

# SNW Dynamic Life Cycle and Welfare 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 Nygaard, Sorensen and Wang (2020) ([Vegard M. Nygaard, 2020](#)). The code companion presents solutions to the dynamic life-cycle problem, and methods for evaluating the marginal gains from allocating additional welfare checks. Tested with [Matlab 2019a](#) ([The MathWorks Inc, 2019](#)).

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

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

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 goal of this repository is to make it easier to find/re-use codes produced for various projects.

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 welfare check increments for households. Allocation functions rely the R optimal allocation package [PrjOptiAlloc](#).

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

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



# Chapter 1

## Parameters

### 1.1 Model Parameters

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

#### 1.1.1 Documentation Run Parameters Docdense

Parameters used for documentation vig.

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

```
-----
xxxxxxxxxxxxxxxxxxxxxxxxxxxxxxxxxxxxx
CONTAINER NAME: mp_params_preftechpricegov Scalars
xxxxxxxxxxxxxxxxxxxxxxxxxxxxx
```

i	idx	value
--	---	-----
Bequests	1	0
a2	2	1.5286
bequests_option	3	1
beta	4	0.97116
cons_allocation_rule	5	2
g_cons	6	0.17576
g_n	7	0.01
gamma	8	2
jret	9	48
r	10	0.04
theta	11	0.56523
throw_in_ocean	12	1

```
-----
xxxxxxxxxxxxxxxxxxxxxxxxxxxxx
CONTAINER NAME: mp_params_intlen Scalars
xxxxxxxxxxxxxxxxxxxxxxxxxxxxx
```

i	idx	value
-	---	-----
n_agrid	1	65
n_educgrid	2	2
n_eta_H_grid	3	61
n_eta_S_grid	4	5

```

n_etagrid      5      5      305
n_jgrid        6      6      83
n_kidsgrid    7      7       5
n_marriedgrid 8      8       2

-----
xxxxxxxxxxxxxxxxxxxxxxxxxxxxxxxxxxxxxx
CONTAINER NAME: mp_params_covid_unemploy ND Array (Matrix etc)
xxxxxxxxxxxxxxxxxxxxxxxxxxxxxxxxxxxxxx
      i   idx  ndim  numel   rowN   colN   sum   mean   std   coefv
      -   ---  ----  -----  ----  ----  -----  -----  -----  -----
inc_grid     1      3      2      201    201     1    578.5  2.8781  1.8836  0.654
pi_unemp    2      6      2      415     83     5    9.5319  0.022968 0.024679  1.07

xxx TABLE:inc_grid xxxxxxxxxxxxxxxxxxxx
      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	0.080278	0.051706	0.041502	0.03538	0.025176
r2	0.080278	0.051706	0.041502	0.03538	0.025176
r3	0.080278	0.051706	0.041502	0.03538	0.025176
r4	0.080278	0.051706	0.041502	0.03538	0.025176
r5	0.080278	0.051706	0.041502	0.03538	0.025176
r6	0.080278	0.051706	0.041502	0.03538	0.025176
r7	0.080278	0.051706	0.041502	0.03538	0.025176
r8	0.080278	0.051706	0.041502	0.03538	0.025176
r9	0.080278	0.051706	0.041502	0.03538	0.025176
r10	0.080278	0.051706	0.041502	0.03538	0.025176
r11	0.080278	0.051706	0.041502	0.03538	0.025176
r12	0.080278	0.051706	0.041502	0.03538	0.025176
r13	0.080278	0.051706	0.041502	0.03538	0.025176
r14	0.070703	0.042132	0.031928	0.025805	0.015601
r15	0.070703	0.042132	0.031928	0.025805	0.015601
r16	0.070703	0.042132	0.031928	0.025805	0.015601
r17	0.070703	0.042132	0.031928	0.025805	0.015601
r18	0.070703	0.042132	0.031928	0.025805	0.015601
r19	0.070703	0.042132	0.031928	0.025805	0.015601
r20	0.070703	0.042132	0.031928	0.025805	0.015601
r21	0.070703	0.042132	0.031928	0.025805	0.015601
r22	0.070703	0.042132	0.031928	0.025805	0.015601
r23	0.070703	0.042132	0.031928	0.025805	0.015601
r24	0.067512	0.038941	0.028736	0.022614	0.01241
r25	0.067512	0.038941	0.028736	0.022614	0.01241
r26	0.067512	0.038941	0.028736	0.022614	0.01241
r27	0.067512	0.038941	0.028736	0.022614	0.01241
r28	0.067512	0.038941	0.028736	0.022614	0.01241
r29	0.067512	0.038941	0.028736	0.022614	0.01241
r30	0.067512	0.038941	0.028736	0.022614	0.01241
r31	0.067512	0.038941	0.028736	0.022614	0.01241
r32	0.067512	0.038941	0.028736	0.022614	0.01241
r33	0.067512	0.038941	0.028736	0.022614	0.01241
r34	0.068576	0.040004	0.0298	0.023678	0.013474
r35	0.068576	0.040004	0.0298	0.023678	0.013474
r36	0.068576	0.040004	0.0298	0.023678	0.013474
r37	0.068576	0.040004	0.0298	0.023678	0.013474
r38	0.068576	0.040004	0.0298	0.023678	0.013474
r39	0.068576	0.040004	0.0298	0.023678	0.013474
r40	0.068576	0.040004	0.0298	0.023678	0.013474
r41	0.068576	0.040004	0.0298	0.023678	0.013474
r42	0.068576	0.040004	0.0298	0.023678	0.013474
r43	0.068576	0.040004	0.0298	0.023678	0.013474
r44	0.080278	0.051706	0.041502	0.03538	0.025176
r45	0.080278	0.051706	0.041502	0.03538	0.025176
r46	0.080278	0.051706	0.041502	0.03538	0.025176
r47	0.080278	0.051706	0.041502	0.03538	0.025176
r48	0.080278	0.051706	0.041502	0.03538	0.025176
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

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

i	idx	value
-	---	-----
TR	1	1 0.0017225
b	2	2 1
n_incgrid	3	4 201
n_welfchecksgrid	4	5 45
scaleconvertor	5	7 58056
xi	6	8 0.75

-----  
xxxxxxxxxxxxxxxxxxxxxxxxxxxxxxxxxxxx  
CONTAINER NAME: mp\_params\_statesgrid ND Array (Matrix etc)  
xxxxxxxxxxxxxxxxxxxxxxxxxxxxxxxxxxxx

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	2 305	305	1	2.0872e-13	6.8433e-16	1.5853
eta_S_grid	3	3	2 305	305	1	-1.7764e-14	-5.8241e-17	2.2112

xxx TABLE:agrid xxxxxxxxxxxxxxxxxxxx  
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 xxxxxxxxxxxxxxxxxxxx
      c1
      -----
r1      -2.6968
r2      -2.6069
r3      -2.517
r4      -2.4271
r5      -2.3372
r6      -2.2473
r7      -2.1574
r8      -2.0675
r9      -1.9777
r10     -1.8878
r11     -1.7979
r12     -1.708
r13     -1.6181
r14     -1.5282
r15     -1.4383
r16     -1.3484
r17     -1.2585
r18     -1.1686
r19     -1.0787
r20     -0.98883
r21     -0.89893
r22     -0.80904
r23     -0.71915
r24     -0.62925
r25     -0.53936
r26     -0.44947
r27     -0.35957
r28     -0.26968
r29     -0.17979
r30     -0.089893
r31     8.0491e-16
r32     0.089893
r33     0.17979
r34     0.26968
r35     0.35957
r36     0.44947
r37     0.53936
r38     0.62925
r39     0.71915
r40     0.80904
r41     0.89893

```

r42	0.98883
r43	1.0787
r44	1.1686
r45	1.2585
r46	1.3484
r47	1.4383
r48	1.5282
r49	1.6181
r50	1.708
r256	-1.708
r257	-1.6181
r258	-1.5282
r259	-1.4383
r260	-1.3484
r261	-1.2585
r262	-1.1686
r263	-1.0787
r264	-0.98883
r265	-0.89893
r266	-0.80904
r267	-0.71915
r268	-0.62925
r269	-0.53936
r270	-0.44947
r271	-0.35957
r272	-0.26968
r273	-0.17979
r274	-0.089893
r275	8.0491e-16
r276	0.089893
r277	0.17979
r278	0.26968
r279	0.35957
r280	0.44947
r281	0.53936
r282	0.62925
r283	0.71915
r284	0.80904
r285	0.89893
r286	0.98883
r287	1.0787
r288	1.1686
r289	1.2585
r290	1.3484
r291	1.4383
r292	1.5282
r293	1.6181
r294	1.708
r295	1.7979
r296	1.8878
r297	1.9777
r298	2.0675
r299	2.1574
r300	2.2473
r301	2.3372
r302	2.4271
r303	2.517
r304	2.6069

```
r305          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  
r256    3.122  
r257    3.122
```

```
r258      3.122
r259      3.122
r260      3.122
r261      3.122
r262      3.122
r263      3.122
r264      3.122
r265      3.122
r266      3.122
r267      3.122
r268      3.122
r269      3.122
r270      3.122
r271      3.122
r272      3.122
r273      3.122
r274      3.122
r275      3.122
r276      3.122
r277      3.122
r278      3.122
r279      3.122
r280      3.122
r281      3.122
r282      3.122
r283      3.122
r284      3.122
r285      3.122
r286      3.122
r287      3.122
r288      3.122
r289      3.122
r290      3.122
r291      3.122
r292      3.122
r293      3.122
r294      3.122
r295      3.122
r296      3.122
r297      3.122
r298      3.122
r299      3.122
r300      3.122
r301      3.122
r302      3.122
r303      3.122
r304      3.122
r305      3.122
```

---

```
xxxxxxxxxxxxxxxxxxxxxxxxxxxxxxxxxxxxx
CONTAINER NAME: mp_params_exotrans ND Array (Matrix etc)
xxxxxxxxxxxxxxxxxxxxxxxxxxxxxxxxxxxxx
```

	i	idx	ndim	numel	rowN	colN	sum	mean
	-	---	----	-----	----	----	-----	-----
cl_mt_pi_jem_kidseta	1	1	2	2.3256e+06	1525	1525	1525	0.00065574
pi_H_eta		2	2	3721	61	61	61	0.016393

pi_S_eta	3	3	2	25	5	5	5	0.2
pi_eta	4	4	2	93025	305	305	305	0.0032787
pi_kids	5	5	5	8300	5	1660	1660	0.2
psi	6	6	2	83	83	1	78.16	0.94169

xxx TABLE:cl\_mt\_pi\_jem\_kidseta xxxxxxxxxxxxxxxxxxxx

	c1	c2	c3	c1523	c1524	c1525
r1	0.005125	0.0027446	0.0018598	0	0	0
r2	0.0025409	0.0026419	0.0027349	0	0	0
r3	0.00090694	0.0016787	0.002655	0	0	0
r4	0.00022557	0.00070391	0.0017014	0	0	0
r5	3.8282e-05	0.00019466	0.00071949	0	0	0
r6	4.3734e-06	3.5476e-05	0.00020067	0	0	0
r7	3.333e-07	4.2565e-06	3.6884e-05	0	0	0
r8	1.6842e-08	3.3588e-07	4.4633e-06	0	0	0
r9	5.6182e-10	1.7412e-08	3.5523e-07	0	0	0
r10	1.2334e-11	5.9238e-10	1.8574e-08	0	0	0
r11	1.7779e-13	1.3212e-11	6.3738e-10	0	0	0
r12	1.6798e-15	1.93e-13	1.4339e-11	0	0	0
r13	1.0388e-17	1.8449e-15	2.1128e-13	0	0	0
r14	4.2001e-20	1.1531e-17	2.0372e-15	0	0	0
r15	1.1095e-22	4.709e-20	1.2844e-17	0	0	0
r16	1.9132e-25	1.2558e-22	5.291e-20	0	0	0
r17	2.1526e-28	2.1857e-25	1.4233e-22	0	0	0
r18	1.5795e-31	2.4815e-28	2.4989e-25	0	0	0
r19	7.5549e-35	1.8372e-31	2.862e-28	0	0	0
r20	2.3549e-38	8.8661e-35	2.1375e-31	0	0	0
r21	4.7821e-42	2.7881e-38	1.0406e-34	0	0	0
r22	6.3249e-46	5.7119e-42	3.301e-38	0	0	0
r23	5.4473e-50	7.6214e-46	6.8221e-42	0	0	0
r24	3.0545e-54	6.6219e-50	9.1828e-46	0	0	0
r25	1.1149e-58	3.7458e-54	8.0487e-50	0	0	0
r26	2.6486e-63	1.3793e-58	4.593e-54	0	0	0
r27	4.0946e-68	3.3055e-63	1.7061e-58	0	0	0
r28	4.119e-73	5.1553e-68	4.1248e-63	0	0	0
r29	2.6959e-78	5.2318e-73	6.4897e-68	0	0	0
r30	1.1479e-83	3.4544e-78	6.6439e-73	0	0	0
r31	3.1796e-89	1.4838e-83	4.4254e-78	0	0	0
r32	5.7288e-95	4.1463e-89	1.9177e-83	0	0	0
r33	6.7133e-101	7.5363e-95	5.4059e-89	0	0	0
r34	5.1166e-107	8.9094e-101	9.9124e-95	0	0	0
r35	2.5362e-113	6.8503e-107	1.1822e-100	0	0	0
r36	8.1749e-120	3.4254e-113	9.1697e-107	0	0	0
r37	1.7135e-126	1.1139e-119	4.6256e-113	0	0	0
r38	2.3355e-133	2.3554e-126	1.5174e-119	0	0	0
r39	2.0699e-140	3.2387e-133	3.237e-126	0	0	0
r40	1.1927e-147	2.8956e-140	4.4902e-133	0	0	0
r41	4.4687e-155	1.6833e-147	4.05e-140	0	0	0
r42	1.0885e-162	6.3622e-155	2.3751e-147	0	0	0
r43	1.7238e-170	1.5634e-162	9.0564e-155	0	0	0
r44	1.7748e-178	2.4978e-170	2.2451e-162	0	0	0
r45	1.1879e-186	2.5943e-178	3.6186e-170	0	0	0
r46	5.1689e-195	1.7518e-186	3.7916e-178	0	0	0
r47	1.4621e-203	7.6897e-195	2.5828e-186	5.8763e-24	0	0
r48	2.6885e-212	2.1943e-203	1.1438e-194	9.0496e-22	5.3421e-24	0
r49	3.2135e-221	4.0705e-212	3.2927e-203	9.3883e-20	8.1948e-22	4.8079e-24

