MAIN;SNW_MP_PARAM=default_docdense;SNW_MP_CONTROL=default_test;time=1334.6119
a2_old:1.439, a2_new:1.439, tm_end_a2:1933.0606
Median household income (target=1.0)=0.99853
Aggregate wealth to aggregate income (target=3.0)=3.0176
counter=4;beta=0.97006;theta=0.56515
Completed SNW_VFI_MAIN_BISEC_VEC;SNW_MP_PARAM=default_docdense;SNW_MP_CONTROL=default_test;time=503.
Completed SNW_DS_MAIN;SNW_MP_PARAM=default_docdense;SNW_MP_CONTROL=default_test;time=1423.8673
a2_old:1.439, a2_new:1.4393, tm_end_a2:2041.1993
Completed SNW_VFI_MAIN_BISEC_VEC;SNW_MP_PARAM=default_docdense;SNW_MP_CONTROL=default_test;time=497.
Completed SNW_DS_MAIN;SNW_MP_PARAM=default_docdense;SNW_MP_CONTROL=default_test;time=1386.4679
a2_old:1.4393, a2_new:1.4393, tm_end_a2:1998.5793
Median household income (target=1.0)=0.99813
Aggregate wealth to aggregate income (target=3.0)=3.0084
counter=5;beta=0.96999;theta=0.56536
Completed SNW_VFI_MAIN_BISEC_VEC;SNW_MP_PARAM=default_docdense;SNW_MP_CONTROL=default_test;time=501.
Completed SNW_DS_MAIN;SNW_MP_PARAM=default_docdense;SNW_MP_CONTROL=default_test;time=1375.2408
a2_old:1.4393, a2_new:1.4393, tm_end_a2:1990.0337
Median household income (target=1.0)=0.99829
Aggregate wealth to aggregate income (target=3.0)=3.0041
counter=6;beta=0.96999;theta=0.56536

```

## 12.2 Model Lockdown Calibration

Taking advantage of `snw_calibrate_lockdown_c` from the [PrjOptiSNW Package](#). This function finds the proportional discount to current utility in one period to account for aggregate reductions in consumption during lockdown.

### 12.2.1 Lock Down Impact on Consumption

”To calibrate the drop in marginal utility, we estimate that 10.9 percent of the goods that make up the consumer price index become highly undesirable, or simply unavailable, during the pandemic: food away from home, public transportation including airlines, and motor fuel. As we use a coefficient of risk aversion equal to one, we simply multiply utility from consumption during the period of the epidemic by a factor of 0.891”

There is one MIT shock period in which households face a one-period change in the current utility of consumption due to lock down. Solve the model and evaluate the effects on aggregate consumption (during the MIT shock period) with different proportional adjustments on consumption given differing intertemporal preference assumptions.

## 12.2.2 Graphical Illustration for Gamma=2 (docdense) and Gamma=1 (dense)

Solved Gamma=2 with docdense (81x5 shocks), and Gamma=1 with dense (7x5) shocks. Did not have time to resolve Gamma=1 with docdense.

Solved for gamma equals to 2, results visualized below.

```
% Percentage C drop desired
fl_c_drop_percent = 0.109;
```

First, grid of proportional one period current utility shifts:

```
% Grid of proportional one period current utility shifts.
[fl_invbtlock_min, fl_invbtlock_max, it_invbtlock_points] = deal(0, 1, 20);
st_grid_type = 'grid_powerspace';
mp_grid_control = containers.Map('KeyType', 'char', 'ValueType', 'any');
mp_grid_control('grid_powerspace_power') = 1.5;
[ar_fl_invbtlock] = ff_saveborr_grid(...
    fl_invbtlock_min, fl_invbtlock_max, it_invbtlock_points, ...
    st_grid_type, mp_grid_control);
ar_fl_invbtlock = 1-ar_fl_invbtlock;
% display
% disp(ar_fl_invbtlock);
```

Second, stored aggregate consumption values from docdense:

```
% From gamma=2 docdense
ar_fl_cons_mean_betaedu_innerwgt_gamma2_docdense = [...
    1.0466,1.0434,1.0374,1.0293,...
    1.0191,1.0067,0.99214,0.97543,...
    0.95642,0.93482,0.90995,0.88078,...
    0.847,0.80734,0.76126,0.70507,...
    0.635, 0.54343, 0.40755, 0.00013065];
% From gamma=1 dense
ar_fl_cons_mean_betaedu_innerwgt_gamma1_dense = [...
    1.2517,1.2467,1.237,1.2228,...
    1.2031,1.1783,1.1489,1.1147,...
    1.0754,1.0311,0.98169,0.92291,...
    0.85528,0.77933,0.69408,0.5964,...
    0.47976, 0.34416, 0.18672, 0.00013642];
```

Third, polynomial fit (4th order) between the 3rd and 14th point:

```
% Generate polynomial fit coefficients
ft_polynomial_gamma2_docdense = polyfit(ar_fl_invbtlock(3:13), ...
    ar_fl_cons_mean_betaedu_innerwgt_gamma2_docdense(3:13), 4);
ft_polynomial_gamma1_dense = polyfit(ar_fl_invbtlock(3:13), ...
    ar_fl_cons_mean_betaedu_innerwgt_gamma1_dense(3:13), 4);
% Evaluate polynomial fits
ar_fl_cons_mean_polyfit_gamma2_docdense = ...
    polyval(ft_polynomial_gamma2_docdense, ar_fl_invbtlock)';
ar_fl_cons_mean_polyfit_gamma1_dense = ...
    polyval(ft_polynomial_gamma1_dense, ar_fl_invbtlock)';
```

Fourth, find which proportional current utility change in 2020 matches a 10.9 percent drop in aggregate consumption in 2020:

```

% Identify the exact point along polynomial where c drops by 10.9 percent
% Gamma = 2, docdense
ar_fl_invbtlock_interpgrid = linspace(0.50, 0.95, 100000);
ar_fit_reduce_grid = 1 - ...
    polyval(ft_polynomial_gamma2_docdense, ar_fl_invbtlock_interpgrid)...
    ./ar_fl_cons_mean_polyfit_gamma2_docdense(1);
[fl_mingap, it_minidx] = min(abs(ar_fit_reduce_grid-fl_c_drop_percent));
fl_fit_best_reduce = ar_fl_invbtlock_interpgrid(it_minidx);
fl_lockdown_u_prop_reduction_gamma2_docdense = (1-fl_fit_best_reduce)*100;
st_reduction_gamma2_docdense = ['current util in 2020 multiply by ', ...
    num2str(fl_fit_best_reduce), ...
    ' for 10.9 percent drop in C'];
% Gamma = 1, dense
ar_fl_invbtlock_interpgrid = linspace(0.50, 0.95, 100000);
ar_fit_reduce_grid = 1 - ...
    polyval(ft_polynomial_gamma1_dense, ar_fl_invbtlock_interpgrid)...
    ./ar_fl_cons_mean_polyfit_gamma1_dense(1);
[fl_mingap, it_minidx] = min(abs(ar_fit_reduce_grid-fl_c_drop_percent));
fl_fit_best_reduce = ar_fl_invbtlock_interpgrid(it_minidx);
fl_lockdown_u_prop_reduction_gamma1_dense = (1-fl_fit_best_reduce)*100;
st_reduction_gamma1_dense = ['current util in 2020 multiply by ', ...
    num2str(fl_fit_best_reduce), ...
    ' for 10.9 percent drop in C'];

```

Third, graphical illustration:

```

for it_graph_type=1:2
    if (it_graph_type == 1)
        st_title_add = 'Zoomed in';
    else
        st_title_add = 'All consumption drop levels';
    end

    for it_gamma=2:1:2
        figure();
        hold on;

        if (it_graph_type == 1 && it_gamma == 1)
            ar_fl_cons_mean_betaedu_innerwgt_select = ...
                ar_fl_cons_mean_betaedu_innerwgt_gamma1_dense(1:12);
            ar_fl_cons_mean_polyfit_select = ...
                ar_fl_cons_mean_polyfit_gamma1_dense(1:12);
            st_gamma = 'Gamma = 1 (crra Parameter, 7x5), (2020 no Trump check, xi=0, b=1)';
            fl_lockdown_u_prop_reduction = fl_lockdown_u_prop_reduction_gamma1_dense;
            st_reduction = st_reduction_gamma1_dense;
        elseif (it_graph_type == 1 && it_gamma == 2)
            ar_fl_cons_mean_betaedu_innerwgt_select = ...
                ar_fl_cons_mean_betaedu_innerwgt_gamma2_docdense(1:12);
            ar_fl_cons_mean_polyfit_select = ...
                ar_fl_cons_mean_polyfit_gamma2_docdense(1:12);
            st_gamma = 'Gamma = 2 (crra Parameter, 81x5), (2020 no Trump check, xi=0, b=1)';
            fl_lockdown_u_prop_reduction = fl_lockdown_u_prop_reduction_gamma2_docdense;
            st_reduction = st_reduction_gamma2_docdense;
        elseif (it_graph_type == 2 && it_gamma == 1)
            ar_fl_cons_mean_betaedu_innerwgt_select = ...
                ar_fl_cons_mean_betaedu_innerwgt_gamma1_dense;
            ar_fl_cons_mean_polyfit_select = ...
                ar_fl_cons_mean_polyfit_gamma1_dense;
            st_gamma = 'Gamma = 1 (crra Parameter, 7x5), (2020 no Trump check, xi=0, b=1)';

```

```

    fl_lockdown_u_prop_reduction = fl_lockdown_u_prop_reduction_gamma1_dense;
    st_reduction = st_reduction_gamma1_dense;
elseif (it_graph_type == 2 && it_gamma == 2)
    ar_fl_cons_mean_betaedu_innerwgt_select = ...
        ar_fl_cons_mean_betaedu_innerwgt_gamma2_docdense;
    ar_fl_cons_mean_polyfit_select = ...
        ar_fl_cons_mean_polyfit_gamma2_docdense;
    st_gamma = 'Gamma = 2 (crra Parameter, 81x5), (2020 no Trump check, xi=0, b=1)';
    fl_lockdown_u_prop_reduction = fl_lockdown_u_prop_reduction_gamma2_docdense;
    st_reduction = st_reduction_gamma2_docdense;
end

ar_fl_invbtlock_select = ar_fl_invbtlock(1:length(ar_fl_cons_mean_betaedu_innerwgt_select));
ar_x = 1-ar_fl_invbtlock_select;
ar_y = -(1-ar_fl_cons_mean_betaedu_innerwgt_select/ar_fl_cons_mean_betaedu_innerwgt_select(1));
ar_y_poly = -(1-ar_fl_cons_mean_polyfit_select/ar_fl_cons_mean_polyfit_select(1));
ar_x = ar_x*100;
ar_y = ar_y*100;
ar_y_poly = ar_y_poly*100;

% Points scatter
scatter(ar_x, ar_y, 300, [57 106 177]./255, 'd');

% Points polynomial approximate
pl_poly = plot(ar_x, ar_y_poly);
pl_poly.Color = [83 81 84]./255;
pl_poly.LineStyle = '-';
pl_poly.LineWidth = 2;

% Actual lines linearly connected
line = plot(ar_x, ar_y);
line.Color = [57 106 177]./255;
line.LineStyle = '--';
line.LineWidth = 3;

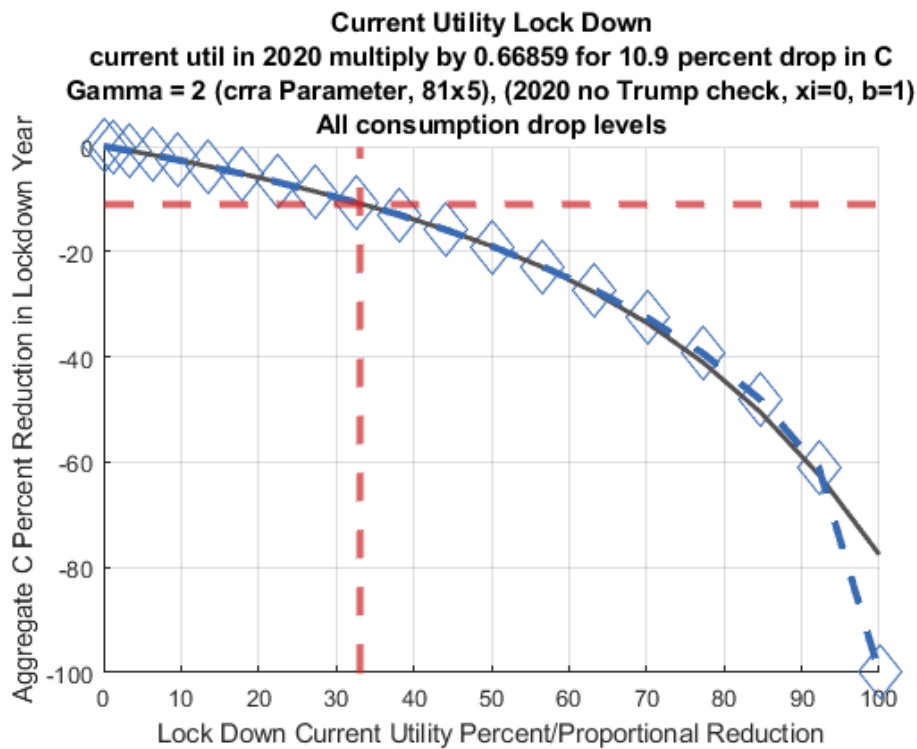
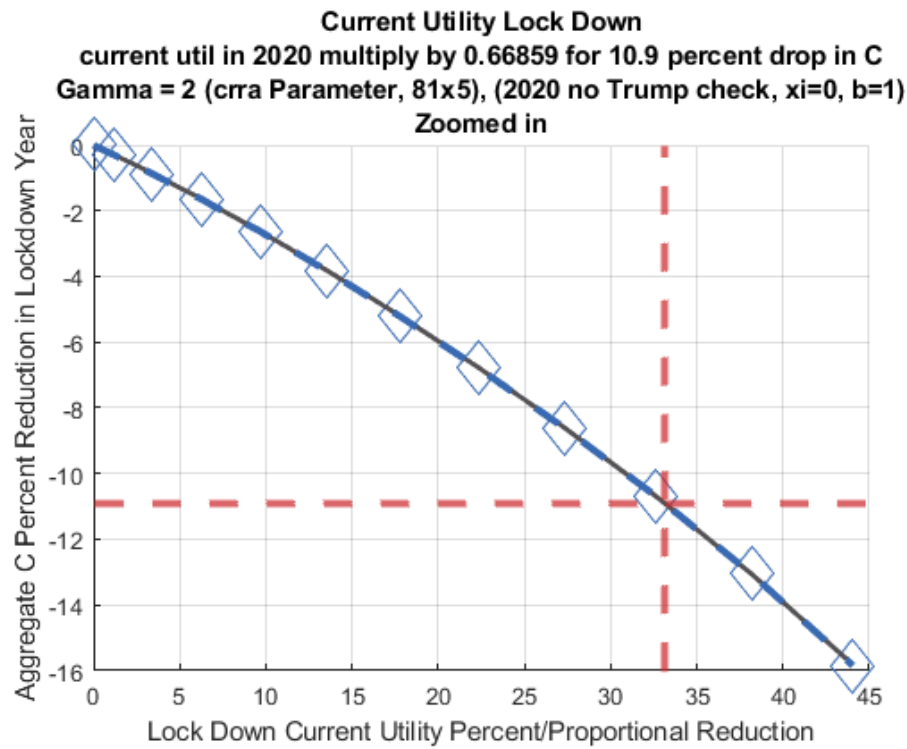
% X-axis for -10.9 percent
yline0 = yline(-10.9);
yline0.HandleVisibility = 'off';
yline0.Color = [204 37 41]./255;
yline0.LineStyle = '--';
yline0.LineWidth = 3;

% Y-axis for -10.9 percent along the polynomial
xline0 = xline(fl_lockdown_u_prop_reduction);
xline0.HandleVisibility = 'off';
xline0.Color = [204 37 41]./255;
xline0.LineStyle = '--';
xline0.LineWidth = 3;

% labeling
title({'Current Utility Lock Down',...
    st_reduction, st_gamma, ...
    st_title_add});
ylabel('Aggregate C Percent Reduction in Lockdown Year');
xlabel('Lock Down Current Utility Percent/Proportional Reduction');
grid on;
end
end

```





Fourth, tabular display for Gamma 2:

```

%% Table Display
% Generate Table
tb_show = array2table([ar_x,ar_y',ar_y_poly']);
it_num_rows = length(ar_x);

% Generate Row and Column Names
cl_col_names = {'Lock Down Util Perc Reduce', 'Agg C Percent Reduc Lockdown Yr', 'Agg C Percent Redu
cl_row_names = strcat('lockdown_', string((1:it_num_rows)));
    
```

```
tb_show.Properties.VariableNames = matlab.lang.makeValidName(cl_col_names);
tb_show.Properties.RowNames = matlab.lang.makeValidName(cl_row_names);
disp(tb_show);
```

	LockDownUtilPercReduce	AggCPercentReducLockdownYr	AggCPercentReducPolynomia
	-----	-----	-----
lockdown_1	0	0	0
lockdown_2	1.2075	-0.30575	-0.29672
lockdown_3	3.4152	-0.87904	-0.86414
lockdown_4	6.2741	-1.653	-1.643
lockdown_5	9.6596	-2.6276	-2.6234
lockdown_6	13.5	-3.8123	-3.8041
lockdown_7	17.746	-5.2035	-5.1879
lockdown_8	22.362	-6.8001	-6.7823
lockdown_9	27.322	-8.6165	-8.6029
lockdown_10	32.601	-10.68	-10.679
lockdown_11	38.183	-13.057	-13.058
lockdown_12	44.051	-15.844	-15.817
lockdown_13	50.193	-19.071	-19.067
lockdown_14	56.596	-22.861	-22.966
lockdown_15	63.25	-27.264	-27.728
lockdown_16	70.147	-32.632	-33.635
lockdown_17	77.277	-39.327	-41.055
lockdown_18	84.634	-48.077	-50.447
lockdown_19	92.21	-61.06	-62.385
lockdown_20	100	-99.988	-77.569

## 12.3 UI Benefit Unemployment Lost Wage Recovery Parameter $b$ Calibration

Taking advantage of [snw\\_calibrate\\_2009\\_b](#) from the [PrjOptiSNW Package](#).

The ratio of UI benefits to wages and salary is 2.1 percent in 2009.  $\xi \in [0, 1]$  governs the duration of unemployment shock for those unemployed. This equals to 0.532 in 2009 ( $\xi = 0$  no wages earned).

We solve for total wage earnings from unemployed and employed in 2009, for employed, same as under steady-state. For unemployed, they lose  $(1 - \xi)$  share of the wage they would otherwise have earned. Our unemployment probability in 2009 is conditional on age and edu groups (SNW\_UNEMP\_2008.m) computed based on rectilinear restriction.

We know total UI amount (multiply its share of total "Wages and salary" by total "wages and salary"). We know how much wage was lost due to  $\xi$ . The ratio of these two levels is  $b$ , which is the parameter that is the share of lost-wage recovered. Note that this is based on exogenous wage earnings, so we do not have to worry about endogenous changes to savings. We will solve for the steady-state distribution, which generates mass of people by age, education, marital status, kids count, etc.

### 12.3.1 Calibrate $b$ with 2.1% UI Benefits to Wages Ratio and $\xi = 0.532$

Using various default parameters, including the default unemployment in 2009 matrix, and the default  $\xi = 0.532$  parameter, compute  $b$ .

```
% Solve parameters
mp_more_inputs = containers.Map('KeyType','char', 'ValueType','any');
mp_more_inputs('fl_ss_non_college') = 0.225;
mp_more_inputs('fl_ss_college') = 0.271;
mp_more_inputs('fl_scaleconvertor') = 54831;
% st_param_group = 'default_small';
```

```

st_param_group = 'default_docdense';
mp_params = snw_mp_param(st_param_group, false, 'tauchen', false, 8, 8, mp_more_inputs);
% Controls
mp_controls = snw_mp_control('default_test');

% no b, solving for b, b set to 0 when solving for wages
xi=0.532; % Proportional reduction in income due to unemployment (xi=0 refers to 0 labor income; xi=
mp_params('xi') = xi;

% Solve for Unemployment Values
mp_controls('bl_print_vfi') = false;
mp_controls('bl_print_vfi_verbose') = false;
mp_controls('bl_print_ds') = false;
mp_controls('bl_print_ds_verbose') = false;
mp_controls('bl_print_calibrate_2009') = true;
mp_controls('bl_print_calibrate_2009_verbose') = false;

% 2.1% UI Benefits to Wages and Salary Ratio
fl_ratio_ui_benefits_to_wage = 0.021;

% Solve
[fl_b_calibrated_by_ui_share, ...
 mp_stats_wage_ui_spending, ...
 mn_earn_tot_wgtd, mn_earn_unemp_wgtd, ...
 mn_earn_unemp_tot_wgtd, mn_earn_unemp_weighted_wgtd] = ...
 snw_calibrate_2009_b(mp_params, mp_controls, ...
 fl_ratio_ui_benefits_to_wage);

Completed SNW_VFI_MAIN_BISEC_VEC;SNW_MP_PARAM=default_docdense;SNW_MP_CONTROL=default_test;time=310.
Completed SNW_DS_MAIN_VEC;SNW_MP_PARAM=default_docdense;SNW_MP_CONTROL=default_test;time=1294.5472
Completed SNW_calibrate_2009;SNW_MP_PARAM=default_docdense;SNW_MP_CONTROL=default_test;time=1668.355
-----
XXXXXXXXXXXXXXXXXXXXXXXXXXXXXXXXXXXXXXXXXXXXXXXXXXXXXXXXXXXX
CONTAINER NAME: mp_stats_wage_ui_spending Scalars
XXXXXXXXXXXXXXXXXXXXXXXXXXXXXXXXXXXXXXXXXXXXXXXXXXXXXXXXXXXX

          i      idx      value
          -      ---      -
fl_b_calibrated_by_ui_share      1      1      0.37451
fl_total_b_spending              2      2      1.1333
fl_total_wage                    3      3      53.969
fl_total_wage_unemp_hhhead        4      4      3.4401
fl_total_wage_unemp_hhhead_and_spouse 5      5      6.0062
fl_total_wage_unemp_hhhead_lost    6      6      3.0262

```

### 12.3.2 Calibrate b with 5.68% UI Benefits to Wages Ratio and $\xi = 0.651$

Change the benefit share and  $\xi$  parameter to COVID values. The  $b$  we find below is not what should be used for COVID, the unemployment probability is based on 2009 crisis still. That is hard-coded into the `snw_calibrate_2009_b` function.

```

% Solve parameters
mp_more_inputs = containers.Map('KeyType','char', 'ValueType','any');
mp_more_inputs('fl_ss_non_college') = 0.225;
mp_more_inputs('fl_ss_college') = 0.271;
mp_more_inputs('fl_scaleconvertor') = 54831;
% st_param_group = 'default_small';
st_param_group = 'default_dense';
mp_params = snw_mp_param(st_param_group, false, 'tauchen', false, 8, 8, mp_more_inputs);

```

```

% Controls
mp_controls = snw_mp_control('default_test');

% no b, solving for b, b set to 0 when solving for wages
xi=0.651; % Proportional reduction in income due to unemployment (xi=0 refers to 0 labor income; xi=
mp_params('xi') = xi;

% Solve for Unemployment Values
mp_controls('bl_print_vfi') = false;
mp_controls('bl_print_vfi_verbose') = false;
mp_controls('bl_print_ds') = false;
mp_controls('bl_print_ds_verbose') = false;
mp_controls('bl_print_calibrate_2009') = true;
mp_controls('bl_print_calibrate_2009_verbose') = false;

% 2.1% UI Benefits to Wages and Salary Ratio
fl_ratio_ui_benefits_to_wage = 0.0568;

% Solve
[fl_b_calibrated_by_ui_share, ...
 mp_stats_wage_ui_spending, ...
 mn_earn_tot_wgtd, mn_earn_unemp_wgtd, ...
 mn_earn_unemp_tot_wgtd, mn_earn_unemp_weighted_wgtd] = ...
 snw_calibrate_2009_b(mp_params, mp_controls, ...
 fl_ratio_ui_benefits_to_wage);

Completed SNW_VFI_MAIN_BISEC_VEC;SNW_MP_PARAM=default_dense;SNW_MP_CONTROL=default_test;time=14.9366
Completed SNW_DS_MAIN_VEC;SNW_MP_PARAM=default_dense;SNW_MP_CONTROL=default_test;time=37.6607
Completed SNW_calibrate_2009;SNW_MP_PARAM=default_dense;SNW_MP_CONTROL=default_test;time=55.5689
-----
XXXXXXXXXXXXXXXXXXXXXXXXXXXXXXXXXXXXXXXXXXXXXXXXXXXX
CONTAINER NAME: mp_stats_wage_ui_spending Scalars
XXXXXXXXXXXXXXXXXXXXXXXXXXXXXXXXXXXXXXXXXXXXXXXXXXXX

          i      idx      value
          -      ---      -
fl_b_calibrated_by_ui_share      1      1      1.3973
fl_total_b_spending              2      2      3.8087
fl_total_wage                    3      3      67.055
fl_total_wage_unemp_hhhead        4      4      5.0843
fl_total_wage_unemp_hhhead_and_spouse 5      5      8.3311
fl_total_wage_unemp_hhhead_lost    6      6      2.7257

```

# Chapter 13

## Summary Statistics

### 13.1 2019 Full States MPC and Distributional Statistics by Marital, Kids, and Income Groups.

In the file here, we consider marital, kids and income groups, and summarize various statistics for each bin.

#### 13.1.1 Test SNW\_EVUVW19\_JAEEMK Defaults Dense

VFI and Distribution

Call the function with defaults.

```
clear all;
st_solu_type = 'bisec_vec';
bl_save_csv = false;

% Solve the VFI Problem and get Value Function
% mp_params = snw_mp_param('default_dense');
% mp_params = snw_mp_param('default_docdense');
mp_params = snw_mp_param('default_moredense_a65zh133zs5_e2m2');
mp_controls = snw_mp_control('default_test');

% set Unemployment Related Variables
xi=0.5; % Proportional reduction in income due to unemployment (xi=0 refers to 0 labor income; xi=1
b=1; % Unemployment insurance replacement rate (b=0 refers to no UI benefits; b=1 refers to 100 perc
TR=100/58056; % Value of a welfare check (can receive multiple checks). TO DO: Update with alternati

mp_params('xi') = xi;
mp_params('b') = b;
mp_params('TR') = TR;

% Solve for Unemployment Values
mp_controls('bl_print_vfi') = false;
mp_controls('bl_print_vfi_verbose') = false;
mp_controls('bl_print_ds') = true;
mp_controls('bl_print_ds_verbose') = true;
mp_controls('bl_print_precompute') = false;
mp_controls('bl_print_precompute_verbose') = false;
mp_controls('bl_print_a4chk') = false;
mp_controls('bl_print_a4chk_verbose') = false;
mp_controls('bl_print_evuvw20_jaeemk') = false;
mp_controls('bl_print_evuvw20_jaeemk_verbose') = false;
```

```

mp_controls('bl_print_evuvw19_jaeemk') = false;
mp_controls('bl_print_evuvw19_jaeemk_verbose') = false;

% Solve the Model to get V working and unemployed
[V_ss,ap_ss,cons_ss,mp_valpol_more_ss] = snw_vfi_main_bisec_vec(mp_params, mp_controls);

Completed SNW_VFI_MAIN_BISEC_VEC;SNW_MP_PARAM=default_moredense_a65zh133zs5_e2m2;SNW_MP_CONTROL=defa

inc_VFI = mp_valpol_more_ss('inc_VFI');
spouse_inc_VFI = mp_valpol_more_ss('spouse_inc_VFI');
total_inc_VFI = inc_VFI + spouse_inc_VFI;
% tax during covid year
mp_params('a2_covidyr') = mp_params('a2_covidyr_manna_heaven');
% Solve unemployment
[V_unemp,~,cons_unemp,~] = snw_vfi_main_bisec_vec(mp_params, mp_controls, V_ss);

Completed SNW_VFI_MAIN_BISEC_VEC 1 Period Unemp Shock;SNW_MP_PARAM=default_moredense_a65zh133zs5_e2m2

[Phi_true, Phi_adj, A_agg, Y_inc_agg, ~, mp_dsvfi_results] = snw_ds_main_vec(mp_params, mp_controls,

SNW_DS_MAIN_VEC ACUMU MASS: Finished Age Group:1 of 82, time-this-age:1.074
SNW_DS_MAIN_VEC ACUMU MASS: Finished Age Group:2 of 82, time-this-age:20.5148
SNW_DS_MAIN_VEC ACUMU MASS: Finished Age Group:3 of 82, time-this-age:23.4908
SNW_DS_MAIN_VEC ACUMU MASS: Finished Age Group:4 of 82, time-this-age:28.525
SNW_DS_MAIN_VEC ACUMU MASS: Finished Age Group:5 of 82, time-this-age:33.2054
SNW_DS_MAIN_VEC ACUMU MASS: Finished Age Group:6 of 82, time-this-age:35.3197
SNW_DS_MAIN_VEC ACUMU MASS: Finished Age Group:7 of 82, time-this-age:37.5611
SNW_DS_MAIN_VEC ACUMU MASS: Finished Age Group:8 of 82, time-this-age:40.226
SNW_DS_MAIN_VEC ACUMU MASS: Finished Age Group:9 of 82, time-this-age:44.3653
SNW_DS_MAIN_VEC ACUMU MASS: Finished Age Group:10 of 82, time-this-age:48.3751
SNW_DS_MAIN_VEC ACUMU MASS: Finished Age Group:11 of 82, time-this-age:49.4182
SNW_DS_MAIN_VEC ACUMU MASS: Finished Age Group:12 of 82, time-this-age:50.6325
SNW_DS_MAIN_VEC ACUMU MASS: Finished Age Group:13 of 82, time-this-age:51.0802
SNW_DS_MAIN_VEC ACUMU MASS: Finished Age Group:14 of 82, time-this-age:52.1717
SNW_DS_MAIN_VEC ACUMU MASS: Finished Age Group:15 of 82, time-this-age:53.2068
SNW_DS_MAIN_VEC ACUMU MASS: Finished Age Group:16 of 82, time-this-age:53.6567
SNW_DS_MAIN_VEC ACUMU MASS: Finished Age Group:17 of 82, time-this-age:53.8811
SNW_DS_MAIN_VEC ACUMU MASS: Finished Age Group:18 of 82, time-this-age:55.0892
SNW_DS_MAIN_VEC ACUMU MASS: Finished Age Group:19 of 82, time-this-age:55.6717
SNW_DS_MAIN_VEC ACUMU MASS: Finished Age Group:20 of 82, time-this-age:56.2143
SNW_DS_MAIN_VEC ACUMU MASS: Finished Age Group:21 of 82, time-this-age:56.5704
SNW_DS_MAIN_VEC ACUMU MASS: Finished Age Group:22 of 82, time-this-age:57.0081
SNW_DS_MAIN_VEC ACUMU MASS: Finished Age Group:23 of 82, time-this-age:57.1682
SNW_DS_MAIN_VEC ACUMU MASS: Finished Age Group:24 of 82, time-this-age:57.3671
SNW_DS_MAIN_VEC ACUMU MASS: Finished Age Group:25 of 82, time-this-age:57.5453
SNW_DS_MAIN_VEC ACUMU MASS: Finished Age Group:26 of 82, time-this-age:57.8356
SNW_DS_MAIN_VEC ACUMU MASS: Finished Age Group:27 of 82, time-this-age:58.0491
SNW_DS_MAIN_VEC ACUMU MASS: Finished Age Group:28 of 82, time-this-age:57.9265
SNW_DS_MAIN_VEC ACUMU MASS: Finished Age Group:29 of 82, time-this-age:57.6332
SNW_DS_MAIN_VEC ACUMU MASS: Finished Age Group:30 of 82, time-this-age:58.1269
SNW_DS_MAIN_VEC ACUMU MASS: Finished Age Group:31 of 82, time-this-age:57.7606
SNW_DS_MAIN_VEC ACUMU MASS: Finished Age Group:32 of 82, time-this-age:57.5816
SNW_DS_MAIN_VEC ACUMU MASS: Finished Age Group:33 of 82, time-this-age:57.3361
SNW_DS_MAIN_VEC ACUMU MASS: Finished Age Group:34 of 82, time-this-age:57.7288
SNW_DS_MAIN_VEC ACUMU MASS: Finished Age Group:35 of 82, time-this-age:56.9154
SNW_DS_MAIN_VEC ACUMU MASS: Finished Age Group:36 of 82, time-this-age:57.2866
SNW_DS_MAIN_VEC ACUMU MASS: Finished Age Group:37 of 82, time-this-age:57.1634
SNW_DS_MAIN_VEC ACUMU MASS: Finished Age Group:38 of 82, time-this-age:57.0388

```

13.1. 2019 FULL STATES MPC AND DISTRIBUTIONAL STATISTICS BY MARITAL, KIDS, AND INCOME GROUP

SNW\_DS\_MAIN\_VEC ACUMU MASS: Finished Age Group:39 of 82, time-this-age:56.6859  
SNW\_DS\_MAIN\_VEC ACUMU MASS: Finished Age Group:40 of 82, time-this-age:56.7277  
SNW\_DS\_MAIN\_VEC ACUMU MASS: Finished Age Group:41 of 82, time-this-age:56.9976  
SNW\_DS\_MAIN\_VEC ACUMU MASS: Finished Age Group:42 of 82, time-this-age:56.6711  
SNW\_DS\_MAIN\_VEC ACUMU MASS: Finished Age Group:43 of 82, time-this-age:56.7355  
SNW\_DS\_MAIN\_VEC ACUMU MASS: Finished Age Group:44 of 82, time-this-age:56.6671  
SNW\_DS\_MAIN\_VEC ACUMU MASS: Finished Age Group:45 of 82, time-this-age:56.1114  
SNW\_DS\_MAIN\_VEC ACUMU MASS: Finished Age Group:46 of 82, time-this-age:55.9357  
SNW\_DS\_MAIN\_VEC ACUMU MASS: Finished Age Group:47 of 82, time-this-age:55.9514  
SNW\_DS\_MAIN\_VEC ACUMU MASS: Finished Age Group:48 of 82, time-this-age:55.4533  
SNW\_DS\_MAIN\_VEC ACUMU MASS: Finished Age Group:49 of 82, time-this-age:58.5505  
SNW\_DS\_MAIN\_VEC ACUMU MASS: Finished Age Group:50 of 82, time-this-age:59.402  
SNW\_DS\_MAIN\_VEC ACUMU MASS: Finished Age Group:51 of 82, time-this-age:59.5814  
SNW\_DS\_MAIN\_VEC ACUMU MASS: Finished Age Group:52 of 82, time-this-age:59.4987  
SNW\_DS\_MAIN\_VEC ACUMU MASS: Finished Age Group:53 of 82, time-this-age:59.3449  
SNW\_DS\_MAIN\_VEC ACUMU MASS: Finished Age Group:54 of 82, time-this-age:59.6498  
SNW\_DS\_MAIN\_VEC ACUMU MASS: Finished Age Group:55 of 82, time-this-age:59.3396  
SNW\_DS\_MAIN\_VEC ACUMU MASS: Finished Age Group:56 of 82, time-this-age:59.4903  
SNW\_DS\_MAIN\_VEC ACUMU MASS: Finished Age Group:57 of 82, time-this-age:59.4659  
SNW\_DS\_MAIN\_VEC ACUMU MASS: Finished Age Group:58 of 82, time-this-age:59.2382  
SNW\_DS\_MAIN\_VEC ACUMU MASS: Finished Age Group:59 of 82, time-this-age:58.2574  
SNW\_DS\_MAIN\_VEC ACUMU MASS: Finished Age Group:60 of 82, time-this-age:58.4884  
SNW\_DS\_MAIN\_VEC ACUMU MASS: Finished Age Group:61 of 82, time-this-age:58.2825  
SNW\_DS\_MAIN\_VEC ACUMU MASS: Finished Age Group:62 of 82, time-this-age:57.4508  
SNW\_DS\_MAIN\_VEC ACUMU MASS: Finished Age Group:63 of 82, time-this-age:56.9986  
SNW\_DS\_MAIN\_VEC ACUMU MASS: Finished Age Group:64 of 82, time-this-age:56.5337  
SNW\_DS\_MAIN\_VEC ACUMU MASS: Finished Age Group:65 of 82, time-this-age:55.94  
SNW\_DS\_MAIN\_VEC ACUMU MASS: Finished Age Group:66 of 82, time-this-age:54.1804  
SNW\_DS\_MAIN\_VEC ACUMU MASS: Finished Age Group:67 of 82, time-this-age:53.4807  
SNW\_DS\_MAIN\_VEC ACUMU MASS: Finished Age Group:68 of 82, time-this-age:52.222  
SNW\_DS\_MAIN\_VEC ACUMU MASS: Finished Age Group:69 of 82, time-this-age:51.6643  
SNW\_DS\_MAIN\_VEC ACUMU MASS: Finished Age Group:70 of 82, time-this-age:50.7393  
SNW\_DS\_MAIN\_VEC ACUMU MASS: Finished Age Group:71 of 82, time-this-age:49.5324  
SNW\_DS\_MAIN\_VEC ACUMU MASS: Finished Age Group:72 of 82, time-this-age:47.7517  
SNW\_DS\_MAIN\_VEC ACUMU MASS: Finished Age Group:73 of 82, time-this-age:45.9439  
SNW\_DS\_MAIN\_VEC ACUMU MASS: Finished Age Group:74 of 82, time-this-age:44.385  
SNW\_DS\_MAIN\_VEC ACUMU MASS: Finished Age Group:75 of 82, time-this-age:42.9  
SNW\_DS\_MAIN\_VEC ACUMU MASS: Finished Age Group:76 of 82, time-this-age:41.3804  
SNW\_DS\_MAIN\_VEC ACUMU MASS: Finished Age Group:77 of 82, time-this-age:35.089  
SNW\_DS\_MAIN\_VEC ACUMU MASS: Finished Age Group:78 of 82, time-this-age:33.9143  
SNW\_DS\_MAIN\_VEC ACUMU MASS: Finished Age Group:79 of 82, time-this-age:32.9597  
SNW\_DS\_MAIN\_VEC ACUMU MASS: Finished Age Group:80 of 82, time-this-age:26.3587  
SNW\_DS\_MAIN\_VEC ACUMU MASS: Finished Age Group:81 of 82, time-this-age:25.2198  
SNW\_DS\_MAIN\_VEC ACUMU MASS: Finished Age Group:82 of 82, time-this-age:22.8558  
SNW\_DS\_MAIN NORMALIZE MASS: Finished Age Group:1 of 82, time-this-age:0.50074  
SNW\_DS\_MAIN NORMALIZE MASS: Finished Age Group:2 of 82, time-this-age:0.078102  
SNW\_DS\_MAIN NORMALIZE MASS: Finished Age Group:3 of 82, time-this-age:0.077705  
SNW\_DS\_MAIN NORMALIZE MASS: Finished Age Group:4 of 82, time-this-age:0.077939  
SNW\_DS\_MAIN NORMALIZE MASS: Finished Age Group:5 of 82, time-this-age:0.07796  
SNW\_DS\_MAIN NORMALIZE MASS: Finished Age Group:6 of 82, time-this-age:0.078664  
SNW\_DS\_MAIN NORMALIZE MASS: Finished Age Group:7 of 82, time-this-age:0.077012  
SNW\_DS\_MAIN NORMALIZE MASS: Finished Age Group:8 of 82, time-this-age:0.077566  
SNW\_DS\_MAIN NORMALIZE MASS: Finished Age Group:9 of 82, time-this-age:0.076968  
SNW\_DS\_MAIN NORMALIZE MASS: Finished Age Group:10 of 82, time-this-age:0.076874  
SNW\_DS\_MAIN NORMALIZE MASS: Finished Age Group:11 of 82, time-this-age:0.07674  
SNW\_DS\_MAIN NORMALIZE MASS: Finished Age Group:12 of 82, time-this-age:0.07736  
SNW\_DS\_MAIN NORMALIZE MASS: Finished Age Group:13 of 82, time-this-age:0.07804  
SNW\_DS\_MAIN NORMALIZE MASS: Finished Age Group:14 of 82, time-this-age:0.077614





13.1. 2019 FULL STATES MPC AND DISTRIBUTIONAL STATISTICS BY MARITAL, KIDS, AND INCOME GROUP

SNW\_DS\_MAIN NORMALIZE MASS: Finished Age Group:73 of 82, time-this-age:0.073002  
 SNW\_DS\_MAIN NORMALIZE MASS: Finished Age Group:74 of 82, time-this-age:0.073612  
 SNW\_DS\_MAIN NORMALIZE MASS: Finished Age Group:75 of 82, time-this-age:0.073039  
 SNW\_DS\_MAIN NORMALIZE MASS: Finished Age Group:76 of 82, time-this-age:0.073474  
 SNW\_DS\_MAIN NORMALIZE MASS: Finished Age Group:77 of 82, time-this-age:0.073582  
 SNW\_DS\_MAIN NORMALIZE MASS: Finished Age Group:78 of 82, time-this-age:0.076234  
 SNW\_DS\_MAIN NORMALIZE MASS: Finished Age Group:79 of 82, time-this-age:0.073668  
 SNW\_DS\_MAIN NORMALIZE MASS: Finished Age Group:80 of 82, time-this-age:0.073745  
 SNW\_DS\_MAIN NORMALIZE MASS: Finished Age Group:81 of 82, time-this-age:0.073108  
 SNW\_DS\_MAIN NORMALIZE MASS: Finished Age Group:82 of 82, time-this-age:0.072892  
 SNW\_DS\_MAIN NORMALIZE MASS: Finished Age Group:83 of 82, time-this-age:0.073316  
 SNW\_DS\_MAIN: Share of population with assets equal to upper bound on asset grid:6.0111e-06  
 SNW\_DS\_MAIN: Accidental bequests are thrown in the ocean  
 SNW\_DS\_MAIN\_VEC tax and spend;it=1;err=0.0010205  
 SNW\_DS\_MAIN\_VEC tax and spend;it=2;err=0.0008547  
 SNW\_DS\_MAIN\_VEC tax and spend;it=3;err=0.0007159  
 SNW\_DS\_MAIN\_VEC tax and spend;it=4;err=0.00059969  
 SNW\_DS\_MAIN\_VEC tax and spend;it=5;err=0.00050237  
 SNW\_DS\_MAIN\_VEC tax and spend;it=6;err=0.00042087  
 SNW\_DS\_MAIN\_VEC tax and spend;it=7;err=0.00035261  
 SNW\_DS\_MAIN\_VEC tax and spend;it=8;err=0.00029542  
 SNW\_DS\_MAIN\_VEC tax and spend;it=9;err=0.00024752  
 SNW\_DS\_MAIN\_VEC tax and spend;it=10;err=0.0002074  
 SNW\_DS\_MAIN\_VEC tax and spend;it=11;err=0.00017378  
 SNW\_DS\_MAIN\_VEC tax and spend;it=12;err=0.00014561  
 SNW\_DS\_MAIN\_VEC tax and spend;it=13;err=0.00012201  
 SNW\_DS\_MAIN\_VEC tax and spend;it=14;err=0.00010224  
 SNW\_DS\_MAIN\_VEC tax and spend;it=15;err=8.567e-05  
 SNW\_DS\_MAIN\_VEC: Number of a2-adjustments (for taxation) used to balance the government budget= 15  
 SNW\_DS\_MAIN\_VEC: Old and updated value of a2=1.5286 1.5353  
 SNW\_DS\_MAIN\_VEC: Aggregates: Cons., Gov. cons., Save, Assets, Income, Bequests 48.78871 11.3586  
 SNW\_DS\_MAIN\_VEC: Resource constraint: C\_t+A\_{t+1}+G\_t=A\_t+Y\_t 258.0346 258.0206  
 Completed SNW\_DS\_MAIN\_VEC;SNW\_MP\_PARAM=default\_moredense\_a65zh133zs5\_e2m2;SNW\_MP\_CONTROL=default\_tes  
 pos = 19 ; key = mp\_controls  
 Map with properties:

Count: 37  
 KeyType: char  
 ValueType: any

pos = 20 ; key = mp\_params  
 Map with properties:

Count: 52  
 KeyType: char  
 ValueType: any