r50	2.4969e-230	4.9085e-221	6.162e-212	6.3716e-18	8.5761e-20	7.4629e-22
r1476	3.4485e-22	3.9622e-20	2.9437e-18	0	0	0
r1477	2.1325e-24	3.7874e-22	4.3374e-20	0	0	0
r1478	8.6227e-27	2.3672e-24	4.1822e-22	0	0	0
r1479	2.2777e-29	9.6675e-27	2.6367e-24	0	0	0
r1480	3.9278e-32	2.5781e-29	1.0862e-26	0	0	0
r1481	4.4192e-35	4.4871e-32	2.922e-29	0	0	0
r1482	3.2426e-38	5.0945e-35	5.1302e-32	0	0	0
r1483	1.551e-41	3.7717e-38	5.8757e-35	0	0	0
r1484	4.8345e-45	1.8202e-41	4.3882e-38	0	0	0
r1485	9.8174e-49	5.7239e-45	2.1363e-41	0	0	0
r1486	1.2985e-52	1.1726e-48	6.7769e-45	0	0	0
r1487	1.1183e-56	1.5647e-52	1.4006e-48	0	0	0
r1488	6.2707e-61	1.3595e-56	1.8852e-52	0	0	0
r1489	2.2888e-65	7.69e-61	1.6524e-56	0	0	0
r1490	5.4374e-70	2.8316e-65	9.4292e-61	0	0	0
r1491	8.4061e-75	6.7861e-70	3.5026e-65	0	0	0
r1492	8.4562e-80	1.0584e-74	8.468e-70	0	0	0
r1493	5.5346e-85	1.0741e-79	1.3323e-74	0	0	0
r1494	2.3566e-90	7.0917e-85	1.364e-79	0	0	0
r1495	6.5276e-96	3.0463e-90	9.0853e-85	0	0	0
r1496	1.1761e-101	8.5122e-96	3.937e-90	0	0	0
r1497	1.3782e-107	1.5472e-101	1.1098e-95	0	0	0
r1498	1.0504e-113	1.8291e-107	2.035e-101	0	0	0
r1499	5.2066e-120	1.4063e-113	2.427e-107	0	0	0
r1500	1.6783e-126	7.0322e-120	1.8825e-113	0	0	0
r1501	3.5178e-133	2.2867e-126	9.4963e-120	0	0	0
r1502	4.7948e-140	4.8355e-133	3.1152e-126	0	0	0
r1503	4.2493e-147	6.6489e-140	6.6455e-133	0	0	0
r1504	2.4486e-154	5.9445e-147	9.2183e-140	0	0	0
r1505	9.174e-162	3.4557e-154	8.3145e-147	0	0	0
r1506	2.2347e-169	1.3061e-161	4.8761e-154	0	0	0
r1507	3.539e-177	3.2097e-169	1.8592e-161	0	0	0
r1508	3.6436e-185	5.1279e-177	4.6092e-169	0	0	0
r1509	2.4388e-193	5.3261e-185	7.4288e-177	0	0	0
r1510	1.0612e-201	3.5964e-193	7.7841e-185	0	0	0
r1511	3.0016e-210	1.5787e-201	5.3025e-193	1.409e-17	0	0
r1512	5.5194e-219	4.5049e-210	2.3481e-201	2.1698e-15	1.2809e-17	0
r1513	6.5973e-228	8.3567e-219	6.7598e-210	2.2511e-13	1.9649e-15	1.1528e-17
r1514	5.126e-237	1.0077e-227	1.265e-218	1.5277e-11	2.0563e-13	1.7894e-15
r1515	2.5889e-246	7.8987e-237	1.5389e-227	6.791e-10	1.4077e-11	1.8943e-13
r1516	8.4994e-256	4.0246e-246	1.2169e-236	1.979e-08	6.3116e-10	1.3141e-11
r1517	1.8137e-265	1.3329e-255	6.2552e-246	3.7848e-07	1.8552e-08	5.986e-10
r1518	2.5158e-275	2.8695e-265	2.09e-255	4.7555e-06	3.5786e-07	1.7944e-08
r1519	2.2681e-285	4.0153e-275	4.539e-265	3.9298e-05	4.5351e-06	3.5512e-07
r1520	1.3291e-295	3.6521e-285	6.4076e-275	0.00021381	3.7798e-05	4.6596e-06
r1521	5.0624e-306	2.159e-295	5.8794e-285	0.00076658	0.0002074	4.0788e-05
r1522	1.2533e-316	8.296e-306	3.5064e-295	0.0018127	0.00074998	0.00024034
r1523	0	2.0719e-316	1.3592e-305	0.0028288	0.0017886	0.0009663
r1524	0	0	3.4246e-316	0.0029139	0.0028149	0.0027072
r1525	0	0	0	0.0019815	0.0029243	0.0054605

xxx TABLE:pi\_H\_eta xxxxxxxxxxxxxxxxxxxxxxx

	c1	c2	c3	c59	c60	c61
r1	0.47329	0.25346	0.17175	0	0	0
r2	0.23465	0.24398	0.25257	0	0	0

r3	0.083755	0.15503	0.24518	0	0	0
r4	0.020831	0.065005	0.15712	0	0	0
r5	0.0035353	0.017977	0.066444	0	0	0
r6	0.00040387	0.0032761	0.018532	0	0	0
r7	3.078e-05	0.00039308	0.0034061	0	0	0
r8	1.5553e-06	3.1018e-05	0.00041218	0	0	0
r9	5.1884e-08	1.608e-06	3.2805e-05	0	0	0
r10	1.139e-09	5.4706e-08	1.7153e-06	0	0	0
r11	1.6419e-11	1.2201e-09	5.8861e-08	0	0	0
r12	1.5512e-13	1.7823e-11	1.3242e-09	0	0	0
r13	9.5928e-16	1.7037e-13	1.9511e-11	0	0	0
r14	3.8788e-18	1.0648e-15	1.8813e-13	0	0	0
r15	1.0246e-20	4.3487e-18	1.1861e-15	0	0	0
r16	1.7668e-23	1.1597e-20	4.8861e-18	0	0	0
r17	1.9879e-26	2.0184e-23	1.3144e-20	0	0	0
r18	1.4586e-29	2.2917e-26	2.3077e-23	0	0	0
r19	6.9768e-33	1.6966e-29	2.6431e-26	0	0	0
r20	2.1747e-36	8.1877e-33	1.9739e-29	0	0	0
r21	4.4162e-40	2.5748e-36	9.6095e-33	0	0	0
r22	5.8409e-44	5.2749e-40	3.0485e-36	0	0	0
r23	5.0305e-48	7.0383e-44	6.3001e-40	0	0	0
r24	2.8208e-52	6.1152e-48	8.4802e-44	0	0	0
r25	1.0296e-56	3.4592e-52	7.4328e-48	0	0	0
r26	2.4459e-61	1.2737e-56	4.2415e-52	0	0	0
r27	3.7813e-66	3.0526e-61	1.5756e-56	0	0	0
r28	3.8039e-71	4.7609e-66	3.8092e-61	0	0	0
r29	2.4896e-76	4.8314e-71	5.9931e-66	0	0	0
r30	1.0601e-81	3.1901e-76	6.1355e-71	0	0	0
r31	2.9363e-87	1.3703e-81	4.0868e-76	0	0	0
r32	5.2904e-93	3.829e-87	1.771e-81	0	0	0
r33	6.1997e-99	6.9596e-93	4.9923e-87	0	0	0
r34	4.7251e-105	8.2277e-99	9.1539e-93	0	0	0
r35	2.3421e-111	6.3261e-105	1.0917e-98	0	0	0
r36	7.5494e-118	3.1633e-111	8.4681e-105	0	0	0
r37	1.5824e-124	1.0286e-117	4.2717e-111	0	0	0
r38	2.1568e-131	2.1752e-124	1.4013e-117	0	0	0
r39	1.9115e-138	2.9909e-131	2.9894e-124	0	0	0
r40	1.1015e-145	2.674e-138	4.1467e-131	0	0	0
r41	4.1268e-153	1.5545e-145	3.7401e-138	0	0	0
r42	1.0052e-160	5.8754e-153	2.1934e-145	0	0	0
r43	1.5919e-168	1.4438e-160	8.3634e-153	0	0	0
r44	1.639e-176	2.3067e-168	2.0733e-160	0	0	0
r45	1.097e-184	2.3958e-176	3.3417e-168	0	0	0
r46	4.7734e-193	1.6178e-184	3.5015e-176	0	0	0
r47	1.3502e-201	7.1013e-193	2.3852e-184	1.2212e-15	0	0
r48	2.4828e-210	2.0264e-201	1.0563e-192	1.8807e-13	1.1102e-15	0
r49	2.9676e-219	3.7591e-210	3.0408e-201	1.9511e-11	1.7031e-13	9.992e-16
r50	2.3058e-228	4.5329e-219	5.6905e-210	1.3242e-09	1.7823e-11	1.551e-13
r51	1.1646e-237	3.5531e-228	6.9224e-219	5.8861e-08	1.2201e-09	1.6419e-11
r52	3.8233e-247	1.8104e-237	5.474e-228	1.7153e-06	5.4706e-08	1.139e-09
r53	8.1587e-257	5.9959e-247	2.8138e-237	3.2805e-05	1.608e-06	5.1884e-08
r54	1.1317e-266	1.2908e-256	9.4014e-247	0.00041218	3.1018e-05	1.5553e-06
r55	1.0203e-276	1.8062e-266	2.0418e-256	0.0034061	0.00039308	3.078e-05
r56	5.9788e-287	1.6428e-276	2.8823e-266	0.018532	0.0032761	0.00040387
r57	2.2772e-297	9.7119e-287	2.6447e-276	0.066444	0.017977	0.0035353
r58	5.6375e-308	3.7318e-297	1.5773e-286	0.15712	0.065005	0.020831
r59	9.0709e-319	9.32e-308	6.1143e-297	0.24518	0.15503	0.083755
r60	0	1.5129e-318	1.5405e-307	0.25257	0.24398	0.23465