```

-----
XXXXXXXXXXXXXXXXXXXXXXXXXXXXXXXXXXXXXXXXXXXXXXXXXXXX
CONTAINER NAME: mp_dsvfi_results ND Array (Matrix etc)
XXXXXXXXXXXXXXXXXXXXXXXXXXXXXXXXXXXXXXXXXXXXXXXXXXXX
    
```

	i	idx	ndim	numel	rowN	colN	sum	mean
SS_ss	1	11	6	7.1754e+07	83	8.645e+05	8.3556e+06	0.116
a_ss	2	16	6	7.1754e+07	83	8.645e+05	2.4595e+09	34.2
ap_ss	3	17	6	7.1754e+07	83	8.645e+05	2.3245e+09	32.3
cons_ss	4	18	6	7.1754e+07	83	8.645e+05	3.5119e+08	4.89

n_ss	5	21	6	7.1754e+07	83	8.645e+05	2.5114e+08	3
tax_ss	6	22	6	7.1754e+07	83	8.645e+05	6.6049e+07	0.92
y_all_ss	7	23	6	7.1754e+07	83	8.645e+05	2.8219e+08	3.93
y_head_earn_ss	8	24	6	7.1754e+07	83	8.645e+05	1.078e+08	1.50
y_head_inc_ss	9	25	6	7.1754e+07	83	8.645e+05	2.1454e+08	2.
y_spouse_inc_ss	10	26	6	7.1754e+07	83	8.645e+05	6.7646e+07	0.942
yshr_SS_ss	11	27	6	7.1754e+07	83	8.645e+05	1.0586e+07	0.147
yshr_interest_ss	12	28	6	7.1754e+07	83	8.645e+05	3.0079e+07	0.41
yshr_nttxss_ss	13	29	6	7.1754e+07	83	8.645e+05	3.7387e+06	0.0521
yshr_tax_ss	14	30	6	7.1754e+07	83	8.645e+05	1.4324e+07	0.199
yshr_wage_ss	15	31	6	7.1754e+07	83	8.645e+05	3.1088e+07	0.433

```

-----
XXXXXXXXXXXXXXXXXXXXXXXXXXXXXXXXXXXXXXXXXXXXXXXXXXXXXXXXXXXX
CONTAINER NAME: mp_dsvfi_results Scalars
XXXXXXXXXXXXXXXXXXXXXXXXXXXXXXXXXXXXXXXXXXXXXXXXXXXXXXXXXXXX

```

	i	idx	value
	--	---	-----
A_agg	1	1	193.39
A_agg_perhh	2	2	4.2232
Aprime_agg	3	3	197.89
Aprime_agg_perhh	4	4	4.3213
Bequests_aux	5	5	2.5593
Bequests_aux_perhh	6	6	0.055887
C_agg	7	7	48.789
C_agg_perhh	8	8	1.0654
SS_spend	9	9	2.3908
SS_spend_perhh	10	10	0.052208
Tax_revenues	11	12	13.735
Tax_revenues_perhh	12	13	0.29994
Y_inc_agg	13	14	64.627
Y_inc_agg_perhh	14	15	1.4113

xxx tb\_outcomes: all stats xxx

OriginalVariableNames	a_ss	ap_ss	cons_ss	n_ss	y_all
-----	-----	-----	-----	-----	-----
{'mean' }	4.2232	4.3213	1.0654	2.3554	1.4635
{'unweighted_sum' }	2228	8.7064e+08	8.2948e+07	21	1.3652e+08
{'sd' }	6.7417	6.779	0.6899	1.4375	1.4563
{'coefofvar' }	1.5964	1.5687	0.64754	0.61029	0.99508
{'gini' }	0.68027	0.68124	0.33738	0.3128	0.44246
{'min' }	0	0	0.036717	1	0.038108
{'max' }	135	163.7	141.66	6	50.873
{'pYis0' }	0.12293	0.10299	0	0	0
{'pYls0' }	0	0	0	0	0
{'pYgr0' }	0.87707	0.89701	1	1	1
{'pYisMINY' }	0.12293	0.10299	6.7731e-07	0.36005	6.7731e-07
{'pYisMAXY' }	6.0111e-06	1.6708e-12	0	0.041101	1.6708e-12
{'p0_01' }	0	0	0.067181	1	0.07102
{'p0_1' }	0	0	0.10544	1	0.11346
{'p1' }	0	0	0.18623	1	0.20359
{'p5' }	0	0	0.27747	1	0.28173
{'p10' }	0	0	0.36103	1	0.35688
{'p20' }	0.064373	0.068222	0.49773	1	0.50299
{'p25' }	0.11124	0.17983	0.56413	1	0.57911
{'p30' }	0.26367	0.37542	0.63091	1	0.65753

13.1. 2019 FULL STATES MPC AND DISTRIBUTIONAL STATISTICS BY MARITAL, KIDS, AND INCOME GROUP

{'p40'	}	0.68544	0.84816	0.77012	2	0.83048
{'p50'	}	1.4131	1.5883	0.91942	2	1.0325
{'p60'	}	2.5301	2.7569	1.0845	2	1.2817
{'p70'	}	4.1199	4.4885	1.2781	3	1.613
{'p75'	}	5.4836	5.7144	1.3935	3	1.8306
{'p80'	}	7.1191	7.2197	1.5293	4	2.1079
{'p90'	}	12.56	12.096	1.9344	5	3.0419
{'p95'	}	16.875	17.457	2.3404	5	4.0251
{'p99'	}	30.548	31.377	3.384	6	6.8588
{'p99_9'	}	56.953	56.953	5.2437	6	14.778
{'p99_99'	}	90.439	88.534	7.4817	6	20.971
{'fl_cov_a_ss'	}	45.451	45.439	3.3942	-1.4049	4.4679
{'fl_cor_a_ss'	}	1	0.99423	0.72975	-0.14496	0.45507
{'fl_cov_ap_ss'	}	45.439	45.955	3.4956	-1.3685	5.3067
{'fl_cor_ap_ss'	}	0.99423	1	0.74743	-0.14043	0.53754
{'fl_cov_cons_ss'	}	3.3942	3.4956	0.47596	0.23909	0.76142
{'fl_cor_cons_ss'	}	0.72975	0.74743	1	0.24109	0.75787
{'fl_cov_n_ss'	}	-1.4049	-1.3685	0.23909	2.0664	0.35987
{'fl_cor_n_ss'	}	-0.14496	-0.14043	0.24109	1	0.17191
{'fl_cov_y_all'	}	4.4679	5.3067	0.76142	0.35987	2.1208
{'fl_cor_y_all'	}	0.45507	0.53754	0.75787	0.17191	1
{'fl_cov_y_head_inc'	}	3.8282	4.1045	0.55948	0.092667	1.1039
{'fl_cor_y_head_inc'	}	0.56819	0.60585	0.81146	0.064504	0.75851
{'fl_cov_y_head_earn'	}	1.8477	2.1508	0.42576	0.19287	0.96246
{'fl_cor_y_head_earn'	}	0.29785	0.34482	0.67071	0.14582	0.71827
{'fl_cov_y_spouse_inc'	}	0.63967	1.2022	0.20194	0.2672	1.0169
{'fl_cor_y_spouse_inc'	}	0.09937	0.18573	0.30656	0.19467	0.73129
{'fl_cov_yshr_interest'	}	0.76424	0.71927	0.037996	-0.066731	-0.0094215
{'fl_cor_yshr_interest'	}	0.67572	0.63246	0.3283	-0.27671	-0.038564
{'fl_cov_yshr_wage'	}	-0.77528	-0.68855	-0.0042957	0.17055	0.10767
{'fl_cor_yshr_wage'	}	-0.34062	-0.30085	-0.018443	0.35142	0.21899
{'fl_cov_yshr_SS'	}	0.011037	-0.030725	-0.033701	-0.10382	-0.09825
{'fl_cor_yshr_SS'	}	0.0069239	-0.019169	-0.2066	-0.30546	-0.28534
{'fl_cov_yshr_tax'	}	0.098159	0.10896	0.018583	0.01337	0.038535
{'fl_cor_yshr_tax'	}	0.41485	0.45797	0.76748	0.26501	0.75395
{'fl_cov_yshr_nttxss'	}	0.087122	0.13969	0.052284	0.11719	0.13679
{'fl_cor_yshr_nttxss'	}	0.050539	0.080586	0.29639	0.31882	0.36733
{'fracByP0_01'	}	0	0	5.5188e-06	0.15286	4.2239e-06
{'fracByP0_1'	}	0	0	8.2593e-05	0.15286	6.444e-05
{'fracByP1'	}	0	0	0.0013857	0.15286	0.0010994
{'fracByP5'	}	0	0	0.010292	0.15286	0.0079949
{'fracByP10'	}	0	0	0.025341	0.15286	0.018888
{'fracByP20'	}	0.00074832	0.00060951	0.065753	0.15286	0.048269
{'fracByP25'	}	0.0014123	0.0020285	0.090679	0.15286	0.066791
{'fracByP30'	}	0.0041719	0.0051595	0.11872	0.15286	0.087944
{'fracByP40'	}	0.016751	0.01877	0.1844	0.40183	0.13867
{'fracByP50'	}	0.045326	0.046338	0.26358	0.40183	0.20207
{'fracByP60'	}	0.095502	0.095716	0.3575	0.40183	0.28072
{'fracByP70'	}	0.17466	0.17847	0.46813	0.56321	0.37901
{'fracByP75'	}	0.24517	0.23715	0.53078	0.56321	0.43771
{'fracByP80'	}	0.32852	0.31134	0.59927	0.75407	0.50477
{'fracByP90'	}	0.56651	0.52814	0.75975	0.8953	0.67658
{'fracByP95'	}	0.70071	0.6954	0.85893	0.8953	0.79526
{'fracByP99'	}	0.90524	0.90259	0.96084	1	0.93132
{'fracByP99_9'	}	0.98567	0.98372	0.99419	1	0.98801
{'fracByP99_99'	}	0.99808	0.9976	0.99922	1	0.99841

% Get Matrixes

```

cl_st_precompute_list = {'a', 'ar_z_ctr_amz', ...
    'inc', 'inc_unemp', 'spouse_inc', 'spouse_inc_unemp', 'ref_earn_wageind_grid',...
    'ap_idx_lower_ss', 'ap_idx_higher_ss', 'ap_idx_lower_weight_ss'};
mp_controls('bl_print_precompute_verbose') = false;
[mp_precompute_res] = snw_hh_precompute(mp_params, mp_controls, cl_st_precompute_list, ap_ss, Phi_tr

```

```

Wage quintile cutoffs=0.47017    0.71433    1.0293    1.5654
Completed SNW_HH_PRECOMPUTE;SNW_MP_PARAM=default_moredense_a65zh133zs5_e2m2;SNW_MP_CONTROL=default_t

```

### 13.1.2 Solve for 2019 Evuvw With 0 and 1 Checks

```

% Call Function
welf_checks = 0;
[ev19_jaeemk_check0, ec19_jaeemk_check0, ev20_jaeemk_check0, ec20_jaeemk_check0] = snw_evuvw19_jaeem
    welf_checks, st_solu_type, mp_params, mp_controls, ...
    V_ss, ap_ss, cons_ss, V_unemp, cons_unemp, mp_precompute_res);

```

```

Completed SNW_A4CHK_WRK_BISEC_VEC;welf_checks=0;TR=0.0017225;SNW_MP_PARAM=default_moredense_a65zh133
Completed SNW_A4CHK_UNEMP_BISEC_VEC;welf_checks=0;TR=0.0017225;xi=0.5;b=1;SNW_MP_PARAM=default_mored
Completed SNW_EVUVW20_JAEEMK;SNW_MP_PARAM=default_moredense_a65zh133zs5_e2m2;SNW_MP_CONTROL=default_
Completed SNW_EVUVW19_JAEEMK_FOC;SNW_MP_PARAM=default_moredense_a65zh133zs5_e2m2;SNW_MP_CONTROL=defa

```

```

% Call Function
welf_checks = 1;
[ev19_jaeemk_check2, ec19_jaeemk_check2, ev20_jaeemk_check2, ec20_jaeemk_check2] = snw_evuvw19_jaeem
    welf_checks, st_solu_type, mp_params, mp_controls, ...
    V_ss, ap_ss, cons_ss, V_unemp, cons_unemp, mp_precompute_res);

```

```

Completed SNW_A4CHK_WRK_BISEC_VEC;welf_checks=1;TR=0.0017225;SNW_MP_PARAM=default_moredense_a65zh133
Completed SNW_A4CHK_UNEMP_BISEC_VEC;welf_checks=1;TR=0.0017225;xi=0.5;b=1;SNW_MP_PARAM=default_mored
Completed SNW_EVUVW20_JAEEMK;SNW_MP_PARAM=default_moredense_a65zh133zs5_e2m2;SNW_MP_CONTROL=default_
Completed SNW_EVUVW19_JAEEMK_FOC;SNW_MP_PARAM=default_moredense_a65zh133zs5_e2m2;SNW_MP_CONTROL=defa

```

Differences between Checks in Expected Value and Expected Consumption

```

mn_V_U_gain_check = ev19_jaeemk_check2 - ev19_jaeemk_check0;
mn_MPC_C_gain_share_check = (ec19_jaeemk_check2 - ec19_jaeemk_check0)./(welf_checks*mp_params('TR'))

```

### 13.1.3 Additional Variables

Create additional Staet-Spac Arrays

```

% (n_jgrid,n_agrid,n_etagrid,n_educgrid,n_marriedgrid,n_kidsgrid);
% Children Array
ar_kids = (1:mp_params('n_kidsgrid')) - 1;
mn_kids = zeros(1,1,1,1,1,length(ar_kids));
mn_kids(1,1,1,1,1,:) = ar_kids;
kids_ss = repmat(mn_kids, [mp_params('n_jgrid'), mp_params('n_agrid'), mp_params('n_etagrid'), ...
    mp_params('n_educgrid'), mp_params('n_marriedgrid'), 1]);
% Marital Status Arrays
ar_marital = (1:mp_params('n_marriedgrid')) - 1;
mn_marital = zeros(1,1,1,1,length(ar_marital),1);
mn_marital(1,1,1,1,1) = ar_marital;
marital_ss = repmat(mn_marital, [mp_params('n_jgrid'), mp_params('n_agrid'), mp_params('n_etagrid'), ...
    mp_params('n_educgrid'), 1, mp_params('n_kidsgrid')]);
% Educational Status Arrays
ar_educ = (1:mp_params('n_educgrid')) - 1;
mn_educ = zeros(1,1,1,length(ar_educ),1,1);
mn_educ(1,1,1,1,1) = ar_educ;
educ_ss = repmat(mn_educ, [mp_params('n_jgrid'), mp_params('n_agrid'), mp_params('n_etagrid'), ...

```

```

    1, mp_params('n_marriedgrid'), mp_params('n_kidsgrid'))]);
% Age Array
ar_age = (1:mp_params('n_jgrid')) + 18;
mn_age = zeros(length(ar_age),1,1,1,1,1);
mn_age(:,1,1,1,1,1) = ar_age;
age_ss = repmat(mn_age, [1, mp_params('n_agrid'), mp_params('n_etagrid'), ...
    mp_params('n_educgrid'), mp_params('n_marriedgrid'), mp_params('n_kidsgrid')]);

```

### 13.1.4 Adjust to Probability Mass Function

```
Phi_true_1 = Phi_true./sum(Phi_true,'all');
```

### 13.1.5 Age Bounds

```

% 1 = 18
min_age = 1

min_age = 1

% retirement, 46+18=64, the year prior to retirement year.
max_age = 46;

```

### 13.1.6 Scale Statistics to Thousands of Dollars

```

a_ss = mp_dsvfi_results('a_ss')*58.056;
ap_ss = mp_dsvfi_results('ap_ss')*58.056;
c_ss = mp_dsvfi_results('cons_ss')*58.056;
n_ss = mp_dsvfi_results('n_ss');
% household head + spousal (realized) income
y_all = mp_dsvfi_results('y_all_ss')*58.056;
y_head_inc = mp_dsvfi_results('y_head_inc_ss')*58.056;
y_spouse_inc = mp_dsvfi_results('y_spouse_inc_ss')*58.056;

yshr_wage = mp_dsvfi_results('yshr_wage_ss');
yshr_SS = mp_dsvfi_results('yshr_SS_ss');
yshr_nttxss = mp_dsvfi_results('yshr_nttxss_ss');

```

### 13.1.7 Distributional Statistics Overall All Ages

```

% construct input data
marital_grp = marital_ss(min_age:82, :, :, :, :);
y_all_grp = y_all(min_age:82, :, :, :, :);
age_ss_grp = age_ss(min_age:82, :, :, :, :);
educ_ss_grp = educ_ss(min_age:82, :, :, :, :);
a_ss_grp = a_ss(min_age:82, :, :, :, :);
ap_ss_grp = ap_ss(min_age:82, :, :, :, :);
mn_MPC_C_gain_share_check_grp = mn_MPC_C_gain_share_check(min_age:82, :, :, :, :);
Phi_true_grp = Phi_true_1(min_age:82, :, :, :, :);
c_ss_grp = c_ss(min_age:82, :, :, :, :);
y_head_inc_grp = y_head_inc(min_age:82, :, :, :, :);
y_spouse_inc_grp = y_spouse_inc(min_age:82, :, :, :, :);
yshr_nttxss_grp = yshr_nttxss(min_age:82, :, :, :, :);

mp_cl_ar_xyz_of_s = containers.Map('KeyType','char', 'ValueType','any');
mp_cl_ar_xyz_of_s('married') = {marital_grp(:), zeros(1)};
mp_cl_ar_xyz_of_s('y_all') = {y_all_grp(:), zeros(1)};
mp_cl_ar_xyz_of_s('age_ss') = {age_ss_grp(:), zeros(1)};
mp_cl_ar_xyz_of_s('educ_ss') = {educ_ss_grp(:), zeros(1)};
mp_cl_ar_xyz_of_s('a_ss') = {a_ss_grp(:), zeros(1)};

```

```

mp_cl_ar_xyz_of_s('ap_ss') = {ap_ss_grp(:), zeros(1)};
mp_cl_ar_xyz_of_s('MPC') = {mn_MPC_C_gain_share_check_grp(:), zeros(1)};
mp_cl_ar_xyz_of_s('Mass') = {Phi_true_grp(:), zeros(1)};
mp_cl_ar_xyz_of_s('c_ss') = {c_ss_grp(:), zeros(1)};
mp_cl_ar_xyz_of_s('y_head_inc') = {y_head_inc_grp(:), zeros(1)};
mp_cl_ar_xyz_of_s('y_spouse') = {y_spouse_inc_grp(:), zeros(1)};
mp_cl_ar_xyz_of_s('yshr_nttxss') = {yshr_nttxss_grp(:), zeros(1)};

mp_cl_ar_xyz_of_s('ar_st_y_name') = ["married", "y_all", "age_ss", "educ_ss", "a_ss", "ap_ss", "MPC"]

% controls
mp_support = containers.Map('KeyType','char', 'ValueType','any');
mp_support('ar_fl_percentiles') = [0.01 10 25 50 75 90 99.99];
mp_support('bl_display_final') = true;
mp_support('bl_display_detail') = false;
mp_support('bl_display_drvm2outcomes') = false;
mp_support('bl_display_drvstats') = false;
mp_support('bl_display_drvm2covcor') = false;

% Call Function
mp_cl_mt_xyz_of_s = ff_simu_stats(Phi_true_grp(:)/sum(Phi_true_grp,'all'), mp_cl_ar_xyz_of_s, mp_sup

xxx tb_outcomes: all stats xxx

```

OriginalVariableNames	married	y_all	age_ss	educ_ss	a_ss
{'mean' }	0.47501	84.974	47.129	0.303	245.22
{'unweighted_sum' }	1	7.9255e+09	4879	1	1.2935e+05
{'sd' }	0.49938	84.549	19.231	0.45956	391.42
{'coefofvar' }	1.0513	0.995	0.40805	1.5167	1.5962
{'gini' }	0.36718	0.44243	0.23101	0.61588	0.68023
{'min' }	0	2.2124	19	0	0
{'max' }	1	2953.5	100	1	7837.6
{'pYis0' }	0.52499	0	0	0.697	0.12285
{'pYls0' }	0	0	0	0	0
{'pYgr0' }	0.47501	1	1	0.303	0.87715
{'pYisMINY' }	0.52499	6.774e-07	0.02184	0.697	0.12285
{'pYisMAXY' }	0.47501	1.671e-12	0.00020326	0.303	6.0119e-06
{'p0_01' }	0	4.1232	19	0	0
{'p10' }	0	20.726	23	0	0
{'p25' }	0	33.631	31	0	6.458
{'p50' }	0	59.948	45	0	82.04
{'p75' }	1	106.28	62	1	318.35
{'p90' }	1	176.61	75	1	729.18
{'p99_99' }	1	1217.5	100	1	5250.6
{'fl_cov_married' }	0.24938	12.618	2.9987e-13	0.026842	31.201
{'fl_cor_married' }	1	0.29884	3.1225e-14	0.11697	0.15962
{'fl_cov_y_all' }	12.618	7148.6	-105.85	6.7259	15059
{'fl_cor_y_all' }	0.29884	1	-0.065099	0.1731	0.45504
{'fl_cov_age_ss' }	2.9987e-13	-105.85	369.84	5.7371e-13	2902
{'fl_cor_age_ss' }	3.1225e-14	-0.065099	1	6.4916e-14	0.38553
{'fl_cov_educ_ss' }	0.026842	6.7259	5.7371e-13	0.21119	20.13
{'fl_cor_educ_ss' }	0.11697	0.1731	6.4916e-14	1	0.11191
{'fl_cov_a_ss' }	31.201	15059	2902	20.13	1.5321e+05
{'fl_cor_a_ss' }	0.15962	0.45504	0.38553	0.11191	1
{'fl_cov_ap_ss' }	31.93	17886	2762.7	20.615	1.5316e+05
{'fl_cor_ap_ss' }	0.16246	0.53751	0.36501	0.11398	0.99423
{'fl_cov_MPC' }	-0.016733	-6.6507	-1.2778	0.0049583	-30.154

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{'fl_cor_MPC' }	-0.13011	-0.30544	-0.258	0.041894	-0.29913
{'fl_cov_Mass' }	-5.1035e-07	-7.3196e-05	-2.691e-05	-2.0525e-07	-0.00031586
{'fl_cor_Mass' }	-0.19258	-0.16313	-0.26368	-0.084158	-0.15206
{'fl_cov_c_ss' }	8.8909	2566.3	57.161	4.6211	11440
{'fl_cor_c_ss' }	0.44452	0.75784	0.074211	0.25106	0.72974
{'fl_cov_y_head_inc' }	1.6909	3720.9	-73.542	4.2898	12903
{'fl_cor_y_head_inc' }	0.058359	0.75849	-0.065909	0.16088	0.56816
{'fl_cov_y_spouse' }	10.927	3427.7	-32.308	2.436	2155.8
{'fl_cor_y_spouse' }	0.3947	0.73129	-0.030304	0.095619	0.09935
{'fl_cov_yshr_nttxss' }	0.022689	7.935	-3.2573	0.0058708	5.0323
{'fl_cor_yshr_nttxss' }	0.1778	0.36727	-0.66283	0.049993	0.050313
{'fracByP0_01' }	0	4.224e-06	0.0088049	0	0
{'fracByP10' }	0	0.018881	0.047593	0	0
{'fracByP25' }	0	0.066793	0.14054	0	0.0014119
{'fracByP50' }	0	0.20209	0.34194	0	0.045325
{'fracByP75' }	1	0.43774	0.62344	1	0.24517
{'fracByP90' }	1	0.6766	0.82958	1	0.56651
{'fracByP99_99' }	1	0.99841	1	1	0.99808

```
tb_dist_stats_all = mp_cl_mt_xyz_of_s('tb_outcomes');
```

#### 13.1.8 Distributional Statistics Overall 18 to 64

Statistics overall distributionally for 18 to 64 year olds.

```
% construct input data
```

```
marital_grp = marital_ss(min_age:max_age, :, :, : ,: ,:);
y_all_grp = y_all(min_age:max_age, :, :, : ,: ,:);
age_ss_grp = age_ss(min_age:max_age, :, :, : ,: ,:);
educ_ss_grp = educ_ss(min_age:max_age, :, :, : ,: ,:);
a_ss_grp = a_ss(min_age:max_age, :, :, : ,: ,:);
ap_ss_grp = ap_ss(min_age:max_age, :, :, : ,: ,:);
mn_MPC_C_gain_share_check_grp = mn_MPC_C_gain_share_check(min_age:max_age, :, :, : ,: ,: ,:);
Phi_true_grp = Phi_true_1(min_age:max_age, :, :, : ,: ,:);
c_ss_grp = c_ss(min_age:max_age, :, :, : ,: ,:);
y_head_inc_grp = y_head_inc(min_age:max_age, :, :, : ,: ,:);
y_spouse_inc_grp = y_spouse_inc(min_age:max_age, :, :, : ,: ,:);
yshr_nttxss_grp = yshr_nttxss(min_age:max_age, :, :, : ,: ,:);
```

```
mp_cl_ar_xyz_of_s = containers.Map('KeyType','char', 'ValueType','any');
mp_cl_ar_xyz_of_s('married') = {marital_grp(:), zeros(1)};
mp_cl_ar_xyz_of_s('y_all') = {y_all_grp(:), zeros(1)};
mp_cl_ar_xyz_of_s('age_ss') = {age_ss_grp(:), zeros(1)};
mp_cl_ar_xyz_of_s('educ_ss') = {educ_ss_grp(:), zeros(1)};
mp_cl_ar_xyz_of_s('a_ss') = {a_ss_grp(:), zeros(1)};
mp_cl_ar_xyz_of_s('ap_ss') = {ap_ss_grp(:), zeros(1)};
mp_cl_ar_xyz_of_s('MPC') = {mn_MPC_C_gain_share_check_grp(:), zeros(1)};
mp_cl_ar_xyz_of_s('Mass') = {Phi_true_grp(:), zeros(1)};
mp_cl_ar_xyz_of_s('c_ss') = {c_ss_grp(:), zeros(1)};
mp_cl_ar_xyz_of_s('y_head_inc') = {y_head_inc_grp(:), zeros(1)};
mp_cl_ar_xyz_of_s('y_spouse') = {y_spouse_inc_grp(:), zeros(1)};
mp_cl_ar_xyz_of_s('yshr_nttxss') = {yshr_nttxss_grp(:), zeros(1)};
```

```
mp_cl_ar_xyz_of_s('ar_st_y_name') = ["married", "y_all", "age_ss", "educ_ss", "a_ss", "ap_ss", "MPC"]
```

```
% controls
```

```
mp_support = containers.Map('KeyType','char', 'ValueType','any');
mp_support('ar_fl_percentiles') = [0.01 10 25 50 75 90 99.99];
mp_support('bl_display_final') = true;
```

```

mp_support('bl_display_detail') = false;
mp_support('bl_display_drvm2outcomes') = false;
mp_support('bl_display_drvstats') = false;
mp_support('bl_display_drvm2covcor') = false;

```

```
% Call Function
```

```
mp_cl_mt_xyz_of_s = ff_simu_stats(Phi_true_grp(:)/sum(Phi_true_grp,'all'), mp_cl_ar_xyz_of_s, mp_sup
```

```
xxx tb_outcomes: all stats xxx
```

OriginalVariableNames	married	y_all	age_ss	educ_ss	a_ss
{'mean' }	0.47501	95.246	39.372	0.303	194.
{'unweighted_sum' }	1	7.7487e+09	1909	1	1.2935e+0
{'sd' }	0.49938	89.631	13.105	0.45956	344.
{'coefofvar' }	1.0513	0.94104	0.33285	1.5167	1.771
{'gini' }	0.36718	0.42428	0.18859	0.61588	0.7157
{'min' }	0	2.2124	19	0	
{'max' }	1	2953.5	64	1	7837.
{'pYis0' }	0.52499	0	0	0.697	0.1462
{'pYls0' }	0	0	0	0	
{'pYgr0' }	0.47501	1	1	0.303	0.8537
{'pYisMINY' }	0.52499	8.6135e-07	0.027771	0.697	0.1462
{'pYisMAXY' }	0.47501	2.1248e-12	0.015675	0.303	5.4766e-0
{'p0_01' }	0	3.9581	19	0	
{'p10' }	0	25.069	22	0	
{'p25' }	0	40.654	28	0	3.737
{'p50' }	0	69.57	38	0	51.66
{'p75' }	1	119.76	50	1	239.1
{'p90' }	1	192.9	58	1	588.4
{'p99_99' }	1	1249.3	64	1	4707.
{'fl_cov_married' }	0.24938	13.756	2.335e-13	0.026842	25.2
{'fl_cor_married' }	1	0.30733	3.5679e-14	0.11697	0.1468
{'fl_cov_y_all' }	13.756	8033.6	270.03	7.5617	1785
{'fl_cor_y_all' }	0.30733	1	0.22988	0.18358	0.5781
{'fl_cov_age_ss' }	2.335e-13	270.03	171.75	4.3386e-15	2241.
{'fl_cor_age_ss' }	3.5679e-14	0.22988	1	7.204e-16	0.4964
{'fl_cov_educ_ss' }	0.026842	7.5617	4.3386e-15	0.21119	15.47
{'fl_cor_educ_ss' }	0.11697	0.18358	7.204e-16	1	0.09776
{'fl_cov_a_ss' }	25.27	17852	2241.5	15.478	1.1868e+0
{'fl_cor_a_ss' }	0.14689	0.57814	0.49648	0.097766	
{'fl_cov_ap_ss' }	26.783	20993	2328.9	16.562	1.2238e+0
{'fl_cor_ap_ss' }	0.15001	0.65507	0.49704	0.1008	0.9935
{'fl_cov_MPC' }	-0.017248	-8.3845	-1.4685	0.0073384	-27.85
{'fl_cor_MPC' }	-0.12735	-0.34491	-0.41317	0.058877	-0.2981
{'fl_cov_Mass' }	-6.2681e-07	-0.00010581	-2.2759e-05	-2.2235e-07	-0.0003165
{'fl_cor_Mass' }	-0.21171	-0.19912	-0.29292	-0.081609	-0.15
{'fl_cov_c_ss' }	8.9405	2911.4	117.7	4.6429	9782.
{'fl_cor_c_ss' }	0.44676	0.81058	0.22412	0.25211	0.7086
{'fl_cov_y_head_inc' }	1.5449	4083.5	215.29	4.8213	1513
{'fl_cor_y_head_inc' }	0.050457	0.74307	0.26794	0.17111	0.7164
{'fl_cov_y_spouse' }	12.211	3950.1	54.733	2.7405	2719.
{'fl_cor_y_spouse' }	0.40608	0.7319	0.069359	0.099033	0.131
{'fl_cov_yshr_nttxss' }	0.0064334	2.2345	0.12412	0.0029398	5.703
{'fl_cor_yshr_nttxss' }	0.38567	0.74633	0.28352	0.1915	0.4956
{'fracByP0_01' }	0	3.6432e-06	0.013402	0	
{'fracByP10' }	0	0.018969	0.056893	0	
{'fracByP25' }	0	0.070975	0.15748	0	0.001135



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{'fracByP50'}	}	0	0.21374	0.35932	0	0.03404
{'fracByP75'}	}	1	0.45357	0.64274	1	0.2134
{'fracByP90'}	}	1	0.69054	0.84608	1	0.5149
{'fracByP99_99'}	}	1	0.99855	1	1	0.9971

```
tb_dist_stats_all_18to64 = mp_cl_mt_xyz_of_s('tb_outcomes');
```

#### 13.1.9 Distributional Statistics By Kids Count

Various statistics, including MPC (of the first check) by Children Count

```
it_row_ctr = 0;
for it_ctr=1:mp_params('n_kidsgrid')
    display(['xxxxxxxxxxxxxxxxxxxxxxxxxxxxxxxxxxxxxxxx']);
    display(['kids =' num2str(ar_kids(it_ctr))]);
    display(['xxxxxxxxxxxxxxxxxxxxxxxxxxxxxxxxxxxxxxxx']);

    % construct input data
    marital_grp = marital_ss(min_age:max_age, :, :, :, it_ctr);
    y_all_grp = y_all(min_age:max_age, :, :, :, it_ctr);
    age_ss_grp = age_ss(min_age:max_age, :, :, :, it_ctr);
    educ_ss_grp = educ_ss(min_age:max_age, :, :, :, it_ctr);
    a_ss_grp = a_ss(min_age:max_age, :, :, :, it_ctr);
    ap_ss_grp = ap_ss(min_age:max_age, :, :, :, it_ctr);
    mn_MPC_C_gain_share_check_grp = mn_MPC_C_gain_share_check(min_age:max_age, :, :, :, it_ctr);
    Phi_true_grp = Phi_true_1(min_age:max_age, :, :, :, it_ctr);
    c_ss_grp = c_ss(min_age:max_age, :, :, :, it_ctr);
    y_head_inc_grp = y_head_inc(min_age:max_age, :, :, :, it_ctr);
    y_spouse_inc_grp = y_spouse_inc(min_age:max_age, :, :, :, it_ctr);
    yshr_nttxss_grp = yshr_nttxss(min_age:max_age, :, :, :, it_ctr);

    mp_cl_ar_xyz_of_s = containers.Map('KeyType','char', 'ValueType','any');
    mp_cl_ar_xyz_of_s('married') = {marital_grp(:), zeros(1)};
    mp_cl_ar_xyz_of_s('y_all') = {y_all_grp(:), zeros(1)};
    mp_cl_ar_xyz_of_s('age_ss') = {age_ss_grp(:), zeros(1)};
    mp_cl_ar_xyz_of_s('educ_ss') = {educ_ss_grp(:), zeros(1)};
    mp_cl_ar_xyz_of_s('a_ss') = {a_ss_grp(:), zeros(1)};
    mp_cl_ar_xyz_of_s('ap_ss') = {ap_ss_grp(:), zeros(1)};
    mp_cl_ar_xyz_of_s('MPC') = {mn_MPC_C_gain_share_check_grp(:), zeros(1)};
    mp_cl_ar_xyz_of_s('Mass') = {Phi_true_grp(:), zeros(1)};
    mp_cl_ar_xyz_of_s('c_ss') = {c_ss_grp(:), zeros(1)};
    mp_cl_ar_xyz_of_s('y_head_inc') = {y_head_inc_grp(:), zeros(1)};
    mp_cl_ar_xyz_of_s('y_spouse') = {y_spouse_inc_grp(:), zeros(1)};
    mp_cl_ar_xyz_of_s('yshr_nttxss') = {yshr_nttxss_grp(:), zeros(1)};

    mp_cl_ar_xyz_of_s('ar_st_y_name') = ["married", "y_all", "age_ss", "educ_ss", "a_ss", "ap_ss", ""];

    % controls
    mp_support = containers.Map('KeyType','char', 'ValueType','any');
    mp_support('ar_fl_percentiles') = [0.01 10 25 50 75 90 99.99];
    mp_support('bl_display_final') = true;
    mp_support('bl_display_detail') = false;
    mp_support('bl_display_drvm2outcomes') = false;
    mp_support('bl_display_drvstats') = false;
    mp_support('bl_display_drvm2covcor') = false;