r61	0	0	2.5227e-318	0.17175	0.25346	0.47329
<b>xxx TABLE:pi_S_eta xxxxxxxxxxxxxxxxxxxxxxxx</b>						
c1	c2	c3	c4	c5		
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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	
<b>xxx TABLE:pi_eta xxxxxxxxxxxxxxxxxxxxxxxx</b>						
c1	c2	c3	c303	c304	c305	
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r1	0.0057857	0.0030985	0.0020995	0	0	0
r2	0.0028684	0.0029825	0.0030875	0	0	0
r3	0.0010239	0.0018951	0.0029973	0	0	0
r4	0.00025465	0.00079465	0.0019207	0	0	0
r5	4.3217e-05	0.00021976	0.00081224	0	0	0
r6	4.9371e-06	4.0049e-05	0.00022654	0	0	0
r7	3.7627e-07	4.8052e-06	4.1638e-05	0	0	0
r8	1.9013e-08	3.7918e-07	5.0387e-06	0	0	0
r9	6.3425e-10	1.9657e-08	4.0102e-07	0	0	0
r10	1.3924e-11	6.6875e-10	2.0969e-08	0	0	0
r11	2.0071e-13	1.4915e-11	7.1954e-10	0	0	0
r12	1.8963e-15	2.1788e-13	1.6187e-11	0	0	0
r13	1.1727e-17	2.0827e-15	2.3851e-13	0	0	0
r14	4.7416e-20	1.3017e-17	2.2998e-15	0	0	0
r15	1.2525e-22	5.3161e-20	1.4499e-17	0	0	0
r16	2.1598e-25	1.4177e-22	5.973e-20	0	0	0
r17	2.4301e-28	2.4674e-25	1.6068e-22	0	0	0
r18	1.7831e-31	2.8014e-28	2.821e-25	0	0	0
r19	8.5288e-35	2.074e-31	3.231e-28	0	0	0
r20	2.6585e-38	1.0009e-34	2.413e-31	0	0	0
r21	5.3985e-42	3.1476e-38	1.1747e-34	0	0	0
r22	7.1402e-46	6.4483e-42	3.7266e-38	0	0	0
r23	6.1496e-50	8.6039e-46	7.7016e-42	0	0	0
r24	3.4482e-54	7.4756e-50	1.0367e-45	0	0	0
r25	1.2586e-58	4.2287e-54	9.0863e-50	0	0	0
r26	2.99e-63	1.5571e-58	5.185e-54	0	0	0
r27	4.6225e-68	3.7316e-63	1.926e-58	0	0	0
r28	4.65e-73	5.8199e-68	4.6565e-63	0	0	0
r29	3.0435e-78	5.9062e-73	7.3263e-68	0	0	0
r30	1.2959e-83	3.8997e-78	7.5004e-73	0	0	0
r31	3.5895e-89	1.6751e-83	4.9959e-78	0	0	0
r32	6.4672e-95	4.6808e-89	2.1649e-83	0	0	0
r33	7.5788e-101	8.5078e-95	6.1028e-89	0	0	0
r34	5.7762e-107	1.0058e-100	1.119e-94	0	0	0
r35	2.8631e-113	7.7334e-107	1.3346e-100	0	0	0
r36	9.2288e-120	3.867e-113	1.0352e-106	0	0	0
r37	1.9344e-126	1.2575e-119	5.2219e-113	0	0	0
r38	2.6366e-133	2.659e-126	1.713e-119	0	0	0
r39	2.3367e-140	3.6562e-133	3.6543e-126	0	0	0
r40	1.3465e-147	3.2689e-140	5.0691e-133	0	0	0
r41	5.0447e-155	1.9003e-147	4.5721e-140	0	0	0
r42	1.2288e-162	7.1823e-155	2.6813e-147	0	0	0

r43	1.9461e-170	1.765e-162	1.0224e-154	0	0	0
r44	2.0036e-178	2.8198e-170	2.5346e-162	0	0	0
r45	1.3411e-186	2.9288e-178	4.085e-170	0	0	0
r46	5.8353e-195	1.9776e-186	4.2804e-178	0	0	0
r47	1.6506e-203	8.681e-195	2.9158e-186	1.4929e-17	0	0
r48	3.0351e-212	2.4772e-203	1.2912e-194	2.2991e-15	1.3572e-17	0
r49	3.6278e-221	4.5953e-212	3.7172e-203	2.3851e-13	2.0819e-15	1.2215e-17
r50	2.8187e-230	5.5412e-221	6.9563e-212	1.6187e-11	2.1788e-13	1.896e-15
r256	1.8963e-15	2.1788e-13	1.6187e-11	0	0	0
r257	1.1727e-17	2.0827e-15	2.3851e-13	0	0	0
r258	4.7416e-20	1.3017e-17	2.2998e-15	0	0	0
r259	1.2525e-22	5.3161e-20	1.4499e-17	0	0	0
r260	2.1598e-25	1.4177e-22	5.973e-20	0	0	0
r261	2.4301e-28	2.4674e-25	1.6068e-22	0	0	0
r262	1.7831e-31	2.8014e-28	2.821e-25	0	0	0
r263	8.5288e-35	2.074e-31	3.231e-28	0	0	0
r264	2.6585e-38	1.0009e-34	2.413e-31	0	0	0
r265	5.3985e-42	3.1476e-38	1.1747e-34	0	0	0
r266	7.1402e-46	6.4483e-42	3.7266e-38	0	0	0
r267	6.1496e-50	8.6039e-46	7.7016e-42	0	0	0
r268	3.4482e-54	7.4756e-50	1.0367e-45	0	0	0
r269	1.2586e-58	4.2287e-54	9.0863e-50	0	0	0
r270	2.99e-63	1.5571e-58	5.185e-54	0	0	0
r271	4.6225e-68	3.7316e-63	1.926e-58	0	0	0
r272	4.65e-73	5.8199e-68	4.6565e-63	0	0	0
r273	3.0435e-78	5.9062e-73	7.3263e-68	0	0	0
r274	1.2959e-83	3.8997e-78	7.5004e-73	0	0	0
r275	3.5895e-89	1.6751e-83	4.9959e-78	0	0	0
r276	6.4672e-95	4.6808e-89	2.1649e-83	0	0	0
r277	7.5788e-101	8.5078e-95	6.1028e-89	0	0	0
r278	5.7762e-107	1.0058e-100	1.119e-94	0	0	0
r279	2.8631e-113	7.7334e-107	1.3346e-100	0	0	0
r280	9.2288e-120	3.867e-113	1.0352e-106	0	0	0
r281	1.9344e-126	1.2575e-119	5.2219e-113	0	0	0
r282	2.6366e-133	2.659e-126	1.713e-119	0	0	0
r283	2.3367e-140	3.6562e-133	3.6543e-126	0	0	0
r284	1.3465e-147	3.2689e-140	5.0691e-133	0	0	0
r285	5.0447e-155	1.9003e-147	4.5721e-140	0	0	0
r286	1.2288e-162	7.1823e-155	2.6813e-147	0	0	0
r287	1.9461e-170	1.765e-162	1.0224e-154	0	0	0
r288	2.0036e-178	2.8198e-170	2.5346e-162	0	0	0
r289	1.3411e-186	2.9288e-178	4.085e-170	0	0	0
r290	5.8353e-195	1.9776e-186	4.2804e-178	0	0	0
r291	1.6506e-203	8.681e-195	2.9158e-186	1.4929e-17	0	0
r292	3.0351e-212	2.4772e-203	1.2912e-194	2.2991e-15	1.3572e-17	0
r293	3.6278e-221	4.5953e-212	3.7172e-203	2.3851e-13	2.0819e-15	1.2215e-17
r294	2.8187e-230	5.5412e-221	6.9563e-212	1.6187e-11	2.1788e-13	1.896e-15
r295	1.4236e-239	4.3435e-230	8.4623e-221	7.1954e-10	1.4915e-11	2.0071e-13
r296	4.6738e-249	2.2131e-239	6.6917e-230	2.0969e-08	6.6875e-10	1.3924e-11
r297	9.9736e-259	7.3296e-249	3.4397e-239	4.0102e-07	1.9657e-08	6.3425e-10
r298	1.3834e-268	1.5779e-258	1.1493e-248	5.0387e-06	3.7918e-07	1.9013e-08
r299	1.2472e-278	2.208e-268	2.496e-258	4.1638e-05	4.8052e-06	3.7627e-07
r300	7.3088e-289	2.0082e-278	3.5235e-268	0.00022654	4.0049e-05	4.9371e-06
r301	2.7838e-299	1.1872e-288	3.233e-278	0.00081224	0.00021976	4.3217e-05
r302	6.8916e-310	4.5619e-299	...			

### 1.1.2 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.

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

```
-----
```

```
xxxxxxxxxxxxxxxxxxxxxxxxxxxxxxxxxxxxx
CONTAINER NAME: mp_params_preftechpricegov Scalars
xxxxxxxxxxxxxxxxxxxxxxxxxxxxxxxxxxxxx
```

	i	idx	value
	--	--	-----
Bequests	1	1	0
a2	2	2	1.5286
bequests_option	3	3	1
beta	4	4	0.86389
cons_allocation_rule	5	5	2
g_cons	6	6	0.17576
g_n	7	7	0.05101
gamma	8	8	2
jret	9	9	13
r	10	10	0.21665
theta	11	11	0.56523
throw_in_ocean	12	12	1

```
-----
```

```
xxxxxxxxxxxxxxxxxxxxxxxxxxxxxxxxxxxxx
CONTAINER NAME: mp_params_intlen Scalars
xxxxxxxxxxxxxxxxxxxxxxxxxxxxxxxxxxxxx
```

	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

```
-----
```

```
xxxxxxxxxxxxxxxxxxxxxxxxxxxxxxxxxxxxx
CONTAINER NAME: mp_params_covid_unemploy ND Array (Matrix etc)
xxxxxxxxxxxxxxxxxxxxxxxxxxxxxxxxxxxxx
```

	i	idx	ndim	numel	rowN	colN	sum	mean	std	coeff
	-	--	----	-----	----	----	-----	-----	-----	-----
inc_grid	1	3	2	201	201	1	578.5	2.8781	1.8836	0.654
pi_unemp	2	6	2	240	48	5	9.5319	0.039716	0.019674	0.495

```
xxx TABLE:inc_grid xxxxxxxxxxxxxxxx
      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	0.080278	0.051706	0.041502	0.03538	0.025176
r2	0.080278	0.051706	0.041502	0.03538	0.025176
r3	0.080278	0.051706	0.041502	0.03538	0.025176
r4	0.080278	0.051706	0.041502	0.03538	0.025176
r5	0.080278	0.051706	0.041502	0.03538	0.025176
r6	0.080278	0.051706	0.041502	0.03538	0.025176
r7	0.080278	0.051706	0.041502	0.03538	0.025176
r8	0.080278	0.051706	0.041502	0.03538	0.025176
r9	0.080278	0.051706	0.041502	0.03538	0.025176
r10	0.080278	0.051706	0.041502	0.03538	0.025176
r11	0.080278	0.051706	0.041502	0.03538	0.025176
r12	0.080278	0.051706	0.041502	0.03538	0.025176
r13	0.080278	0.051706	0.041502	0.03538	0.025176

r14	0.070703	0.042132	0.031928	0.025805	0.015601
r15	0.070703	0.042132	0.031928	0.025805	0.015601
r16	0.070703	0.042132	0.031928	0.025805	0.015601
r17	0.070703	0.042132	0.031928	0.025805	0.015601
r18	0.070703	0.042132	0.031928	0.025805	0.015601
r19	0.070703	0.042132	0.031928	0.025805	0.015601
r20	0.070703	0.042132	0.031928	0.025805	0.015601
r21	0.070703	0.042132	0.031928	0.025805	0.015601
r22	0.070703	0.042132	0.031928	0.025805	0.015601
r23	0.070703	0.042132	0.031928	0.025805	0.015601
r24	0.067512	0.038941	0.028736	0.022614	0.01241
r25	0.067512	0.038941	0.028736	0.022614	0.01241
r26	0.067512	0.038941	0.028736	0.022614	0.01241
r27	0.067512	0.038941	0.028736	0.022614	0.01241
r28	0.067512	0.038941	0.028736	0.022614	0.01241
r29	0.067512	0.038941	0.028736	0.022614	0.01241
r30	0.067512	0.038941	0.028736	0.022614	0.01241
r31	0.067512	0.038941	0.028736	0.022614	0.01241
r32	0.067512	0.038941	0.028736	0.022614	0.01241
r33	0.067512	0.038941	0.028736	0.022614	0.01241
r34	0.068576	0.040004	0.0298	0.023678	0.013474
r35	0.068576	0.040004	0.0298	0.023678	0.013474
r36	0.068576	0.040004	0.0298	0.023678	0.013474
r37	0.068576	0.040004	0.0298	0.023678	0.013474
r38	0.068576	0.040004	0.0298	0.023678	0.013474
r39	0.068576	0.040004	0.0298	0.023678	0.013474
r40	0.068576	0.040004	0.0298	0.023678	0.013474
r41	0.068576	0.040004	0.0298	0.023678	0.013474
r42	0.068576	0.040004	0.0298	0.023678	0.013474
r43	0.068576	0.040004	0.0298	0.023678	0.013474
r44	0.080278	0.051706	0.041502	0.03538	0.025176
r45	0.080278	0.051706	0.041502	0.03538	0.025176
r46	0.080278	0.051706	0.041502	0.03538	0.025176
r47	0.080278	0.051706	0.041502	0.03538	0.025176
r48	0.080278	0.051706	0.041502	0.03538	0.025176

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

	i	idx	value
-	-	---	-----
TR	1	1	0.0017225
b	2	2	1
n_incgrid	3	4	201
n_welfchecksgrid	4	5	45
scaleconvertor	5	7	58056
xi	6	8	0.75

-----  
xxxxxxxxxxxxxxxxxxxxxxxxxxxxxxxxxxxx  
CONTAINER NAME: mp\_params\_statesgrid ND Array (Matrix etc)  
xxxxxxxxxxxxxxxxxxxxxxxxxxxxxxxxxxxx

	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

xxx TABLE:agrid xxxxxxxxxxxxxxxxxxxxxxxx
      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)
xxxxxxxxxxxxxxxxxxxxxxxxxxxxxxxxxxxxx