    % Call Function
    mp_cl_mt_xyz_of_s = ff_simu_stats(Phi_true_grp(:)/sum(Phi_true_grp,'all'), mp_cl_ar_xyz_of_s, mp
```

```

it_kids = ar_kids(it_ctr);

tb_dist_stats = mp_cl_mt_xyz_of_s('tb_outcomes');

fl_married_mean = tb_dist_stats{"married", "mean"};

fl_age_mean = tb_dist_stats{"age_ss", "mean"};
fl_age_p50 = tb_dist_stats{"age_ss", "p50"};

fl_educ_mean = tb_dist_stats{"educ_ss", "mean"};

fl_a_mean = tb_dist_stats{"a_ss", "mean"};
fl_a_p50 = tb_dist_stats{"a_ss", "p50"};

fl_ap_mean = tb_dist_stats{"ap_ss", "mean"};
fl_ap_p50 = tb_dist_stats{"ap_ss", "p50"};

fl_y_all_mean = tb_dist_stats{"y_all", "mean"};
fl_y_all_p50 = tb_dist_stats{"y_all", "p50"};

fl_mpc_mean = tb_dist_stats{"MPC", "mean"};
fl_mpc_p50 = tb_dist_stats{"MPC", "p50"};

fl_mass = tb_dist_stats{"Mass", "unweighted_sum"};

fl_c_ss_mean = tb_dist_stats{"c_ss", "mean"};
fl_c_ss_p50 = tb_dist_stats{"c_ss", "p50"};

fl_y_head_inc_mean = tb_dist_stats{"y_head_inc", "mean"};
fl_y_spouse_mean = tb_dist_stats{"y_spouse", "mean"};

ar_store_stats = [it_kids, fl_married_mean, ...
    fl_age_mean, fl_age_p50, fl_educ_mean, ...
    fl_a_mean, fl_a_p50, fl_ap_mean, fl_ap_p50, ...
    fl_y_all_mean, fl_y_all_p50, ...
    fl_mpc_mean, fl_mpc_p50, ...
    fl_mass, ...
    fl_c_ss_mean, fl_c_ss_p50, ...
    fl_y_head_inc_mean, fl_y_spouse_mean];

it_row_ctr = it_row_ctr + 1;

if (it_row_ctr>1)
    mt_store_stats_by_k = [mt_store_stats_by_k;ar_store_stats];
else
    mt_store_stats_by_k = [ar_store_stats];
end
end

```

```

xxxxxxxxxxxxxxxxxxxxxxxxxxxxxxxxxxxxxxxx

```

```

kids =0

```

```

xxxxxxxxxxxxxxxxxxxxxxxxxxxxxxxxxxxxxxxx

```

```

xxx tb_outcomes: all stats xxx

```

OriginalVariableNames	married	y_all	age_ss	educ_ss	a_ss
{'mean' }	0.34092	95.696	42.81	0.29837	267.84
{'unweighted_sum' }	1	1.9045e+09	1909	1	1.2935e+05





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{'sd' }	0.49283	87.576	10.518	0.46162	238.29
{'coefofvar' }	0.84337	0.91781	0.29375	1.4993	1.9174
{'gini' }	0.22818	0.41656	0.16465	0.60873	0.73697
{'min' }	0	2.2124	19	0	0
{'max' }	1	2551.1	64	1	7837.6
{'pYis0' }	0.41564	0	0	0.69211	0.1963
{'pYls0' }	0	0	0	0	0
{'pYgr0' }	0.58436	1	1	0.30789	0.8037
{'pYisMINY' }	0.41564	4.0938e-07	0.014906	0.69211	0.1963
{'pYisMAXY' }	0.58436	1.0736e-12	0.0019534	0.30789	9.1954e-07
{'p0_01' }	0	4.1232	19	0	0
{'p10' }	0	26.204	23	0	0
{'p25' }	0	41.871	27	0	0.80724
{'p50' }	1	70.257	35	0	29.898
{'p75' }	1	120.84	43	1	146.89
{'p90' }	1	190.32	51	1	363.77
{'p99_99' }	1	1122.5	64	1	3737.2
{'fl_cov_married' }	0.24288	12.863	0.51579	0.025827	25.491
{'fl_cor_married' }	1	0.29802	0.099501	0.11352	0.21706
{'fl_cov_y_all' }	12.863	7669.6	228.36	8.3133	11413
{'fl_cor_y_all' }	0.29802	1	0.2479	0.20564	0.54689
{'fl_cov_age_ss' }	0.51579	228.36	110.63	0.45675	1116.6
{'fl_cor_age_ss' }	0.099501	0.2479	1	0.094068	0.44549
{'fl_cov_educ_ss' }	0.025827	8.3133	0.45675	0.21309	15.009
{'fl_cor_educ_ss' }	0.11352	0.20564	0.094068	1	0.13644
{'fl_cov_a_ss' }	25.491	11413	1116.6	15.009	56783
{'fl_cor_a_ss' }	0.21706	0.54689	0.44549	0.13644	1
{'fl_cov_ap_ss' }	27.147	14327	1160.8	16.023	58304
{'fl_cor_ap_ss' }	0.22214	0.65975	0.44505	0.13997	0.9867
{'fl_cov_MPC' }	-0.055633	-12.184	-1.1929	-0.0029873	-25.836
{'fl_cor_MPC' }	-0.35573	-0.43842	-0.3574	-0.020393	-0.34167
{'fl_cov_Mass' }	-4.6541e-07	-7.3755e-05	-9.0248e-06	-2.4395e-07	-0.0001563
{'fl_cor_Mass' }	-0.32688	-0.29151	-0.29699	-0.18292	-0.22704
{'fl_cov_c_ss' }	8.1321	2864.5	129.17	5.2868	7092.7
{'fl_cor_c_ss' }	0.40653	0.80585	0.30257	0.28216	0.73333
{'fl_cov_y_head_inc' }	1.6658	3681.5	154.09	5.3399	9372.8
{'fl_cor_y_head_inc' }	0.058412	0.72644	0.25315	0.1999	0.67972
{'fl_cov_y_spouse' }	11.197	3988.2	74.272	2.9734	2040.1
{'fl_cor_y_spouse' }	0.37578	0.75322	0.11679	0.10654	0.1416
{'fl_cov_yshr_nttxss' }	0.0064177	2.1485	0.10113	0.0033688	3.5399
{'fl_cor_yshr_nttxss' }	0.39977	0.75315	0.29517	0.22404	0.45606
{'fracByP0_01' }	0	3.7828e-06	0.0079094	0	0
{'fracByP10' }	0	0.019866	0.075143	0	0
{'fracByP25' }	0	0.073594	0.17417	0	0.00024523
{'fracByP50' }	1	0.21851	0.40471	0	0.027182
{'fracByP75' }	1	0.4596	0.65078	1	0.20572
{'fracByP90' }	1	0.69638	0.85987	1	0.47333
{'fracByP99_99' }	1	0.99869	1	1	0.99695

xx

kids =3

xx

xxx tb\_outcomes: all stats xxx

OriginalVariableNames	married	y_all	age_ss	educ_ss	a_ss
{'mean' }	0.69032	96.012	35.356	0.30365	101.
{'unweighted_sum' }	1	1.6091e+09	1909	1	1.2935e+0

{'sd'	}	0.46236	83.53	9.1314	0.45983	196.5
{'coefofvar'	}	0.66978	0.86999	0.25827	1.5143	1.940
{'gini'	}	0.12198	0.40117	0.14344	0.61493	0.729
{'min'	}	0	2.2124	19	0	
{'max'	}	1	2381.6	64	1	7837.
{'pYis0'	}	0.30968	0	0	0.69635	0.1917
{'pYls0'	}	0	0	0	0	
{'pYgr0'	}	0.69032	1	1	0.30365	0.8082
{'pYisMINY'	}	0.30968	2.133e-07	0.007718	0.69635	0.1917
{'pYisMAXY'	}	0.69032	3.4711e-13	0.00070368	0.30365	3.1947e-0
{'p0_01'	}	0	4.4187	19	0	
{'p10'	}	0	28.136	24	0	
{'p25'	}	0	44.054	28	0	0.8072
{'p50'	}	1	72.443	34	0	29.89
{'p75'	}	1	122.12	42	1	100.9
{'p90'	}	1	185.9	48	1	276.8
{'p99_99'	}	1	1027.1	64	1	3306.
{'fl_cov_married'	}	0.21378	9.9452	0.39867	0.02286	16.46
{'fl_cor_married'	}	1	0.25751	0.094427	0.10752	0.1811
{'fl_cov_y_all'	}	9.9452	6977.2	176.66	8.4101	8663.
{'fl_cor_y_all'	}	0.25751	1	0.23161	0.21896	0.527
{'fl_cov_age_ss'	}	0.39867	176.66	83.382	0.55101	713.
{'fl_cor_age_ss'	}	0.094427	0.23161	1	0.13123	0.397
{'fl_cov_educ_ss'	}	0.02286	8.4101	0.55101	0.21145	12.95
{'fl_cor_educ_ss'	}	0.10752	0.21896	0.13123	1	0.1433
{'fl_cov_a_ss'	}	16.463	8663.4	713.9	12.958	3864
{'fl_cor_a_ss'	}	0.18113	0.5276	0.3977	0.14334	
{'fl_cov_ap_ss'	}	17.437	11197	743.03	13.851	3960
{'fl_cor_ap_ss'	}	0.184	0.65402	0.397	0.14696	0.9828
{'fl_cov_MPC'	}	-0.061242	-11.95	-0.93092	-0.0093462	-21.83
{'fl_cor_MPC'	}	-0.42463	-0.45863	-0.32683	-0.065159	-0.3561
{'fl_cov_Mass'	}	-2.6557e-07	-3.5455e-05	-3.3149e-06	-1.3715e-07	-6.3012e-0
{'fl_cor_Mass'	}	-0.38696	-0.28596	-0.24457	-0.20093	-0.2159
{'fl_cov_c_ss'	}	6.6057	2725.3	105	5.4818	5577.
{'fl_cor_c_ss'	}	0.35578	0.81251	0.28636	0.29687	0.706
{'fl_cov_y_head_inc'	}	1.3302	3539.8	118.35	5.592	7371.
{'fl_cor_y_head_inc'	}	0.05051	0.744	0.22755	0.2135	0.6583
{'fl_cov_y_spouse'	}	8.6149	3437.4	58.307	2.8181	1291.
{'fl_cor_y_spouse'	}	0.3324	0.73415	0.11391	0.10933	0.1172
{'fl_cov_yshr_nttxss'	}	0.0052966	1.9936	0.078236	0.0034153	2.582
{'fl_cor_yshr_nttxss'	}	0.36767	0.76604	0.27499	0.23838	0.4216
{'fracByP0_01'	}	0	4.0037e-06	0.0041476	0	
{'fracByP10'	}	0	0.021316	0.072166	0	
{'fracByP25'	}	0	0.078153	0.18337	0	0.0003122
{'fracByP50'	}	1	0.22773	0.39789	0	0.03805
{'fracByP75'	}	1	0.47322	0.69228	1	0.1876
{'fracByP90'	}	1	0.7065	0.86	1	0.4594
{'fracByP99_99'	}	1	0.9988	1	1	0.9967

xx

kids =4

xx

xxx tb\_outcomes: all stats xxx

OriginalVariableNames	married	y_all	age_ss	educ_ss	a_ss	
{'mean'	}	0.78724	91.676	35.383	0.29511	81.61
{'unweighted_sum'	}	1	1.4702e+09	1909	1	1.2935e+0

13.1. 2019 FULL STATES MPC AND DISTRIBUTIONAL STATISTICS BY MARITAL, KIDS, AND INCOME GROUP

{'sd'	}	0.40926	74.133	7.9178	0.45609	164.
{'coefofvar'	}	0.51987	0.80864	0.22378	1.5455	2.013
{'gini'	}	0.054374	0.38168	0.12297	0.62738	0.7274
{'min'	}	0	2.2124	19	0	
{'max'	}	1	2113.2	64	1	7837.
{'pYis0'	}	0.21276	0	0	0.70489	0.1891
{'pYls0'	}	0	0	0	0	
{'pYgr0'	}	0.78724	1	1	0.29511	0.8108
{'pYisMINY'	}	0.21276	9.2536e-08	0.0035072	0.70489	0.1891
{'pYisMAXY'	}	0.78724	2.0254e-13	0.00027556	0.29511	1.1672e-0
{'p0_01'	}	0	4.7807	19	0	
{'p10'	}	0	29.13	26	0	
{'p25'	}	1	44.24	29	0	0.8072
{'p50'	}	1	71.8	35	0	29.89
{'p75'	}	1	115.49	41	1	82.0
{'p90'	}	1	172.56	46	1	239.1
{'p99_99'	}	1	888.01	64	1	2910.
{'fl_cov_married'	}	0.16749	5.9174	0.25239	0.018555	8.620
{'fl_cor_married'	}	1	0.19504	0.077888	0.099404	0.128
{'fl_cov_y_all'	}	5.9174	5495.7	126.24	7.9495	6630.
{'fl_cor_y_all'	}	0.19504	1	0.21507	0.23511	0.5443
{'fl_cov_age_ss'	}	0.25239	126.24	62.692	0.61699	463.
{'fl_cor_age_ss'	}	0.077888	0.21507	1	0.17085	0.3564
{'fl_cov_educ_ss'	}	0.018555	7.9495	0.61699	0.20802	10.80
{'fl_cor_educ_ss'	}	0.099404	0.23511	0.17085	1	0.1442
{'fl_cov_a_ss'	}	8.6206	6630.3	463.7	10.809	2699
{'fl_cor_a_ss'	}	0.1282	0.54435	0.35644	0.14424	
{'fl_cov_ap_ss'	}	8.7102	8295.7	479.98	11.425	2761
{'fl_cor_ap_ss'	}	0.12468	0.65556	0.35513	0.14675	0.9845
{'fl_cov_MPC'	}	-0.04739	-10.199	-0.82379	-0.011367	-17.74
{'fl_cor_MPC'	}	-0.39132	-0.46494	-0.3516	-0.084227	-0.3649
{'fl_cov_Mass'	}	-1.0116e-07	-1.7179e-05	-1.6822e-06	-8.6576e-08	-3.0647e-0
{'fl_cor_Mass'	}	-0.30657	-0.28741	-0.26349	-0.23543	-0.2313
{'fl_cov_c_ss'	}	4.4325	2483.7	79.686	5.416	4382.
{'fl_cor_c_ss'	}	0.27632	0.85476	0.25676	0.30296	0.680
{'fl_cov_y_head_inc'	}	0.92362	3408.6	90.849	5.7717	5998.
{'fl_cor_y_head_inc'	}	0.03994	0.81373	0.20306	0.22396	0.6461
{'fl_cov_y_spouse'	}	4.9938	2087.1	35.394	2.1778	631.8
{'fl_cor_y_spouse'	}	0.28208	0.65082	0.10334	0.11038	0.08889
{'fl_cov_yshr_nttxss'	}	0.0035289	1.7418	0.059073	0.0033945	1.929
{'fl_cor_yshr_nttxss'	}	0.29013	0.79058	0.25104	0.25043	0.3950
{'fracByP0_01'	}	0	4.5191e-06	0.0018833	0	
{'fracByP10'	}	0	0.023539	0.08684	0	
{'fracByP25'	}	1	0.083914	0.18322	0	0.0003800
{'fracByP50'	}	1	0.24018	0.44948	0	0.05909
{'fracByP75'	}	1	0.48959	0.71178	1	0.2009
{'fracByP90'	}	1	0.71753	0.86506	1	0.4875
{'fracByP99_99'	}	1	0.9989	1	1	0.9960

13.1.10 Distributional Statistics By Marital Status and Kids Count

Various statistics, including MPC (of the first check) by Marital Status and Kids COunt

```

it_row_ctr = 0;
for it_marry_ctr=1:mp_params('n_marriedgrid')

    display(['']);
    display(['']);
    display(['-----']);

```

```

display(['-----']);
display(['-----']);
display(['-----']);
display(['xxxxxxxxxxxxxxxxxxxxxxxxxxxxxxxxxxxxxxxx']);
display(['Marital = ' num2str(ar_marital(it_marry_ctr))]);
display(['xxxxxxxxxxxxxxxxxxxxxxxxxxxxxxxxxxxxxxxx']);
display(['-----']);
display(['-----']);

for it_kids_ctr=1:mp_params('n_kidsgrid')
    display(['xxxxxxxxxxxxxxxxxxxxxxxxxxxxxxxxxxxxxxxx']);
    display(['Marital = ' num2str(ar_marital(it_marry_ctr)) ' and kids = ' num2str(ar_kids(it_kids_ctr))]);
    display(['xxxxxxxxxxxxxxxxxxxxxxxxxxxxxxxxxxxxxxxx']);

    % construct input data
    y_all_grp = y_all(min_age:max_age, :, :, : ,it_marry_ctr ,it_ctr);
    age_ss_grp = age_ss(min_age:max_age, :, :, : ,it_marry_ctr, it_kids_ctr);
    educ_ss_grp = educ_ss(min_age:max_age, :, :, : ,it_marry_ctr, it_kids_ctr);
    a_ss_grp = a_ss(min_age:max_age, :, :, : ,it_marry_ctr, it_kids_ctr);
    ap_ss_grp = ap_ss(min_age:max_age, :, :, : ,it_marry_ctr, it_kids_ctr);
    mn_MPC_C_gain_share_check_grp = mn_MPC_C_gain_share_check(min_age:max_age, :, :, : ,it_marry_ctr, it_kids_ctr);
    Phi_true_grp = Phi_true_1(min_age:max_age, :, :, : ,it_marry_ctr, it_kids_ctr);
    c_ss_grp = c_ss(min_age:max_age, :, :, : ,it_marry_ctr, it_kids_ctr);
    y_head_inc_grp = y_head_inc(min_age:max_age, :, :, : ,it_marry_ctr, it_kids_ctr);
    y_spouse_inc_grp = y_spouse_inc(min_age:max_age, :, :, : ,it_marry_ctr, it_kids_ctr);
    yshr_nttxss_grp = yshr_nttxss(min_age:max_age, :, :, : ,it_marry_ctr, it_kids_ctr);

    mp_cl_ar_xyz_of_s = containers.Map('KeyType','char', 'ValueType','any');
    mp_cl_ar_xyz_of_s('y_all') = {y_all_grp(:), zeros(1)};
    mp_cl_ar_xyz_of_s('age_ss') = {age_ss_grp(:), zeros(1)};
    mp_cl_ar_xyz_of_s('educ_ss') = {educ_ss_grp(:), zeros(1)};
    mp_cl_ar_xyz_of_s('a_ss') = {a_ss_grp(:), zeros(1)};
    mp_cl_ar_xyz_of_s('ap_ss') = {ap_ss_grp(:), zeros(1)};
    mp_cl_ar_xyz_of_s('MPC') = {mn_MPC_C_gain_share_check_grp(:), zeros(1)};
    mp_cl_ar_xyz_of_s('Mass') = {Phi_true_grp(:), zeros(1)};
    mp_cl_ar_xyz_of_s('c_ss') = {c_ss_grp(:), zeros(1)};
    mp_cl_ar_xyz_of_s('y_head_inc') = {y_head_inc_grp(:), zeros(1)};
    mp_cl_ar_xyz_of_s('y_spouse') = {y_spouse_inc_grp(:), zeros(1)};
    mp_cl_ar_xyz_of_s('yshr_nttxss') = {yshr_nttxss_grp(:), zeros(1)};

    mp_cl_ar_xyz_of_s('ar_st_y_name') = ["y_all", "age_ss", "educ_ss", "a_ss", "ap_ss", "MPC", "Mass", "c_ss", "y_head_inc", "y_spouse", "yshr_nttxss"];

    % controls
    mp_support = containers.Map('KeyType','char', 'ValueType','any');
    mp_support('ar_fl_percentiles') = [0.01 10 25 50 75 90 99.99];
    mp_support('bl_display_final') = true;
    mp_support('bl_display_detail') = false;
    mp_support('bl_display_drvm2outcomes') = false;
    mp_support('bl_display_drvstats') = false;
    mp_support('bl_display_drvm2covcor') = false;

    % Call Function
    mp_cl_mt_xyz_of_s = ff_simu_stats(Phi_true_grp(:)/sum(Phi_true_grp,'all'), mp_cl_ar_xyz_of_s);

    it_marital = ar_marital(it_marry_ctr);
    it_kids = ar_kids(it_kids_ctr);

    tb_dist_stats = mp_cl_mt_xyz_of_s('tb_outcomes');

```



13.1. 2019 FULL STATES MPC AND DISTRIBUTIONAL STATISTICS BY MARITAL, KIDS, AND INCOME GROUP

```
fl_age_mean = tb_dist_stats{"age_ss", "mean"};
fl_age_p50 = tb_dist_stats{"age_ss", "p50"};

fl_educ_mean = tb_dist_stats{"educ_ss", "mean"};

fl_a_mean = tb_dist_stats{"a_ss", "mean"};
fl_a_p50 = tb_dist_stats{"a_ss", "p50"};

fl_ap_mean = tb_dist_stats{"ap_ss", "mean"};
fl_ap_p50 = tb_dist_stats{"ap_ss", "p50"};

fl_y_all_mean = tb_dist_stats{"y_all", "mean"};
fl_y_all_p50 = tb_dist_stats{"y_all", "p50"};

fl_mpc_mean = tb_dist_stats{"MPC", "mean"};
fl_mpc_p50 = tb_dist_stats{"MPC", "p50"};

fl_mass = tb_dist_stats{"Mass", "unweighted_sum"};

fl_c_ss_mean = tb_dist_stats{"c_ss", "mean"};
fl_c_ss_p50 = tb_dist_stats{"c_ss", "p50"};

fl_y_head_inc_mean = tb_dist_stats{"y_head_inc", "mean"};
fl_y_spouse_mean = tb_dist_stats{"y_spouse", "mean"};

ar_store_stats = [it_marital, it_kids, ...
    fl_age_mean, fl_age_p50, fl_educ_mean, ...
    fl_a_mean, fl_a_p50, fl_ap_mean, fl_ap_p50, ...
    fl_y_all_mean, fl_y_all_p50, ...
    fl_mpc_mean, fl_mpc_p50, ...
    fl_mass, ...
    fl_c_ss_mean, fl_c_ss_p50, ...
    fl_y_head_inc_mean, fl_y_spouse_mean];

it_row_ctr = it_row_ctr + 1;

if (it_row_ctr>1)
    mt_store_stats_by_mk = [mt_store_stats_by_mk;ar_store_stats];
else
    mt_store_stats_by_mk = [ar_store_stats];
end
end
end

0x0 empty char array

0x0 empty char array

-----
-----
-----
-----
XXXXXXXXXXXXXXXXXXXXXXXXXXXXXXXXXXXXXXXXX
Marital =0
XXXXXXXXXXXXXXXXXXXXXXXXXXXXXXXXXXXXXXXXX
-----
-----
XXXXXXXXXXXXXXXXXXXXXXXXXXXXXXXXXXXXXXXXX
```

Marital =0 and kids =0

xx

xxx tb\_outcomes: all stats xxx

OriginalVariableNames	y_all	age_ss	educ_ss	a_ss	ap_ss
{'mean' }	71.752	42.174	0.25604	195.11	208.1
{'unweighted_sum' }	1.7831e+08	1909	1	1.2935e+05	1.6068e+0
{'sd' }	62.288	14.196	0.43644	339.77	352.4
{'coefofvar' }	0.8681	0.33661	1.7046	1.7414	1.693
{'gini' }	0.40852	0.1892	0.68372	0.7026	0.6989
{'min' }	2.2124	19	0	0	
{'max' }	1414.1	64	1	7837.6	8386.
{'pYis0' }	0	0	0.74396	0.11911	0.08185
{'pYls0' }	0	0	0	0	
{'pYgr0' }	1	1	0.25604	0.88089	0.9181
{'pYisMINY' }	1.9394e-06	0.036566	0.74396	0.11911	0.08185
{'pYisMAXY' }	1.1947e-09	0.024953	0.25604	5.4117e-06	5.9148e-1
{'p0_01' }	3.6063	19	0	0	
{'p10' }	20.129	22	0	0	0.2008
{'p25' }	31.931	29	0	3.7372	6.563
{'p50' }	53.79	44	0	65.686	70.53
{'p75' }	90.494	55	1	239.18	258.9
{'p90' }	143.31	61	1	525.49	583.8
{'p99_99' }	816.36	64	1	4974.3	5033.
{'fl_cov_y_all' }	3879.8	217.85	3.8458	17148	1823
{'fl_cor_y_all' }	1	0.24637	0.14147	0.81024	0.8304
{'fl_cov_age_ss' }	217.85	201.53	-0.25515	2124.1	2205.
{'fl_cor_age_ss' }	0.24637	1	-0.041181	0.44036	0.4407
{'fl_cov_educ_ss' }	3.8458	-0.25515	0.19048	8.5838	9.279
{'fl_cor_educ_ss' }	0.14147	-0.041181	1	0.057885	0.06032
{'fl_cov_a_ss' }	17148	2124.1	8.5838	1.1544e+05	1.1966e+0
{'fl_cor_a_ss' }	0.81024	0.44036	0.057885	1	0.9992
{'fl_cov_ap_ss' }	18233	2205.5	9.2793	1.1966e+05	1.2423e+0
{'fl_cor_ap_ss' }	0.83049	0.44078	0.060323	0.99922	
{'fl_cov_MPC' }	-4.5809	-1.3124	0.020725	-17.446	-18.64
{'fl_cor_MPC' }	-0.30887	-0.38826	0.19943	-0.21564	-0.2221
{'fl_cov_Mass' }	-0.00012497	-5.6686e-05	-3.0201e-07	-0.00063245	-0.0006678
{'fl_cor_Mass' }	-0.21994	-0.43773	-0.075858	-0.20405	-0.2077
{'fl_cov_c_ss' }	1859.9	85.521	2.2319	8778.5	9253.
{'fl_cor_c_ss' }	0.97519	0.19675	0.16702	0.84382	0.857
{'fl_cov_y_head_inc' }	3879.8	217.85	3.8458	17148	1823
{'fl_cor_y_head_inc' }	1	0.24637	0.14147	0.81024	0.8304
{'fl_cov_y_spouse' }	0	0	0	0	
{'fl_cor_y_spouse' }	NaN	NaN	NaN	NaN	NaN
{'fl_cov_yshr_nttxss' }	1.7036	0.14382	0.0019345	6.9206	7.370
{'fl_cor_yshr_nttxss' }	0.79998	0.29631	0.12964	0.59576	0.6116
{'fracByP0_01' }	4.4303e-06	0.016474	0	0	
{'fracByP10' }	0.020773	0.059565	0	0	5.8512e-0
{'fracByP25' }	0.075454	0.14379	0	0.0011338	0.001658
{'fracByP50' }	0.22298	0.3659	0	0.043403	0.03929
{'fracByP75' }	0.46643	0.67037	1	0.22326	0.2188
{'fracByP90' }	0.70129	0.88673	1	0.49372	0.5010
{'fracByP99_99' }	0.99869	1	1	0.99759	0.9971

xx

Marital =0 and kids =1

xx

13.1. 2019 FULL STATES MPC AND DISTRIBUTIONAL STATISTICS BY MARITAL, KIDS, AND INCOME GROUP

xxx tb\_outcomes: all stats xxx

OriginalVariableNames	y_all	age_ss	educ_ss	a_ss	ap_ss
{'mean' }	65.867	36.118	0.25753	94.382	101.22
{'unweighted_sum' }	1.7831e+08	1909	1	1.2935e+05	1.5913e+09
{'sd' }	56.932	11.182	0.43728	214.92	223.55
{'coefofvar' }	0.86435	0.3096	1.6979	2.2771	2.2087
{'gini' }	0.40364	0.17438	0.68158	0.79318	0.79099
{'min' }	2.2124	19	0	0	0
{'max' }	1414.1	64	1	7837.6	8291.1
{'pYis0' }	0	0	0.74247	0.23563	0.21309
{'pYls0' }	0	0	0	0	0
{'pYgr0' }	1	1	0.25753	0.76437	0.78691
{'pYisMINY' }	1.6845e-06	0.020845	0.74247	0.23563	0.21309
{'pYisMAXY' }	3.4305e-10	0.0031122	0.25753	8.262e-07	1.6379e-10
{'p0_01' }	3.5188	19	0	0	0
{'p10' }	19.292	22	0	0	0
{'p25' }	30.023	26	0	0.029898	0.23918
{'p50' }	49.454	35	0	10.255	14.159
{'p75' }	82.311	45	1	82.04	100.97
{'p90' }	130.49	52	1	276.88	293.79
{'p99_99' }	764.17	64	1	3737.2	3751.1
{'fl_cov_y_all' }	3241.3	152.53	4.1103	9427.3	10125
{'fl_cor_y_all' }	1	0.23959	0.16511	0.77047	0.79555
{'fl_cov_age_ss' }	152.53	125.05	0.19904	967.92	1008
{'fl_cor_age_ss' }	0.23959	1	0.040704	0.40274	0.40323
{'fl_cov_educ_ss' }	4.1103	0.19904	0.19121	5.7853	6.3576
{'fl_cor_educ_ss' }	0.16511	0.040704	1	0.061559	0.065037
{'fl_cov_a_ss' }	9427.3	967.92	5.7853	46190	47995
{'fl_cor_a_ss' }	0.77047	0.40274	0.061559	1	0.99895
{'fl_cov_ap_ss' }	10125	1008	6.3576	47995	49975
{'fl_cor_ap_ss' }	0.79555	0.40323	0.065037	0.99895	1
{'fl_cov_MPC' }	-8.9788	-1.3659	0.021532	-20.591	-22.11
{'fl_cor_MPC' }	-0.45848	-0.35509	0.14315	-0.27853	-0.28753
{'fl_cov_Mass' }	-4.8054e-05	-1.3242e-05	-1.409e-07	-0.00013616	-0.0001451
{'fl_cor_Mass' }	-0.33303	-0.46722	-0.12714	-0.24996	-0.25609
{'fl_cov_c_ss' }	1766.6	76.831	2.5674	5341.5	5695.3
{'fl_cor_c_ss' }	0.98556	0.21823	0.18649	0.7894	0.80918
{'fl_cov_y_head_inc' }	3241.3	152.53	4.1103	9427.3	10125
{'fl_cor_y_head_inc' }	1	0.23959	0.16511	0.77047	0.79555
{'fl_cov_y_spouse' }	0	0	0	0	0
{'fl_cor_y_spouse' }	NaN	NaN	NaN	NaN	NaN
{'fl_cov_yshr_nttxss' }	1.5555	0.10317	0.0024166	3.8467	4.1371
{'fl_cor_yshr_nttxss' }	0.80522	0.2719	0.16288	0.5275	0.54542
{'fracByP0_01' }	4.7258e-06	0.010966	0	0	0
{'fracByP10' }	0.021712	0.068419	0	0	0
{'fracByP25' }	0.078097	0.15825	0	6.9352e-06	3.5474e-05
{'fracByP50' }	0.22713	0.37923	0	0.0099825	0.010737
{'fracByP75' }	0.46939	0.67298	1	0.11689	0.12619
{'fracByP90' }	0.70221	0.85638	1	0.39992	0.38891
{'fracByP99_99' }	0.99866	1	1	0.99622	0.99554

xx

Marital =0 and kids =2

xx

xxx tb\_outcomes: all stats xxx

OriginalVariableNames	y_all	age_ss	educ_ss	a_ss	ap_ss
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13.1. 2019 FULL STATES MPC AND DISTRIBUTIONAL STATISTICS BY MARITAL, KIDS, AND INCOME GROUP

{'mean' }	63.898	34.068	0.22983	48.134	51.95
{'unweighted_sum' }	1.7831e+08	1909	1	1.2935e+05	1.5774e+0
{'sd' }	54.001	7.9772	0.42073	134.32	141.0
{'coefofvar' }	0.84511	0.23415	1.8306	2.7906	2.715
{'gini' }	0.39521	0.12909	0.72073	0.86678	0.8694
{'min' }	2.2124	19	0	0	
{'max' }	1414.1	64	1	7837.6	8183.
{'pYis0' }	0	0	0.77017	0.45656	0.4513
{'pYls0' }	0	0	0	0	
{'pYgr0' }	1	1	0.22983	0.54344	0.5486
{'pYisMINY' }	6.8879e-07	0.0083137	0.77017	0.45656	0.4513
{'pYisMAXY' }	1.1096e-11	0.00013776	0.22983	2.4752e-08	1.1431e-1
{'p0_01' }	3.6125	19	0	0	
{'p10' }	19.479	24	0	0	
{'p25' }	29.928	28	0	0	
{'p50' }	48.607	33	0	0.23918	0.498
{'p75' }	79.715	39	0	29.898	37.19
{'p90' }	125.03	45	1	146.89	152.5
{'p99_99' }	727.36	64	1	2546.8	263
{'fl_cov_y_all' }	2916.1	86.208	4.4997	5525	6009.
{'fl_cor_y_all' }	1	0.20012	0.19805	0.76171	0.7889
{'fl_cov_age_ss' }	86.208	63.635	0.47515	327.14	343.3
{'fl_cor_age_ss' }	0.20012	1	0.14157	0.30531	0.3051
{'fl_cov_educ_ss' }	4.4997	0.47515	0.17701	3.7005	4.224
{'fl_cor_educ_ss' }	0.19805	0.14157	1	0.065482	0.07117
{'fl_cov_a_ss' }	5525	327.14	3.7005	18042	1892
{'fl_cor_a_ss' }	0.76171	0.30531	0.065482	1	0.9986
{'fl_cov_ap_ss' }	6009.3	343.36	4.2241	18921	1989
{'fl_cor_ap_ss' }	0.78891	0.30515	0.071177	0.99863	
{'fl_cov_MPC' }	-14.294	-1.1063	-0.0020988	-20.435	-22.07
{'fl_cor_MPC' }	-0.611	-0.32013	-0.011516	-0.35119	-0.3612
{'fl_cov_Mass' }	-4.6648e-05	-5.1607e-06	-2.1548e-07	-7.4065e-05	-7.9832e-0
{'fl_cor_Mass' }	-0.3662	-0.27425	-0.21712	-0.23375	-0.2399
{'fl_cov_c_ss' }	1734.9	49.892	2.92	3306.4	3575.
{'fl_cor_c_ss' }	0.99009	0.19275	0.21389	0.75862	0.7812
{'fl_cov_y_head_inc' }	2916.1	86.208	4.4997	5525	6009.
{'fl_cor_y_head_inc' }	1	0.20012	0.19805	0.76171	0.7889
{'fl_cov_y_spouse' }	0	0	0	0	
{'fl_cor_y_spouse' }	NaN	NaN	NaN	NaN	NaN
{'fl_cov_yshr_nttxss' }	1.4552	0.059225	0.0028436	2.1663	2.353
{'fl_cor_yshr_nttxss' }	0.81051	0.2233	0.20329	0.4851	0.5018
{'fracByP0_01' }	5.1241e-06	0.0046366	0	0	
{'fracByP10' }	0.022798	0.072031	0	0	
{'fracByP25' }	0.081073	0.1985	0	0	
{'fracByP50' }	0.23275	0.41302	0	0.00019689	0.0001865
{'fracByP75' }	0.47593	0.67505	0	0.056161	0.05684
{'fracByP90' }	0.70691	0.86752	1	0.31708	0.2910
{'fracByP99_99' }	0.99868	1	1	0.99425	0.9938

xx

Marital =0 and kids =4

xx

xxx tb\_outcomes: all stats xxx

OriginalVariableNames	y_all	age_ss	educ_ss	a_ss	ap_ss
{'mean' }	63.864	34.197	0.2079	41.099	44.67
{'unweighted_sum' }	1.7831e+08	1909	1	1.2935e+05	1.5749e+0

{'sd'	}	53.609	7.1538	0.4058	120.68	127.2
{'coefofvar'	}	0.83942	0.2092	1.9519	2.9363	2.849
{'gini'	}	0.39289	0.11447	0.75112	0.88249	0.8837
{'min'	}	2.2124	19	0	0	
{'max'	}	1414.1	64	1	7837.6	8164.
{'pYis0'	}	0	0	0.7921	0.50485	0.4925
{'pYls0'	}	0	0	0	0	
{'pYgr0'	}	1	1	0.2079	0.49515	0.5074
{'pYisMINY'	}	4.3493e-07	0.0045732	0.7921	0.50485	0.4925
{'pYisMAXY'	}	1.4837e-12	4.6124e-05	0.2079	5.166e-09	1.5175e-1
{'p0_01'	}	3.6887	19	0	0	
{'p10'	}	19.685	25	0	0	
{'p25'	}	30.153	29	0	0	
{'p50'	}	48.75	34	0	0	0.02989
{'p75'	}	79.548	39	0	21.796	27.79
{'p90'	}	124.62	44	1	122.46	130.0
{'p99_99'	}	721.01	63	1	2377.1	2423.
{'fl_cov_y_all'	}	2873.9	71.941	4.4963	4930.8	539
{'fl_cor_y_all'	}	1	0.18759	0.20668	0.76216	0.7900
{'fl_cov_age_ss'	}	71.941	51.176	0.5437	238.82	251.8
{'fl_cor_age_ss'	}	0.18759	1	0.18729	0.27663	0.2765
{'fl_cov_educ_ss'	}	4.4963	0.5437	0.16468	3.6463	4.175
{'fl_cor_educ_ss'	}	0.20668	0.18729	1	0.074456	0.08084
{'fl_cov_a_ss'	}	4930.8	238.82	3.6463	14564	1533
{'fl_cor_a_ss'	}	0.76216	0.27663	0.074456	1	0.9985
{'fl_cov_ap_ss'	}	5391	251.85	4.1759	15338	1620
{'fl_cor_ap_ss'	}	0.79005	0.27658	0.080846	0.99852	
{'fl_cov_MPC'	}	-14.976	-1.0328	-0.010238	-18.883	-20.53
{'fl_cor_MPC'	}	-0.63881	-0.33014	-0.057692	-0.35781	-0.3689
{'fl_cov_Mass'	}	-2.7333e-05	-2.6204e-06	-1.3997e-07	-3.8707e-05	-4.2009e-0
{'fl_cor_Mass'	}	-0.36608	-0.263	-0.24765	-0.2303	-0.2369
{'fl_cov_c_ss'	}	1727	42.146	2.9107	2959.6	3218.
{'fl_cor_c_ss'	}	0.9908	0.1812	0.22061	0.75427	0.7777
{'fl_cov_y_head_inc'	}	2873.9	71.941	4.4963	4930.8	539
{'fl_cor_y_head_inc'	}	1	0.18759	0.20668	0.76216	0.7900
{'fl_cov_y_spouse'	}	0	0	0	0	
{'fl_cor_y_spouse'	}	NaN	NaN	NaN	NaN	NaN
{'fl_cov_yshr_nttxss'	}	1.437	0.049376	0.0028207	1.8938	2.069
{'fl_cor_yshr_nttxss'	}	0.81163	0.20899	0.21047	0.47516	0.4922
{'fracByP0_01'	}	5.1325e-06	0.0025409	0	0	
{'fracByP10'	}	0.022996	0.072385	0	0	
{'fracByP25'	}	0.081963	0.20856	0	0	
{'fracByP50'	}	0.23436	0.45949	0	0	4.2228e-0
{'fracByP75'	}	0.47776	0.70775	0	0.041779	0.04305
{'fracByP90'	}	0.70826	0.87861	1	0.2851	0.266
{'fracByP99_99'	}	0.99869	0.99991	1	0.99427	0.9933

0x0 empty char array

0x0 empty char array