```

	c1	c2	c3	c13	c14	c15		
cl_mt_pi_jem_kidseta	1	1	2	225	15	15	15	0.066667 0.200
pi_H_eta	2	2	2	25	5	5	5	0.2 0.385
pi_eta	3	4	2	25	5	5	5	0.2 0.385
pi_kids	4	5	5	648	3	216	216	0.33333 0.356
psi	5	6	2	18	18	1	14.251	0.79171 0.312
<b>xxx TABLE:cl_mt_pi_jem_kidseta xxxxxxxxxxxxxxxxxxxxxxxx</b>								
r1	0.8194	0.066439	4.258e-10	1.3413e-12	0	0	0	
r2	0.0023536	0.85739	0.026096	8.2205e-05	7.2608e-14	0	0	
r3	1.0239e-12	0.008585	0.86867	0.0027364	2.7043e-05	3.2254e-15		
r4	1.1339e-29	2.3049e-11	0.026096	8.2205e-05	0.0027009	7.414e-06		
r5	2.525e-54	1.6656e-27	4.258e-10	1.3413e-12	0.00020929	0.0025812		
r6	0.047493	0.0038508	2.468e-11	1.3763e-10	0	0	0	
r7	0.00013641	0.049695	0.0015125	0.0084347	7.4499e-12	0	0	
r8	5.9343e-14	0.00049759	0.050348	0.28077	0.0027748	3.3094e-13		
r9	6.5721e-31	1.3359e-12	0.0015125	0.0084347	0.27712	0.00076071		
r10	1.4635e-55	9.6537e-29	2.468e-11	1.3763e-10	0.021474	0.26484		
r11	0.00013898	0.00011269	7.2224e-13	4.4952e-10	0	0		
r12	3.9921e-06	0.0014543	4.4263e-05	0.02755	2.4333e-11	0		
r13	1.7366e-15	1.4562e-05	0.0014734	0.91706	0.0090632	1.0809e-12		
r14	1.9233e-32	3.9096e-14	4.4263e-05	0.02755	0.90515	0.0024847		
r15	4.2828e-57	2.8251e-30	7.2224e-13	4.4952e-10	0.07014	0.86505		
<b>xxx TABLE:pi_H_eta xxxxxxxxxxxxxxxxxxxxxxxx</b>								
r1	0.925	0.075001	4.8068e-10	0	0	0		
r2	0.0026569	0.96788	0.029459	2.602e-11	0	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			
<b>xxx TABLE:pi_eta xxxxxxxxxxxxxxxxxxxxxxxx</b>								
r1	0.925	0.075001	4.8068e-10	0	0	0		
r2	0.0026569	0.96788	0.029459	2.602e-11	0	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			
<b>xxx TABLE:pi_kids xxxxxxxxxxxxxxxxxxxxxxxx</b>								
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		
<b>xxx TABLE:psi xxxxxxxxxxxxxxxxxxxxxxxx</b>								
	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

-----
xxxxxxxxxxxxxxxxxxxxxxxxxxxxxxxxxxxxxx
CONTAINER NAME: mp_params_exotrans Scalars
xxxxxxxxxxxxxxxxxxxxxxxxxxxxxxxxxxxxxx
          i      idx      value
          -      ---      -----
pi_S_eta   1        3        1

-----
xxxxxxxxxxxxxxxxxxxxxxxxxxxxxxxxxxxxxx
CONTAINER NAME: mp_params_typelife ND Array (Matrix etc)
xxxxxxxxxxxxxxxxxxxxxxxxxxxxxxxxxxxxxx
          i      idx      ndim      numel      rowN      colN      sum      mean      std      coefvar
          -      ---      ---      -----      ----      ----      -----      -----      -----      -----
SS         1        1        2        36        18        2        3.2218    0.089493    0.12913    1.443
epsilon    2        2        2        36        18        2        39.526     1.0979    0.85451    0.77828

xxx TABLE:SS xxxxxxxxxxxxxxxxxxxx
          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     0.24433  0.29263
r14     0.24433  0.29263
```

r15	0.24433	0.29263
r16	0.24433	0.29263
r17	0.24433	0.29263
r18	0.24433	0.29263

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

xxxxxxxxxxxxxxxxxxxxxxxxxxxxxxxxxxxxx

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

xxxxxxxxxxxxxxxxxxxxxxxxxxxxxxxxxxxxx

	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 xxxxxxxxxxxxxxxxxxxxx
      c1      c2
      -----
r1     0.5635    0.4365
r2     0.4364    0.5636

-----
xxxxxxxxxxxxxxxxxxxxxxxxxxxxxxxxxxxxx
CONTAINER NAME: mp_params_stat String
xxxxxxxxxxxxxxxxxxxxxxxxxxxxxxxxxxxxx
      i      idx          string
      ---  ---
st_old_age_depend    "1"    "2"    "Old-age dependency ratio (ratio of 65+/(18-64))=0.1155"

```

### 1.1.3 Parameters Used for Paper Simulations

Using 266 household head income shocks. Requires 150GB of memory.

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

## 1.2 Model Controls

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

### 1.2.1 Test SNW\_MP\_CONTROLS Defaults

Call the function with defaults.

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

```

pos = 21 ; key = options
fmincon options:

Options used by current Algorithm ('interior-point'):
(Other available algorithms: 'active-set', 'sqp', 'sqp-legacy', 'trust-region-reflective')

Set properties:
    Display: 'off'

Default properties:
    Algorithm: 'interior-point'
    CheckGradients: 0
    ConstraintTolerance: 1.0000e-06
    FiniteDifferenceStepSize: 'sqrt(eps)'
    FiniteDifferenceType: 'forward'
    HessianApproximation: 'bfgs'
        HessianFcn: []
    HessianMultiplyFcn: []
    HonorBounds: 1
    MaxFunctionEvaluations: 3000
        MaxIterations: 1000
        ObjectiveLimit: -1.0000e+20
    OptimalityTolerance: 1.0000e-06
        OutputFcn: []
        PlotFcn: []
    ScaleProblem: 0
    SpecifyConstraintGradient: 0
    SpecifyObjectiveGradient: 0
        StepTolerance: 1.0000e-10
    SubproblemAlgorithm: 'factorization'
        TypicalX: 'ones(numberOfVariables,1)'
    UseParallel: 0

Show options not used by current Algorithm ('interior-point')

pos = 22 ; key = options2
fsolve options:

Options used by current Algorithm ('trust-region-dogleg'):
(Other available algorithms: 'levenberg-marquardt', 'trust-region')

Set properties:
    Display: 'off'

Default properties:
    Algorithm: 'trust-region-dogleg'
    CheckGradients: 0
    FiniteDifferenceStepSize: 'sqrt(eps)'
        FiniteDifferenceType: 'forward'
        FunctionTolerance: 1.0000e-06
    MaxFunctionEvaluations: '100*numberOfVariables'
        MaxIterations: 400
    OptimalityTolerance: 1.0000e-06
        OutputFcn: []
        PlotFcn: []
    SpecifyObjectiveGradient: 0
        StepTolerance: 1.0000e-06
        TypicalX: 'ones(numberOfVariables,1)'

```

```

UseParallel: 0

Show options not used by current Algorithm ('trust-region-dogleg')

-----
xxxxxxxxxxxxxxxxxxxxxxxxxxxxxxxxxxxxxx
CONTAINER NAME: mp_controls Scalars
xxxxxxxxxxxxxxxxxxxxxxxxxxxxxxxxxxxxxx
      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_ds_store_all    6        6      0
bl_print_a4chk     7        7      1
bl_print_a4chk_verbose 8        8      0
bl_print_ds        9        9      1
bl_print_ds_verbose 10       10     0
bl_print_vfi       11       11     1
bl_print_vfi_verbose 12       12     0
bl_print_vu_vw     13       13     1
bl_print_vu_vw_verbose 14       14     0
bl_timer         15       15     1
bl_vfi_store_all 16       16     0
err            17       17     1
fl_max_trchk_perc_increase 18       18     1.5
nonlcon         19       20     NaN
tol            20       23     0.005

-----
xxxxxxxxxxxxxxxxxxxxxxxxxxxxxxxxxxxxxx
CONTAINER NAME: mp_controls String
xxxxxxxxxxxxxxxxxxxxxxxxxxxxxxxxxxxxxx
      i      idx      string
      ---      ---      -----
mp_params_name    "1"      "19"      "default_base"

```

# Chapter 2

## Solving the Dynamic Life Cycle Problem

### 2.1 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. More Dense Solution Analysis.

#### 2.1.1 Test SNW\_VFI\_MAIN\_BISECT\_VEC Defaults More Dense

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:1.3477
SNW_VFI_MAIN_BISEC_VEC: Finished Age Group:82 of 82, time-this-age:2.772
SNW_VFI_MAIN_BISEC_VEC: Finished Age Group:81 of 82, time-this-age:2.6886
SNW_VFI_MAIN_BISEC_VEC: Finished Age Group:80 of 82, time-this-age:2.6034
SNW_VFI_MAIN_BISEC_VEC: Finished Age Group:79 of 82, time-this-age:2.4025
SNW_VFI_MAIN_BISEC_VEC: Finished Age Group:78 of 82, time-this-age:2.5892
SNW_VFI_MAIN_BISEC_VEC: Finished Age Group:77 of 82, time-this-age:2.4135
SNW_VFI_MAIN_BISEC_VEC: Finished Age Group:76 of 82, time-this-age:2.5798
SNW_VFI_MAIN_BISEC_VEC: Finished Age Group:75 of 82, time-this-age:2.4211
SNW_VFI_MAIN_BISEC_VEC: Finished Age Group:74 of 82, time-this-age:2.5768
SNW_VFI_MAIN_BISEC_VEC: Finished Age Group:73 of 82, time-this-age:2.5754
SNW_VFI_MAIN_BISEC_VEC: Finished Age Group:72 of 82, time-this-age:2.6072
SNW_VFI_MAIN_BISEC_VEC: Finished Age Group:71 of 82, time-this-age:2.5104
SNW_VFI_MAIN_BISEC_VEC: Finished Age Group:70 of 82, time-this-age:2.5658
SNW_VFI_MAIN_BISEC_VEC: Finished Age Group:69 of 82, time-this-age:2.4148
SNW_VFI_MAIN_BISEC_VEC: Finished Age Group:68 of 82, time-this-age:2.5182
SNW_VFI_MAIN_BISEC_VEC: Finished Age Group:67 of 82, time-this-age:2.3762
SNW_VFI_MAIN_BISEC_VEC: Finished Age Group:66 of 82, time-this-age:2.5053
SNW_VFI_MAIN_BISEC_VEC: Finished Age Group:65 of 82, time-this-age:2.4224
SNW_VFI_MAIN_BISEC_VEC: Finished Age Group:64 of 82, time-this-age:2.5013
SNW_VFI_MAIN_BISEC_VEC: Finished Age Group:63 of 82, time-this-age:2.4094
SNW_VFI_MAIN_BISEC_VEC: Finished Age Group:62 of 82, time-this-age:2.4546
SNW_VFI_MAIN_BISEC_VEC: Finished Age Group:61 of 82, time-this-age:2.3964
SNW_VFI_MAIN_BISEC_VEC: Finished Age Group:60 of 82, time-this-age:2.5196
SNW_VFI_MAIN_BISEC_VEC: Finished Age Group:59 of 82, time-this-age:2.3948
SNW_VFI_MAIN_BISEC_VEC: Finished Age Group:58 of 82, time-this-age:2.5256
```