```

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xxxxxxxxxxxxxxxxxxxxxxxxxxxxxxxxxxxxxxxx
Marital =1
xxxxxxxxxxxxxxxxxxxxxxxxxxxxxxxxxxxxxxxx

```

13.1. 2019 FULL STATES MPC AND DISTRIBUTIONAL STATISTICS BY MARITAL, KIDS, AND INCOME GROUP

xx

Marital =1 and kids =0

xx

xxx tb\_outcomes: all stats xxx

OriginalVariableNames	y_all	age_ss	educ_ss	a_ss	ap_ss
{'mean' }	109.57	44.041	0.38021	408.45	434.2
{'unweighted_sum' }	1.2919e+09	1909	1	1.2935e+05	8.4753e+09
{'sd' }	83.584	15.135	0.48544	498.74	514.1
{'coefofvar' }	0.76282	0.34365	1.2768	1.2211	1.184
{'gini' }	0.3692	0.18905	0.50257	0.57853	0.57485
{'min' }	2.4223	19	0	0	0
{'max' }	2113.2	64	1	7837.6	9503.9
{'pYis0' }	0	0	0.61979	0.07588	0.036618
{'pYls0' }	0	0	0	0	0
{'pYgr0' }	1	1	0.38021	0.92412	0.96338
{'pYisMINY' }	5.1901e-09	0.043093	0.61979	0.07588	0.036618
{'pYisMAXY' }	2.4329e-11	0.038439	0.38021	1.8938e-05	1.2944e-11
{'p0_01' }	6.597	19	0	0	0
{'p10' }	35.716	21	0	1.9135	3.7372
{'p25' }	54.783	29	0	51.664	59.412
{'p50' }	88.064	48	0	239.18	270.71
{'p75' }	137.9	58	1	588.48	634.2
{'p90' }	204.71	62	1	1074.4	1074.4
{'p99_99' }	967.74	64	1	5833.4	5977.2
{'fl_cov_y_all' }	6986.3	361.95	5.7657	27155	31359
{'fl_cor_y_all' }	1	0.28612	0.1421	0.65142	0.72978
{'fl_cov_age_ss' }	361.95	229.06	-0.85351	4123.7	4247.6
{'fl_cor_age_ss' }	0.28612	1	-0.11617	0.5463	0.54592
{'fl_cov_educ_ss' }	5.7657	-0.85351	0.23565	16.048	17.247
{'fl_cor_educ_ss' }	0.1421	-0.11617	1	0.066283	0.069108
{'fl_cov_a_ss' }	27155	4123.7	16.048	2.4874e+05	2.541e+05
{'fl_cor_a_ss' }	0.65142	0.5463	0.066283	1	0.99103
{'fl_cov_ap_ss' }	31359	4247.6	17.247	2.541e+05	2.643e+05
{'fl_cor_ap_ss' }	0.72978	0.54592	0.069108	0.99103	1
{'fl_cov_MPC' }	-4.5371	-1.4233	0.0094147	-28.557	-30.413
{'fl_cor_MPC' }	-0.3463	-0.59994	0.12373	-0.36528	-0.37741
{'fl_cov_Mass' }	-7.4044e-05	-2.2911e-05	5.5246e-08	-0.00041977	-0.00044771
{'fl_cor_Mass' }	-0.19462	-0.33257	0.025002	-0.18491	-0.19132
{'fl_cov_c_ss' }	2941.3	188.87	4.2928	16348	17228
{'fl_cor_c_ss' }	0.86319	0.30611	0.21692	0.80402	0.82201
{'fl_cov_y_head_inc' }	4857.1	318.48	4.4672	25709	27033
{'fl_cor_y_head_inc' }	0.85851	0.31089	0.13595	0.76156	0.77684
{'fl_cov_y_spouse' }	4673.1	95.4	2.8501	3173.5	9494.5
{'fl_cor_y_spouse' }	0.59164	0.066703	0.06213	0.067335	0.19543
{'fl_cov_yshr_nttxss' }	1.6494	0.13956	0.0013995	6.3032	7.2859
{'fl_cor_yshr_nttxss' }	0.7665	0.35816	0.11198	0.49089	0.55047
{'fracByP0_01' }	5.3214e-06	0.018591	0	0	0
{'fracByP10' }	0.024266	0.049706	0	0.00015705	0.00034862
{'fracByP25' }	0.086535	0.1342	0	0.010018	0.010404
{'fracByP50' }	0.24796	0.35975	0	0.097271	0.098709

### 13.1.11 Distributional Statistics By Marital Status, Kids Count and Income Bins

Various statistics, including MPC (of the first check) by Marital Status and Kids Count and income bins

```

it_row_ctr = 0;
for it_marry_ctr=1:mp_params('n_marriedgrid')

    display(['']);
    display(['']);
    display(['-----']);
    display(['-----']);
    display(['-----']);
    display(['-----']);
    display(['xxxxxxxxxxxxxxxxxxxxxxxxxxxxxxxxxxxx']);
    display(['Marital = ' num2str(ar_marital(it_marry_ctr))]);
    display(['xxxxxxxxxxxxxxxxxxxxxxxxxxxxxxxxxxxx']);
    display(['-----']);
    display(['-----']);

for it_kids_ctr=1:mp_params('n_kidsgrid')
    display(['xxxxxxxxxxxxxxxxxxxxxxxxxxxxxxxxxxxx']);
    display(['Marital = ' num2str(ar_marital(it_marry_ctr)) ' and kids = ' num2str(ar_kids(it_kids_ctr))]);
    display(['xxxxxxxxxxxxxxxxxxxxxxxxxxxxxxxxxxxx']);

% construct input data
y_all_grp = y_all(min_age:max_age, :, :, : ,it_marry_ctr ,it_ctr);
age_ss_grp = age_ss(min_age:max_age, :, :, : ,it_marry_ctr, it_kids_ctr);
educ_ss_grp = educ_ss(min_age:max_age, :, :, : ,it_marry_ctr, it_kids_ctr);
a_ss_grp = a_ss(min_age:max_age, :, :, : ,it_marry_ctr, it_kids_ctr);
ap_ss_grp = ap_ss(min_age:max_age, :, :, : ,it_marry_ctr, it_kids_ctr);
mn_MPC_C_gain_share_check_grp = mn_MPC_C_gain_share_check(min_age:max_age, :, :, : ,it_marry_ctr, it_kids_ctr);
Phi_true_grp = Phi_true_1(min_age:max_age, :, :, : ,it_marry_ctr, it_kids_ctr);
c_ss_grp = c_ss(min_age:max_age, :, :, : ,it_marry_ctr, it_kids_ctr);
y_head_inc_grp = y_head_inc(min_age:max_age, :, :, : ,it_marry_ctr, it_kids_ctr);
y_spouse_inc_grp = y_spouse_inc(min_age:max_age, :, :, : ,it_marry_ctr, it_kids_ctr);
yshr_nttxss_grp = yshr_nttxss(min_age:max_age, :, :, : ,it_marry_ctr, it_kids_ctr);

% Income Bins
ar_y_all = y_all_grp(:);
ar_age_ss = age_ss_grp(:);
ar_educ_ss = educ_ss_grp(:);
ar_a_ss = a_ss_grp(:);
ar_ap_ss = ap_ss_grp(:);
ar_mn_MPC_C_gain_share_check = mn_MPC_C_gain_share_check_grp(:);
ar_Phi_true = Phi_true_grp(:);
ar_c_ss = c_ss_grp(:);
ar_y_head_inc = y_head_inc_grp(:);
ar_y_spouse_inc = y_spouse_inc_grp(:);
ar_yshr_nttxss = yshr_nttxss_grp(:);

% income bins loop
for it_y_all_ctr=1:6

    % Current y group index
    % y is in thousands of dollars
    y_all_start = (it_y_all_ctr-1)*20;
    if (it_y_all_ctr == 6)

```



## 13.1. 2019 FULL STATES MPC AND DISTRIBUTIONAL STATISTICS BY MARITAL, KIDS, AND INCOME GROUP

```

        y_all_end = max(ar_y_all);
    else
        y_all_end = it_y_all_ctr*20;
    end

    display(['xxxxxxxxxxxxxxxxxxxxxxxxxxxxxxxxxxxxxxxx']);
    display(['Marital = ' num2str(ar_marital(it_marry_ctr)) ', kids = ' num2str(ar_kids(it_kid
    display(['xxxxxxxxxxxxxxxxxxxxxxxxxxxxxxxxxxxxxxxx']);

    ar_y_idx = (ar_y_all >= y_all_start & ar_y_all <y_all_end);

    ar_mky_y_all = ar_y_all(ar_y_idx);
    ar_mky_age_ss = ar_age_ss(ar_y_idx);
    ar_mky_educ_ss = ar_educ_ss(ar_y_idx);
    ar_mky_a_ss = ar_a_ss(ar_y_idx);
    ar_mky_ap_ss = ar_ap_ss(ar_y_idx);
    ar_mky_mn_MPC_C_gain_share_check = ar_mn_MPC_C_gain_share_check(ar_y_idx);
    ar_mky_Phi_true = ar_Phi_true(ar_y_idx);
    ar_mky_c_ss = ar_c_ss(ar_y_idx);
    ar_mky_y_head_inc = ar_y_head_inc(ar_y_idx);
    ar_mky_y_spouse_inc = ar_y_spouse_inc(ar_y_idx);
    ar_mky_yshr_nttxss = ar_yshr_nttxss(ar_y_idx);

    mp_cl_ar_xyz_of_s = containers.Map('KeyType','char', 'ValueType','any');
    mp_cl_ar_xyz_of_s('y_all') = {ar_mky_y_all(:), zeros(1)};
    mp_cl_ar_xyz_of_s('age_ss') = {ar_mky_age_ss(:), zeros(1)};
    mp_cl_ar_xyz_of_s('educ_ss') = {ar_mky_educ_ss(:), zeros(1)};
    mp_cl_ar_xyz_of_s('a_ss') = {ar_mky_a_ss(:), zeros(1)};
    mp_cl_ar_xyz_of_s('ap_ss') = {ar_mky_ap_ss(:), zeros(1)};
    mp_cl_ar_xyz_of_s('MPC') = {ar_mky_mn_MPC_C_gain_share_check(:), zeros(1)};
    mp_cl_ar_xyz_of_s('Mass') = {ar_mky_Phi_true(:), zeros(1)};
    mp_cl_ar_xyz_of_s('c_ss') = {ar_mky_c_ss(:), zeros(1)};
    mp_cl_ar_xyz_of_s('y_head_inc') = {ar_mky_y_head_inc(:), zeros(1)};
    mp_cl_ar_xyz_of_s('y_spouse') = {ar_mky_y_spouse_inc(:), zeros(1)};
    mp_cl_ar_xyz_of_s('yshr_nttxss') = {ar_mky_yshr_nttxss(:), zeros(1)};
    mp_cl_ar_xyz_of_s('ar_st_y_name') = ["y_all", "age_ss", "educ_ss", "a_ss", "ap_ss", "MPC

% controls
mp_support = containers.Map('KeyType','char', 'ValueType','any');
mp_support('ar_fl_percentiles') = [0.01 10 25 50 75 90 99.99];
mp_support('bl_display_final') = true;
mp_support('bl_display_detail') = false;
mp_support('bl_display_drvm2outcomes') = false;
mp_support('bl_display_drvstats') = false;
mp_support('bl_display_drvm2covcor') = false;

% Call Function
mp_cl_mt_xyz_of_s = ff_simu_stats(ar_mky_Phi_true(:)/sum(ar_mky_Phi_true,'all'), mp_cl_a

    it_marital = ar_marital(it_marry_ctr);
    it_kids = ar_kids(it_kids_ctr);
    fl_y_all_start = y_all_start;
    fl_y_all_end = y_all_end;

    tb_dist_stats = mp_cl_mt_xyz_of_s('tb_outcomes');
    fl_age_mean = tb_dist_stats{"age_ss", "mean"};
    fl_age_p50 = tb_dist_stats{"age_ss", "p50"};

```



13.1. 2019 FULL STATES MPC AND DISTRIBUTIONAL STATISTICS BY MARITAL, KIDS, AND INCOME GROUP

XXXXXXXXXXXXXXXXXXXXXXXXXXXXXXXXXXXX

XXXXXXXXXXXXXXXXXXXXXXXXXXXXXXXXXXXX

Marital =0, kids =0, ybin =0 to 20

XXXXXXXXXXXXXXXXXXXXXXXXXXXXXXXXXXXX

xxx tb\_outcomes: all stats xxx

OriginalVariableNames	y_all	age_ss	educ_ss	a_ss	ap_ss
{'mean' }	14.688	34.974	0.18182	2.7226	2.6703
{'unweighted_sum' }	8.4083e+05	1909	1	2690.8	5.2986e+06
{'sd' }	3.6764	14.501	0.3857	10.125	9.7397
{'coefofvar' }	0.25031	0.41462	2.1213	3.7189	3.6474
{'gini' }	0.141	0.23128	0.78641	0.92249	0.92536
{'min' }	2.2124	19	0	0	0
{'max' }	20	64	1	413.31	409.12
{'pYis0' }	0	0	0.81818	0.53967	0.49704
{'pYls0' }	0	0	0	0	0
{'pYgr0' }	1	1	0.18182	0.46033	0.50296
{'pYisMINY' }	1.9988e-05	0.084859	0.81818	0.53967	0.49704
{'pYisMAXY' }	4.7568e-12	0.01496	0.18182	1.4916e-11	0
{'p0_01' }	2.6052	19	0	0	0
{'p10' }	9.307	20	0	0	0
{'p25' }	12.172	22	0	0	0
{'p50' }	15.236	30	0	0	0.011132
{'p75' }	17.778	48	0	0.23918	0.48535
{'p90' }	19.14	58	1	6.458	6.0051
{'p99_99' }	19.999	64	1	174.36	166.76
{'fl_cov_y_all' }	13.516	5.6455	0.0023525	6.9774	7.1104
{'fl_cor_y_all' }	1	0.1059	0.001659	0.18744	0.19857
{'fl_cov_age_ss' }	5.6455	210.28	-1.0046	57.763	56.482
{'fl_cor_age_ss' }	0.1059	1	-0.17962	0.39342	0.39991
{'fl_cov_educ_ss' }	0.0023525	-1.0046	0.14876	-0.29328	-0.29618
{'fl_cor_educ_ss' }	0.001659	-0.17962	1	-0.0751	-0.078843
{'fl_cov_a_ss' }	6.9774	57.763	-0.29328	102.52	98.523
{'fl_cor_a_ss' }	0.18744	0.39342	-0.0751	1	0.99907
{'fl_cov_ap_ss' }	7.1104	56.482	-0.29618	98.523	94.862
{'fl_cor_ap_ss' }	0.19857	0.39991	-0.078843	0.99907	1
{'fl_cov_MPC' }	-0.53539	-2.7127	0.035745	-1.3183	-1.3069
{'fl_cor_MPC' }	-0.41675	-0.53535	0.26522	-0.37261	-0.38399
{'fl_cov_Mass' }	6.2968e-06	-7.1893e-05	-3.4162e-07	-1.6308e-05	-1.5421e-05
{'fl_cor_Mass' }	0.18379	-0.53201	-0.095046	-0.17284	-0.1699
{'fl_cov_c_ss' }	11.292	6.0576	0.0049126	9.8651	9.6441
{'fl_cor_c_ss' }	0.98267	0.13365	0.0040749	0.31172	0.31679
{'fl_cov_y_head_inc' }	13.516	5.6455	0.0023525	6.9774	7.1104
{'fl_cor_y_head_inc' }	1	0.1059	0.001659	0.18744	0.19857
{'fl_cov_y_spouse' }	0	0	0	0	0
{'fl_cor_y_spouse' }	NaN	NaN	NaN	NaN	NaN
{'fl_cov_yshr_nttxss' }	0.052502	0.022189	1.0001e-05	0.025753	0.026154
{'fl_cor_yshr_nttxss' }	0.99014	0.10609	0.0017978	0.17635	0.18618
{'fracByP0_01' }	1.8388e-05	0.0461	0	0	0
{'fracByP10' }	0.051228	0.088792	0	0	0
{'fracByP25' }	0.16212	0.16288	0	0	0
{'fracByP50' }	0.39701	0.3352	0	0	6.3754e-06
{'fracByP75' }	0.68371	0.60992	0	0.013023	0.018274
{'fracByP90' }	0.86704	0.84015	1	0.16055	0.12661
{'fracByP99_99' }	1	1	1	0.99661	0.99334

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Marital =0, kids =0, ybin =20 to 40

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xxx tb\_outcomes: all stats xxx

OriginalVariableNames	y_all	age_ss	educ_ss	a_ss	ap_ss
{'mean' }	29.952	38.525	0.20638	25.273	26.927
{'unweighted_sum' }	1.9087e+06	1909	1	7355.4	1.8539e+07
{'sd' }	5.6854	14.456	0.4047	44.204	44.499
{'coefofvar' }	0.18982	0.37522	1.961	1.7491	1.6525
{'gini' }	0.10955	0.2128	0.7532	0.72521	0.71433
{'min' }	20	19	0	0	0
{'max' }	40	64	1	890.69	885.93
{'pYis0' }	0	0	0.79362	0.16854	0.10132
{'pYls0' }	0	0	0	0	0
{'pYgr0' }	1	1	0.20638	0.83146	0.89868
{'pYisMINY' }	8.0995e-288	0.055295	0.79362	0.16854	0.10132
{'pYisMAXY' }	4.4783e-07	0.018337	0.20638	8.9396e-13	0
{'p0_01' }	20.004	19	0	0	0
{'p10' }	22.011	20	0	0	0
{'p25' }	25.065	25	0	0.80724	1.0692
{'p50' }	30.008	37	0	6.458	6.7423
{'p75' }	34.798	52	0	29.898	33.25
{'p90' }	37.826	59	1	82.04	83.859
{'p99_99' }	39.999	64	1	413.31	407.97
{'fl_cov_y_all' }	32.324	7.6438	0.038871	72.305	78.269
{'fl_cor_y_all' }	1	0.093006	0.016894	0.28771	0.30937
{'fl_cov_age_ss' }	7.6438	208.96	-0.73238	386.27	403.49
{'fl_cor_age_ss' }	0.093006	1	-0.12519	0.60451	0.62727
{'fl_cov_educ_ss' }	0.038871	-0.73238	0.16379	-2.1597	-2.3263
{'fl_cor_educ_ss' }	0.016894	-0.12519	1	-0.12073	-0.12918
{'fl_cov_a_ss' }	72.305	386.27	-2.1597	1954	1964.7
{'fl_cor_a_ss' }	0.28771	0.60451	-0.12073	1	0.99885
{'fl_cov_ap_ss' }	78.269	403.49	-2.3263	1964.7	1980.1
{'fl_cor_ap_ss' }	0.30937	0.62727	-0.12918	0.99885	1
{'fl_cov_MPC' }	-0.30518	-1.6691	0.062231	-3.0143	-3.2123
{'fl_cor_MPC' }	-0.208	-0.4474	0.59583	-0.26423	-0.27972
{'fl_cov_Mass' }	-4.5536e-06	-9.611e-05	3.7003e-08	-0.00013723	-0.00014127
{'fl_cor_Mass' }	-0.059962	-0.49775	0.0068451	-0.23242	-0.23768
{'fl_cov_c_ss' }	19.905	-11.1	0.19764	47.044	47.213
{'fl_cor_c_ss' }	0.88176	-0.19338	0.12299	0.26804	0.26721
{'fl_cov_y_head_inc' }	32.324	7.6438	0.038871	72.305	78.269
{'fl_cor_y_head_inc' }	1	0.093006	0.016894	0.28771	0.30937
{'fl_cov_y_spouse' }	0	0	0	0	0
{'fl_cor_y_spouse' }	NaN	NaN	NaN	NaN	NaN
{'fl_cov_yshr_nttxss' }	0.058292	0.013838	6.9651e-05	0.12878	0.13941
{'fl_cor_yshr_nttxss' }	0.99551	0.092947	0.016711	0.28287	0.30419
{'fracByP0_01' }	0.00010275	0.02727	0	0	0
{'fracByP10' }	0.070196	0.052525	0	0	0
{'fracByP25' }	0.18834	0.15502	0	0.0035395	0.0030822
{'fracByP50' }	0.4181	0.33724	0	0.038073	0.032523
{'fracByP75' }	0.68834	0.64594	0	0.19439	0.19244
{'fracByP90' }	0.87021	0.84782	1	0.53295	0.49305
{'fracByP99_99' }	0.99996	1	1	0.99833	0.99827

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Marital =0, kids =0, ybin =40 to 60

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13.1. 2019 FULL STATES MPC AND DISTRIBUTIONAL STATISTICS BY MARITAL, KIDS, AND INCOME GROUP

xxx tb\_outcomes: all stats xxx

OriginalVariableNames	y_all	age_ss	educ_ss	a_ss	ap_ss
{'mean' }	49.366	41.657	0.23457	81.386	87.44
{'unweighted_sum' }	2.5368e+06	1909	1	13261	2.8595e+0
{'sd' }	5.7595	14.091	0.42373	93.65	93.9
{'coefofvar' }	0.11667	0.33826	1.8064	1.1507	1.074
{'gini' }	0.067274	0.1907	0.71409	0.55942	0.5484
{'min' }	40	19	0	0	
{'max' }	60	64	1	1394.9	1389.
{'pYis0' }	0	0	0.76543	0.074319	0.03470
{'pYls0' }	0	0	0	0	
{'pYgr0' }	1	1	0.23457	0.92568	0.9652
{'pYisMINY' }	1.1988e-05	0.035852	0.76543	0.074319	0.03470
{'pYisMAXY' }	2.6918e-19	0.022889	0.23457	1.725e-14	
{'p0_01' }	40.004	19	0	0	
{'p10' }	41.738	22	0	1.9135	4.178
{'p25' }	44.289	28	0	10.255	15.82
{'p50' }	49.163	43	0	51.664	56.52
{'p75' }	54.155	54	0	122.46	130.2
{'p90' }	57.677	60	1	205.07	213.8
{'p99_99' }	59.997	64	1	729.18	718.6
{'fl_cov_y_all' }	33.172	5.7383	0.031749	121.07	129.8
{'fl_cor_y_all' }	1	0.070707	0.013009	0.22446	0.2398
{'fl_cov_age_ss' }	5.7383	198.55	-0.52991	911.38	944.6
{'fl_cor_age_ss' }	0.070707	1	-0.088752	0.69065	0.7133
{'fl_cov_educ_ss' }	0.031749	-0.52991	0.17955	-5.8166	-6.25
{'fl_cor_educ_ss' }	0.013009	-0.088752	1	-0.14658	-0.1569
{'fl_cov_a_ss' }	121.07	911.38	-5.8166	8770.3	8794.
{'fl_cor_a_ss' }	0.22446	0.69065	-0.14658	1	0.9991
{'fl_cov_ap_ss' }	129.84	944.69	-6.252	8794.3	883
{'fl_cor_ap_ss' }	0.23985	0.71331	-0.15698	0.99911	
{'fl_cov_MPC' }	-0.09046	-0.71366	0.029802	-2.9986	-3.239
{'fl_cor_MPC' }	-0.096943	-0.31261	0.43412	-0.19763	-0.2127
{'fl_cov_Mass' }	-4.8663e-06	-5.8353e-05	-1.5517e-07	-0.00023117	-0.0002379
{'fl_cor_Mass' }	-0.088148	-0.43205	-0.038205	-0.25753	-0.264
{'fl_cov_c_ss' }	17.041	-28.838	0.46008	70.248	61.26
{'fl_cor_c_ss' }	0.62733	-0.43394	0.23022	0.15905	0.1382
{'fl_cov_y_head_inc' }	33.172	5.7383	0.031749	121.07	129.8
{'fl_cor_y_head_inc' }	1	0.070707	0.013009	0.22446	0.2398
{'fl_cov_y_spouse' }	0	0	0	0	
{'fl_cor_y_spouse' }	NaN	NaN	NaN	NaN	NaN
{'fl_cov_yshr_nttxss' }	0.032789	0.0057148	3.1401e-05	0.11935	0.1280
{'fl_cor_yshr_nttxss' }	0.99787	0.071088	0.012989	0.22339	0.2387
{'fracByP0_01' }	8.1986e-05	0.016353	0	0	
{'fracByP10' }	0.082731	0.059676	0	0.00080736	0.001552
{'fracByP25' }	0.21327	0.13822	0	0.013027	0.01831
{'fracByP50' }	0.44964	0.36454	0	0.12623	0.1133
{'fracByP75' }	0.7111	0.65402	0	0.38755	0.3665
{'fracByP90' }	0.88093	0.85769	1	0.66284	0.654
{'fracByP99_99' }	0.99988	1	1	0.99951	0.9991

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Marital =0, kids =0, ybin =60 to 80

xx

xxx tb\_outcomes: all stats xxx

OriginalVariableNames	y_all	age_ss	educ_ss	a_ss	ap_ss
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{'mean' }	69.288	43.863	0.26092	158.1	169.5
{'unweighted_sum' }	3.0245e+06	1909	1	20103	3.6714e+0
{'sd' }	5.7381	13.54	0.43913	144.91	144.6
{'coefofvar' }	0.082816	0.30869	1.683	0.91655	0.8531
{'gini' }	0.047737	0.17193	0.67675	0.46696	0.4577
{'min' }	60	19	0	0	
{'max' }	79.999	64	1	1913.5	1907.
{'pYis0' }	0	0	0.73908	0.036459	0.006283
{'pYls0' }	0	0	0	0	
{'pYgr0' }	1	1	0.26092	0.96354	0.9937
{'pYisMINY' }	7.0785e-08	0.024362	0.73908	0.036459	0.006283
{'pYisMAXY' }	1.0527e-08	0.027901	0.26092	8.7298e-17	
{'p0_01' }	60.004	19	0	0	
{'p10' }	61.586	23	0	10.255	18.69
{'p25' }	64.221	32	0	39.794	54.13
{'p50' }	68.93	46	0	122.46	134.9
{'p75' }	74.224	56	1	239.18	250.8
{'p90' }	77.547	61	1	363.77	373.
{'p99_99' }	79.989	64	1	1074.4	1050.
{'fl_cov_y_all' }	32.926	4.1151	0.027108	145.03	154.4
{'fl_cor_y_all' }	1	0.052966	0.010758	0.17442	0.1861
{'fl_cov_age_ss' }	4.1151	183.33	-0.37329	1400.5	143
{'fl_cor_age_ss' }	0.052966	1	-0.062782	0.71382	0.7342
{'fl_cov_educ_ss' }	0.027108	-0.37329	0.19284	-9.2359	-9.793
{'fl_cor_educ_ss' }	0.010758	-0.062782	1	-0.14514	-0.1541
{'fl_cov_a_ss' }	145.03	1400.5	-9.2359	20999	2094
{'fl_cor_a_ss' }	0.17442	0.71382	-0.14514	1	0.999
{'fl_cov_ap_ss' }	154.46	1438	-9.7931	20944	2091
{'fl_cor_ap_ss' }	0.18612	0.73429	-0.15419	0.9993	
{'fl_cov_MPC' }	-0.032152	-0.1128	0.0061122	-0.71422	-0.7941
{'fl_cor_MPC' }	-0.10557	-0.15696	0.26224	-0.092863	-0.1034
{'fl_cov_Mass' }	-2.7754e-06	-2.3008e-05	-3.5426e-07	-0.00016592	-0.0001677
{'fl_cor_Mass' }	-0.091883	-0.32281	-0.15325	-0.21751	-0.2203
{'fl_cov_c_ss' }	15.819	-34.276	0.57801	165.89	143.
{'fl_cor_c_ss' }	0.46921	-0.43083	0.22402	0.19483	0.1688
{'fl_cov_y_head_inc' }	32.926	4.1151	0.027108	145.03	154.4
{'fl_cor_y_head_inc' }	1	0.052966	0.010758	0.17442	0.1861
{'fl_cov_y_spouse' }	0	0	0	0	
{'fl_cor_y_spouse' }	NaN	NaN	NaN	NaN	NaN
{'fl_cov_yshr_nttxss' }	0.020855	0.0026153	1.697e-05	0.091765	0.0977
{'fl_cor_yshr_nttxss' }	0.99874	0.053079	0.010619	0.17402	0.185
{'fracByP0_01' }	0.00013554	0.010553	0	0	
{'fracByP10' }	0.087755	0.048541	0	0.0025063	0.004513
{'fracByP25' }	0.2241	0.14456	0	0.028727	0.03673
{'fracByP50' }	0.46426	0.38247	0	0.18419	0.1735
{'fracByP75' }	0.72225	0.68941	1	0.48388	0.4489
{'fracByP90' }	0.88703	0.88024	1	0.74634	0.7160
{'fracByP99_99' }	0.99995	1	1	0.99979	0.9993

xx

Marital =0, kids =0, ybin =80 to 100

xx

xxx tb\_outcomes: all stats xxx

OriginalVariableNames	y_all	age_ss	educ_ss	a_ss	ap_ss
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13.1. 2019 FULL STATES MPC AND DISTRIBUTIONAL STATISTICS BY MARITAL, KIDS, AND INCOME GROUP

{'mean' }	89.313	45.289	0.28587	244.08	261.1
{'unweighted_sum' }	3.4629e+06	1909	1	26756	4.4356e+0
{'sd' }	5.7791	13.023	0.45183	194.1	192.8
{'coefofvar' }	0.064706	0.28755	1.5805	0.79522	0.7385
{'gini' }	0.037295	0.15841	0.6408	0.4125	0.4039
{'min' }	80.001	19	0	0	
{'max' }	100	64	1	2377.1	2370.
{'pYis0' }	0	0	0.71413	0.020853	1.1851e-1
{'pYls0' }	0	0	0	0	
{'pYgr0' }	1	1	0.28587	0.97915	
{'pYisMINY' }	0	0.018972	0.71413	0.020853	1.1851e-1
{'pYisMAXY' }	3.7911e-06	0.02925	0.28587	1.1813e-15	
{'p0_01' }	80.012	19	0	0	0.7904
{'p10' }	81.54	25	0	29.898	43.52
{'p25' }	84.27	35	0	100.91	114.2
{'p50' }	88.922	48	0	205.07	224.4
{'p75' }	94.198	56	1	363.77	378.8
{'p90' }	97.585	61	1	525.49	536.5
{'p99_99' }	100	64	1	1281.9	1273.
{'fl_cov_y_all' }	33.398	2.1956	0.039297	150.26	159.6
{'fl_cor_y_all' }	1	0.029174	0.01505	0.13396	0.1432
{'fl_cov_age_ss' }	2.1956	169.59	-0.29823	1813.9	1849.
{'fl_cor_age_ss' }	0.029174	1	-0.050684	0.71759	0.7365
{'fl_cov_educ_ss' }	0.039297	-0.29823	0.20415	-12.356	-12.92
{'fl_cor_educ_ss' }	0.01505	-0.050684	1	-0.14089	-0.148
{'fl_cov_a_ss' }	150.26	1813.9	-12.356	37675	3741
{'fl_cor_a_ss' }	0.13396	0.71759	-0.14089	1	0.9994
{'fl_cov_ap_ss' }	159.68	1849.7	-12.922	37410	3719
{'fl_cor_ap_ss' }	0.14327	0.73653	-0.1483	0.99942	
{'fl_cov_MPC' }	-0.0031027	0.051957	0.0006815	0.63872	0.6402
{'fl_cor_MPC' }	-0.05432	0.40366	0.15261	0.33294	0.3358
{'fl_cov_Mass' }	-1.4164e-06	-8.0012e-06	-3.1745e-07	-9.5448e-05	-9.4333e-0
{'fl_cor_Mass' }	-0.083209	-0.20859	-0.23854	-0.16695	-0.1660
{'fl_cov_c_ss' }	15.988	-34.182	0.59583	378.89	341.3
{'fl_cor_c_ss' }	0.39229	-0.3722	0.187	0.27681	0.2509
{'fl_cov_y_head_inc' }	33.398	2.1956	0.039297	150.26	159.6
{'fl_cor_y_head_inc' }	1	0.029174	0.01505	0.13396	0.1432
{'fl_cov_y_spouse' }	0	0	0	0	
{'fl_cor_y_spouse' }	NaN	NaN	NaN	NaN	NaN
{'fl_cov_yshr_nttxss' }	0.014829	0.0010034	1.7131e-05	0.066952	0.07114
{'fl_cor_yshr_nttxss' }	0.99914	0.030003	0.014763	0.13431	0.1436
{'fracByP0_01' }	0.00042007	0.0079591	0	0	5.0103e-0
{'fracByP10' }	0.090622	0.05099	0	0.0059303	0.008103
{'fracByP25' }	0.22976	0.15254	0	0.060679	0.05259
{'fracByP50' }	0.47206	0.40219	0	0.22278	0.212
{'fracByP75' }	0.72831	0.67181	1	0.53644	0.4926
{'fracByP90' }	0.88939	0.87436	1	0.78432	0.7455
{'fracByP99_99' }	1	1	1	0.99942	0.9994

xx

Marital =0, kids =0, ybin =100 to 1414.0634

xx

xxx tb\_outcomes: all stats xxx

OriginalVariableNames	y_all	age_ss	educ_ss	a_ss	ap_ss
{'mean' }	164.25	47.879	0.35462	603.16	641.9
{'unweighted_sum' }	1.6654e+08	1909	1	1.2935e+05	1.4733e+0

{'sd'	}	74.664	11.785	0.4784	524.59	535.2
{'coefofvar'	}	0.45456	0.24615	1.349	0.86973	0.8337
{'gini'	}	0.20972	0.13265	0.54013	0.41585	0.4099
{'min'	}	100	19	0	0	2.660
{'max'	}	1413.7	64	1	7837.6	8386.
{'pYis0'	}	0	0	0.64538	0.008464	
{'pYls0'	}	0	0	0	0	
{'pYgr0'	}	1	1	0.35462	0.99154	
{'pYisMINY'	}	8.0846e-15	0.0084319	0.64538	0.008464	
{'pYisMAXY'	}	9.784e-09	0.035671	0.35462	2.5784e-05	2.8187e-0
{'p0_01'	}	100.01	19	0	0	8.390
{'p10'	}	105.91	30	0	122.46	146.1
{'p25'	}	116.38	40	0	239.18	290.4
{'p50'	}	140.36	50	0	467.15	508.3
{'p75'	}	184.67	58	1	807.24	835.4
{'p90'	}	250.3	62	1	1175.1	1271.
{'p99_99'	}	1005.7	64	1	6140.4	6451.
{'fl_cov_y_all'	}	5574.6	82.616	3.9383	27029	2868
{'fl_cor_y_all'	}	1	0.093888	0.11026	0.6901	0.7178
{'fl_cov_age_ss'	}	82.616	138.9	-0.051378	3187.5	3233.
{'fl_cor_age_ss'	}	0.093888	1	-0.0091126	0.51557	0.5126
{'fl_cov_educ_ss'	}	3.9383	-0.051378	0.22886	1.1548	1.862
{'fl_cor_educ_ss'	}	0.11026	-0.0091126	1	0.0046015	0.007275
{'fl_cov_a_ss'	}	27029	3187.5	1.1548	2.7519e+05	2.8051e+0
{'fl_cor_a_ss'	}	0.6901	0.51557	0.0046015	1	0.9990
{'fl_cov_ap_ss'	}	28687	3233.7	1.8629	2.8051e+05	2.8647e+0
{'fl_cor_ap_ss'	}	0.71786	0.51265	0.0072754	0.99906	
{'fl_cov_MPC'	}	-0.0039422	0.067815	-2.0374e-06	1.5699	1.574
{'fl_cor_MPC'	}	-0.0078548	0.85602	-0.00063355	0.44519	0.4376
{'fl_cov_Mass'	}	-3.2407e-05	-4.7599e-07	-1.5824e-07	-0.00016835	-0.0001761
{'fl_cor_Mass'	}	-0.36338	-0.033813	-0.27693	-0.26869	-0.2755
{'fl_cov_c_ss'	}	2511	15.67	2.2388	14895	1549
{'fl_cor_c_ss'	}	0.94083	0.037196	0.13092	0.79429	0.8098
{'fl_cov_y_head_inc'	}	5574.6	82.616	3.9383	27029	2868
{'fl_cor_y_head_inc'	}	1	0.093888	0.11026	0.6901	0.7178
{'fl_cov_y_spouse'	}	0	0	0	0	
{'fl_cor_y_spouse'	}	NaN	NaN	NaN	NaN	NaN
{'fl_cov_yshr_nttxss'	}	0.64609	0.011641	0.00050086	3.1347	3.324
{'fl_cor_yshr_nttxss'	}	0.90808	0.10365	0.10987	0.62707	0.6518
{'fracByP0_01'	}	7.5135e-05	0.003346	0	0	1.097e-0
{'fracByP10'	}	0.062666	0.056801	0	0.013271	0.01293
{'fracByP25'	}	0.16403	0.16984	0	0.057688	0.06415
{'fracByP50'	}	0.35792	0.40929	0	0.223	0.2196
{'fracByP75'	}	0.60086	0.72112	1	0.50267	0.4758
{'fracByP90'	}	0.79433	0.90509	1	0.70917	0.7129
{'fracByP99_99'	}	0.99932	1	1	0.99885	0.9988

### 13.1.12 Store Aggregate To File

Store Several Files:

1. Overall Aggregate Statistics All Distribution
2. Aggregate Statistics Only for 18 to 64 year olds
3. Group Statistics by Kids
4. Group Statistics by Marital + Kids
5. Group Statistics by Marital + Kids + Income Bins



### 13.1. 2019 FULL STATES MPC AND DISTRIBUTIONAL STATISTICS BY MARITAL, KIDS, AND INCOME GROUP

```
if (bl_save_csv)
    % All Stats All Ages
    mp_path = snw_mp_path('fan');
    spt_simu_results_csv = mp_path('spt_simu_results_csv');
    writetable(tb_dist_stats_all, [spt_simu_results_csv 'stats_all_allages.csv'], 'WriteRowNames', t
    % All Stats 18 to 64 Year old
    mp_path = snw_mp_path('fan');
    spt_simu_results_csv = mp_path('spt_simu_results_csv');
    writetable(tb_dist_stats_all_18to64, [spt_simu_results_csv 'stats_all_18t64.csv'], 'WriteRowName
    % Group by K: Kids only
    tb_store_stats_by_k = array2table(mt_store_stats_by_k, 'VariableNames', ...
        {'kids', 'married_mean' ...
        'age_mean', 'age_p50', 'educ_mean', ...
        'a_mean', 'a_p50', 'ap_mean', 'ap_p50', ...
        'y_all_mean', 'y_all_p50', ...
        'mpc_mean', 'mpc_p50', ...
        'mass',...
        'c_ss_mean', 'c_ss_p50', ...
        'y_head_inc_mean', 'y_spouse_mean'});
    mp_path = snw_mp_path('fan');
    spt_simu_results_csv = mp_path('spt_simu_results_csv');
    writetable(tb_store_stats_by_k, [spt_simu_results_csv 'stats_by_kids.csv']);
    % Group by MK: marry + kids only
    tb_store_stats_by_mk = array2table(mt_store_stats_by_mk, 'VariableNames', ...
        {'marital', 'kids', ...
        'age_mean', 'age_p50', 'educ_mean', ...
        'a_mean', 'a_p50', 'ap_mean', 'ap_p50', ...
        'y_all_mean', 'y_all_p50', ...
        'mpc_mean', 'mpc_p50', ...
        'mass',...
        'c_ss_mean', 'c_ss_p50', ...
        'y_head_inc_mean', 'y_spouse_mean'});
    mp_path = snw_mp_path('fan');
    spt_simu_results_csv = mp_path('spt_simu_results_csv');
    writetable(tb_store_stats_by_mk, [spt_simu_results_csv 'stats_by_marital_kids.csv']);
    % Group by MKY
    tb_store_stats_by_mky = array2table(mt_store_stats_by_mky, 'VariableNames', ...
        {'marital', 'kids', 'y_all_start', 'y_all_end', ...
        'age_mean', 'age_p50', 'educ_mean', ...
        'a_mean', 'a_p50', 'ap_mean', 'ap_p50', ...
        'y_all_mean', 'y_all_p50', ...
        'mpc_mean', 'mpc_p50', ...
        'mass',...
        'c_ss_mean', 'c_ss_p50', ...
        'y_head_inc_mean', 'y_spouse_mean'});
    mp_path = snw_mp_path('fan');
    spt_simu_results_csv = mp_path('spt_simu_results_csv');
    writetable(tb_store_stats_by_mky, [spt_simu_results_csv 'stats_by_marital_kids_20kincbins.csv'])
end
```

#### 13.1.13 Store Key Stats to Compare to Key US Distributional Statistics

Earning, income and Wealth.

Income = interest earnings + Social Security + labor income + spousal income. This is equal to `y_all`.

Earnings = labor income + spousal income.

% Income Variable

```
if (min(abs(total_inc_VFI*58.056 - y_all), [], 'all')>0)
```

```

    error('something is wrong, total_inc_VFI should be equal to y_all');
end
income = y_all;
% Earning variable
% earn*fl_earn_ratio generated earn_VFI
earning = (mp_valpol_more_ss('earn_VFI') + spouse_inc_VFI)*58.056;
% Wealth Variable
wealth = a_ss;

```

Generate Key Statistics for these three variables only, distributional Statistics Overall All Ages:

```

% construct input data
income_grp = income(min_age:82, :, :, : ,: ,:);
earning_grp = earning(min_age:82, :, :, : ,: ,:);
wealth_grp = wealth(min_age:82, :, :, : ,: ,:);
Phi_true_grp = Phi_true_1(min_age:82, :, :, : ,: ,:);

mp_cl_ar_xyz_of_s = containers.Map('KeyType','char', 'ValueType','any');
mp_cl_ar_xyz_of_s('earning') = {earning_grp(:), zeros(1)};
mp_cl_ar_xyz_of_s('income') = {income_grp(:), zeros(1)};
mp_cl_ar_xyz_of_s('wealth') = {wealth_grp(:), zeros(1)};
mp_cl_ar_xyz_of_s('earninglog') = {log(earning_grp(:)), zeros(1)};
mp_cl_ar_xyz_of_s('incomelog') = {log(income_grp(:)), zeros(1)};
mp_cl_ar_xyz_of_s('wealthlog') = {log(wealth_grp(:)), zeros(1)};
mp_cl_ar_xyz_of_s('ar_st_y_name') = ["earning", "income", "wealth", "earninglog", "incomelog", "weal

% controls
mp_support = containers.Map('KeyType','char', 'ValueType','any');
mp_support('ar_fl_percentiles') = [20 30 40 60 50 80 90 95 99];
mp_support('bl_display_final') = true;
mp_support('bl_display_detail') = false;
mp_support('bl_display_drvm2outcomes') = false;
mp_support('bl_display_drvstats') = false;
mp_support('bl_display_drvm2covcor') = false;

% Call Function
mp_cl_mt_xyz_of_s = ff_simu_stats(Phi_true_grp(:)/sum(Phi_true_grp,'all'), mp_cl_ar_xyz_of_s, mp_sup

```

xxx tb\_outcomes: all stats xxx

OriginalVariableNames	earning	income	wealth	earninglog	incomelog	w
{'mean' }	72.136	84.974	245.22	-Inf	4.1042	
{'unweighted_sum' }	9.5943e+07	7.9255e+09	1.2935e+05	-Inf	1.1455e+08	
{'sd' }	80.749	84.549	391.42	NaN	0.81216	
{'coefofvar' }	1.1194	0.995	1.5962	NaN	0.19789	
{'gini' }	0.51369	0.44243	0.68023	NaN	0.11243	
{'min' }	0	2.2124	0	-Inf	0.79408	
{'max' }	2640	2953.5	7837.6	7.8785	7.9907	
{'pYis0' }	0.10578	0	0.12285	0	0	
{'pYls0' }	0	0	0	0.10695	0	
{'pYgr0' }	0.89422	1	0.87715	0.89305	1	
{'pYisMINY' }	0.10578	6.774e-07	0.12285	0.10578	6.774e-07	
{'pYisMAXY' }	1.5964e-10	1.671e-12	6.0119e-06	1.5964e-10	1.671e-12	6
{'p20' }	15.969	29.216	3.7372	2.7707	3.3747	
{'p30' }	29.464	38.184	15.308	3.3832	3.6424	
{'p40' }	40.761	48.225	39.794	3.7077	3.8759	
{'p60' }	65.423	74.426	146.89	4.1809	4.3098	
{'p50' }	52.252	59.948	82.04	3.9561	4.0935	

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{'p80' }	108.96	122.39	413.31	4.691	4.8072
{'p90' }	159.7	176.61	729.18	5.0733	5.1739
{'p95' }	211.84	233.69	979.69	5.3558	5.454
{'p99' }	356.31	398.22	1773.5	5.8758	5.987
{'fl_cov_earning' }	6520.5	6671.7	8382.5	NaN	53.875
{'fl_cor_earning' }	1	0.97721	0.26521	NaN	0.82149
{'fl_cov_income' }	6671.7	7148.6	15059	NaN	57.878
{'fl_cor_income' }	0.97721	1	0.45504	NaN	0.84286
{'fl_cov_wealth' }	8382.5	15059	1.5321e+05	NaN	141.72
{'fl_cor_wealth' }	0.26521	0.45504	1	NaN	0.4458
{'fl_cov_earninglog' }	NaN	NaN	NaN	NaN	NaN
{'fl_cor_earninglog' }	NaN	NaN	NaN	NaN	NaN
{'fl_cov_incomelog' }	53.875	57.878	141.72	NaN	0.65961
{'fl_cor_incomelog' }	0.82149	0.84286	0.4458	NaN	1
{'fl_cov_wealthlog' }	NaN	NaN	NaN	NaN	NaN
{'fl_cor_wealthlog' }	NaN	NaN	NaN	NaN	NaN
{'fracByP20' }	0.012671	0.04827	0.00074821	NaN	0.14532
{'fracByP30' }	0.044498	0.08795	0.0041711	NaN	0.23096
{'fracByP40' }	0.093262	0.13869	0.016749	NaN	0.32262
{'fracByP60' }	0.23895	0.28076	0.095501	NaN	0.52207
{'fracByP50' }	0.15762	0.20209	0.045325	NaN	0.41971
{'fracByP80' }	0.47178	0.50479	0.32852	NaN	0.74357
{'fracByP90' }	0.65353	0.6766	0.56651	NaN	0.86486
{'fracByP95' }	0.78022	0.79527	0.70071	NaN	0.92947
{'fracByP99' }	0.92468	0.93132	0.90524	NaN	0.98459

```

tb_dist_stats_all = mp_cl_mt_xyz_of_s('tb_outcomes');
% Select columns
tb_dist_stats_all_save = tb_dist_stats_all(1:3,:);
ar_st_columns = ["coefofvar", "gini", "varianceoflog", ...
                "p99p50ratio", "p90p50ratio", "meantomedian", "p50p30ratio", ...
                "fracP0toP20", "fracP20toP40", "fracP40toP60", "fracP60toP80", "fracP80toP100", ...
                "fracP90toP95", "fracP95toP99", "fracP99toP100"];

varianceoflog = tb_dist_stats_all{4:6,"sd"}.^2;

p99p50ratio = tb_dist_stats_all_save{:, "p99"}./tb_dist_stats_all_save{:, "p50"};
p90p50ratio = tb_dist_stats_all_save{:, "p90"}./tb_dist_stats_all_save{:, "p50"};
meantomedian = tb_dist_stats_all_save{:, "mean"}./tb_dist_stats_all_save{:, "p50"};
p50p30ratio = tb_dist_stats_all_save{:, "p50"}./tb_dist_stats_all_save{:, "p30"};
fracP0toP20 = tb_dist_stats_all_save{:, "fracByP20"};
fracP20toP40 = tb_dist_stats_all_save{:, "fracByP40"} - tb_dist_stats_all_save{:, "fracByP20"};
fracP40toP60 = tb_dist_stats_all_save{:, "fracByP60"} - tb_dist_stats_all_save{:, "fracByP40"};
fracP60toP80 = tb_dist_stats_all_save{:, "fracByP80"} - tb_dist_stats_all_save{:, "fracByP60"};
fracP80toP100 = 1 - tb_dist_stats_all_save{:, "fracByP80"};

fracP90toP95 = tb_dist_stats_all_save{:, "fracByP95"} - tb_dist_stats_all_save{:, "fracByP90"};
fracP95toP99 = tb_dist_stats_all_save{:, "fracByP99"} - tb_dist_stats_all_save{:, "fracByP95"};
fracP99toP100 = 1 - tb_dist_stats_all_save{:, "fracByP99"};

tb_dist_stats_all_save = addvars(tb_dist_stats_all_save, varianceoflog, 'Before', 'gini');
tb_dist_stats_all_save = addvars(tb_dist_stats_all_save, p99p50ratio);
tb_dist_stats_all_save = addvars(tb_dist_stats_all_save, p90p50ratio);
tb_dist_stats_all_save = addvars(tb_dist_stats_all_save, meantomedian);
tb_dist_stats_all_save = addvars(tb_dist_stats_all_save, p50p30ratio);
tb_dist_stats_all_save = addvars(tb_dist_stats_all_save, fracP0toP20);
tb_dist_stats_all_save = addvars(tb_dist_stats_all_save, fracP20toP40);
tb_dist_stats_all_save = addvars(tb_dist_stats_all_save, fracP40toP60);

```

```

tb_dist_stats_all_save = addvars(tb_dist_stats_all_save, fracP60toP80);
tb_dist_stats_all_save = addvars(tb_dist_stats_all_save, fracP80toP100);

tb_dist_stats_all_save = addvars(tb_dist_stats_all_save, fracP90toP95);
tb_dist_stats_all_save = addvars(tb_dist_stats_all_save, fracP95toP99);
tb_dist_stats_all_save = addvars(tb_dist_stats_all_save, fracP99toP100);
disp(tb_dist_stats_all_save(:, ar_st_columns));

```

	coefofvar	gini	varianceoflog	p99p50ratio	p90p50ratio	meantomedian
	-----	-----	-----	-----	-----	-----
earning	1.1194	0.51369	NaN	6.819	3.0563	1.3805
income	0.995	0.44243	0.65961	6.6427	2.946	1.4174
wealth	1.5962	0.68023	NaN	21.618	8.8881	2.989

```
% Core Stats Table
```

```

if (bl_save_csv)
    mp_path = snw_mp_path('fan');
    spt_simu_results_csv = mp_path('spt_simu_results_csv');
    writetable(tb_dist_stats_all_save(:, ar_st_columns), [spt_simu_results_csv 'stats_all_allages_vr
end

```

Statistics overall distributionally for 18 to 64 year olds.

```
% construct input data
```

```

income_grp = income(min_age:max_age, :, :, : ,: ,:);
earning_grp = earning(min_age:max_age, :, :, : ,: ,:);
wealth_grp = wealth(min_age:max_age, :, :, : ,: ,:);
Phi_true_grp = Phi_true_1(min_age:max_age, :, :, : ,: ,:);

```

```

mp_cl_ar_xyz_of_s = containers.Map('KeyType','char', 'ValueType','any');
mp_cl_ar_xyz_of_s('income') = {income_grp(:), zeros(1)};
mp_cl_ar_xyz_of_s('earning') = {earning_grp(:), zeros(1)};
mp_cl_ar_xyz_of_s('wealth') = {wealth_grp(:), zeros(1)};
mp_cl_ar_xyz_of_s('earninglog') = {log(earning_grp(:)), zeros(1)};
mp_cl_ar_xyz_of_s('incomelog') = {log(income_grp(:)), zeros(1)};
mp_cl_ar_xyz_of_s('wealthlog') = {log(wealth_grp(:)), zeros(1)};
mp_cl_ar_xyz_of_s('ar_st_y_name') = ["earning", "income", "wealth", "earninglog", "incomelog", "weal

```

```
% controls
```

```

mp_support = containers.Map('KeyType','char', 'ValueType','any');
mp_support('ar_fl_percentiles') = [20 30 40 60 50 80 90 95 99];
mp_support('bl_display_final') = true;
mp_support('bl_display_detail') = false;
mp_support('bl_display_drvm2outcomes') = false;
mp_support('bl_display_drvstats') = false;
mp_support('bl_display_drvm2covcor') = false;

```

```
% Call Function
```

```
mp_cl_mt_xyz_of_s = ff_simu_stats(Phi_true_grp(:)/sum(Phi_true_grp,'all'), mp_cl_ar_xyz_of_s, mp_sup
```

```
xxx tb_outcomes: all stats xxx
```

OriginalVariableNames	earning	income	wealth	earninglog	incomelog	w
-----	-----	-----	-----	-----	-----	-----
{'mean' }	87.466	95.246	194.5	4.1711	4.2425	
{'unweighted_sum' }	9.394e+07	7.7487e+09	1.2935e+05	1.5445e+06	1.116e+08	
{'sd' }	82.434	89.631	344.5	0.76834	0.79264	
{'coefofvar' }	0.94247	0.94104	1.7712	0.1842	0.18683	

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{'gini'}	}	0.417	0.42428	0.71579	0.10382	0.1055
{'min'}	}	2.2124	2.2124	0	0.79408	0.79408
{'max'}	}	2640	2953.5	7837.6	7.8785	7.9907
{'pYis0'}	}	0	0	0.14627	0	0
{'pYls0'}	}	0	0	0	0	0
{'pYgr0'}	}	1	1	0.85373	1	1
{'pYisMINY'}	}	8.617e-07	8.6135e-07	0.14627	8.617e-07	8.6135e-07
{'pYisMAXY'}	}	2.0299e-10	2.1248e-12	5.4766e-06	2.0299e-10	2.1248e-12
{'p20'}	}	34.093	35.624	0.80724	3.5291	3.573
{'p30'}	}	43.249	45.828	6.458	3.767	3.8249
{'p40'}	}	52.993	56.888	29.898	3.9702	4.0411
{'p60'}	}	77.857	85.184	100.91	4.3549	4.4448
{'p50'}	}	64.26	69.57	51.664	4.1629	4.2423
{'p80'}	}	124.43	137.12	318.35	4.8237	4.9209
{'p90'}	}	175.33	192.9	588.48	5.1667	5.2621
{'p95'}	}	227.34	250.34	890.69	5.4265	5.5228
{'p99'}	}	384.15	427.18	1640.6	5.951	6.0572
{'fl_cov_earning'}	}	6795.4	7319.6	13105	53.1	53.884
{'fl_cor_earning'}	}	1	0.99065	0.46144	0.83837	0.82467
{'fl_cov_income'}	}	7319.6	8033.6	17852	58.043	59.852
{'fl_cor_income'}	}	0.99065	1	0.57814	0.84283	0.84246
{'fl_cov_wealth'}	}	13105	17852	1.1868e+05	123.58	149.2
{'fl_cor_wealth'}	}	0.46144	0.57814	1	0.46687	0.5464
{'fl_cov_earninglog'}	}	53.1	58.043	123.58	0.59034	0.6043
{'fl_cor_earninglog'}	}	0.83837	0.84283	0.46687	1	0.99226
{'fl_cov_incomelog'}	}	53.884	59.852	149.2	0.6043	0.62827
{'fl_cor_incomelog'}	}	0.82467	0.84246	0.5464	0.99226	1
{'fl_cov_wealthlog'}	}	NaN	NaN	NaN	NaN	NaN
{'fl_cor_wealthlog'}	}	NaN	NaN	NaN	NaN	NaN
{'fracByP20'}	}	0.053802	0.050961	0.00014055	0.14882	0.14762
{'fracByP30'}	}	0.098055	0.093694	0.0021143	0.23646	0.23488
{'fracByP40'}	}	0.153	0.14753	0.015697	0.3292	0.32764
{'fracByP60'}	}	0.30069	0.29468	0.079605	0.52874	0.52766
{'fracByP50'}	}	0.21981	0.21374	0.034043	0.42667	0.42529
{'fracByP80'}	}	0.52452	0.52079	0.28918	0.74816	0.7478
{'fracByP90'}	}	0.69236	0.69054	0.51495	0.86758	0.86757
{'fracByP95'}	}	0.80576	0.80501	0.69371	0.93096	0.93099
{'fracByP99'}	}	0.93293	0.93437	0.90041	0.98483	0.98492

```

tb_dist_stats_all = mp_cl_mt_xyz_of_s('tb_outcomes');
% Select columns
tb_dist_stats_all_save = tb_dist_stats_all(1:3,:);
ar_st_columns = ["coefofvar", "gini", "varianceoflog", ...
                "p99p50ratio", "p90p50ratio", "meantomedian", "p50p30ratio", ...
                "fracP0toP20", "fracP20toP40", "fracP40toP60", "fracP60toP80", "fracP80toP100", ...
                "fracP90toP95", "fracP95toP99", "fracP99toP100"];

varianceoflog = tb_dist_stats_all{4:6,"sd"}.^2;

p99p50ratio = tb_dist_stats_all_save{:, "p99"}./tb_dist_stats_all_save{:, "p50"};
p90p50ratio = tb_dist_stats_all_save{:, "p90"}./tb_dist_stats_all_save{:, "p50"};
meantomedian = tb_dist_stats_all_save{:, "mean"}./tb_dist_stats_all_save{:, "p50"};
p50p30ratio = tb_dist_stats_all_save{:, "p50"}./tb_dist_stats_all_save{:, "p30"};
fracP0toP20 = tb_dist_stats_all_save{:, "fracByP20"};
fracP20toP40 = tb_dist_stats_all_save{:, "fracByP40"} - tb_dist_stats_all_save{:, "fracByP20"};
fracP40toP60 = tb_dist_stats_all_save{:, "fracByP60"} - tb_dist_stats_all_save{:, "fracByP40"};
fracP60toP80 = tb_dist_stats_all_save{:, "fracByP80"} - tb_dist_stats_all_save{:, "fracByP60"};
fracP80toP100 = 1 - tb_dist_stats_all_save{:, "fracByP80"};

```

```
fracP90toP95 = tb_dist_stats_all_save(:, "fracByP95") - tb_dist_stats_all_save(:, "fracByP90");
fracP95toP99 = tb_dist_stats_all_save(:, "fracByP99") - tb_dist_stats_all_save(:, "fracByP95");
fracP99toP100 = 1 - tb_dist_stats_all_save(:, "fracByP99");
```

```
tb_dist_stats_all_save = addvars(tb_dist_stats_all_save, varianceoflog, 'Before', 'gini');
tb_dist_stats_all_save = addvars(tb_dist_stats_all_save, p99p50ratio);
tb_dist_stats_all_save = addvars(tb_dist_stats_all_save, p90p50ratio);
tb_dist_stats_all_save = addvars(tb_dist_stats_all_save, meantomedian);
tb_dist_stats_all_save = addvars(tb_dist_stats_all_save, p50p30ratio);
tb_dist_stats_all_save = addvars(tb_dist_stats_all_save, fracP0toP20);
tb_dist_stats_all_save = addvars(tb_dist_stats_all_save, fracP20toP40);
tb_dist_stats_all_save = addvars(tb_dist_stats_all_save, fracP40toP60);
tb_dist_stats_all_save = addvars(tb_dist_stats_all_save, fracP60toP80);
tb_dist_stats_all_save = addvars(tb_dist_stats_all_save, fracP80toP100);
```

```
tb_dist_stats_all_save = addvars(tb_dist_stats_all_save, fracP90toP95);
tb_dist_stats_all_save = addvars(tb_dist_stats_all_save, fracP95toP99);
tb_dist_stats_all_save = addvars(tb_dist_stats_all_save, fracP99toP100);
disp(tb_dist_stats_all_save(:, ar_st_columns));
```

	coefofvar	gini	varianceoflog	p99p50ratio	p90p50ratio	meantomedian
	-----	-----	-----	-----	-----	-----
earning	0.94247	0.417	0.59034	5.978	2.7285	1.3611
income	0.94104	0.42428	0.62827	6.1403	2.7727	1.3691
wealth	1.7712	0.71579	NaN	31.755	11.391	3.7648

```
% Core Stats Table
```

```
if (bl_save_csv)
```

```
    mp_path = snw_mp_path('fan');
```

```
    spt_simu_results_csv = mp_path('spt_simu_results_csv');
```

```
    writetable(tb_dist_stats_all_save(:, ar_st_columns), [spt_simu_results_csv 'stats_all_18t64_vrrc
```

```
end
```

## Chapter 14

# Selected Comparative Statistics

### 14.1 Value and Consumption Low vs Higher Interest Rates Results Comparison

This is the example vignette for function: `snw_vfi_main_bisec_vec` from the [PrjOptiSNW Package](#). This function solves for the  $V(\text{states})$  for individuals at lower and higher savings interest rates. Note that welfare improves for all when interest rates go up for savings in a model where borrowing is not allowed. However, a change in the interest rate generates an income effect (higher resources) and changes the relative price of consumption today vs. tomorrow. The change in income increases the incentive to consume, but the change in relative price depresses incentives to consume today. The combined effect of rising interest rate on savings on consumption/savings differs by the state-space; households might overall consume more or less depending on their state-space.

#### 14.1.1 Solve Model at 4 Percent Interest Rate

Solve the benchmark model at 4 percent savings interest rate.

```
% mp_params = snw_mp_param('default_dense');
mp_params = snw_mp_param('default_docdense');
mp_params('beta') = 0.95;
fl_higher_r = 0.04;
fl_lower_r = 0.02;
mp_params('r') = fl_higher_r;
mp_controls = snw_mp_control('default_test');
mp_controls('bl_print_vfi') = false;
mp_controls('bl_print_vfi_verbose') = false;
mp_controls('bl_timer') = true;
[V_ss_r04,~,cons_ss_r04,~] = snw_vfi_main_bisec_vec(mp_params, mp_controls);
```

Completed SNW\_VFI\_MAIN\_BISEC\_VEC;SNW\_MP\_PARAM=default\_docdense;SNW\_MP\_CONTROL=default\_test;time=496.

#### 14.1.2 Solve Model at 2 Percent Interest Rate

Solve the benchmark model at 2 percent savings interest rate.

```
mp_params('r') = fl_lower_r;
mp_controls = snw_mp_control('default_test');
mp_controls('bl_print_vfi') = false;
mp_controls('bl_print_vfi_verbose') = false;
mp_controls('bl_timer') = true;
[V_ss_r02,~,cons_ss_r02,~] = snw_vfi_main_bisec_vec(mp_params, mp_controls);
```

Completed SNW\_VFI\_MAIN\_BISEC\_VEC;SNW\_MP\_PARAM=default\_docdense;SNW\_MP\_CONTROL=default\_test;time=495.

### 14.1.3 Generate Interest Rate Comparison Matrixes

Take the difference between 4 percent and 2 percent savings interest rate results. When interest rates are higher, greater incentive to save, but leads to heterogeneous responses by income and other characteristics, note that this changes both relative prices as well as total resource/budget, so there is both income and price effects that differ in magnitudes depending on the individual's statespace. Welfare does improve for all higher higher  $r$ . Welfare is converted to units in fixed life-time consumption.

```
gamma = mp_params('gamma');
mn_V_gain_r = snw_hh_welfare(V_ss_r04, gamma) - snw_hh_welfare(V_ss_r02, gamma);
mn_C_gain_r = cons_ss_r04 - cons_ss_r02;
fl_r_gap = fl_higher_r - fl_lower_r;
```

### 14.1.4 Dense Param Results Define Frames

Define the matrix dimensions names and dimension vector values. Policy and Value Functions share the same ND dimensional structure.

```
% Grids:
age_grid = 18:100;
agrid = mp_params('agrid');
eta_H_grid = mp_params('eta_H_grid');
eta_S_grid = mp_params('eta_S_grid');
ar_st_eta_HS_grid = string(cellstr([num2str(eta_H_grid', 'hz=%3.2f;'), num2str(eta_S_grid', 'wz=%3.2f;')], 'wz=%3.2f;'));
edu_grid = [0,1];
marry_grid = [0,1];
kids_grid = (1:1:mp_params('n_kidsgrid'))';
% NaN(n_jgrid,n_agrid,n_etagrid,n_educgrid,n_marriedgrid,n_kidsgrid);
cl_mp_datasetdesc = {};
cl_mp_datasetdesc{1} = containers.Map({'name', 'labval'}, {'age', age_grid});
cl_mp_datasetdesc{2} = containers.Map({'name', 'labval'}, {'savings', agrid});
cl_mp_datasetdesc{3} = containers.Map({'name', 'labval'}, {'eta', 1:length(eta_H_grid)});
cl_mp_datasetdesc{4} = containers.Map({'name', 'labval'}, {'edu', edu_grid});
cl_mp_datasetdesc{5} = containers.Map({'name', 'labval'}, {'marry', marry_grid});
cl_mp_datasetdesc{6} = containers.Map({'name', 'labval'}, {'kids', kids_grid});
```

### 14.1.5 Analyze Difference in V and C with Higher and Lower Savings Interest Rate

The difference between V and C with higher and lower  $r$ .

```
% Generate some Data
mp_support_graph = containers.Map('KeyType', 'char', 'ValueType', 'any');
mp_support_graph('cl_st_xtitle') = {'Savings States, a'};
mp_support_graph('st_legend_loc') = 'eastoutside';
mp_support_graph('bl_graph_logy') = true; % do not log
mp_support_graph('it_legend_select') = 21; % how many shock legends to show
mp_support_graph('cl_colors') = 'jet';
```

```
MEAN(MN_V_GAIN(A,Z))
```

Tabulate value and policies along savings and shocks:

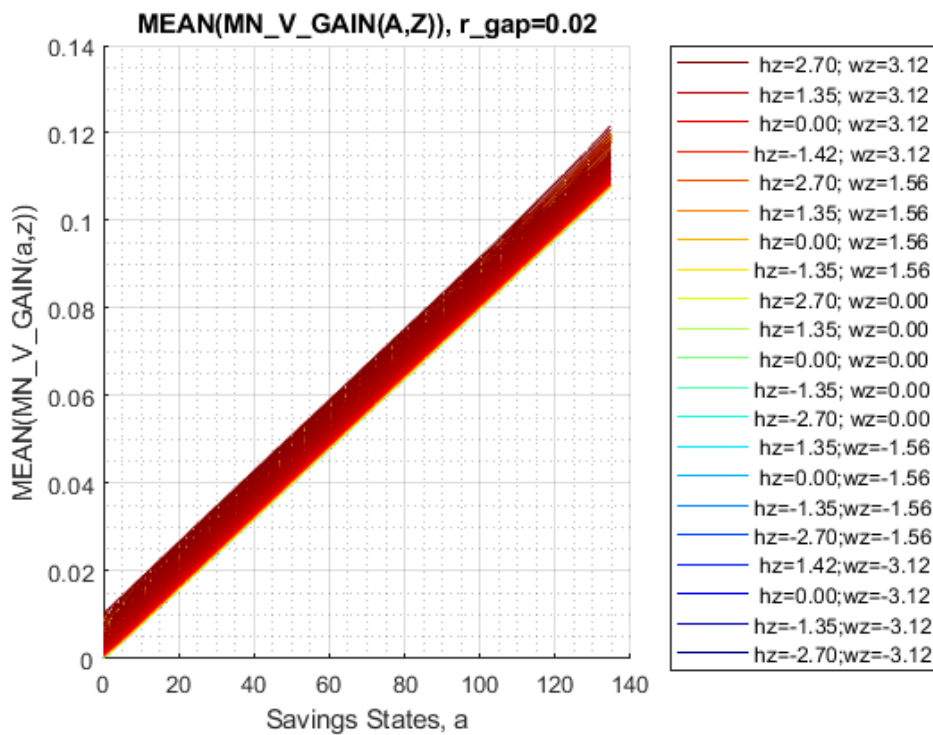
```
% Set
ar_permute = [1,4,5,6,3,2];
% Value Function
st_title = ['MEAN(MN_V_Gain(A,Z)), r_gap=' num2str(fl_r_gap) ];
tb_az_v = ff_summ_nd_array(st_title, mn_V_gain_r, true, ["mean"], 4, 1, cl_mp_datasetdesc, ar_permut
```

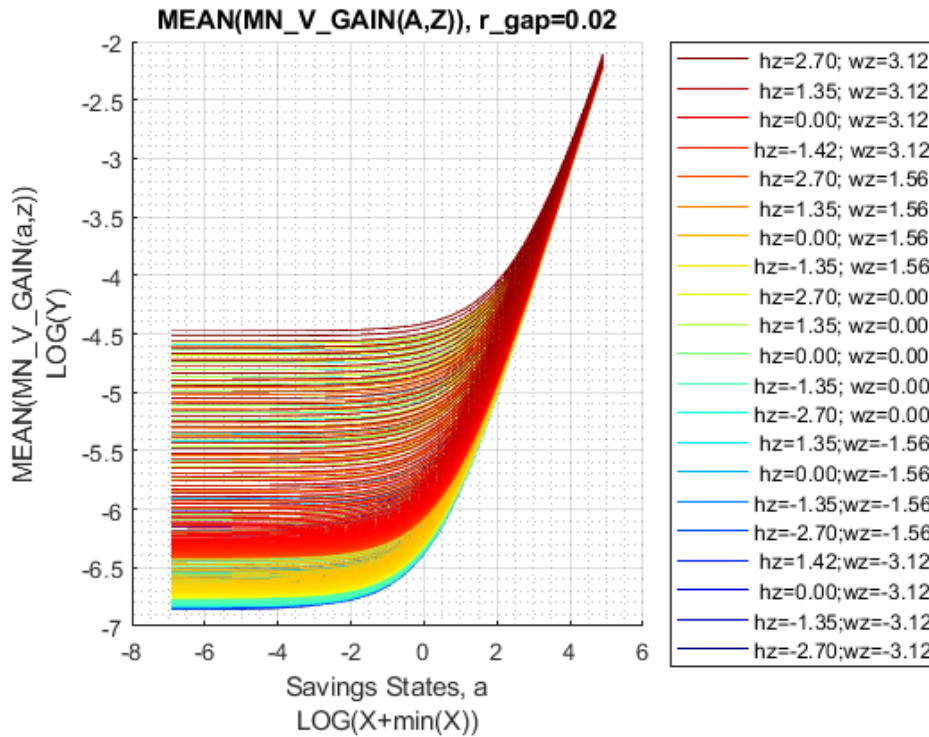
```
xxx MEAN(MN_V_Gain(A,Z)), r_gap=0.02 xxxxxxxxxxxxxxxxxxxxxxxxxxxxxxxx
  group      savings      mean_eta_1      mean_eta_2      mean_eta_3      mean_eta_4      mean_eta_5      mea
```



1                    0    4.6652e-05    4.802e-05    4.9487e-05    5.1045e-05    5.2688e-05    5.4

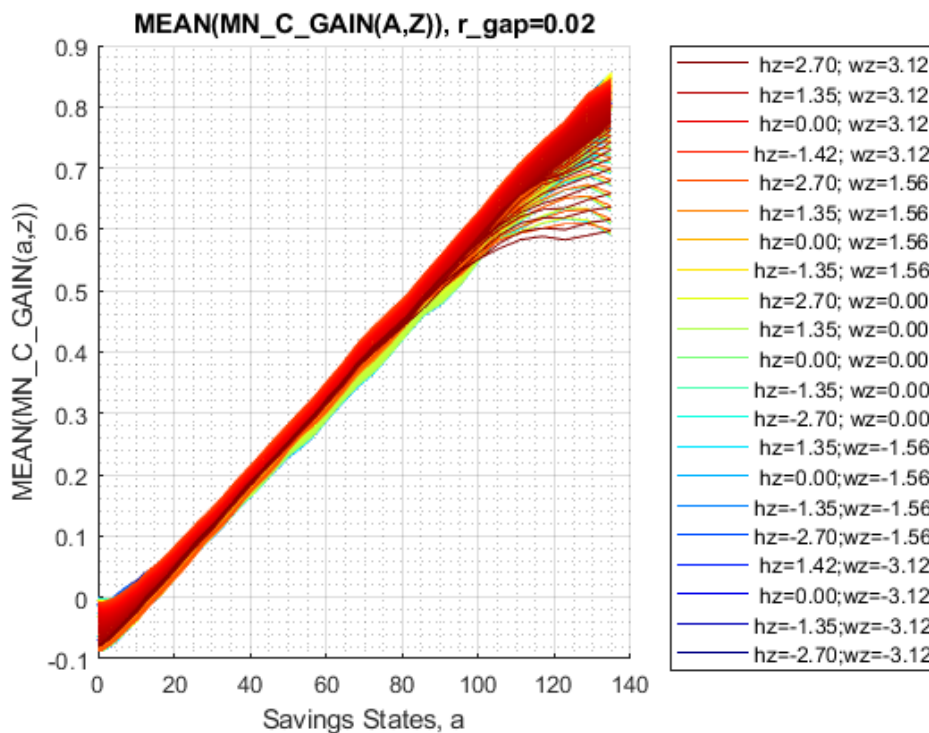
```
st_title = ['MEAN(MN_V_GAIN(A,Z)), r_gap=' num2str(fl_r_gap) ''];
mp_support_graph('cl_st_graph_title') = {st_title};
mp_support_graph('cl_st_ytitle') = {'MEAN(MN_V_GAIN(a,z))'};
ff_graph_grid((tb_az_v{1:end, 3:end})', ar_st_eta_HS_grid, agrid, mp_support_graph);
```

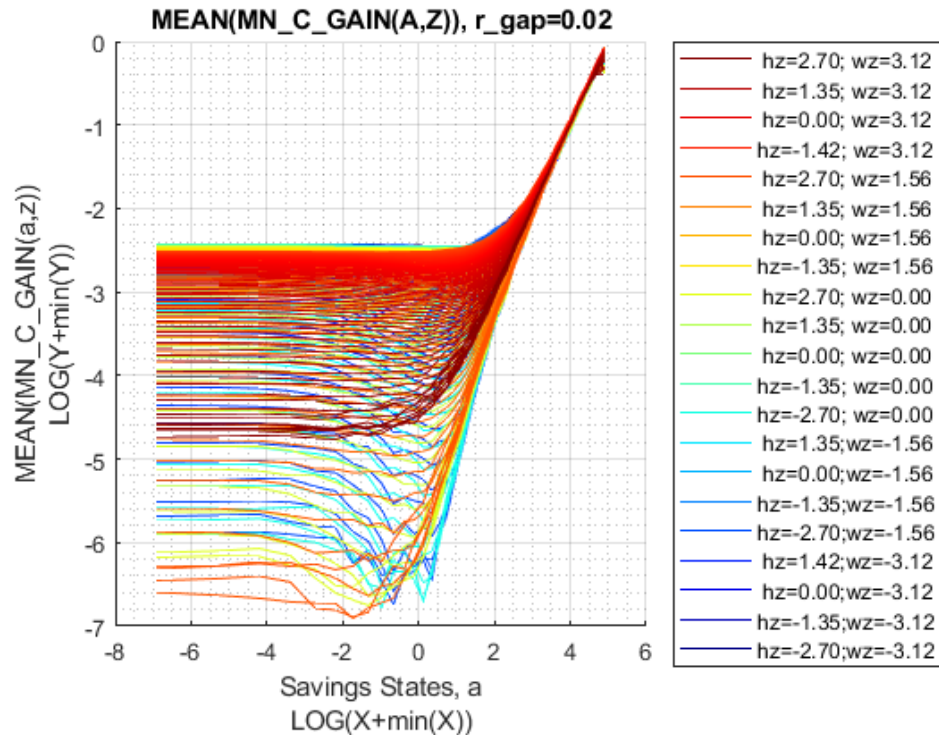




Graph Mean Consumption:

```
st_title = ['MEAN(MN\C\_GAIN(A,Z)), r\_gap=' num2str(fl_r_gap) ''];
mp_support_graph('cl_st_graph_title') = {st_title};
mp_support_graph('cl_st_ytitle') = {'MEAN(MN\C\_GAIN(a,z))'};
ff_graph_grid((tb_az_c{1:end, 3:end})', ar_st_eta_HS_grid, agrid, mp_support_graph);
```





### 14.1.6 Analyze Kids and Marriage and Age

Aggregating over education, savings, and shocks, what are the differential effects of Marriage and Age.