```

SNW_VFI_MAIN_BISEC_VEC: Finished Age Group:57 of 82, time-this-age:2.3984
SNW_VFI_MAIN_BISEC_VEC: Finished Age Group:56 of 82, time-this-age:2.5195
SNW_VFI_MAIN_BISEC_VEC: Finished Age Group:55 of 82, time-this-age:2.4202
SNW_VFI_MAIN_BISEC_VEC: Finished Age Group:54 of 82, time-this-age:2.5087
SNW_VFI_MAIN_BISEC_VEC: Finished Age Group:53 of 82, time-this-age:2.3967
SNW_VFI_MAIN_BISEC_VEC: Finished Age Group:52 of 82, time-this-age:2.5908
SNW_VFI_MAIN_BISEC_VEC: Finished Age Group:51 of 82, time-this-age:2.4273
SNW_VFI_MAIN_BISEC_VEC: Finished Age Group:50 of 82, time-this-age:2.4934
SNW_VFI_MAIN_BISEC_VEC: Finished Age Group:49 of 82, time-this-age:2.4106
SNW_VFI_MAIN_BISEC_VEC: Finished Age Group:48 of 82, time-this-age:2.4987
SNW_VFI_MAIN_BISEC_VEC: Finished Age Group:47 of 82, time-this-age:2.5508
SNW_VFI_MAIN_BISEC_VEC: Finished Age Group:46 of 82, time-this-age:2.6959
SNW_VFI_MAIN_BISEC_VEC: Finished Age Group:45 of 82, time-this-age:2.5636
SNW_VFI_MAIN_BISEC_VEC: Finished Age Group:44 of 82, time-this-age:2.6548
SNW_VFI_MAIN_BISEC_VEC: Finished Age Group:43 of 82, time-this-age:2.5629
SNW_VFI_MAIN_BISEC_VEC: Finished Age Group:42 of 82, time-this-age:2.6513
SNW_VFI_MAIN_BISEC_VEC: Finished Age Group:41 of 82, time-this-age:2.542
SNW_VFI_MAIN_BISEC_VEC: Finished Age Group:40 of 82, time-this-age:2.6668
SNW_VFI_MAIN_BISEC_VEC: Finished Age Group:39 of 82, time-this-age:2.543
SNW_VFI_MAIN_BISEC_VEC: Finished Age Group:38 of 82, time-this-age:2.6489
SNW_VFI_MAIN_BISEC_VEC: Finished Age Group:37 of 82, time-this-age:2.5832
SNW_VFI_MAIN_BISEC_VEC: Finished Age Group:36 of 82, time-this-age:2.6481
SNW_VFI_MAIN_BISEC_VEC: Finished Age Group:35 of 82, time-this-age:2.6059
SNW_VFI_MAIN_BISEC_VEC: Finished Age Group:34 of 82, time-this-age:2.7
SNW_VFI_MAIN_BISEC_VEC: Finished Age Group:33 of 82, time-this-age:2.5998
SNW_VFI_MAIN_BISEC_VEC: Finished Age Group:32 of 82, time-this-age:2.6749
SNW_VFI_MAIN_BISEC_VEC: Finished Age Group:31 of 82, time-this-age:2.5805
SNW_VFI_MAIN_BISEC_VEC: Finished Age Group:30 of 82, time-this-age:2.649
SNW_VFI_MAIN_BISEC_VEC: Finished Age Group:29 of 82, time-this-age:2.5965
SNW_VFI_MAIN_BISEC_VEC: Finished Age Group:28 of 82, time-this-age:2.6474
SNW_VFI_MAIN_BISEC_VEC: Finished Age Group:27 of 82, time-this-age:2.593
SNW_VFI_MAIN_BISEC_VEC: Finished Age Group:26 of 82, time-this-age:2.6669
SNW_VFI_MAIN_BISEC_VEC: Finished Age Group:25 of 82, time-this-age:2.6025
SNW_VFI_MAIN_BISEC_VEC: Finished Age Group:24 of 82, time-this-age:2.6214
SNW_VFI_MAIN_BISEC_VEC: Finished Age Group:23 of 82, time-this-age:2.5912
SNW_VFI_MAIN_BISEC_VEC: Finished Age Group:22 of 82, time-this-age:2.7036
SNW_VFI_MAIN_BISEC_VEC: Finished Age Group:21 of 82, time-this-age:2.5499
SNW_VFI_MAIN_BISEC_VEC: Finished Age Group:20 of 82, time-this-age:2.6382
SNW_VFI_MAIN_BISEC_VEC: Finished Age Group:19 of 82, time-this-age:2.6067
SNW_VFI_MAIN_BISEC_VEC: Finished Age Group:18 of 82, time-this-age:2.6643
SNW_VFI_MAIN_BISEC_VEC: Finished Age Group:17 of 82, time-this-age:2.5918
SNW_VFI_MAIN_BISEC_VEC: Finished Age Group:16 of 82, time-this-age:2.6505
SNW_VFI_MAIN_BISEC_VEC: Finished Age Group:15 of 82, time-this-age:2.6052
SNW_VFI_MAIN_BISEC_VEC: Finished Age Group:14 of 82, time-this-age:2.6762
SNW_VFI_MAIN_BISEC_VEC: Finished Age Group:13 of 82, time-this-age:2.6089
SNW_VFI_MAIN_BISEC_VEC: Finished Age Group:12 of 82, time-this-age:2.6791
SNW_VFI_MAIN_BISEC_VEC: Finished Age Group:11 of 82, time-this-age:2.6401
SNW_VFI_MAIN_BISEC_VEC: Finished Age Group:10 of 82, time-this-age:2.8111
SNW_VFI_MAIN_BISEC_VEC: Finished Age Group:9 of 82, time-this-age:2.6367
SNW_VFI_MAIN_BISEC_VEC: Finished Age Group:8 of 82, time-this-age:2.6476
SNW_VFI_MAIN_BISEC_VEC: Finished Age Group:7 of 82, time-this-age:2.6136
SNW_VFI_MAIN_BISEC_VEC: Finished Age Group:6 of 82, time-this-age:2.69
SNW_VFI_MAIN_BISEC_VEC: Finished Age Group:5 of 82, time-this-age:2.6314
SNW_VFI_MAIN_BISEC_VEC: Finished Age Group:4 of 82, time-this-age:2.6429
SNW_VFI_MAIN_BISEC_VEC: Finished Age Group:3 of 82, time-this-age:2.6004
SNW_VFI_MAIN_BISEC_VEC: Finished Age Group:2 of 82, time-this-age:2.7677
SNW_VFI_MAIN_BISEC_VEC: Finished Age Group:1 of 82, time-this-age:2.625
Completed SNW_VFI_MAIN_BISEC_VEC;SNW_MP_PARAM=default_docdense;SNW_MP_CONTROL=default_base;time=213.

```

### 2.1.2 More 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_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});
```

### 2.1.3 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];
```

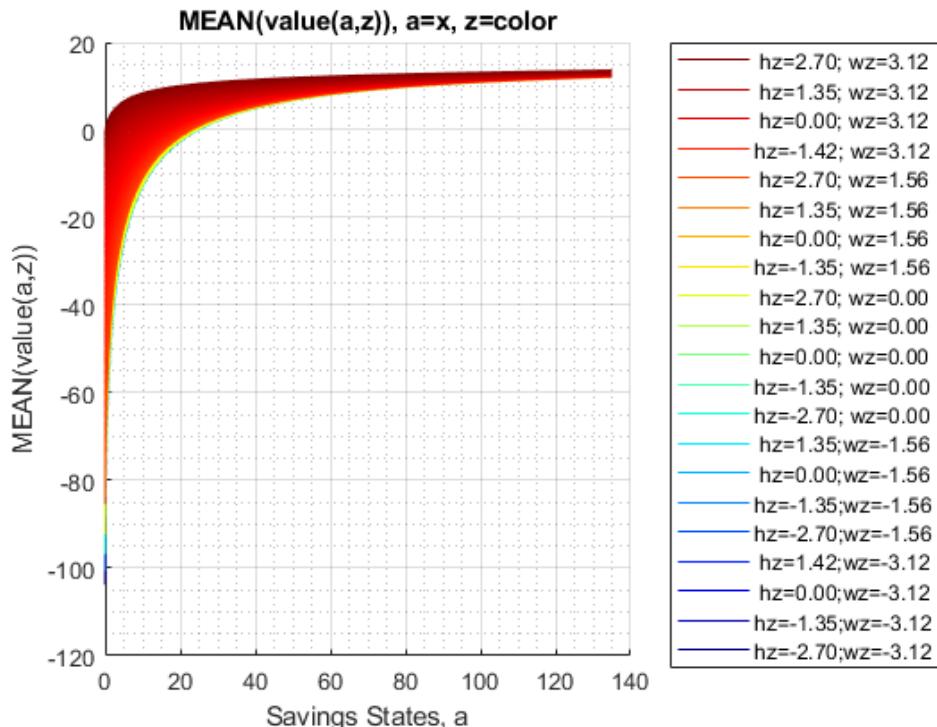
**al\_permit** = 1,  
% Value Function

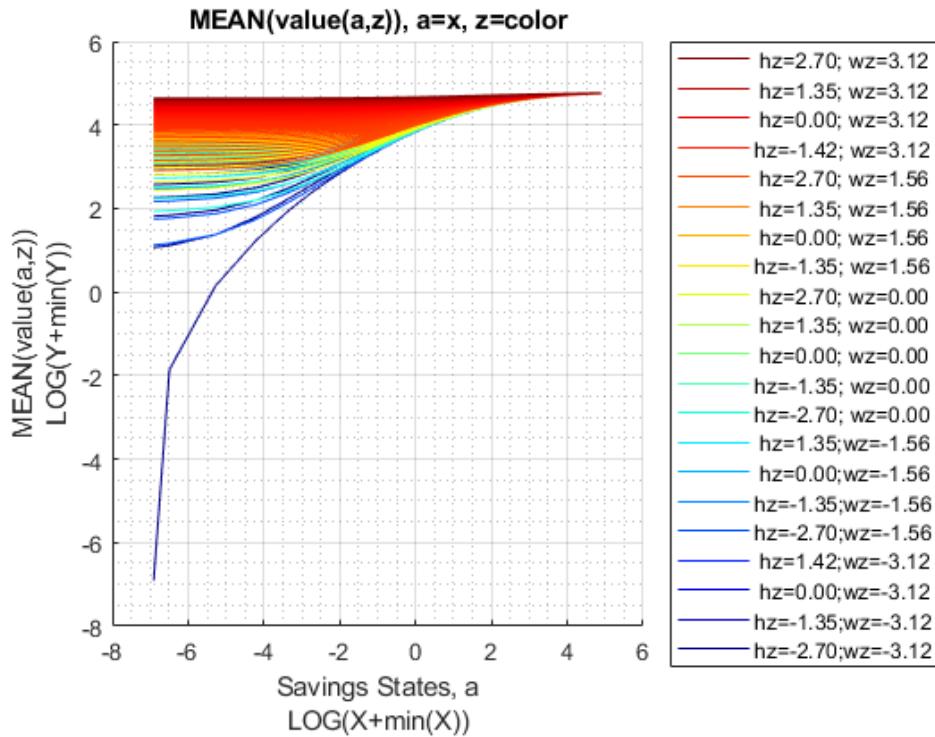
```
% Value Function
tb_az_v = ff_summ_nd_array("MEAN(VAL(A,Z))", V_VFI, true, ["mean"], 4, 1, cl_mp_datasetdesc, ar_perm)

xxx MEAN(VAL(A,Z)) xxxxxxxxxxxxxxxxxxxxxxxxx
    group      savings      mean_eta_1      mean_eta_2      mean_eta_3      mean_eta_4      mean_eta_5      mean_eta_6
    -----      -----      -----      -----      -----      -----      -----      -----
        1          0     -103.74     -100.83     -97.586     -94.14     -90.628     -87.162
```

xxx MEAN(C(A,Z))	group	savings	mean_eta_1	mean_eta_2	mean_eta_3	mean_eta_4	mean_eta_5	mea
-----	1	0	0.14271	0.14506	0.14755	0.15021	0.15304	0.

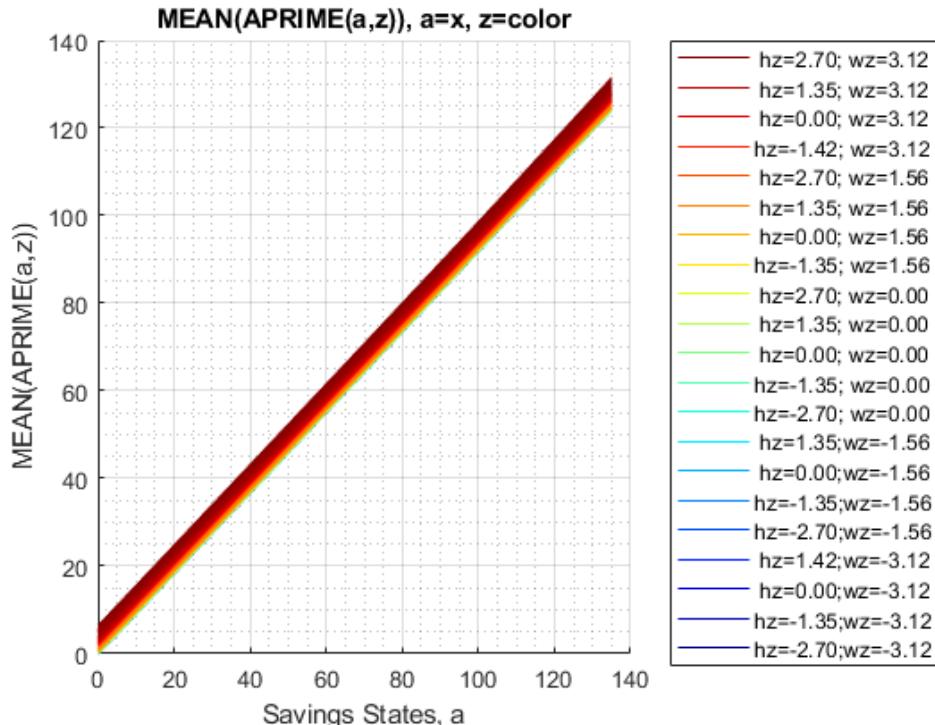
```
mp_support_graph('cl_st_graph_title') = {'MEAN(value(a,z)), a=x, z=color'};
mp_support_graph('cl_st_ytitle') = {'MEAN(value(a,z))'};
ff_graph_grid((tb_az_v{1:end, 3:end}'), ar_st_eta_HS_grid, agrid, mp_support_graph);
```

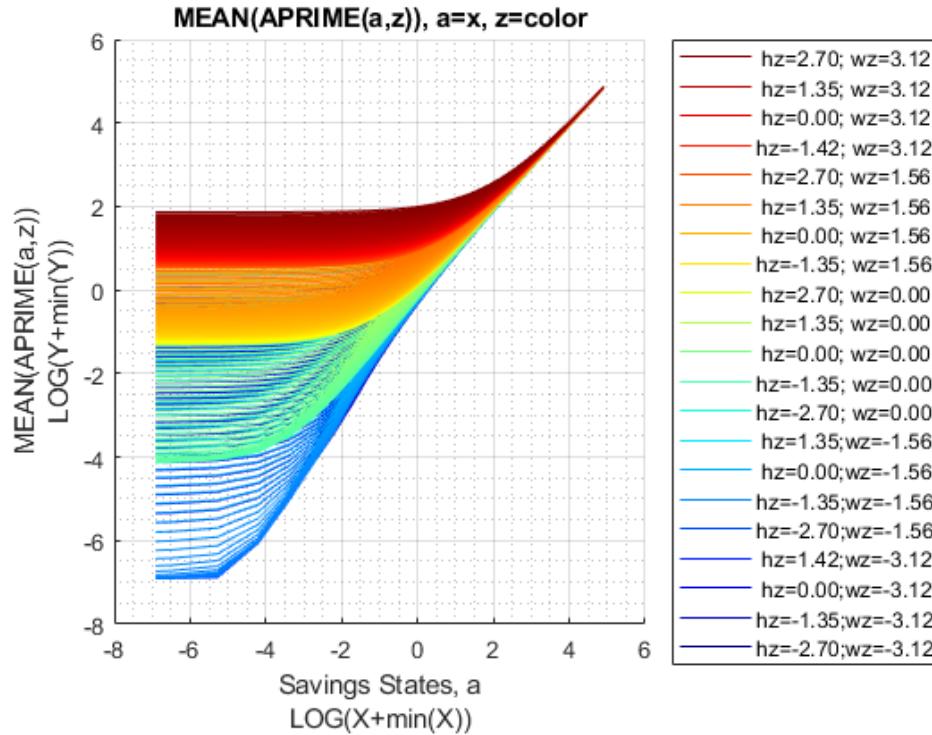




Graph Mean Savings Choices:

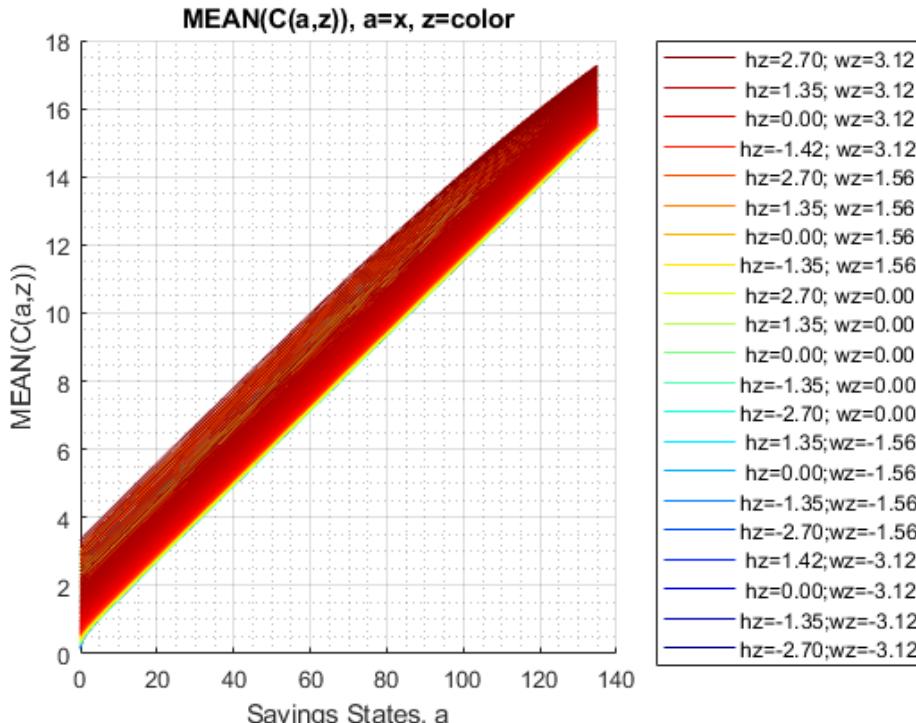
```
mp_support_graph('cl_st_graph_title') = {'MEAN(APRIME(a,z)), a=x, z=color'};
mp_support_graph('cl_st_ytitle') = {'MEAN(APRIME(a,z))'};
ff_graph_grid((tb_az_ap{1:end, 3:end}'), ar_st_eta_HS_grid, agrid, mp_support_graph);
```

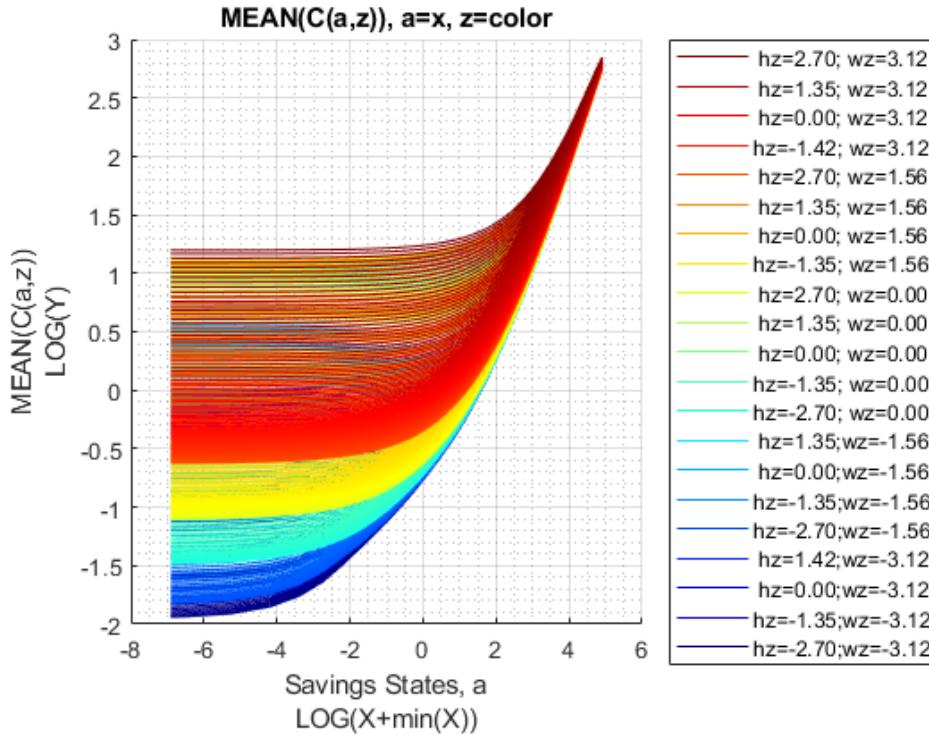




Graph Mean Consumption:

```
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);
```





#### 2.1.4 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...
```

group	kids	marry	mean_age_18	mean_age_19	mean_age_20	mean_age_21	mean_age_22
1	1	0	-9.6123	-8.574	-7.5952	-6.6749	-5.8609
2	2	0	-17.183	-15.851	-14.558	-13.309	-12.171

3	3	0	-20.909	-19.563	-18.242	-16.949	-15.768
4	4	0	-24.758	-23.406	-22.06	-20.727	-19.5
5	5	0	-27.561	-26.288	-25.009	-23.73	-22.552
6	1	1	2.1559	3.0013	3.7773	4.4944	5.1268
7	2	1	-2.4375	-1.4691	-0.55596	0.31118	1.0968
8	3	1	-4.6483	-3.672	-2.7454	-1.8583	-1.0517
9	4	1	-7.2434	-6.2806	-5.3574	-4.4633	-3.6454
10	5	1	-9.2948	-8.3935	-7.5263	-6.6822	-5.9134

```
% Aprime Choice
```

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

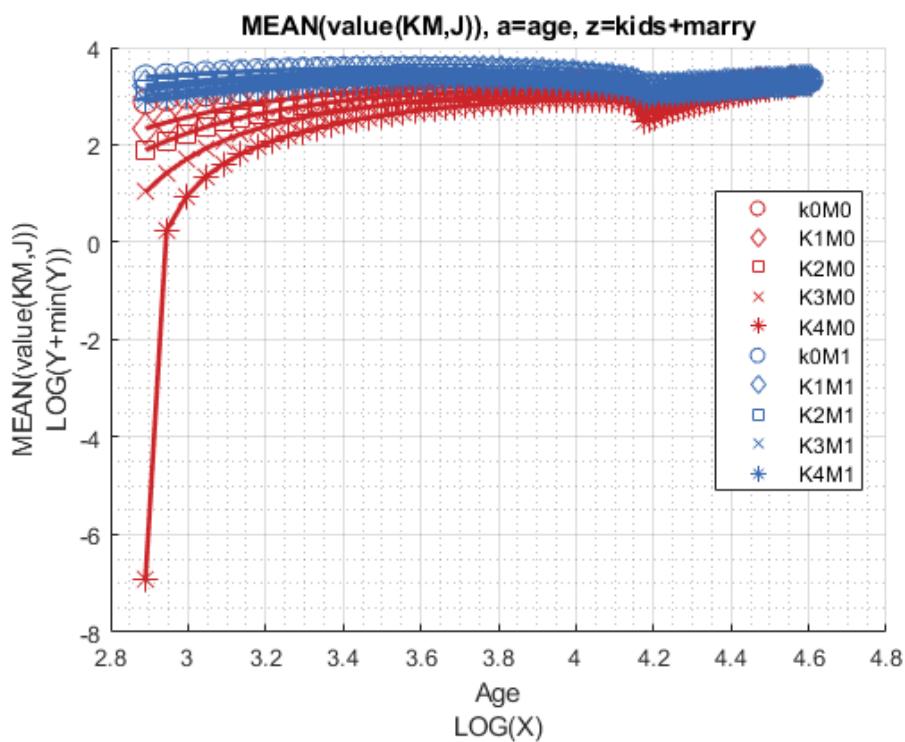
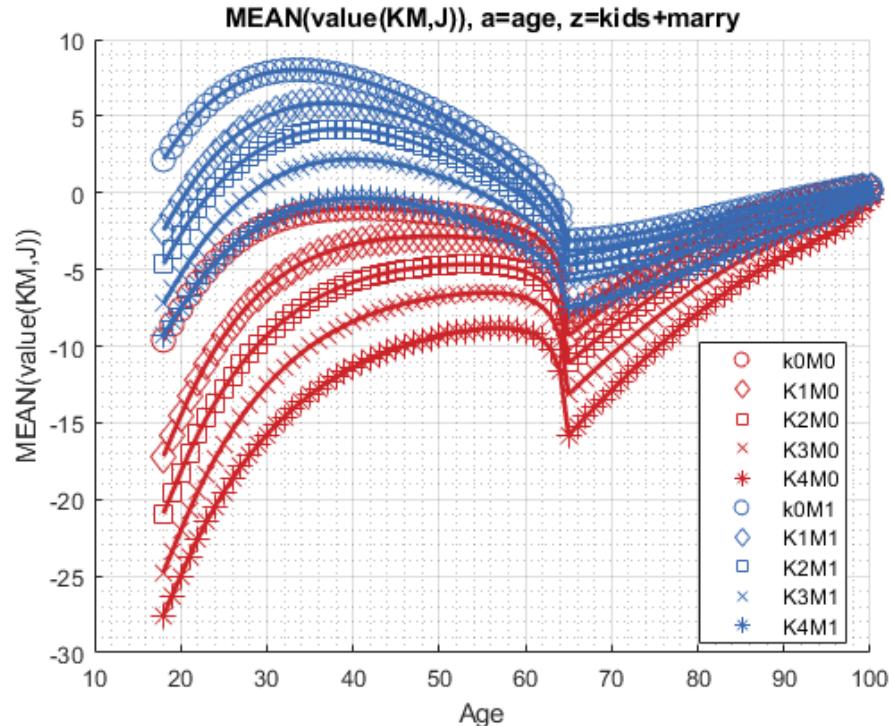
xxx MEAN(AP(KM,J))		xxxxxxxxxxxxxxxxxxxxxxxxxxxxxx					
group	kids	marry	mean_age_18	mean_age_19	mean_age_20	mean_age_21	mean_age_22
1	1	0	34.494	34.456	34.416	34.452	34.489
2	2	0	34.3	34.256	34.21	34.238	34.268
3	3	0	34.146	34.101	34.055	34.082	34.11
4	4	0	34.053	34.01	33.964	33.991	34.02
5	5	0	33.97	33.929	33.885	33.915	33.946
6	1	1	35.208	35.246	35.285	35.413	35.545
7	2	1	34.951	34.976	35	35.11	35.222
8	3	1	34.708	34.724	34.739	34.838	34.939
9	4	1	34.506	34.516	34.523	34.613	34.704
10	5	1	34.221	34.218	34.212	34.286	34.363

```
% Consumption Choices tb_az_c = ff_summ_nd_array("MEAN(C(KM,J))", cons_VFI, true, ["mean"], 3, 1, cl_mp_datasetdesc, ar_permute);
```

xxx MEAN(C(KM,J))		xxxxxxxxxxxxxxxxxxxxxxxxxxxxxx					
group	kids	marry	mean_age_18	mean_age_19	mean_age_20	mean_age_21	mean_age_22
1	1	0	2.0632	2.102	2.1418	2.184	2.2244
2	2	0	2.2579	2.3019	2.348	2.3975	2.4457
3	3	0	2.4119	2.4563	2.503	2.5537	2.6031
4	4	0	2.5046	2.5481	2.594	2.6445	2.6938
5	5	0	2.5877	2.6287	2.6724	2.7207	2.7678
6	1	1	2.6183	2.6787	2.7402	2.8051	2.8674
7	2	1	2.681	2.7395	2.8002	2.8656	2.9293
8	3	1	2.7896	2.8462	2.9054	2.9698	3.0325
9	4	1	2.8528	2.9056	2.9612	3.0222	3.0816
10	5	1	2.9174	2.966	3.0172	3.0737	3.1281