```
% Generate some Data
mp_support_graph = containers.Map('KeyType', 'char', 'ValueType', 'any');
ar_row_grid = [...
    "k0M0", "k1M0", "k2M0", "k3M0", "k4M0", ...
    "k0M1", "k1M1", "k2M1", "k3M1", "k4M1"];
mp_support_graph('cl_st_xtitle') = {'Age'};
mp_support_graph('st_legend_loc') = 'best';
mp_support_graph('bl_graph_logy') = true; % do not log
mp_support_graph('st_rounding') = '6.2f'; % format shock legend
mp_support_graph('cl_scatter_shapes') = {...
    'o', 'd', 's', 'x', '*', ...
    'o', 'd', 's', 'x', '*'};
mp_support_graph('cl_colors') = {...
    'red', 'red', 'red', 'red', 'red'...
    'blue', 'blue', 'blue', 'blue', 'blue'};
MEAN(VAL(KM,J)), MEAN(AP(KM,J)), MEAN(C(KM,J))
```

Tabulate value and policies:

```
% Set
% NaN(n_jgrid,n_agrid,n_etagrid,n_educgrid,n_marriedgrid,n_kidsgrid);
ar_permute = [2,3,4,1,6,5];
% Value Function
st_title = ['MEAN(MN_V_Gain(KM,J)), r_gap=' num2str(fl_r_gap) ];
tb_az_v = ff_summ_nd_array(st_title, mn_V_gain_r, true, ["mean"], 3, 1, cl_mp_datasetdesc, ar_permut
```

xxx	MEAN(MN_V_Gain(KM,J)), r_gap=0.02 xxxxxxxxxxxxxxxxxxxxxxxxxxxxxxx						
group	kids	marry	mean_age_18	mean_age_19	mean_age_20	mean_age_21	mean_age_22
----	----	-----	-----	-----	-----	-----	-----
1	1	0	0.015087	0.015546	0.016026	0.01653	0.017025

2	2	0	0.011707	0.012061	0.012444	0.012858	0.013278
3	3	0	0.010499	0.010777	0.011081	0.011412	0.011749
4	4	0	0.0094894	0.0097107	0.0099547	0.010224	0.0105
5	5	0	0.00886	0.0090319	0.0092234	0.0094371	0.0096558
6	1	1	0.010229	0.010593	0.010984	0.011405	0.011831
7	2	1	0.008528	0.0087978	0.0090932	0.0094182	0.0097531
8	3	1	0.0079012	0.0081252	0.0083716	0.0086439	0.0089244
9	4	1	0.0073246	0.0075062	0.0077075	0.0079319	0.0081637
10	5	1	0.00696	0.0071075	0.0072717	0.0074553	0.007644

% Consumption Function

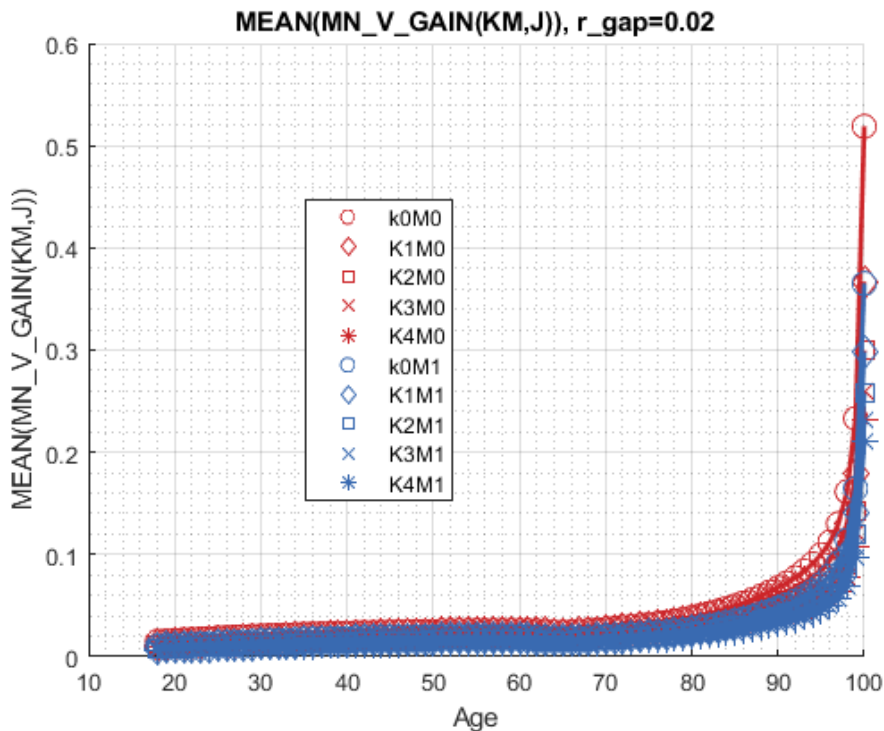
```
st_title = ['MEAN(MN_C_Gain(KM,J)), r_gap=' num2str(fl_r_gap) ];
tb_az_c = ff_summ_nd_array(st_title, mn_C_gain_r, true, ["mean"], 3, 1, cl_mp_datasetdesc, ar_permut
```

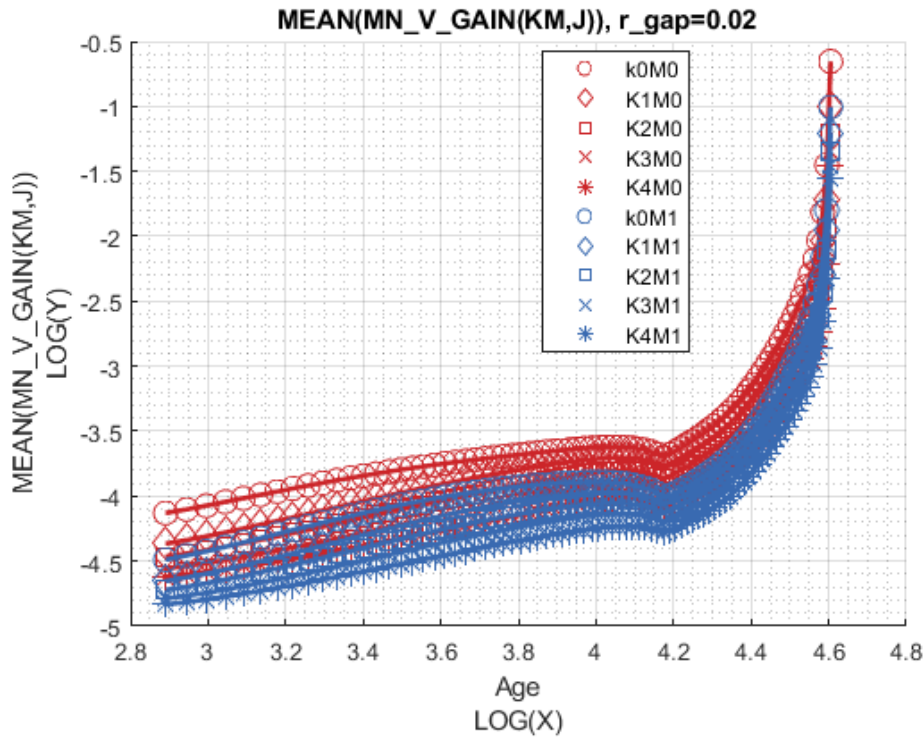
```
xxx MEAN(MN_C_Gain(KM,J)), r_gap=0.02 xxxxxxxxxxxxxxxxxxxxxxxxxxxxxxxxxxxx
```

group	kids	marry	mean_age_18	mean_age_19	mean_age_20	mean_age_21	mean_age_2
1	1	0	0.055699	0.056856	0.058874	0.061289	0.064119
2	2	0	0.051038	0.052145	0.054007	0.055436	0.057546
3	3	0	0.050801	0.05338	0.054644	0.055147	0.05643
4	4	0	0.050711	0.052919	0.054103	0.053992	0.05454
5	5	0	0.052196	0.053297	0.054608	0.053912	0.053811
6	1	1	-0.022203	-0.022187	-0.021707	-0.021466	-0.020507
7	2	1	-0.019706	-0.020509	-0.020942	-0.02173	-0.021723
8	3	1	-0.016291	-0.017215	-0.017899	-0.019714	-0.02062
9	4	1	-0.013267	-0.013589	-0.013895	-0.016006	-0.017459
10	5	1	-0.0131	-0.012701	-0.011796	-0.013633	-0.014917

Graph Mean Values:

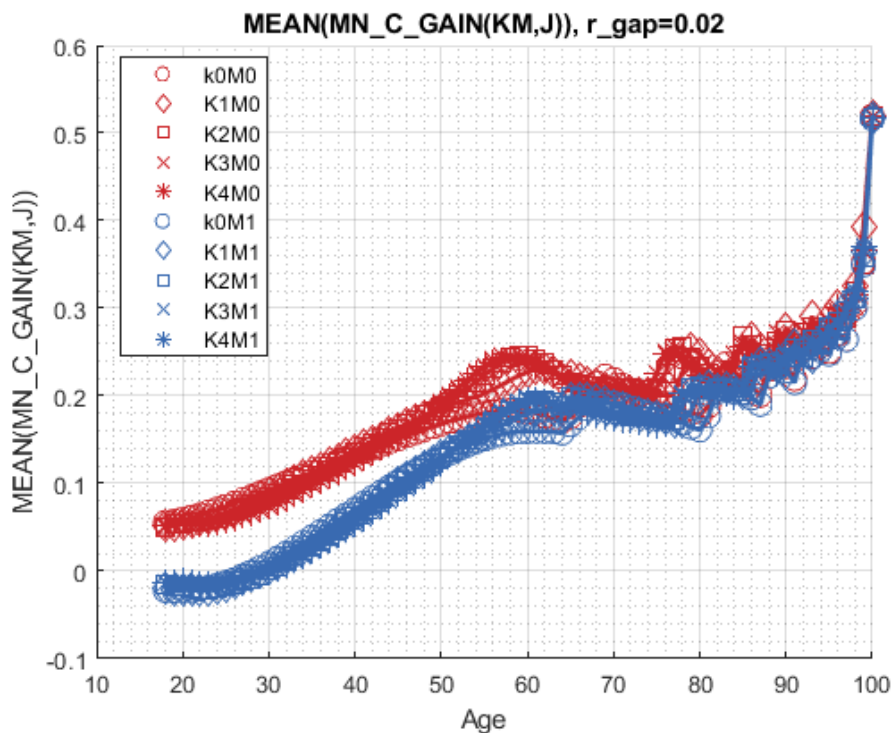
```
st_title = ['MEAN(MN_V_GAIN(KM,J)), r_gap=' num2str(fl_r_gap) '];
mp_support_graph('cl_st_graph_title') = {st_title};
mp_support_graph('cl_st_ytitle') = {'MEAN(MN_V_GAIN(KM,J))'};
ff_graph_grid((tb_az_v{1:end, 4:end}), ar_row_grid, age_grid, mp_support_graph);
```

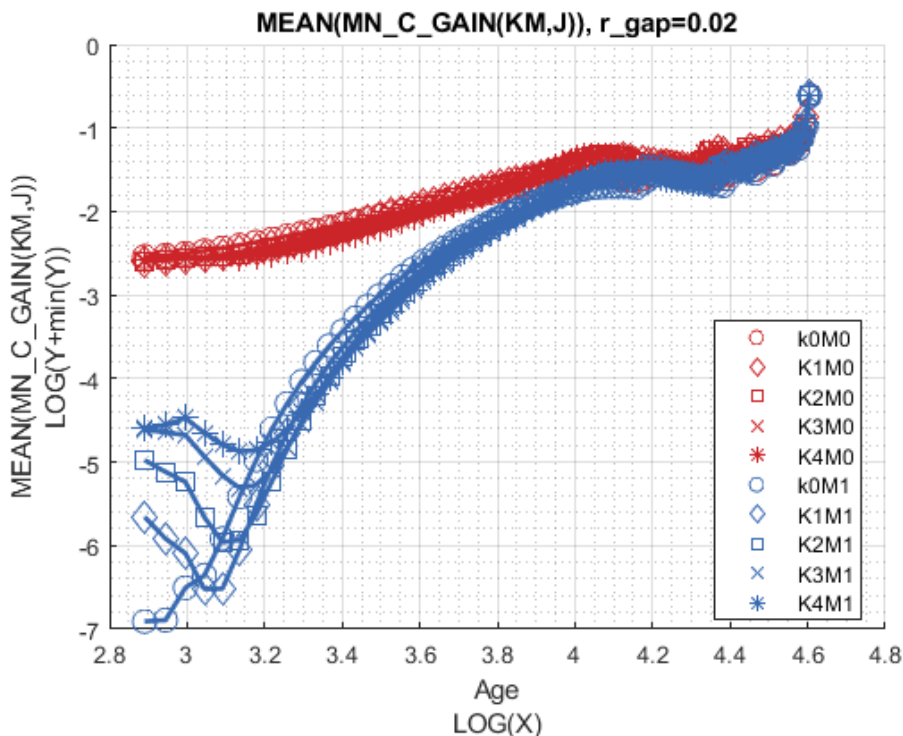




Graph Mean Consumption:

```
st_title = ['MEAN(MN\C\_GAIN(KM,J)), r\_gap=' num2str(fl_r_gap) ''];
mp_support_graph('cl_st_graph_title') = {st_title};
mp_support_graph('cl_st_ytitle') = {'MEAN(MN\C\_GAIN(KM,J))'};
ff_graph_grid((tb_az_c{1:end, 4:end}), ar_row_grid, age_grid, mp_support_graph);
```





### 14.1.7 Analyze Education and Marriage

Aggregating over education, savings, and shocks, what are the differential effects of Marriage and Age.

```
% Generate some Data
mp_support_graph = containers.Map('KeyType', 'char', 'ValueType', 'any');
ar_row_grid = ["E0M0", "E1M0", "E0M1", "E1M1"];
mp_support_graph('cl_st_xtitle') = {'Age'};
mp_support_graph('st_legend_loc') = 'best';
mp_support_graph('bl_graph_logy') = true; % do not log
mp_support_graph('st_rounding') = '6.2f'; % format shock legend
mp_support_graph('cl_scatter_shapes') = {'*', 'p', '*', 'p' };
mp_support_graph('cl_colors') = {'red', 'red', 'blue', 'blue'};
```

```
MEAN(VAL(EM,J)), MEAN(AP(EM,J)), MEAN(C(EM,J))
```

Tabulate value and policies:

```
% Set
% NaN(n_jgrid,n_agrid,n_etagrid,n_educgrid,n_marriedgrid,n_kidsgrid);
ar_permute = [2,3,6,1,4,5];
% Value Function
st_title = ['MEAN(MN_V_Gain(EM,J)), r_gap=' num2str(fl_r_gap) ];
tb_az_v = ff_summ_nd_array(st_title, mn_V_gain_r, true, ["mean"], 3, 1, cl_mp_datasetdesc, ar_permut
```

```
xxx MEAN(MN_V_Gain(EM,J)), r_gap=0.02 xxxxxxxxxxxxxxxxxxxxxxxxxxxxxxx
```

group	edu	marry	mean_age_18	mean_age_19	mean_age_20	mean_age_21	mean_age_22
1	0	0	0.011474	0.011736	0.012012	0.012305	0.012599
2	1	0	0.010783	0.011115	0.011479	0.011879	0.012285
3	0	1	0.0084099	0.0086195	0.0088444	0.0090861	0.0093328
4	1	1	0.0079671	0.0082324	0.0085268	0.0088556	0.0091936

% Consumption

```
st_title = ['MEAN(MN_C_Gain(EM,J)), r_gap=' num2str(fl_r_gap) ];
```

14.1. VALUE AND CONSUMPTION LOW VS HIGHER INTEREST RATES RESULTS COMPARISON407

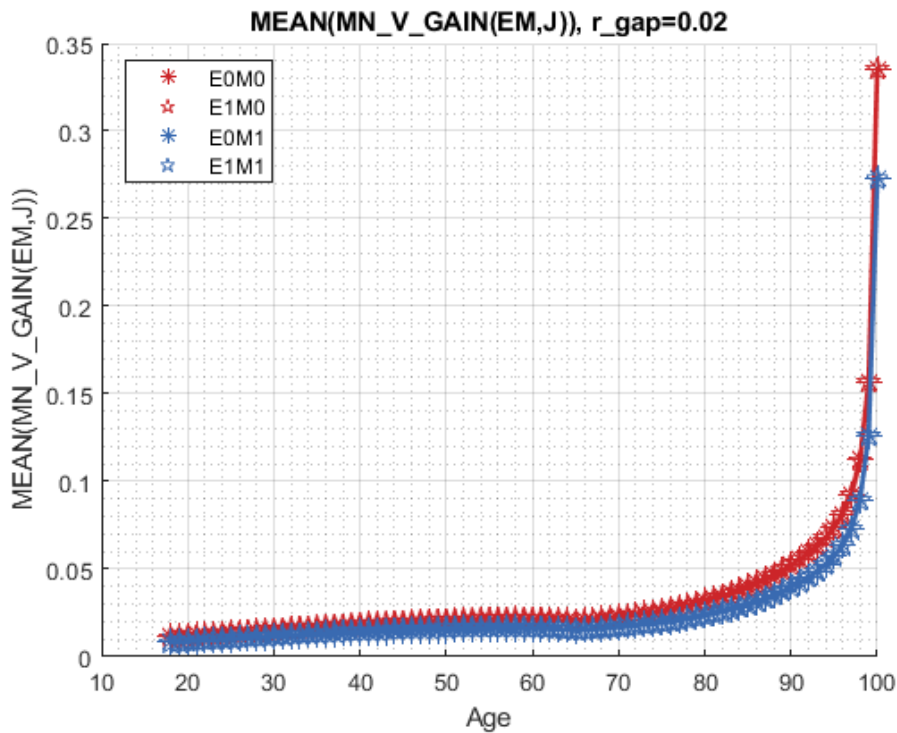
```
tb_az_c = ff_summ_nd_array(st_title, mn_C_gain_r, true, ["mean"], 3, 1, cl_mp_datasetdesc, ar_permut
```

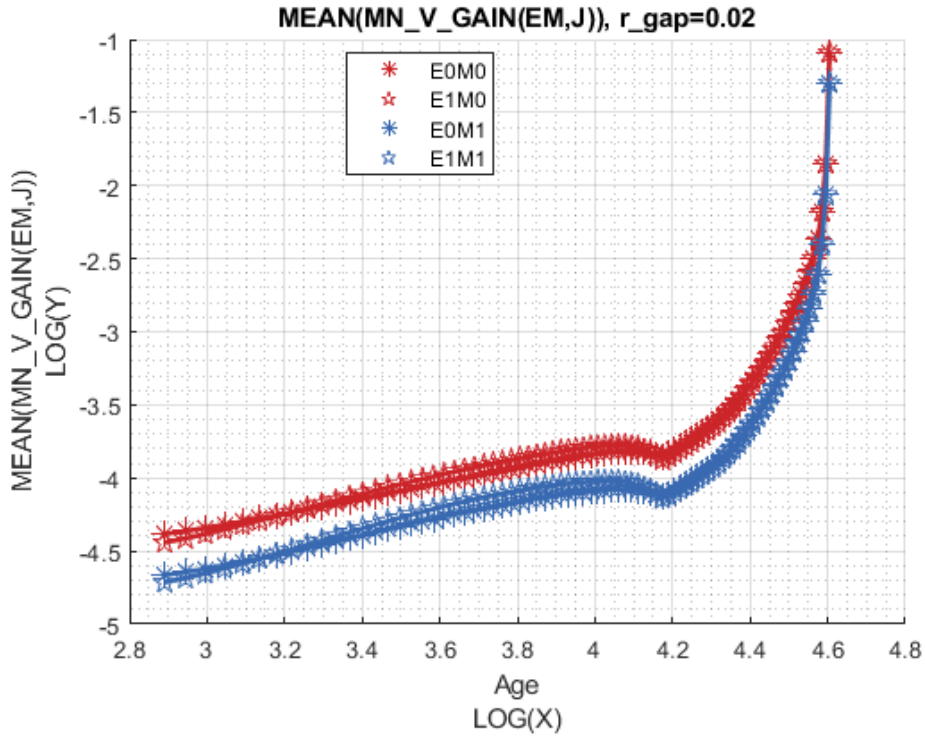
```
xxx MEAN(MN_C_Gain(EM,J)), r_gap=0.02 xxxxxxxxxxxxxxxxxxxxxxxxxxxxxxx
```

group	edu	marry	mean_age_18	mean_age_19	mean_age_20	mean_age_21	mean_age_22
1	0	0	0.06916	0.070507	0.072258	0.07446	0.076888
2	1	0	0.035018	0.036932	0.038237	0.03745	0.037691
3	0	1	-0.0014877	-0.001014	-0.00023405	0.00057466	0.0018134
4	1	1	-0.032339	-0.033466	-0.034261	-0.037595	-0.039904

Graph Mean Values:

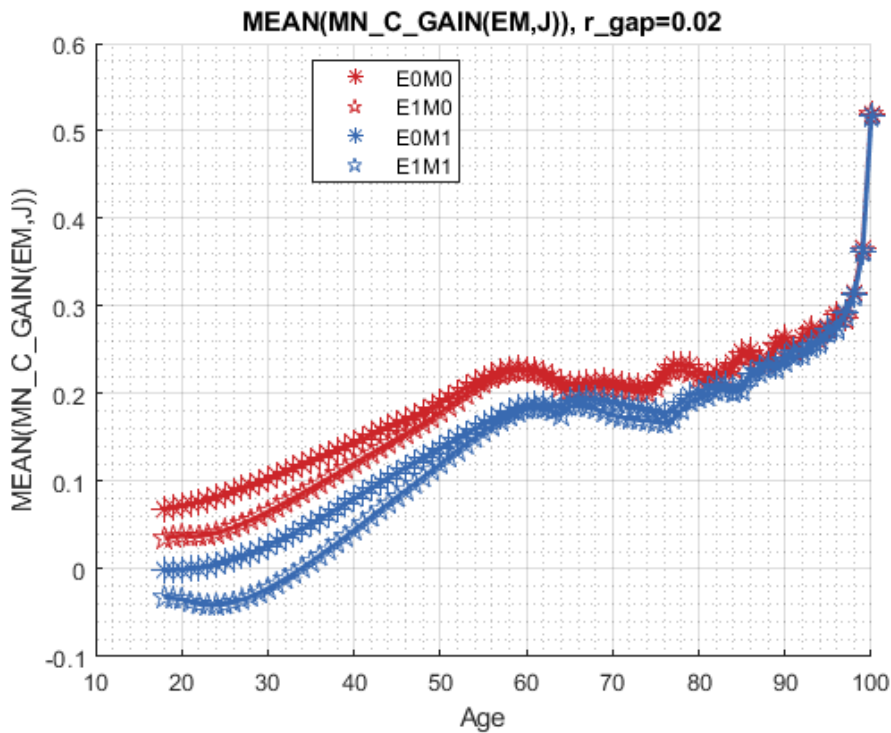
```
st_title = ['MEAN(MN_V_GAIN(EM,J)), r_gap=' num2str(fl_r_gap) ''];
mp_support_graph('cl_st_graph_title') = {st_title};
mp_support_graph('cl_st_ytitle') = {'MEAN(MN_V_GAIN(EM,J))'};
ff_graph_grid((tb_az_v{1:end, 4:end}), ar_row_grid, age_grid, mp_support_graph);
```



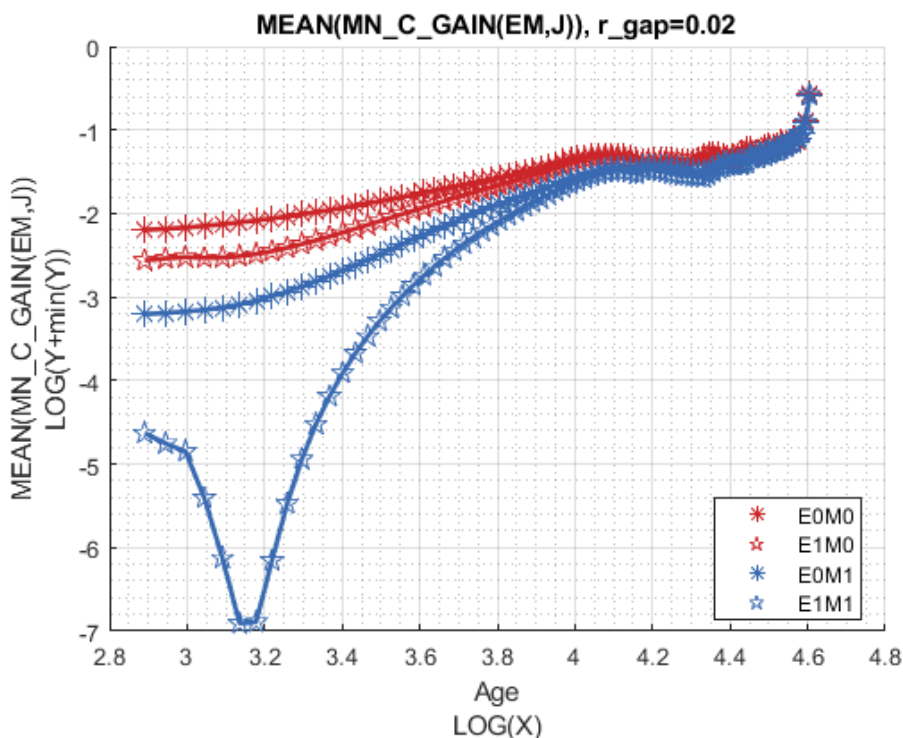


Graph Mean Consumption:

```
st_title = ['MEAN(MN\C\_GAIN(EM,J)), r\_gap=' num2str(fl_r_gap) ''];
mp_support_graph('cl_st_graph_title') = {st_title};
mp_support_graph('cl_st_ytitle') = {'MEAN(MN\C\_GAIN(EM,J))'};
ff_graph_grid((tb_az_c{1:end, 4:end}), ar_row_grid, age_grid, mp_support_graph);
```







## 14.2 Value and Consumption Low vs Higher Unemployment Insurance Comparison

This is the example vignette for function: `snw_vfi_main_bisec_vec` from the [PrjOptiSNW Package](#). This function solves for the  $V(\text{states}, \text{unemployed})$  assuming individuals suffer from unemployment spell, but with different UI (unemployment benefits). Higher UI benefits leads to value/welfare and also higher consumption.

### 14.2.1 Solve the Steady-State non-unemployment Problem

Solve for Value/Policy in non-COVID years, then solve for covid year value/policy given covid shocks. COVID lasts one period.

```
% mp_params = snw_mp_param('default_dense');
mp_params = snw_mp_param('default_docdense');
mp_params('beta') = 0.95;
mp_controls = snw_mp_control('default_test');
mp_controls('bl_print_vfi') = false;
mp_controls('bl_timer') = true;
[V_ss,~,cons_ss,~] = snw_vfi_main_bisec_vec(mp_params, mp_controls);
```

Completed SNW\_VFI\_MAIN\_BISEC\_VEC;SNW\_MP\_PARAM=default\_docdense;SNW\_MP\_CONTROL=default\_test;time=491.

```
-----
XXXXXXXXXXXXXXXXXXXXXXXXXXXXXXXXXXXXXXXXXXXXXXXXXXXX
CONTAINER NAME: mp_outcomes ND Array (Matrix etc)
XXXXXXXXXXXXXXXXXXXXXXXXXXXXXXXXXXXXXXXXXXXXXXXXXXXX
```

	i	idx	ndim	numel	rowN	colN	sum	mean	std
V_VFI	1	1	6	4.37e+07	83	5.265e+05	-6.6619e+08	-15.245	21.86
ap_VFI	2	2	6	4.37e+07	83	5.265e+05	1.3967e+09	31.962	36.42
cons_VFI	3	3	6	4.37e+07	83	5.265e+05	2.3276e+08	5.3263	8.441

xxx TABLE:V\_VFI xxxxxxxxxxxxxxxxxxxxxxxx

	c1	c2	c3	c4	c5	c526496	c526497	c526498
r1	-293.96	-293.57	-291.09	-285.44	-276.41	-4.3584	-4.2643	-4.171
r2	-284.42	-284.03	-281.55	-275.97	-267.24	-4.2519	-4.1612	-4.071
r3	-274.87	-274.48	-272.03	-266.62	-258.33	-4.1429	-4.0559	-3.969
r4	-265.22	-264.86	-262.58	-257.53	-249.74	-4.0309	-3.9475	-3.864
r5	-256.51	-256.17	-254.04	-249.3	-241.96	-3.9252	-3.8452	-3.765
r79	-13.642	-13.628	-13.535	-13.298	-12.896	-0.22092	-0.21058	-0.2008
r80	-12.283	-12.269	-12.176	-11.939	-11.537	-0.16979	-0.16182	-0.154
r81	-10.605	-10.591	-10.498	-10.261	-9.8589	-0.11712	-0.11163	-0.1064
r82	-8.3494	-8.3358	-8.2424	-8.0055	-7.6035	-0.065333	-0.062242	-0.0593
r83	-5.0665	-5.0529	-4.9595	-4.7226	-4.3206	-0.020968	-0.019972	-0.01903

xxx TABLE:ap\_VFI xxxxxxxxxxxxxxxxxxxxxxxx

	c1	c2	c3	c4	c5	c526496	c526497	c526498	c5264
r1	0	0	0.00051498	0.0066578	0.021589	112.13	117.67	123.4	129.3
r2	0	0	0.00051498	0.0057684	0.020245	112.17	117.71	123.43	129.3
r3	0	0	0.00020768	0.0041456	0.018539	112.2	117.73	123.45	129.3
r4	0	0	0.00010346	0.0041199	0.018307	112.86	118.39	124.11	130.0
r5	0	0	5.2907e-06	0.0041199	0.018091	113.53	119.07	124.79	130.7
r79	0	0	0	0	0	81.091	85.364	89.335	93.25
r80	0	0	0	0	0	76.124	79.747	83.431	86.98
r81	0	0	0	0	0	67.945	70.639	73.673	76.99
r82	0	0	0	0	0	50.126	53.467	56.302	57.88
r83	0	0	0	0	0	0	0	0	0

xxx TABLE:cons\_VFI xxxxxxxxxxxxxxxxxxxxxxxx

	c1	c2	c3	c4	c5	c526496	c526497	c526498
r1	0.036717	0.037251	0.040477	0.044486	0.049324	12.265	12.55	12.844
r2	0.036717	0.037251	0.040477	0.045375	0.050668	12.501	12.787	13.082
r3	0.036717	0.037251	0.040784	0.046998	0.052374	12.755	13.042	13.337
r4	0.038144	0.038678	0.042314	0.048449	0.054031	13	13.289	13.584
r5	0.039534	0.040068	0.043802	0.049839	0.055635	13.236	13.525	13.821
r79	0.19737	0.19791	0.20163	0.21175	0.23145	35.811	37.362	39.409
r80	0.19737	0.19791	0.20163	0.21175	0.23145	40.752	42.953	45.286
r81	0.19737	0.19791	0.20163	0.21175	0.23145	48.909	52.039	55.022
r82	0.19737	0.19791	0.20163	0.21175	0.23145	66.71	69.193	72.375
r83	0.19737	0.19791	0.20163	0.21175	0.23145	116.82	122.65	128.66

### 14.2.2 Solve Problem in MIT Unemployed State with High and Low Unemployment Insurance

Shared xi value, 50 percent income loss. This is a one-time MIT shock that changes choices today in the sense of changing the resource state-space, but does not change forward expectations.

xi=0.5; % xi=0 full income loss from covid shock, xi=1, no covid income losses

Solve for  $b = 0$ , no unemployment insurance.

fl\_b\_lower = 0.0;

fl\_b\_higher= 0.5;

b=fl\_b\_lower; % b=0 means no UI benefits compensating COVID, b=1 if full income replacement

mp\_params('xi') = xi;

mp\_params('b') = b;

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```
mp_params('a2_covidyr') = mp_params('a2_covidyr_manna_heaven');
% mp_params('a2_covidyr') = mp_params('a2_covidyr_tax_fully_pay');
[V_unemp_b_0p0,~,cons_unemp_b_0p0,~] = snw_vfi_main_bisec_vec(mp_params, mp_controls, V_ss);
```

Completed SNW\_VFI\_MAIN\_BISEC\_VEC 1 Period Unemp Shock;SNW\_MP\_PARAM=default\_docdense;SNW\_MP\_CONTROL=d

CONTAINER NAME: mp\_outcomes ND Array (Matrix etc)

	i	idx	ndim	numel	rowN	colN	sum	mean	std
V_VFI	1	1	6	4.37e+07	83	5.265e+05	-6.8822e+08	-15.749	22.87
ap_VFI	2	2	6	4.37e+07	83	5.265e+05	1.3605e+09	31.134	36.29
cons_VFI	3	3	6	4.37e+07	83	5.265e+05	2.2887e+08	5.2375	8.443

xxx TABLE:V\_VFI xxxxxxxxxxxxxxxxxxxxxxx

	c1	c2	c3	c4	c5	c526496	c526497	c526498
r1	-320.42	-318.92	-310.39	-296.97	-284.58	-4.4406	-4.3429	-4.246
r2	-310.88	-309.38	-300.85	-287.43	-275.14	-4.3331	-4.239	-4.146
r3	-301.33	-299.83	-291.3	-277.88	-265.85	-4.2231	-4.1327	-4.043
r4	-290.68	-289.29	-281.32	-268.6	-257.1	-4.1145	-4.0276	-3.941
r5	-281.05	-279.76	-272.29	-260.2	-249.16	-4.0121	-3.9284	-3.845
r79	-13.642	-13.628	-13.535	-13.298	-12.896	-0.22291	-0.21238	-0.2024
r80	-12.283	-12.269	-12.176	-11.939	-11.537	-0.17128	-0.16316	-0.1555
r81	-10.605	-10.591	-10.498	-10.261	-9.8589	-0.11815	-0.11254	-0.1072
r82	-8.3494	-8.3358	-8.2424	-8.0055	-7.6035	-0.065887	-0.062757	-0.05982
r83	-5.0665	-5.0529	-4.9595	-4.7226	-4.3206	-0.021146	-0.020134	-0.01918

xxx TABLE:ap\_VFI xxxxxxxxxxxxxxxxxxxxxxx

	c1	c2	c3	c4	c5	c526496	c526497	c526498	c526499	c526500
r1	0	0	0	0	0.0083625	107.54	113.09	118.82	124.74	130.86
r2	0	0	0	0	0.0074731	107.45	112.99	118.72	124.64	130.75
r3	0	0	0	0	0.0058503	107.33	112.88	118.61	124.52	130.64
r4	0	0	0	0	0.0049981	107.54	113.08	118.81	124.73	130.85
r5	0	0	0	0	0.004174	107.76	113.3	119.03	124.95	131.07
r79	0	0	0	0	0	80.462	84.34	88.311	92.234	96.324
r80	0	0	0	0	0	75.113	78.736	82.42	85.975	90.439
r81	0	0	0	0	0	66.945	69.639	72.673	76.669	81.091
r82	0	0	0	0	0	50.126	53.467	55.311	56.953	60.587
r83	0	0	0	0	0	0	0	0	0	0

xxx TABLE:cons\_VFI xxxxxxxxxxxxxxxxxxxxxxx

	c1	c2	c3	c4	c5	c526496	c526497	c526498
r1	0.018623	0.019158	0.022901	0.033062	0.044486	11.989	12.265	12.55
r2	0.018623	0.019158	0.022901	0.033062	0.045375	12.223	12.501	12.787
r3	0.018623	0.019158	0.022901	0.033062	0.046998	12.476	12.755	13.042
r4	0.019354	0.019888	0.023632	0.033792	0.048579	12.72	13	13.289
r5	0.020066	0.020601	0.024344	0.034504	0.050114	12.955	13.236	13.525
r79	0.19737	0.19791	0.20163	0.21175	0.23145	35.417	37.362	39.409
r80	0.19737	0.19791	0.20163	0.21175	0.23145	40.752	42.953	45.286
r81	0.19737	0.19791	0.20163	0.21175	0.23145	48.909	52.039	55.022

r82	0.19737	0.19791	0.20163	0.21175	0.23145	65.719	68.202	72.375
r83	0.19737	0.19791	0.20163	0.21175	0.23145	115.84	121.66	127.68

Solve for  $b = 0.5$ , 50 percent unemployment insurance, meaning 50 percent of lost income is recovered.

```
b=fl_b_higher; % b=0 means no UI benefits compensating COVID, b=1 if full income replacement
mp_params('xi') = xi;
mp_params('b') = b;
mp_params('a2_covidyr') = mp_params('a2_covidyr_manna_heaven');
% mp_params('a2_covidyr') = mp_params('a2_covidyr_tax_fully_pay');
[V_unemp_b_0p5,~,cons_unemp_b_0p5,~] = snw_vfi_main_bisec_vec(mp_params, mp_controls, V_ss);
```

Completed SNW\_VFI\_MAIN\_BISEC\_VEC 1 Period Unemp Shock;SNW\_MP\_PARAM=default\_docdense;SNW\_MP\_CONTROL=d

CONTAINER NAME: mp\_outcomes ND Array (Matrix etc)

	i	idx	ndim	numel	rowN	colN	sum	mean	std
V_VFI	1	1	6	4.37e+07	83	5.265e+05	-6.7567e+08	-15.462	22.25
ap_VFI	2	2	6	4.37e+07	83	5.265e+05	1.3783e+09	31.541	36.3
cons_VFI	3	3	6	4.37e+07	83	5.265e+05	2.3114e+08	5.2893	8.440

xxx TABLE:V\_VFI xxxxxxxxxxxxxxxxxxxxxxx

	c1	c2	c3	c4	c5	c526496	c526497	c526498
r1	-302.8	-302.11	-297.97	-290.4	-280.12	-4.3991	-4.3032	-4.208
r2	-293.25	-292.57	-288.43	-280.86	-270.8	-4.2921	-4.1998	-4.108
r3	-283.7	-283.02	-278.88	-271.34	-261.75	-4.1826	-4.094	-4.006
r4	-273.72	-273.09	-269.23	-262.13	-253.1	-4.0721	-3.987	-3.902
r5	-264.7	-264.11	-260.51	-253.79	-245.27	-3.9679	-3.8861	-3.805
r79	-13.642	-13.628	-13.535	-13.298	-12.896	-0.22191	-0.21148	-0.2016
r80	-12.283	-12.269	-12.176	-11.939	-11.537	-0.17053	-0.16249	-0.154
r81	-10.605	-10.591	-10.498	-10.261	-9.8589	-0.11764	-0.11208	-0.1068
r82	-8.3494	-8.3358	-8.2424	-8.0055	-7.6035	-0.065608	-0.062497	-0.05959
r83	-5.0665	-5.0529	-4.9595	-4.7226	-4.3206	-0.021056	-0.020052	-0.01911

xxx TABLE:ap\_VFI xxxxxxxxxxxxxxxxxxxxxxx

	c1	c2	c3	c4	c5	c526496	c526497	c526498	c526499
r1	0	0	0	0.0011815	0.013905	109.98	115.52	121.26	127.18
r2	0	0	0	0.00090277	0.013905	109.95	115.49	121.22	127.14
r3	0	0	0	0.00051498	0.013905	109.9	115.45	121.18	127.1
r4	0	0	0	0.00051498	0.013905	110.34	115.88	121.61	127.53
r5	0	0	0	0.00048777	0.013905	110.79	116.33	122.06	127.98
r79	0	0	0	0	0	80.974	84.852	88.823	92.746
r80	0	0	0	0	0	75.619	79.241	82.926	86.481
r81	0	0	0	0	0	67.445	70.139	73.173	76.669
r82	0	0	0	0	0	50.126	53.467	55.806	57.389
r83	0	0	0	0	0	0	0	0	0

xxx TABLE:cons\_VFI xxxxxxxxxxxxxxxxxxxxxxx

	c1	c2	c3	c4	c5	c526496	c526497	c526498
r1	0.027723	0.028258	0.031999	0.040974	0.048028	11.989	12.265	12.55

r2	0.027723	0.028258	0.031999	0.041253	0.048028	12.223	12.501	12.787
r3	0.027723	0.028258	0.031999	0.041641	0.048028	12.476	12.755	13.042
r4	0.028805	0.029339	0.033081	0.042722	0.049108	12.72	13	13.289
r5	0.029859	0.030394	0.034135	0.043802	0.050161	12.955	13.236	13.525
r79	0.19737	0.19791	0.20163	0.21175	0.23145	35.417	37.362	39.409
r80	0.19737	0.19791	0.20163	0.21175	0.23145	40.752	42.953	45.286
r81	0.19737	0.19791	0.20163	0.21175	0.23145	48.909	52.039	55.022
r82	0.19737	0.19791	0.20163	0.21175	0.23145	66.215	68.697	72.375
r83	0.19737	0.19791	0.20163	0.21175	0.23145	116.33	122.15	128.17

### 14.2.3 Generate UI Comparison Matrixes

Find the deviation in value and consumption between higher and lower UI world. Welfare is converted to units in fixed life-time consumption.

```
gamma = mp_params('gamma');
mn_V_U_gain_moreUI = snw_hh_welfare(V_unemp_b_0p5, gamma) - snw_hh_welfare(V_unemp_b_0p0, gamma);
mn_C_U_gain_moreUI = cons_unemp_b_0p5 - cons_unemp_b_0p0;
```

### 14.2.4 Dense Param Results Define Frames

Define the matrix dimensions names and dimension vector values. Policy and Value Functions share the same ND dimensional structure.

```
% Grids:
age_grid = 18:100;
agrid = mp_params('agrid');
eta_H_grid = mp_params('eta_H_grid');
eta_S_grid = mp_params('eta_S_grid');
ar_st_eta_HS_grid = string(cellstr([num2str(eta_H_grid), 'hz=%3.2f;'], num2str(eta_S_grid), 'wz=%3.2f;'], 'wz=%3.2f;'));
edu_grid = [0,1];
marry_grid = [0,1];
kids_grid = (1:1:mp_params('n_kidsgrid'))';
% NaN(n_jgrid,n_agrid,n_etagrid,n_educgrid,n_marriedgrid,n_kidsgrid);
cl_mp_datasetdesc = {};
cl_mp_datasetdesc{1} = containers.Map({'name', 'labval'}, {'age', age_grid});
cl_mp_datasetdesc{2} = containers.Map({'name', 'labval'}, {'savings', agrid});
cl_mp_datasetdesc{3} = containers.Map({'name', 'labval'}, {'eta', 1:length(eta_H_grid)});
cl_mp_datasetdesc{4} = containers.Map({'name', 'labval'}, {'edu', edu_grid});
cl_mp_datasetdesc{5} = containers.Map({'name', 'labval'}, {'marry', marry_grid});
cl_mp_datasetdesc{6} = containers.Map({'name', 'labval'}, {'kids', kids_grid});
```