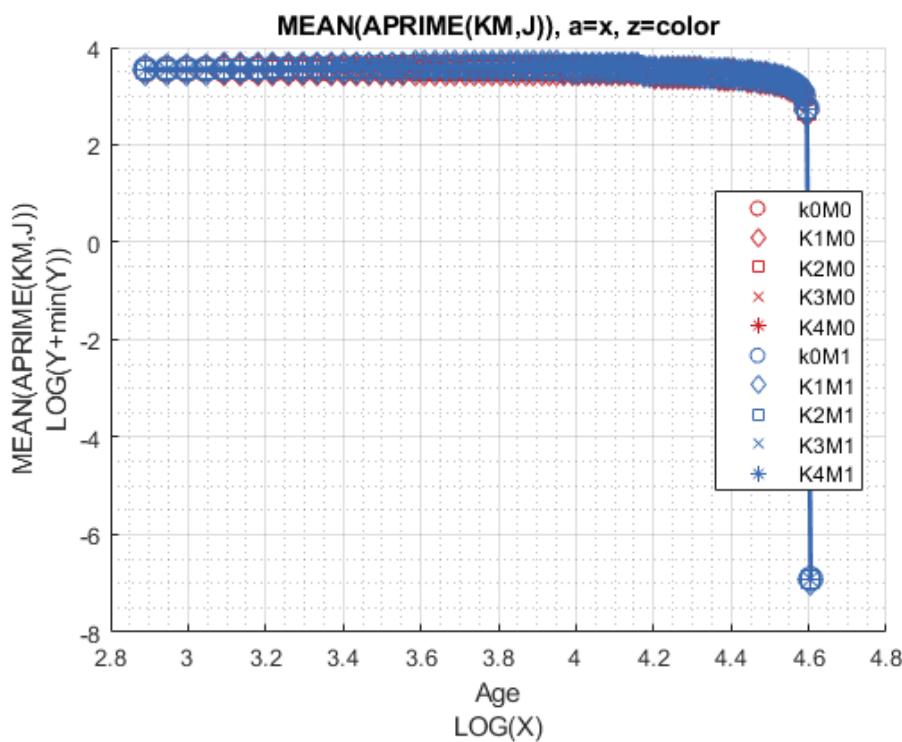
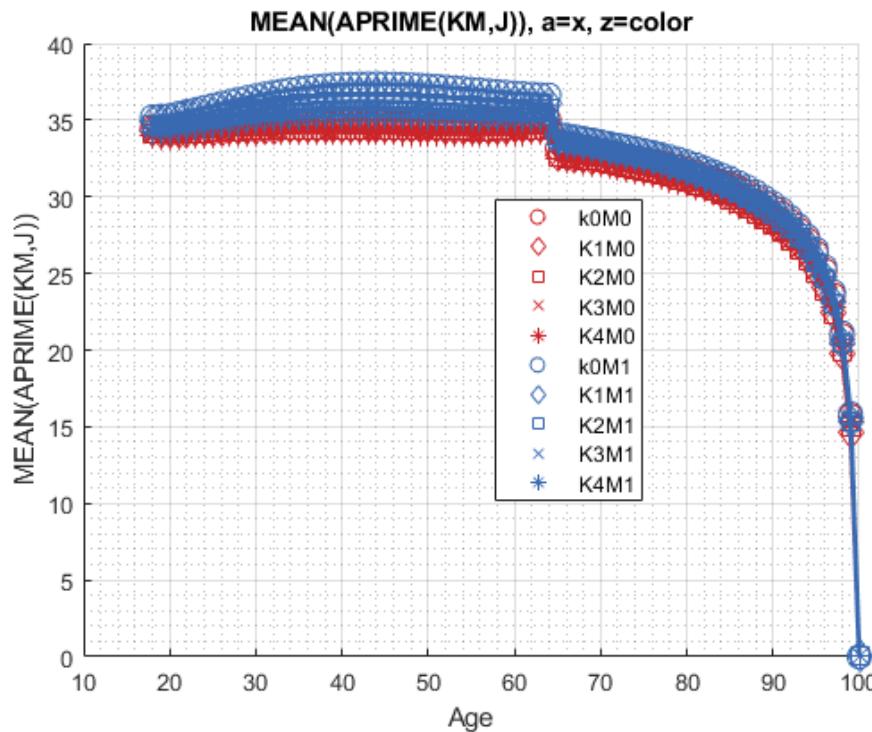
Graph Mean Values:

```
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);
```



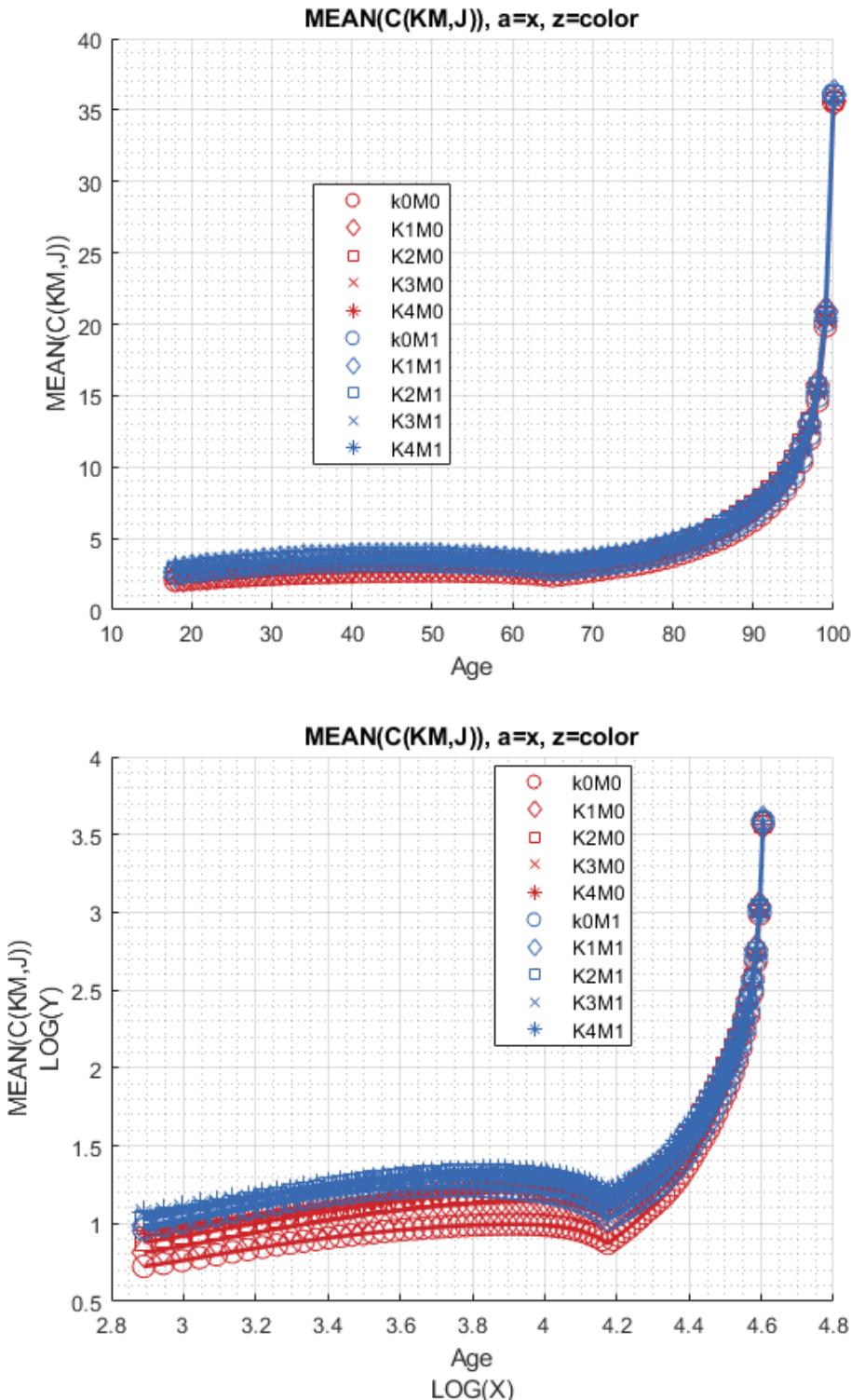
Graph Mean Savings Choices:

```
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);
```



### 2.1.5 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)) xxxxxxxxxxxxxxxxxxxxxxxxx
group edu marry mean_age_18 mean_age_19 mean_age_20 mean_age_21 mean_age_22
---- --- ---- -----
1 0 0 -23.27 -22.094 -20.941 -19.811 -18.761
2 1 0 -16.739 -15.379 -14.045 -12.745 -11.58
3 0 1 -6.6189 -5.6779 -4.7885 -3.9435 -3.1707
4 1 1 -1.9684 -1.0477 -0.17465 0.66417 1.4159

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

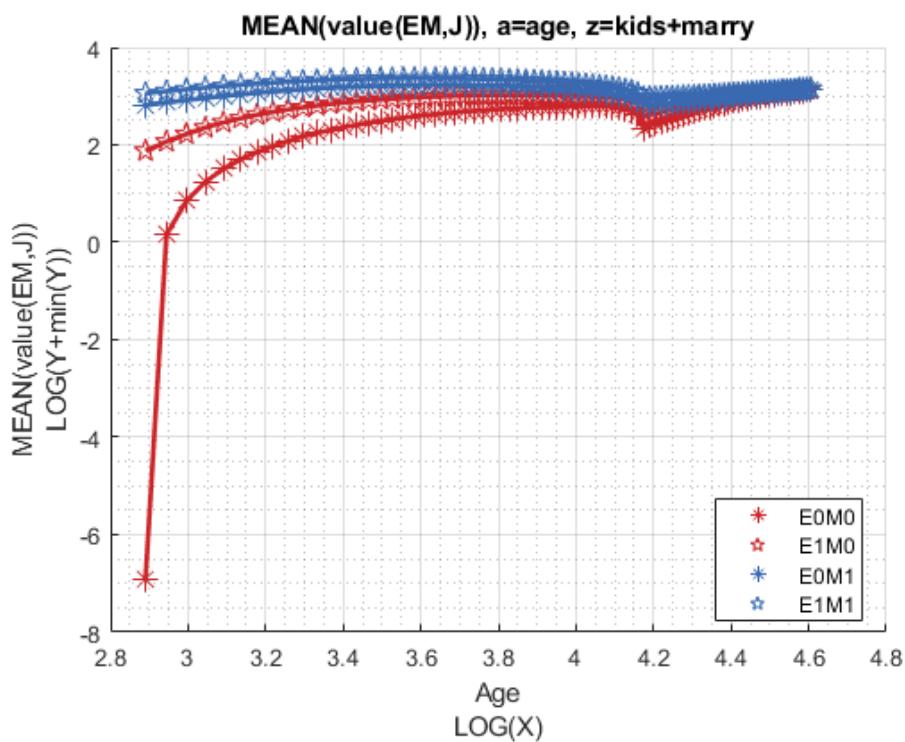
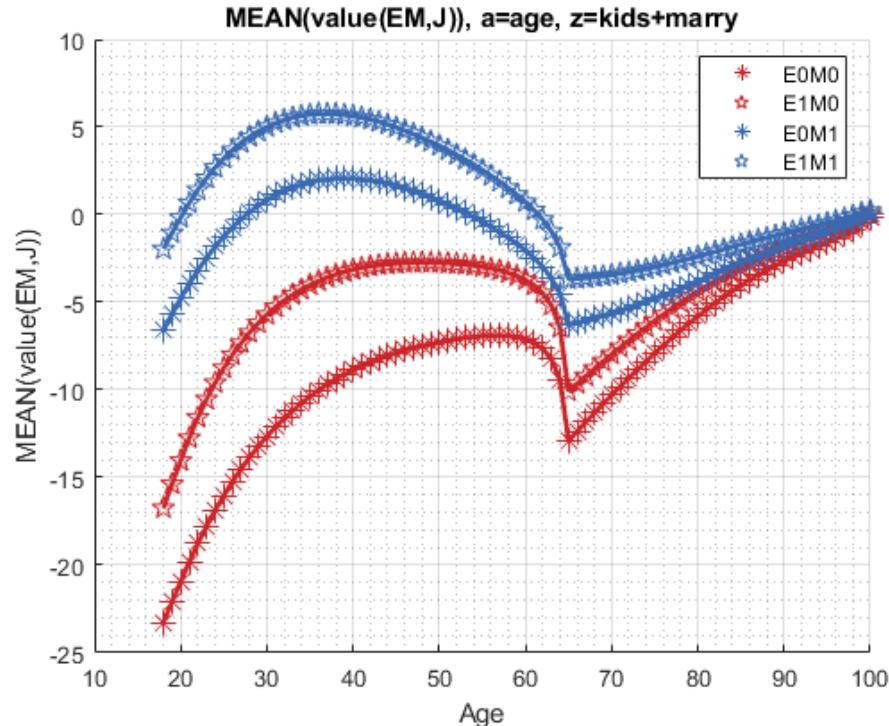
xxx MEAN(AP(EKM,J)) xxxxxxxxxxxxxxxxxxxxxxxxx
group edu marry mean_age_18 mean_age_19 mean_age_20 mean_age_21 mean_age_22
---- --- ---- -----
1 0 0 34.294 34.261 34.226 34.237 34.247
2 1 0 34.091 34.04 33.986 34.035 34.087
3 0 1 34.769 34.789 34.809 34.88 34.951
4 1 1 34.669 34.683 34.695 34.824 34.958