### 14.2.5 Analyze Difference in V and C with Higher and Lower UI

The difference between V and C with higher and lower UI.

```
% Generate some Data
mp_support_graph = containers.Map('KeyType', 'char', 'ValueType', 'any');
mp_support_graph('cl_st_xtitle') = {'Savings States, a'};
mp_support_graph('st_legend_loc') = 'eastoutside';
mp_support_graph('bl_graph_logy') = true; % do not log
mp_support_graph('it_legend_select') = 21; % how many shock legends to show
mp_support_graph('cl_colors') = 'jet';
```

```
MEAN(MN_V_GAIN(A,Z))
```

Tabulate value and policies along savings and shocks:

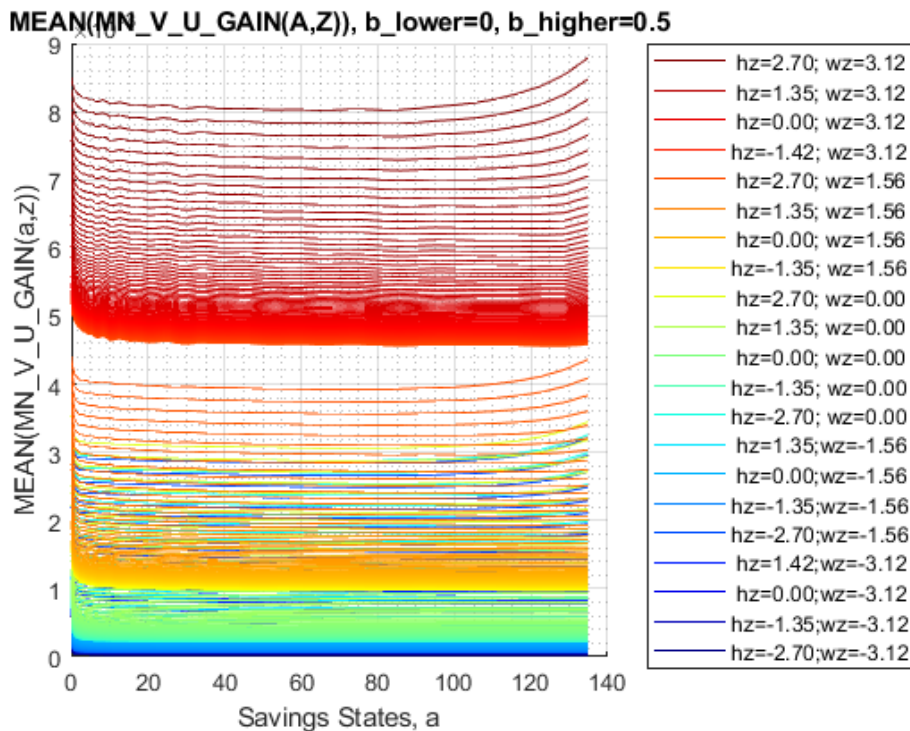
```
% Set
ar_permute = [1,4,5,6,3,2];
% Value Function
st_title = ['MEAN(MN_V_U_GAIN(A,Z)), b_lower=' num2str(fl_b_lower) ', b_higher=' num2str(fl_b_high)'];
```

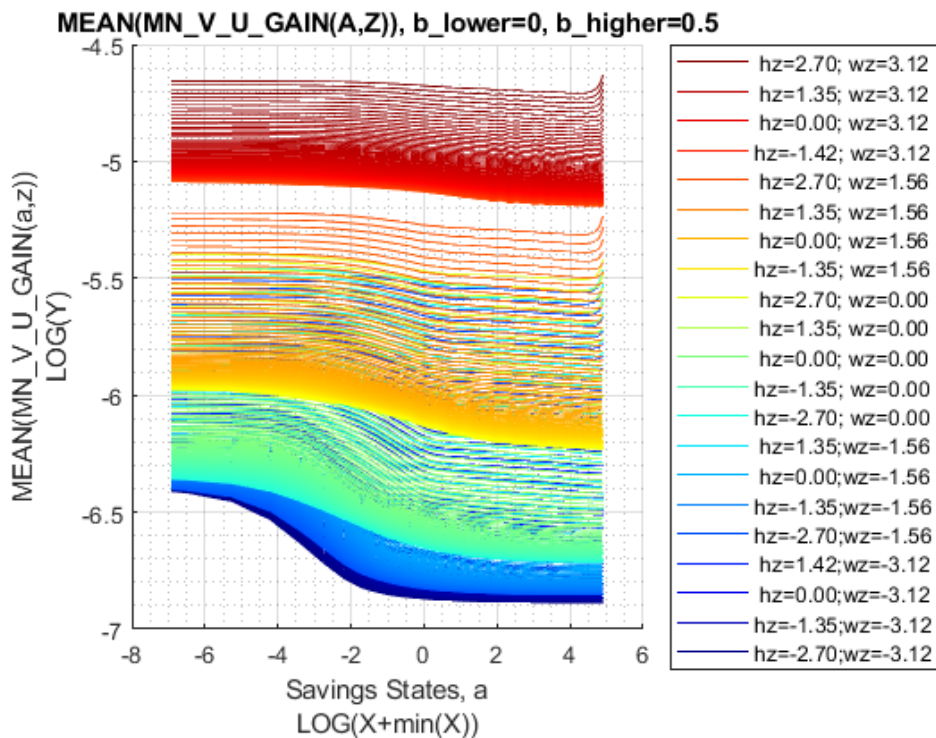
```
tb_az_v = ff_summ_nd_array(st_title, mn_V_U_gain_moreUI, true, ["mean"], 4, 1, cl_mp_datasetdesc, ar
```

```
xxx MEAN(MN_V_U_GAIN(A,Z)), b_lower=0, b_higher=0.5 xxxxxxxxxxxxxxxxxxxxxxxxxxxxxxxxxxxx
```

group	savings	mean_eta_1	mean_eta_2	mean_eta_3	mean_eta_4	mean_eta_5	mea
1	0	0.00064445	0.00064585	0.00064898	0.0006533	0.00065831	0.0

```
st_title = ['MEAN(MN_V_U_GAIN(A,Z)), b_lower=' num2str(fl_b_lower) ', b_higher=' num2str(fl_b_h
mp_support_graph('cl_st_graph_title') = {st_title};
mp_support_graph('cl_st_ytitle') = {'MEAN(MN_V_U_GAIN(a,z))'};
ff_graph_grid((tb_az_v{1:end, 3:end}),' , ar_st_eta_HS_grid, agrid, mp_support_graph);
```

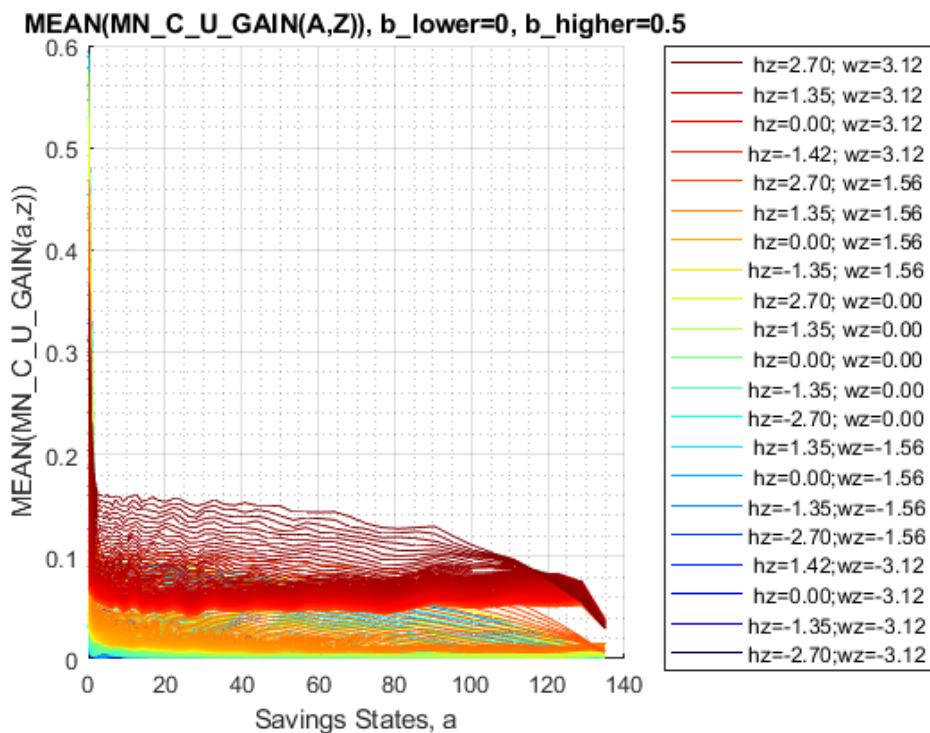


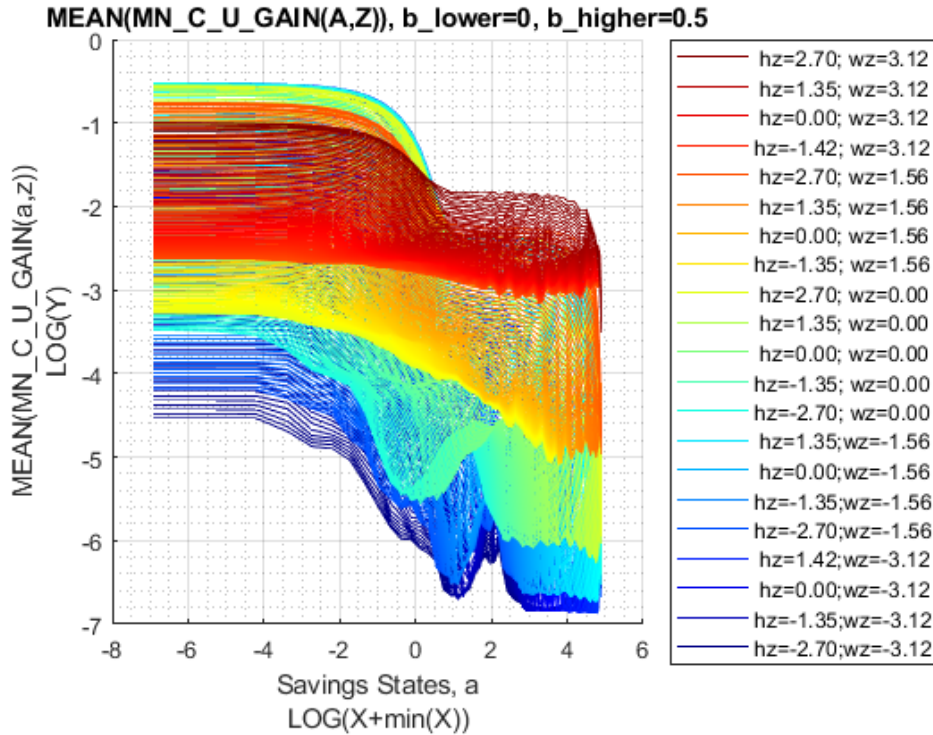


Graph Mean Consumption:

```

st_title = ['MEAN(MN\C_U_GAIN(A,Z)), b_lower=' num2str(fl_b_lower) ', b_higher=' num2str(fl_b_higher)'];
mp_support_graph('cl_st_graph_title') = {st_title};
mp_support_graph('cl_st_ytitle') = {'MEAN(MN\C_U_GAIN(a,z))'};
ff_graph_grid((tb_az_c{1:end, 3:end}'), ar_st_eta_HS_grid, agrid, mp_support_graph);
    
```





### 14.2.6 Analyze Kids and Marriage and Age

Aggregating over education, savings, and shocks, what are the differential effects of Marriage and Age.

```
% Generate some Data
mp_support_graph = containers.Map('KeyType', 'char', 'ValueType', 'any');
ar_row_grid = [...
    "k0M0", "k1M0", "k2M0", "k3M0", "k4M0", ...
    "k0M1", "k1M1", "k2M1", "k3M1", "k4M1"];
mp_support_graph('cl_st_xtitle') = {'Age'};
mp_support_graph('st_legend_loc') = 'best';
mp_support_graph('bl_graph_logy') = true; % do not log
mp_support_graph('st_rounding') = '6.2f'; % format shock legend
mp_support_graph('cl_scatter_shapes') = {...
    'o', 'd', 's', 'x', '*'}, ...
    'o', 'd', 's', 'x', '*'};
mp_support_graph('cl_colors') = {...
    'red', 'red', 'red', 'red', 'red'...
    'blue', 'blue', 'blue', 'blue', 'blue'};
```

```
MEAN(VAL(KM,J)), MEAN(AP(KM,J)), MEAN(C(KM,J))
```

Tabulate value and policies:

```
% Set
% NaN(n_jgrid,n_agrid,n_etagrid,n_educgrid,n_marriedgrid,n_kidsgrid);
ar_permute = [2,3,4,1,6,5];
% Value Function
st_title = ['MEAN(MN_V_U_GAIN(KM,J)), b_lower=' num2str(fl_b_lower) ', b_higher=' num2str(fl_b_high)
tb_az_v = ff_summ_nd_array(st_title, mn_V_U_gain_moreUI, true, ["mean"], 3, 1, cl_mp_datasetdesc, ar
```

xxx	MEAN(MN_V_U_GAIN(KM,J)), b_lower=0, b_higher=0.5 xxxxxxxxxxxxxxxxxxxxxxxxxxxxxxx						
group	kids	marry	mean_age_18	mean_age_19	mean_age_20	mean_age_21	mean_age_2
----	----	----	-----	-----	-----	-----	-----
1	1	0	0.00055672	0.00057552	0.00059522	0.00063544	0.00067622



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2	2	0	0.00048244	0.00050035	0.00051966	0.00055508	0.00059141
3	3	0	0.00046167	0.00047833	0.00049636	0.00052804	0.00056045
4	4	0	0.00043771	0.00045259	0.00046877	0.00049707	0.00052603
5	5	0	0.00042439	0.00043747	0.00045169	0.0004768	0.00050238
6	1	1	0.0008562	0.00090669	0.00095849	0.0010295	0.0011022
7	2	1	0.00071993	0.00075882	0.00079903	0.00085585	0.00091452
8	3	1	0.00066704	0.00070046	0.00073484	0.00078384	0.0008343
9	4	1	0.00061227	0.00064001	0.00066838	0.00070987	0.00075249
10	5	1	0.00055284	0.00057485	0.000597	0.00063042	0.00066449

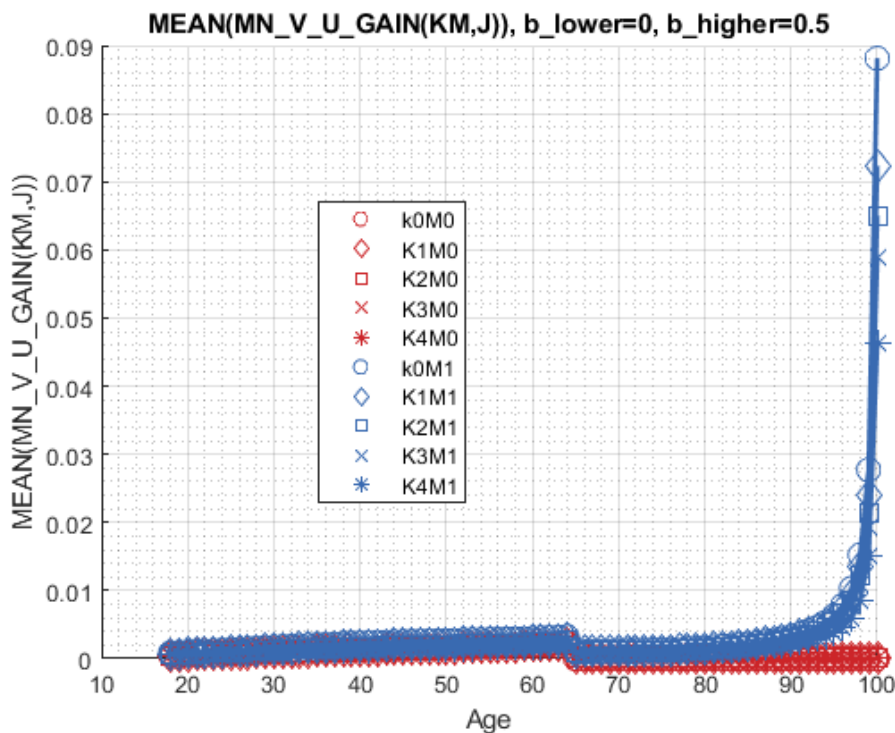
% Consumption Function

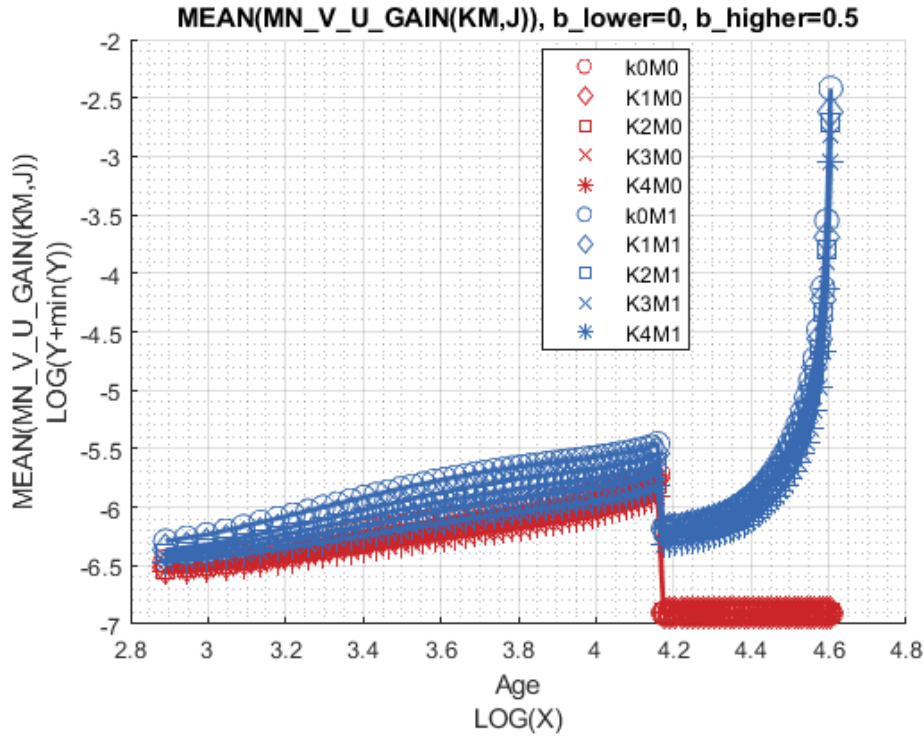
```
st_title = ['MEAN(MN_C_U_GAIN(KM,J)), b_lower=' num2str(fl_b_lower) ', b_higher=' num2str(fl_b_high)'];
tb_az_c = ff_summ_nd_array(st_title, mn_C_U_gain_moreUI, true, ["mean"], 3, 1, cl_mp_datasetdesc, ar_row_grid);
```

group	kids	marry	mean_age_18	mean_age_19	mean_age_20	mean_age_21	mean_age_2
1	1	0	0.045263	0.048116	0.050981	0.053114	0.054711
2	2	0	0.052245	0.055222	0.058311	0.061472	0.064326
3	3	0	0.05831	0.061181	0.064294	0.06802	0.071488
4	4	0	0.061725	0.064563	0.067634	0.07166	0.075434
5	5	0	0.065016	0.067757	0.070896	0.07514	0.079088
6	1	1	0.07018	0.073094	0.076227	0.079837	0.083882
7	2	1	0.075602	0.078727	0.081843	0.085263	0.088392
8	3	1	0.079512	0.083393	0.087172	0.091625	0.095741
9	4	1	0.078346	0.082109	0.086013	0.091418	0.096514
10	5	1	0.076598	0.080189	0.084089	0.089192	0.09394

Graph Mean Values:

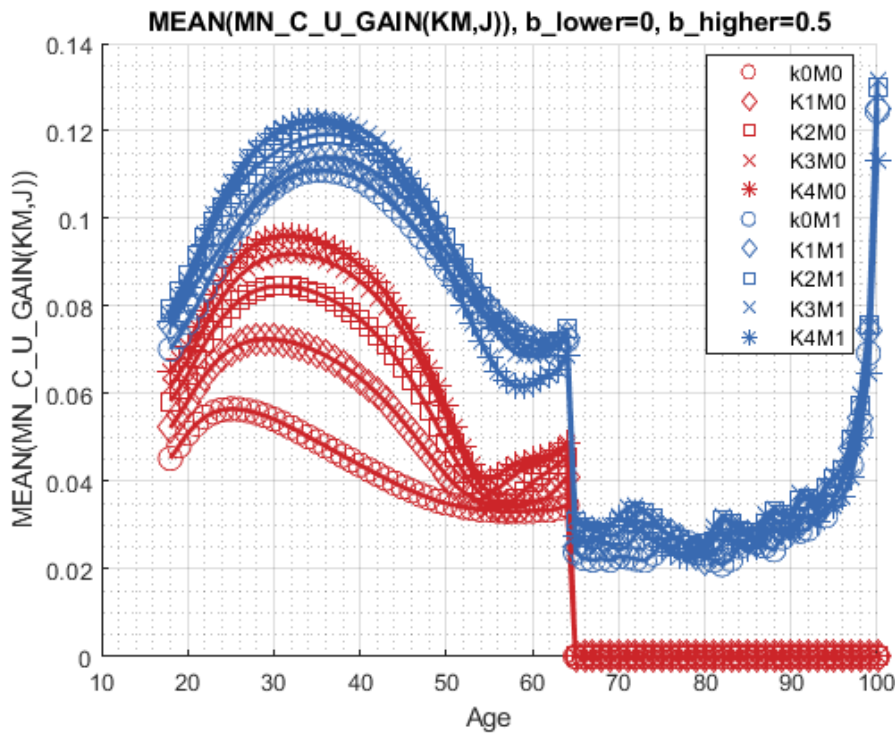
```
st_title = ['MEAN(MN_V_U_GAIN(KM,J)), b_lower=' num2str(fl_b_lower) ', b_higher=' num2str(fl_b_high)'];
mp_support_graph('cl_st_graph_title') = {st_title};
mp_support_graph('cl_st_ytitle') = {'MEAN(MN_V_U_GAIN(KM,J))'};
ff_graph_grid((tb_az_v{1:end, 4:end}), ar_row_grid, age_grid, mp_support_graph);
```

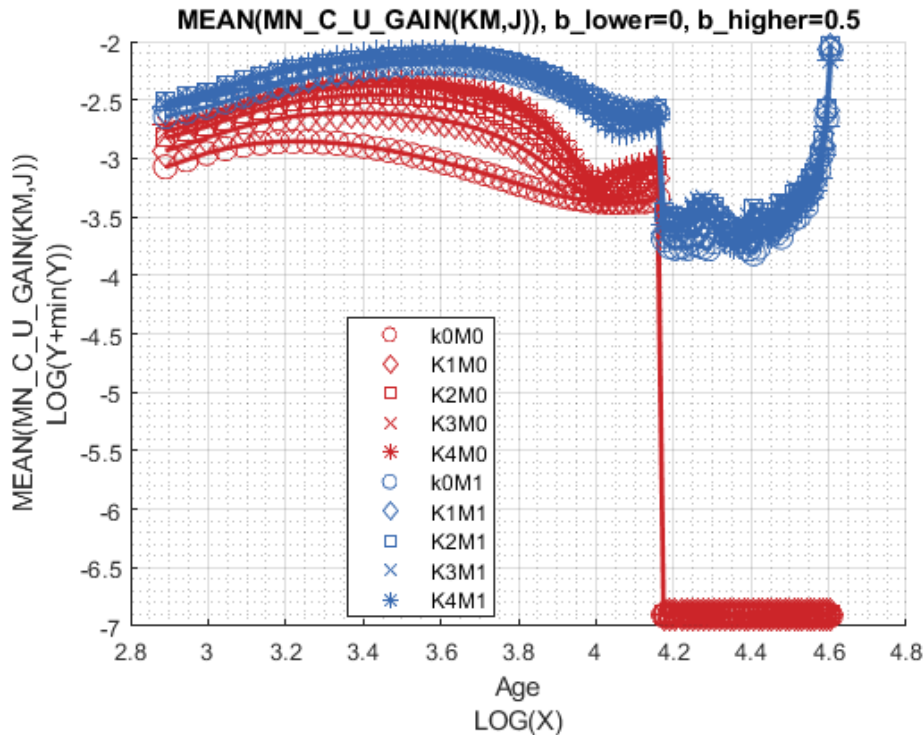




Graph Mean Consumption:

```
st_title = ['MEAN(MN\C_U_GAIN(KM,J)), b_lower=' num2str(fl_b_lower) ', b_higher=' num2str(fl_b_higher)'];
mp_support_graph('cl_st_graph_title') = {st_title};
mp_support_graph('cl_st_ytitle') = {'MEAN(MN\C_U_GAIN(KM,J))'};
ff_graph_grid((tb_az_c{1:end, 4:end}), ar_row_grid, age_grid, mp_support_graph);
```





### 14.2.7 Analyze Education and Marriage

Aggregating over education, savings, and shocks, what are the differential effects of Marriage and Age.

```
% Generate some Data
mp_support_graph = containers.Map('KeyType', 'char', 'ValueType', 'any');
ar_row_grid = ["E0M0", "E1M0", "E0M1", "E1M1"];
mp_support_graph('cl_st_xtitle') = {'Age'};
mp_support_graph('st_legend_loc') = 'best';
mp_support_graph('bl_graph_logy') = true; % do not log
mp_support_graph('st_rounding') = '6.2f'; % format shock legend
mp_support_graph('cl_scatter_shapes') = {'*', 'p', '*', 'p'};
mp_support_graph('cl_colors') = {'red', 'red', 'blue', 'blue'};
MEAN(VA(EM,J)), MEAN(AP(EM,J)), MEAN(C(EM,J))
```

Tabulate value and policies:

```
% Set
% NaN(n_jgrid,n_agrid,n_etagrid,n_educgrid,n_marriedgrid,n_kidsgrid);
ar_permute = [2,3,6,1,4,5];
% Value Function
st_title = ['MEAN(MN_V_U_GAIN(EM,J)), b_lower=' num2str(fl_b_lower) ', b_higher=' num2str(fl_b_high)'];
tb_az_v = ff_summ_nd_array(st_title, mn_V_U_gain_moreUI, true, ["mean"], 3, 1, cl_mp_datasetdesc, ar_permute);
```

xxx	MEAN(MN_V_U_GAIN(EM,J)), b_lower=0, b_higher=0.5				xxxxxxxxxxxxxxxxxxxxxxxxxxxxxxxx			
group	edu	marry	mean_age_18	mean_age_19	mean_age_20	mean_age_21	mean_age_22	
1	0	0	0.00044711	0.00045939	0.00047231	0.00049626	0.00052045	
2	1	0	0.00049806	0.00051832	0.00054037	0.00058072	0.00062215	
3	0	1	0.00062246	0.00065265	0.00068378	0.00072512	0.00076731	
4	1	1	0.00074086	0.00077968	0.00081932	0.00087866	0.0009399	

```
% Consumption
st_title = ['MEAN(MN_C_U_GAIN(EM,J)), b_lower=' num2str(fl_b_lower) ', b_higher=' num2str(fl_b_high)'];
```

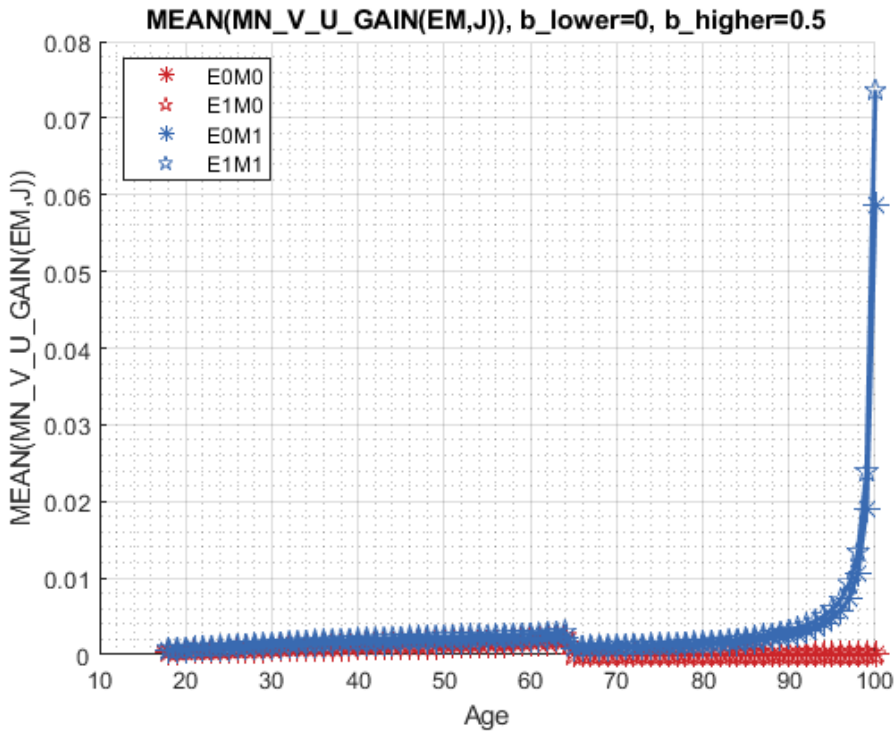
```
tb_az_c = ff_summ_nd_array(st_title, mn_C_U_gain_moreUI, true, ["mean"], 3, 1, cl_mp_datasetdesc, ar
```

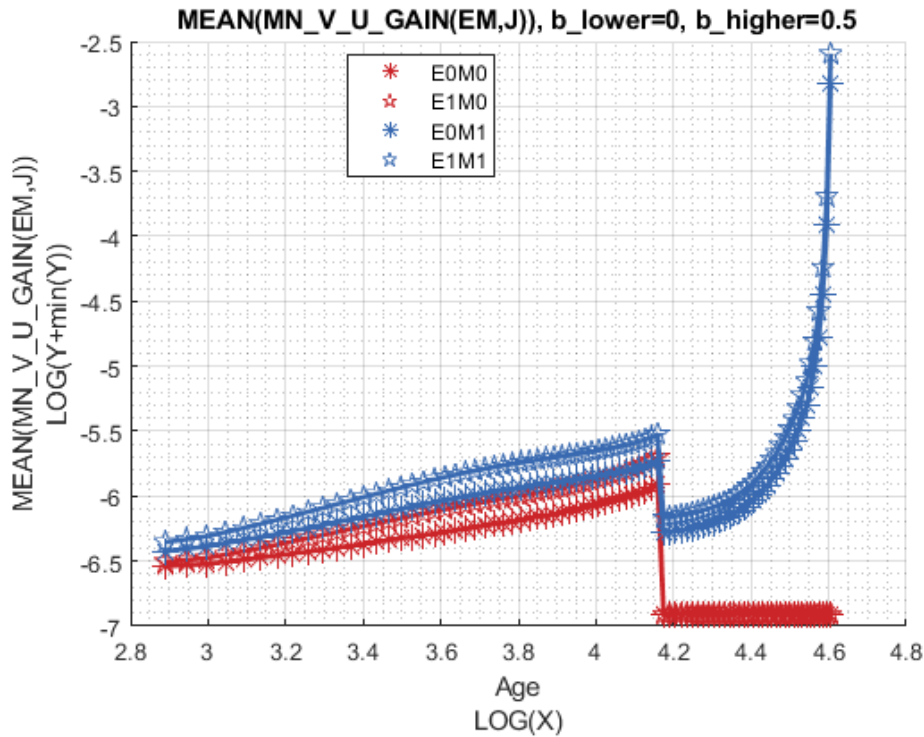
```
xxx MEAN(MN_C_U_GAIN(EM,J)), b_lower=0, b_higher=0.5 xxxxxxxxxxxxxxxxxxxxxxxxxxxxxxxxxxxx
```

group	edu	marry	mean_age_18	mean_age_19	mean_age_20	mean_age_21	mean_age_22
1	0	0	0.047852	0.050213	0.052704	0.054124	0.05542
2	1	0	0.065172	0.068522	0.072143	0.077638	0.082599
3	0	1	0.06735	0.070027	0.072677	0.075227	0.077714
4	1	1	0.084746	0.088978	0.093461	0.099707	0.10567

Graph Mean Values:

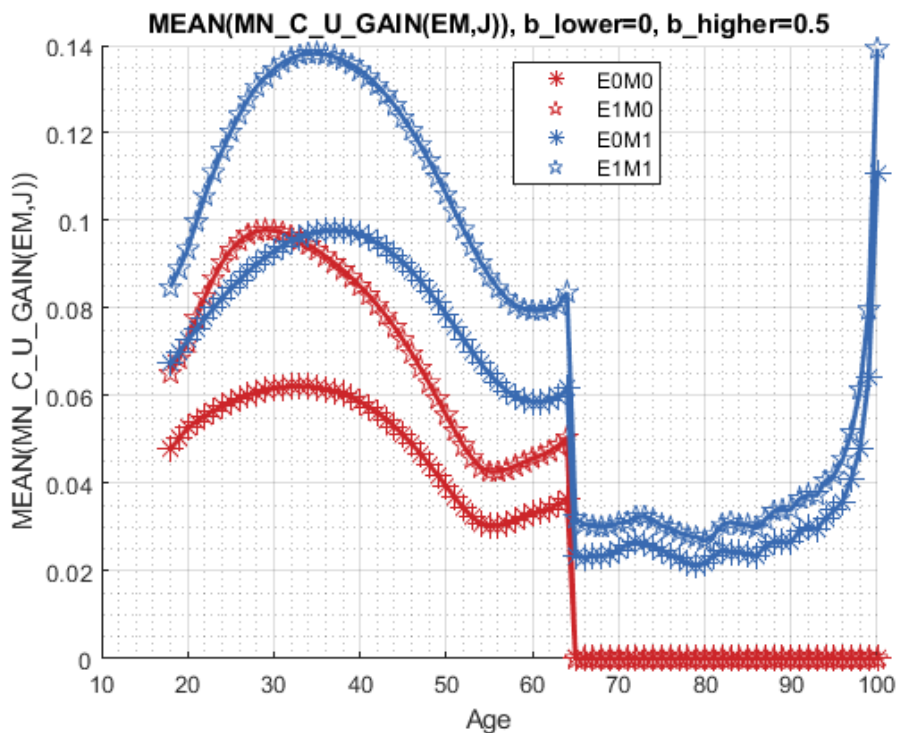
```
st_title = ['MEAN(MN_V_U_GAIN(EM,J)), b_lower=' num2str(fl_b_lower) ', b_higher=' num2str(fl_b_
mp_support_graph('cl_st_graph_title') = {st_title};
mp_support_graph('cl_st_ytitle') = {'MEAN(MN_V_U_GAIN(EM,J))'};
ff_graph_grid((tb_az_v{1:end, 4:end}), ar_row_grid, age_grid, mp_support_graph);
```

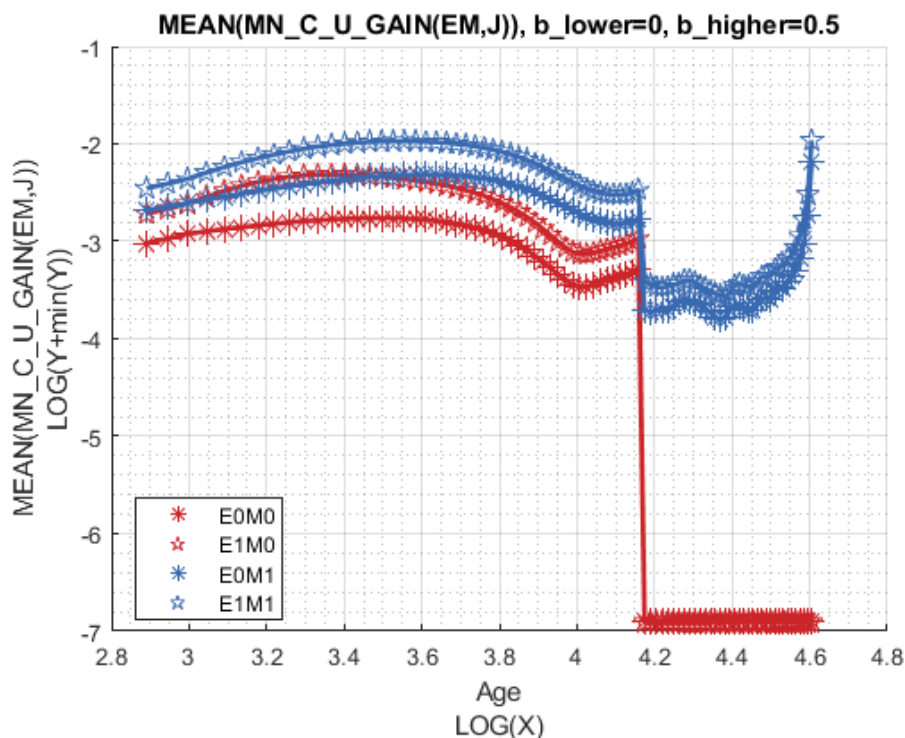




Graph Mean Consumption:

```
st_title = ['MEAN(MN\C_U_GAIN(EM,J)), b_lower=' num2str(fl_b_lower) ', b_higher=' num2str(fl_b_higher)'];
mp_support_graph('cl_st_graph_title') = {st_title};
mp_support_graph('cl_st_ytitle') = {'MEAN(MN\C_U_GAIN(EM,J))'};
ff_graph_grid((tb_az_c{1:end, 4:end}), ar_row_grid, age_grid, mp_support_graph);
```





### 14.3 Value and Consumption Low vs Higher Discount Factor Comparison

This is the example vignette for function: `snw_vfi_main_bisec_vec` from the [PrjOptiSNW Package](#). This function solves for the  $V(\text{states})$  for individuals at lower and higher discount factor  $\beta$ . We allow for  $\beta$  heterogeneity in the model to consider both patient and impatient households. The key difference is that patient households are more willing to save and will consume less.

#### 14.3.1 Solve Model at $\beta = 0.95$

Our high type households have  $\beta = 0.95$ .

```
% mp_params = snw_mp_param('default_dense');
mp_params = snw_mp_param('default_docdense');
fl_higher_beta = 0.95;
fl_lower_beta = 0.60;
mp_params('beta') = fl_higher_beta;
mp_controls = snw_mp_control('default_test');
mp_controls('bl_print_vfi') = false;
mp_controls('bl_print_vfi_verbose') = false;
mp_controls('bl_timer') = true;
[V_ss_beta95,~,cons_ss_beta95,~] = snw_vfi_main_bisec_vec(mp_params, mp_controls);
```

Completed SNW\_VFI\_MAIN\_BISEC\_VEC;SNW\_MP\_PARAM=default\_docdense;SNW\_MP\_CONTROL=default\_test;time=490.

#### 14.3.2 Solve Model at $\beta = 0.60$

Our high type households have  $\beta = 0.60$ .

```
mp_params('beta') = fl_lower_beta;
mp_controls = snw_mp_control('default_test');
mp_controls('bl_print_vfi') = false;
mp_controls('bl_print_vfi_verbose') = false;
mp_controls('bl_timer') = true;
```

```
[V_ss_beta60,~,cons_ss_beta60,~] = snw_vfi_main_bisec_vec(mp_params, mp_controls);
```

```
Completed SNW_VFI_MAIN_BISEC_VEC;SNW_MP_PARAM=default_docdense;SNW_MP_CONTROL=default_test;time=487.
```

### 14.3.3 Generate $\beta$ Comparison Matrixes

Take the difference between  $\beta = 0.95$  percent and  $\beta = 0.60$  consumption and value n-dimensional matrixes. Welfare is converted to units in fixed life-time consumption. Note that for example:  $\log(0.5) + 0 \cdot \log(0.5) > \log(0.5) + 0.99 \cdot \log(0.5)$ , in another word,  $V$  is higher with lower  $\beta$  if utility per-period is a negative value. Note our  $\gamma = 2$  for the CRRA parameter. We can compare  $V$  relatively across choices for the same individual, but less meaningfully across individuals with varying preferences.

```
gamma = mp_params('gamma');
mn_V_gain_beta = snw_hh_welfare(V_ss_beta95, gamma) - snw_hh_welfare(V_ss_beta60, gamma);
mn_C_gain_beta = cons_ss_beta95 - cons_ss_beta60;
fl_beta_gap = fl_higher_beta - fl_lower_beta;
```

### 14.3.4 Dense Param Results Define Frames

Define the matrix dimensions names and dimension vector values. Policy and Value Functions share the same ND dimensional structure.

```
% Grids:
age_grid = 18:100;
agrid = mp_params('agrid');
eta_H_grid = mp_params('eta_H_grid');
eta_S_grid = mp_params('eta_S_grid');
ar_st_eta_HS_grid = string(cellstr([num2str(eta_H_grid), 'hz=%3.2f;'], num2str(eta_S_grid), 'wz=%3.2f;'));
edu_grid = [0,1];
marry_grid = [0,1];
kids_grid = (1:1:mp_params('n_kidsgrid'))';
% NaN(n_jgrid,n_agrid,n_etagrid,n_educgrid,n_marriedgrid,n_kidsgrid);
cl_mp_datasetdesc = {};
cl_mp_datasetdesc{1} = containers.Map({'name', 'labval'}, {'age', age_grid});
cl_mp_datasetdesc{2} = containers.Map({'name', 'labval'}, {'savings', agrid});
cl_mp_datasetdesc{3} = containers.Map({'name', 'labval'}, {'eta', 1:length(eta_H_grid)});
cl_mp_datasetdesc{4} = containers.Map({'name', 'labval'}, {'edu', edu_grid});
cl_mp_datasetdesc{5} = containers.Map({'name', 'labval'}, {'marry', marry_grid});
cl_mp_datasetdesc{6} = containers.Map({'name', 'labval'}, {'kids', kids_grid});
```

### 14.3.5 Analyze Difference in $V$ and $C$ with Higher and Lower $\beta$

The difference between  $V$  and  $C$  with higher and lower  $\beta$ .

```
% Generate some Data
mp_support_graph = containers.Map('KeyType', 'char', 'ValueType', 'any');
mp_support_graph('cl_st_xtitle') = {'Savings States, a'};
mp_support_graph('st_legend_loc') = 'eastoutside';
mp_support_graph('bl_graph_logy') = true; % do not log
mp_support_graph('it_legend_select') = 21; % how many shock legends to show
mp_support_graph('cl_colors') = 'jet';
```

```
MEAN(MN_V_GAIN(A,Z))
```

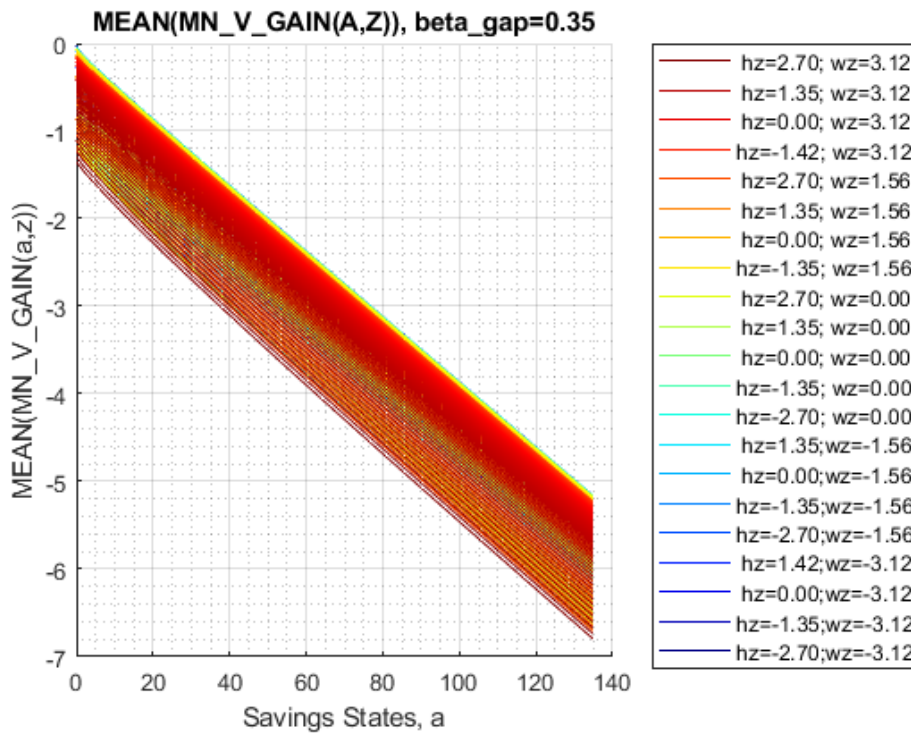
Tabulate value and policies along savings and shocks:

```
% Set
ar_permute = [1,4,5,6,3,2];
% Value Function
st_title = ['MEAN(MN_V_Gain(A,Z)), beta_gap=' num2str(fl_beta_gap) ];
tb_az_v = ff_summ_nd_array(st_title, mn_V_gain_beta, true, ["mean"], 4, 1, cl_mp_datasetdesc, ar_permute);
```

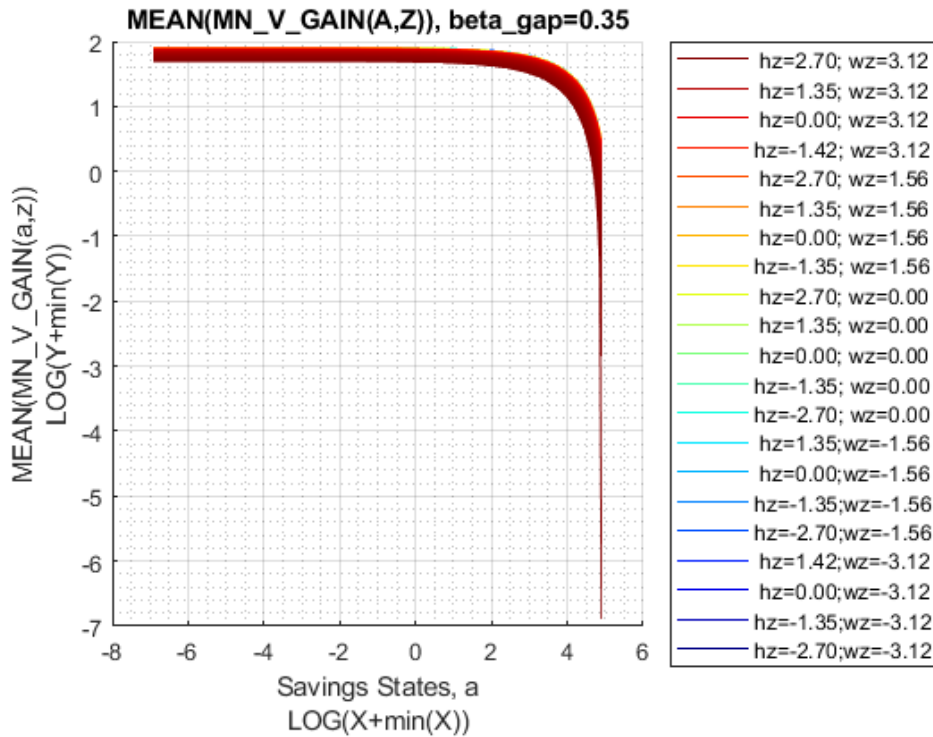
```
xxx MEAN(MN_V_Gain(A,Z)), beta_gap=0.35 xxxxxxxxxxxxxxxxxxxxxxxxxxxxxxxx
```

group	savings	mean_eta_1	mean_eta_2	mean_eta_3	mean_eta_4	mean_eta_5	mea
1	0	-0.024097	-0.024617	-0.025187	-0.025805	-0.026469	-0.

```
st_title = ['MEAN(MN_V_GAIN(A,Z)), beta_gap=' num2str(fl_beta_gap) ''];
mp_support_graph('cl_st_graph_title') = {st_title};
mp_support_graph('cl_st_ytitle') = {'MEAN(MN_V_GAIN(a,z))'};
ff_graph_grid((tb_az_v{1:end, 3:end})', ar_st_eta_HS_grid, agrid, mp_support_graph);
```

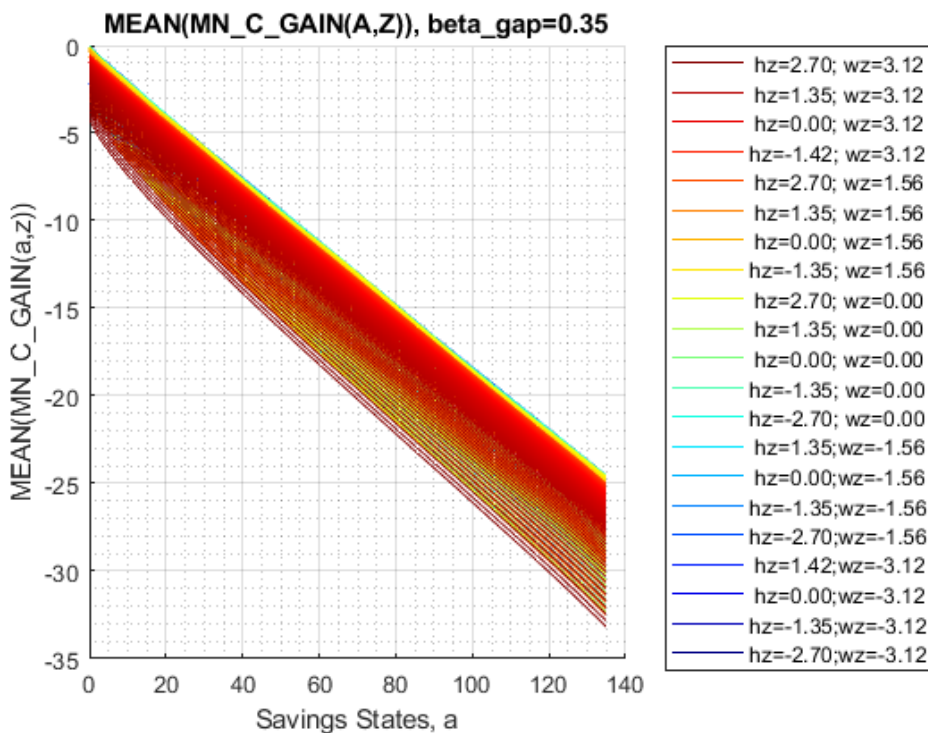


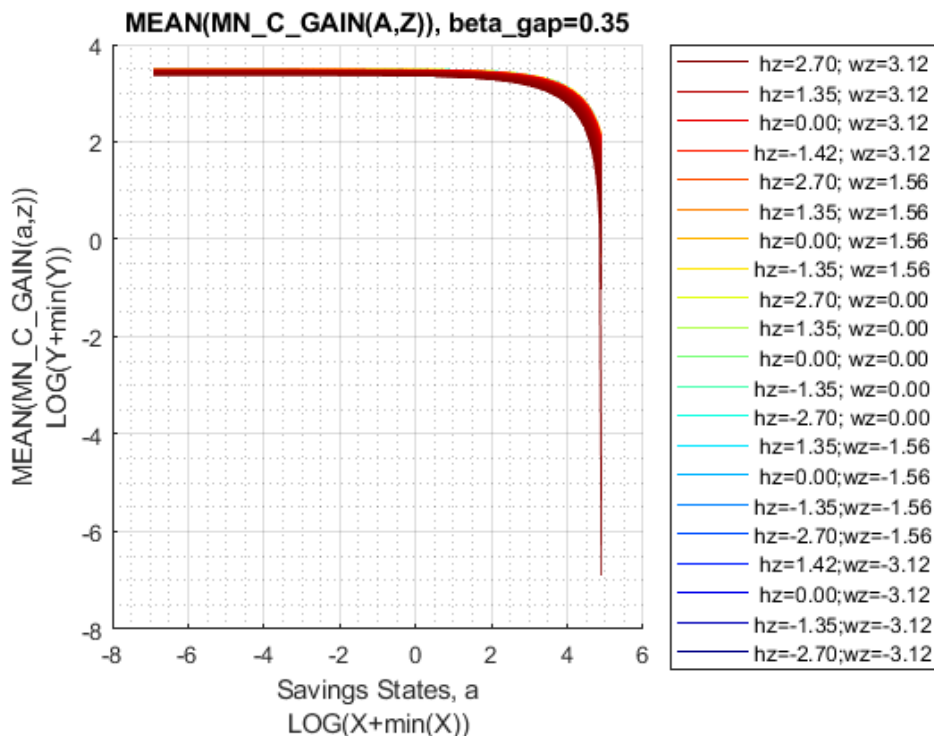




Graph Mean Consumption:

```
st_title = ['MEAN(MN\C\_GAIN(A,Z)), beta\_gap=' num2str(fl_beta_gap) ''];
mp_support_graph('cl_st_graph_title') = {st_title};
mp_support_graph('cl_st_ytitle') = {'MEAN(MN\C\_GAIN(a,z))'};
ff_graph_grid((tb_az_c{1:end, 3:end}'), ar_st_eta_HS_grid, agrid, mp_support_graph);
```





### 14.3.6 Analyze Kids and Marriage and Age

Aggregating over education, savings, and shocks, what are the differential effects of Marriage and Age.

```
% Generate some Data
mp_support_graph = containers.Map('KeyType', 'char', 'ValueType', 'any');
ar_row_grid = [...
    "k0M0", "K1M0", "K2M0", "K3M0", "K4M0", ...
    "k0M1", "K1M1", "K2M1", "K3M1", "K4M1"];
mp_support_graph('cl_st_xtitle') = {'Age'};
mp_support_graph('st_legend_loc') = 'best';
mp_support_graph('bl_graph_logy') = true; % do not log
mp_support_graph('st_rounding') = '6.2f'; % format shock legend
mp_support_graph('cl_scatter_shapes') = {...
    'o', 'd', 's', 'x', '*', ...
    'o', 'd', 's', 'x', '*'};
mp_support_graph('cl_colors') = {...
    'red', 'red', 'red', 'red', 'red'...
    'blue', 'blue', 'blue', 'blue', 'blue'};
```

MEAN(VAL(KM,J)), MEAN(AP(KM,J)), MEAN(C(KM,J))

Tabulate value and policies:

```
% Set
% NaN(n_jgrid,n_agrid,n_etagrid,n_educgrid,n_marriedgrid,n_kidsgrid);
ar_permute = [2,3,4,1,6,5];
% Value Function
st_title = ['MEAN(MN_V_Gain(KM,J)), beta_gap=' num2str(fl_beta_gap) ];
tb_az_v = ff_summ_nd_array(st_title, mn_V_gain_beta, true, ["mean"], 3, 1, cl_mp_datasetdesc, ar_per
```

xxx	MEAN(MN_V_Gain(KM,J))	beta_gap=0.35	xxxxxxxxxxxxxxxxxxxxxxxxxxxxxxxx					
group	kids	marry	mean_age_18	mean_age_19	mean_age_20	mean_age_21	mean_age_22	
----	----	----	-----	-----	-----	-----	-----	-----
1	1	0	-2.3297	-2.3646	-2.4033	-2.4467	-2.4886	

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2	2	0	-1.6829	-1.7078	-1.7361	-1.7685	-1.8005
3	3	0	-1.4479	-1.4653	-1.4856	-1.5093	-1.5326
4	4	0	-1.2769	-1.2904	-1.3063	-1.3254	-1.3441
5	5	0	-1.1689	-1.1787	-1.1908	-1.2057	-1.2203
6	1	1	-1.8594	-1.8945	-1.9328	-1.9753	-2.0168
7	2	1	-1.4942	-1.5203	-1.5493	-1.5821	-1.6145
8	3	1	-1.3397	-1.3604	-1.3836	-1.4101	-1.4362
9	4	1	-1.2093	-1.2257	-1.2444	-1.2661	-1.2875
10	5	1	-1.1227	-1.1351	-1.1495	-1.1667	-1.1835

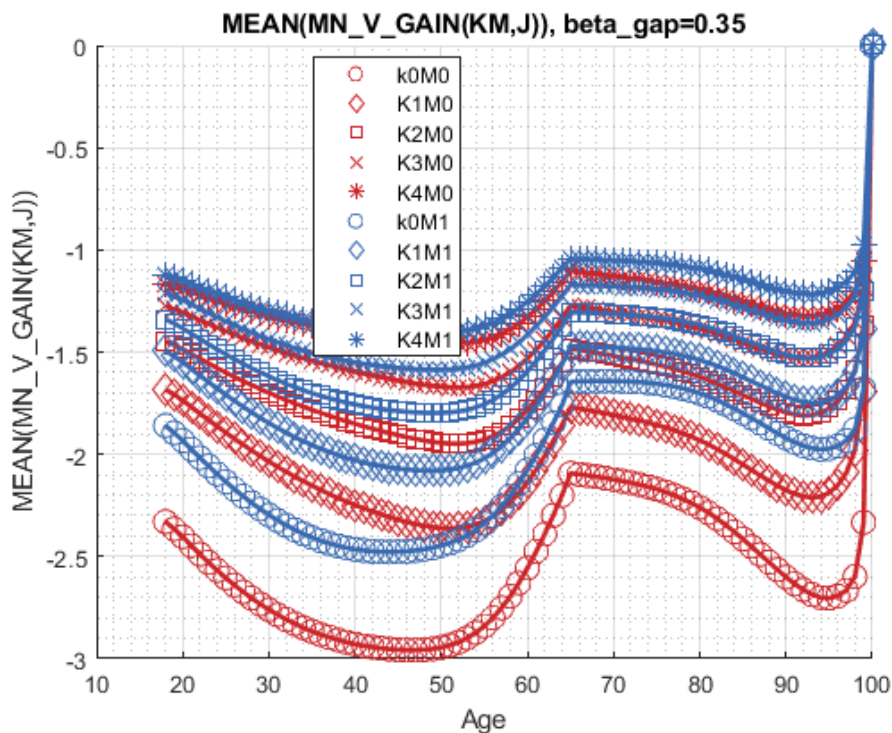
% Consumption Function

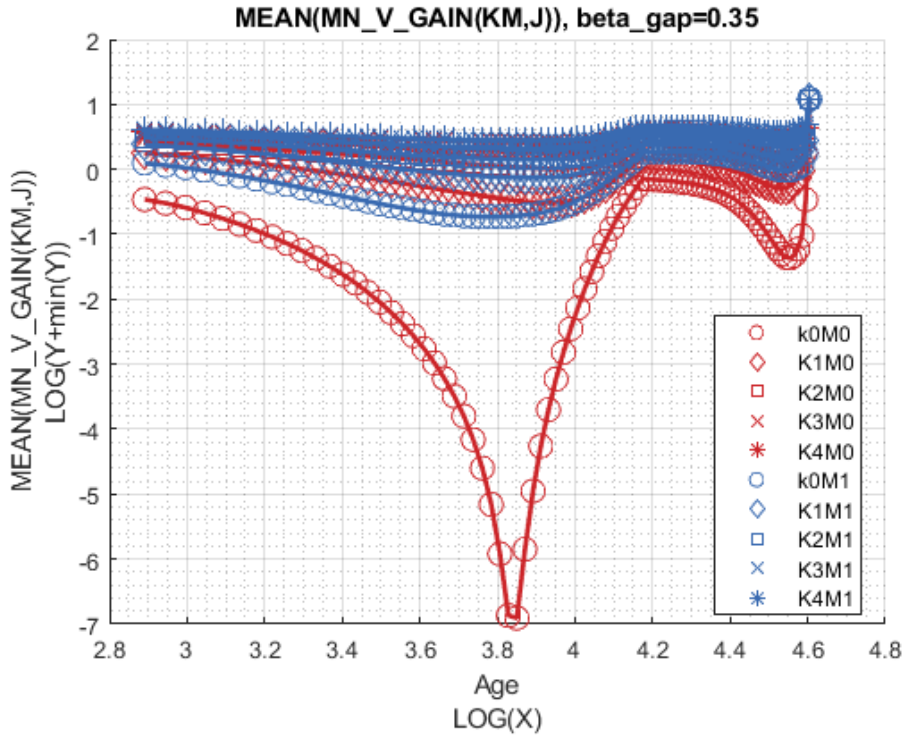
```
st_title = ['MEAN(MN_C_Gain(KM,J)), beta_gap=' num2str(fl_beta_gap) ];
tb_az_c = ff_summ_nd_array(st_title, mn_C_gain_beta, true, ["mean"], 3, 1, cl_mp_datasetdesc, ar_per
```

xxx	MEAN(MN_C_Gain(KM,J)),	beta_gap=0.35	xxxxxxxxxxxxxxxxxxxxxxxxxxxxxxxx	mean_age_18	mean_age_19	mean_age_20	mean_age_21	mean_age_2
group	kids	marry						
1	1	0		-7.8284	-7.878	-7.942	-8.0313	-8.1185
2	2	0		-7.7474	-7.7919	-7.8514	-7.9374	-8.0227
3	3	0		-7.8502	-7.8841	-7.9298	-8.0042	-8.0781
4	4	0		-7.8498	-7.8791	-7.9197	-7.989	-8.0577
5	5	0		-7.882	-7.9053	-7.9401	-8.0028	-8.0648
6	1	1		-8.3054	-8.3892	-8.4885	-8.6164	-8.7429
7	2	1		-8.1032	-8.1784	-8.2681	-8.3867	-8.5041
8	3	1		-8.1357	-8.2006	-8.2817	-8.3905	-8.4971
9	4	1		-8.0781	-8.1343	-8.207	-8.3071	-8.4058
10	5	1		-8.051	-8.0944	-8.154	-8.2396	-8.3246

Graph Mean Values:

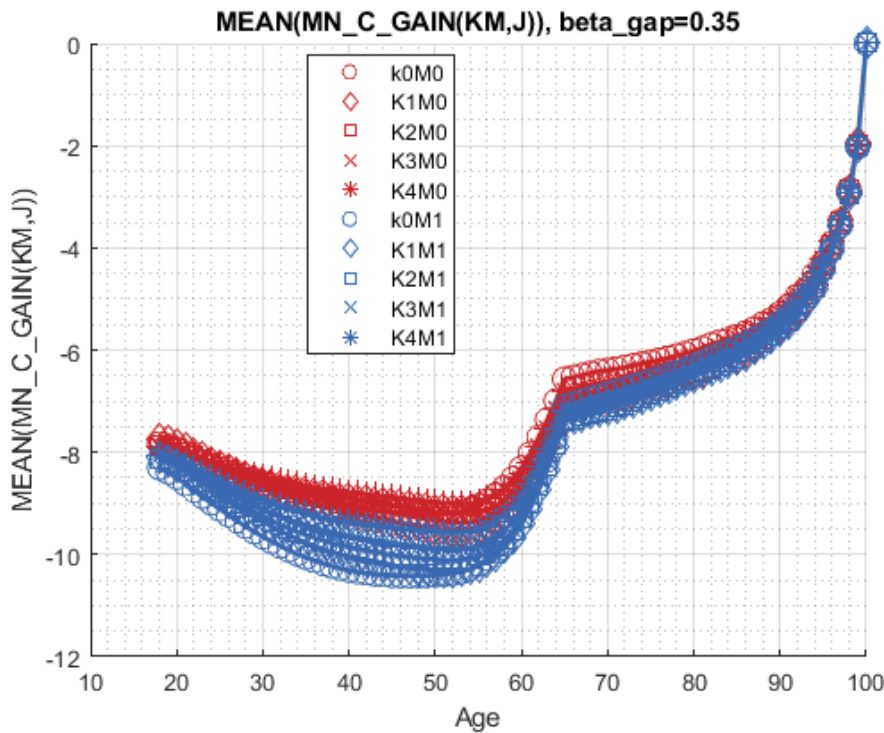
```
st_title = ['MEAN(MN_V_GAIN(KM,J)), beta_gap=' num2str(fl_beta_gap) ''];
mp_support_graph('cl_st_graph_title') = {st_title};
mp_support_graph('cl_st_ytitle') = {'MEAN(MN_V_GAIN(KM,J))'};
ff_graph_grid((tb_az_v{1:end, 4:end}), ar_row_grid, age_grid, mp_support_graph);
```

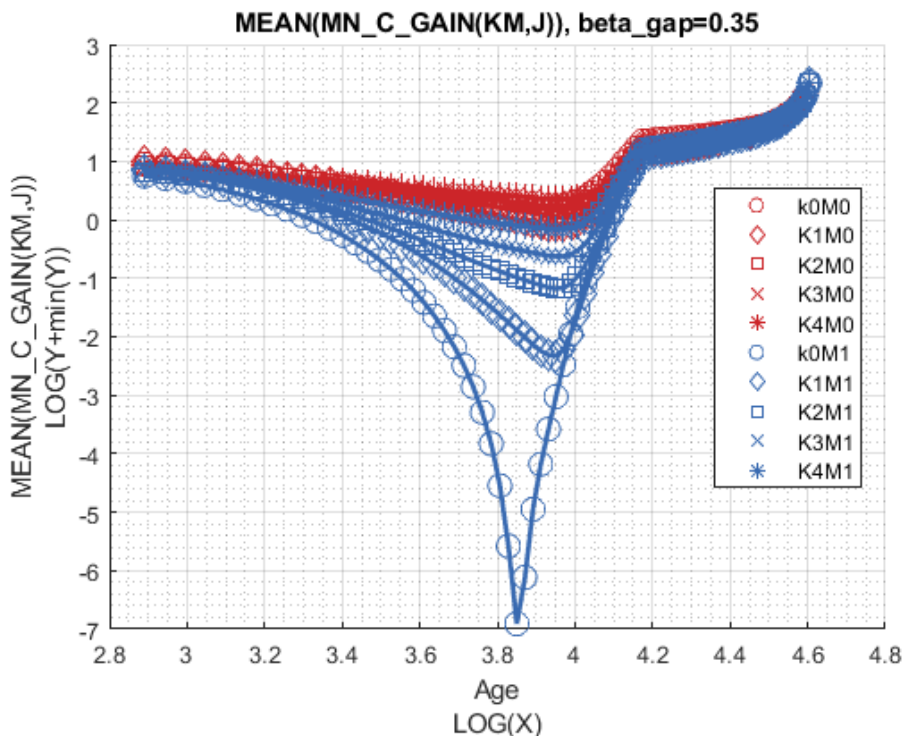




Graph Mean Consumption:

```
st_title = ['MEAN(MN\C\_GAIN(KM,J)), beta\_gap=' num2str(fl_beta_gap) ''];
mp_support_graph('cl_st_graph_title') = {st_title};
mp_support_graph('cl_st_ytitle') = {'MEAN(MN\C\_GAIN(KM,J))'};
ff_graph_grid((tb_az_c{1:end, 4:end}), ar_row_grid, age_grid, mp_support_graph);
```





### 14.3.7 Analyze Education and Marriage

Aggregating over education, savings, and shocks, what are the differential effects of Marriage and Age.

```
% Generate some Data
mp_support_graph = containers.Map('KeyType', 'char', 'ValueType', 'any');
ar_row_grid = ["E0M0", "E1M0", "E0M1", "E1M1"];
mp_support_graph('cl_st_xtitle') = {'Age'};
mp_support_graph('st_legend_loc') = 'best';
mp_support_graph('bl_graph_logy') = true; % do not log
mp_support_graph('st_rounding') = '6.2f'; % format shock legend
mp_support_graph('cl_scatter_shapes') = {'*', 'p', '*', 'p' };
mp_support_graph('cl_colors') = {'red', 'red', 'blue', 'blue'};
```

MEAN(VAL(EM,J)), MEAN(AP(EM,J)), MEAN(C(EM,J))

Tabulate value and policies:

```
% Set
% NaN(n_jgrid,n_agrid,n_etagrid,n_educgrid,n_marriedgrid,n_kidsgrid);
ar_permute = [2,3,6,1,4,5];
% Value Function
st_title = ['MEAN(MN_V_Gain(EM,J)), beta_gap=' num2str(fl_beta_gap) ];
tb_az_v = ff_summ_nd_array(st_title, mn_V_gain_beta, true, ["mean"], 3, 1, cl_mp_datasetdesc, ar_per
```

xxx	MEAN(MN_V_Gain(EM,J)), beta_gap=0.35			xxxxxxxxxxxxxxxxxxxxxxxxxxxxxxxx			
group	edu	marry	mean_age_18	mean_age_19	mean_age_20	mean_age_21	mean_age_22
1	0	0	-1.5742	-1.5897	-1.6068	-1.6259	-1.6446
2	1	0	-1.5882	-1.613	-1.642	-1.6763	-1.7098
3	0	1	-1.3891	-1.4066	-1.4256	-1.4464	-1.4669
4	1	1	-1.421	-1.4478	-1.4783	-1.5137	-1.5485

```
% Consumption
st_title = ['MEAN(MN_C_Gain(EM,J)), beta_gap=' num2str(fl_beta_gap) ];
```

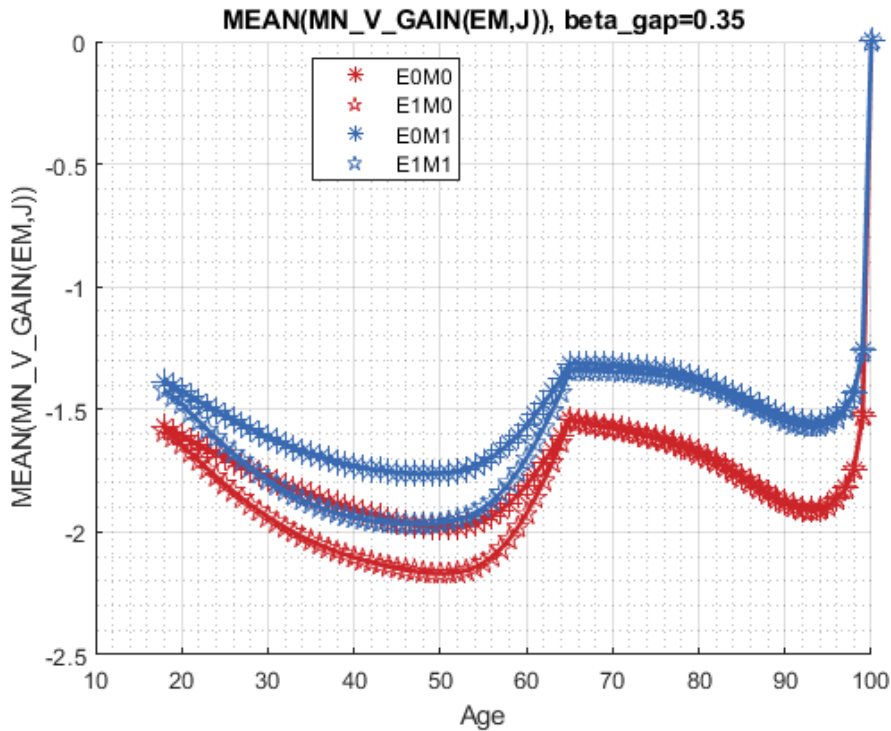
```
tb_az_c = ff_summ_nd_array(st_title, mn_C_gain_beta, true, ["mean"], 3, 1, cl_mp_datasetdesc, ar_per
```

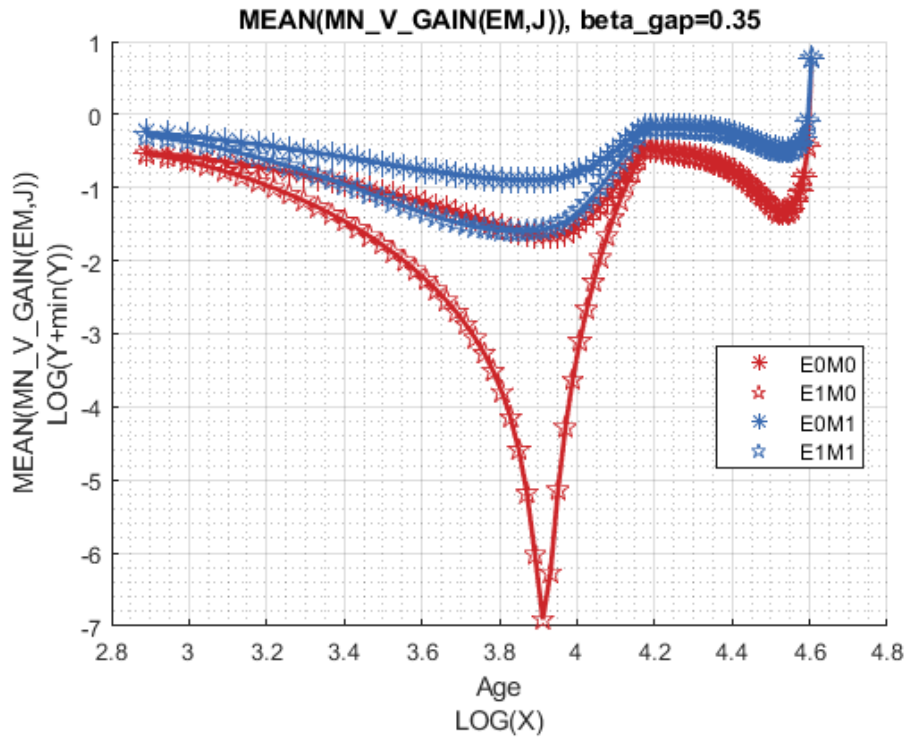
```
xxx MEAN(MN_C_Gain(EM,J)), beta_gap=0.35 xxxxxxxxxxxxxxxxxxxxxxxxxxxxxxxx
```

group	edu	marry	mean_age_18	mean_age_19	mean_age_20	mean_age_21	mean_age_22
1	0	0	-7.8968	-7.9208	-7.9537	-8.0028	-8.0505
2	1	0	-7.7663	-7.8145	-7.8794	-7.983	-8.0863
3	0	1	-8.1784	-8.2294	-8.2887	-8.3652	-8.4396
4	1	1	-8.091	-8.1694	-8.2711	-8.4109	-8.5502

Graph Mean Values:

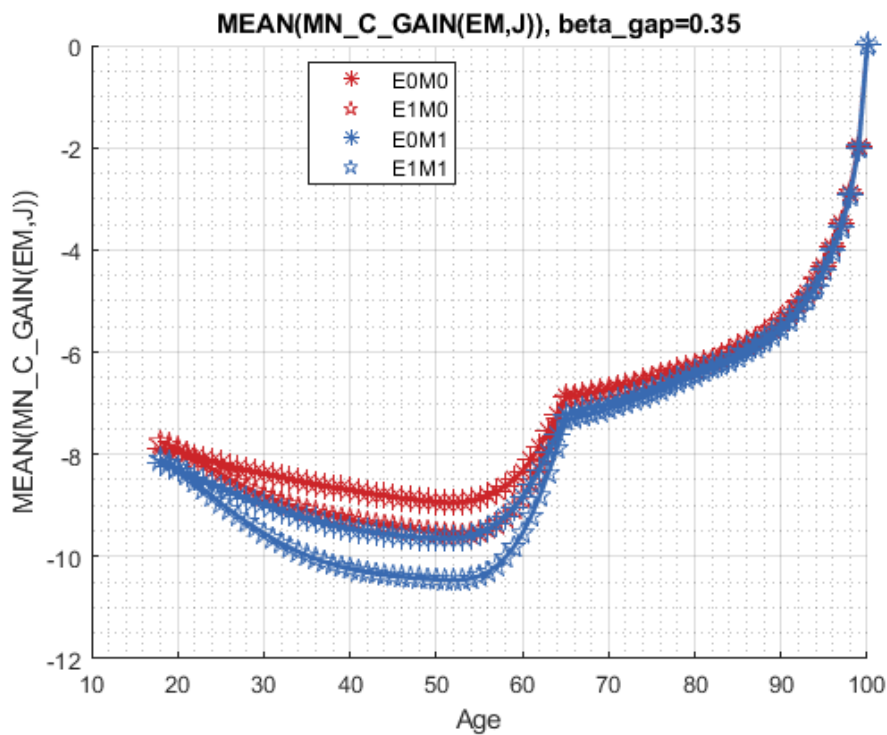
```
st_title = ['MEAN(MN_V_GAIN(EM,J)), beta_gap=' num2str(fl_beta_gap) ''];
mp_support_graph('cl_st_graph_title') = {st_title};
mp_support_graph('cl_st_ytitle') = {'MEAN(MN_V_GAIN(EM,J))'};
ff_graph_grid((tb_az_v{1:end, 4:end}), ar_row_grid, age_grid, mp_support_graph);
```

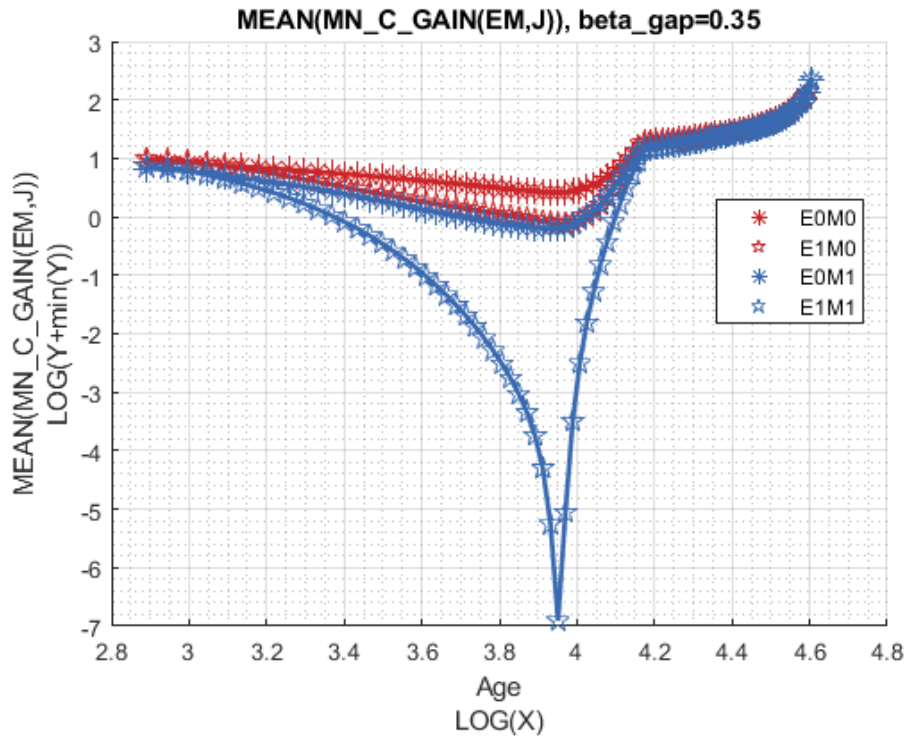




Graph Mean Consumption:

```
st_title = ['MEAN(MN\C\_GAIN(EM,J)), beta\_gap=' num2str(fl_beta_gap) ''];
mp_support_graph('cl_st_graph_title') = {st_title};
mp_support_graph('cl_st_ytitle') = {'MEAN(MN\C\_GAIN(EM,J))'};
ff_graph_grid((tb_az_c{1:end, 4:end}), ar_row_grid, age_grid, mp_support_graph);
```







# Appendix A

## Index and Code Links

### A.1 ~~## Selected Comparative Statistics links links~~



# Bibliography

The MathWorks Inc (2019). *MATLAB*. Matlab package version 2019b.

Xie, Y. (2020). *bookdown: Authoring Books and Technical Documents with R Markdown*. R package version 0.18.