% 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)) xxxxxxxxxxxxxxxxxxxxxxxxx
group edu marry mean_age_18 mean_age_19 mean_age_20 mean_age_21 mean_age_22
---- --- ---- -----
1 0 0 2.2635 2.2969 2.3317 2.3683 2.4043
2 1 0 2.4666 2.5178 2.572 2.6319 2.6896
3 0 1 2.6261 2.6712 2.7175 2.7661 2.8135
4 1 1 2.9175 2.9832 3.0522 3.1285 3.202
```

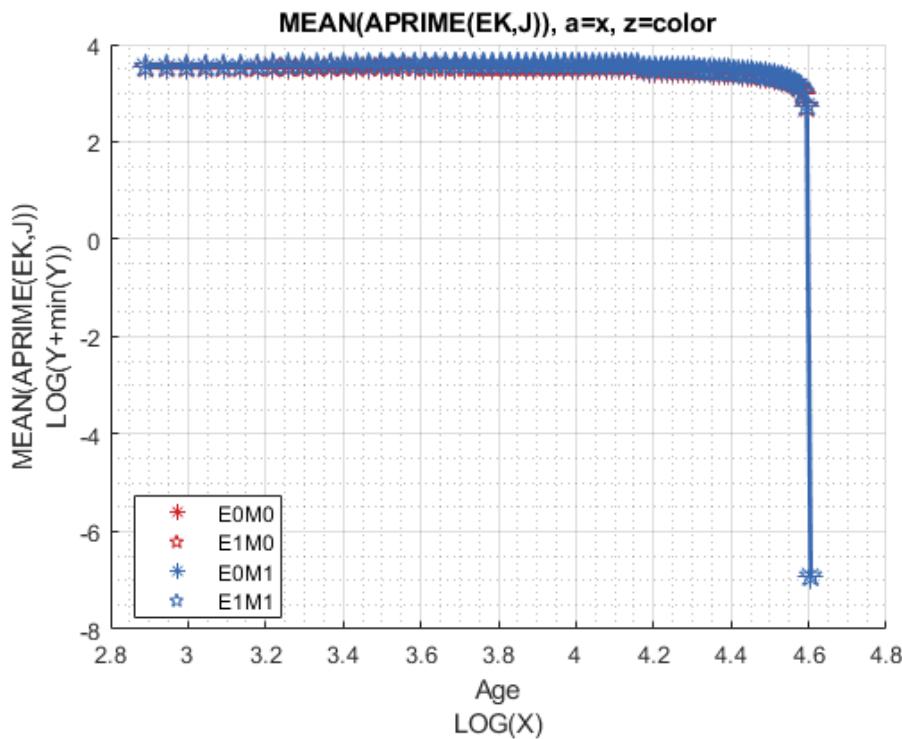
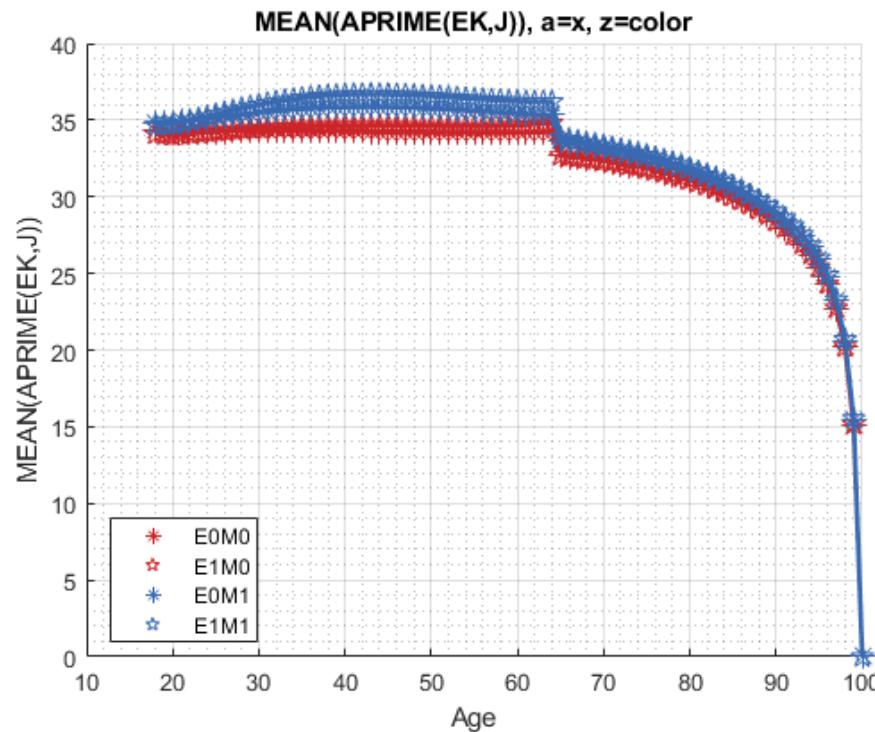
Graph Mean Values:

```
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);
```



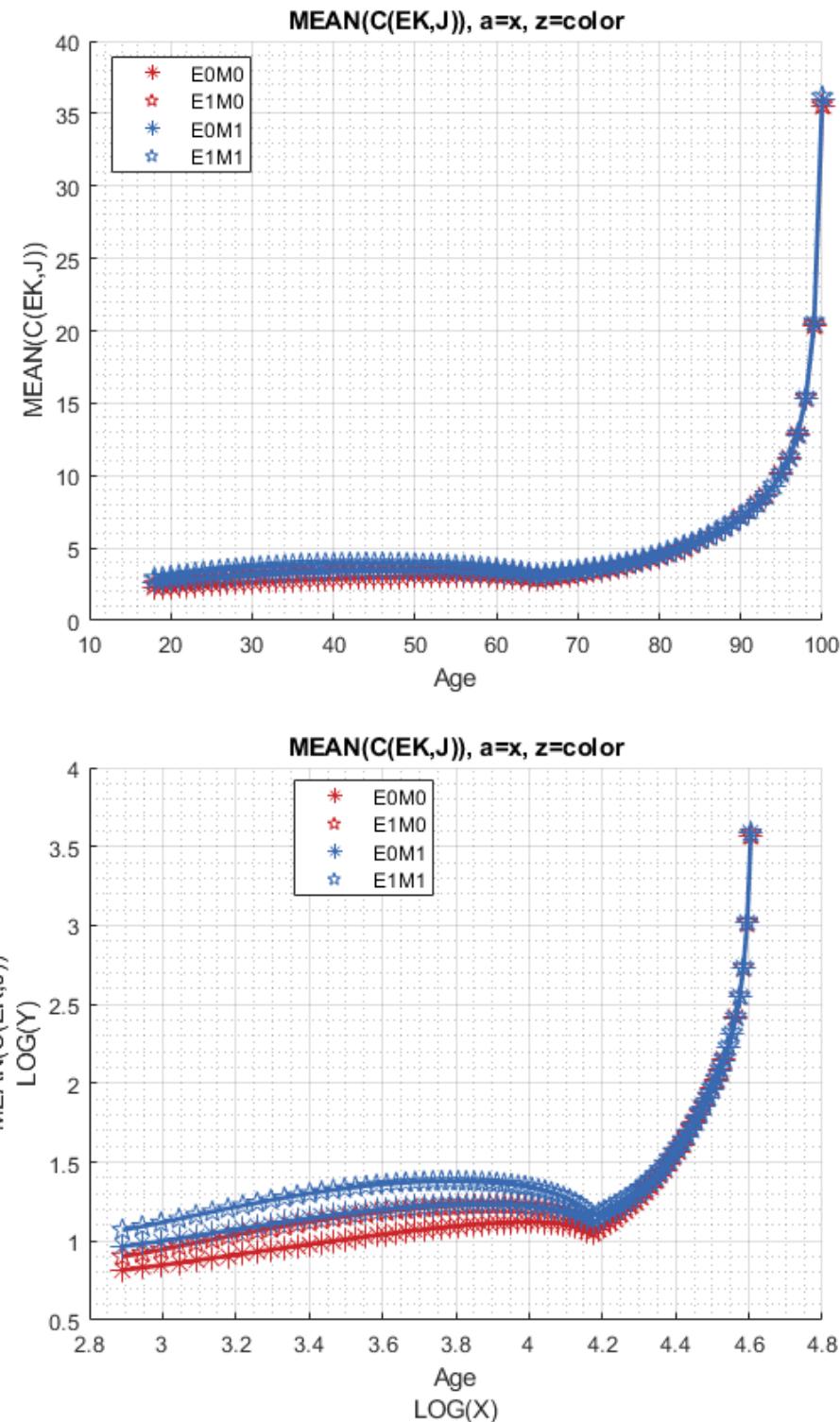
Graph Mean Savings Choices:

```
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 3

## Alternative Value Function Solution Testing

### 3.1 SNW\_VFI\_PARAM Small Solution Analysis

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.

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

Call the function with defaults.

```
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
```

#### 3.1.2 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=%3.2f'));
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_xttitle') = {'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);
% Aprime Choice
tb_az_ap = ff_summ_nd_array("MEAN(AP(A,Z))", ap_VFI, true, ["mean"], 4, 1, cl_mp_datasetdesc, ar_permute);
```

```
% Consumption Choices tb_az_c = ff_summ_nd_array("MEAN(C(A,Z))", cons_VFI, true, ["mean"], 4, 1, cl_mp_datasetdesc, ar_permute);
```

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);
```

### 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", "k0M1", "K1M1", "K2M1"];
mp_support_graph('cl_st_xttitle') = {'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_permute);
% Aprime Choice
tb_az_ap = ff_summ_nd_array("MEAN(AP(KM,J))", ap_VFI, true, ["mean"], 3, 1, cl_mp_datasetdesc, ar_permute);
```

```
% Consumption Choices tb_az_c = ff_summ_nd_array("MEAN(C(KM,J))", cons_VFI, true, ["mean"], 3, 1, cl_mp_datasetdesc, ar_permute);
```

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 = ["EOM0", "E1M0", "EOM1", "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  
% Aprime Choice  
tb_az_ap = ff_summ_nd_array("MEAN(AP(EKM,J))", ap_VFI, true, ["mean"], 3, 1, cl_mp_datasetdesc, ar_p  
% Consumption Choices  
tb_az_c = ff_summ_nd_array("MEAN(C(EKM,J))", cons_VFI, true, ["mean"], 3, 1, cl_mp_datasetdesc, ar_p
```

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);
```

## 3.2 SNW\_VFI\_MAIN\_GRID\_SEARCH Small Solution Analysis

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.

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

Call the function with defaults.

```
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 5.839670 seconds.
Completed SNW_VFI_MAIN_GRID_SEARCH;SNW_MP_PARAM=default_small;SNW_MP_CONTROL=default_base
```

### 3.2.2 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=%3.2f'));
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});
```

### 3.2.3 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_xttitle') = {'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)) xxxxxxxxxxxxxxxxxxxxxxxxx
group      savings      mean_Hshock__0_91976      mean_Hshock__0_45988      mean_Hshock_0      mean_Hsho
-----      -----
1           0           -7.2621                  -5.3086                 -3.7492                -2.
2          0.0097656     -7.1445                  -5.2223                 -3.6785                -2.
3          0.078125      -6.489                   -4.7412                 -3.2884                -2.
4          0.26367       -5.3573                  -3.8789                 -2.6221                -1.
5           0.625        -4.0454                  -2.8494                 -1.8168                -0.8.
6           1.2207       -2.7343                  -1.8181                 -0.98298               -0.2.
7           2.1094       -1.5234                  -0.86783                -0.22453               0.3.
8           3.3496       -0.46769                 -0.030108                0.4355                0.8.
9            5           0.39914                 0.68023                 0.99893               1.
10          7.1191        1.0817                  1.2609                 1.4733                1.
11          9.7656        1.6112                  1.7245                 1.8649                2.
12          12.998         2.0172                  2.0904                 2.183                 2.
13          16.875         2.3301                  2.3771                 2.439                 2.
14          21.455         2.5712                  2.6024                 2.6436                2.
15          26.797         2.758                   2.779                 2.8073                2.
16          32.959         2.9047                  2.9189                 2.9383                2.
17            40           3.0205                  3.0304                 3.044                 3.
18          47.979         3.1125                  3.1195                 3.1293                3.
19          56.953         3.1866                  3.1917                 3.1987                3.
20          66.982         3.2468                  3.2505                 3.2556                3.
21          78.125         3.296                   3.2988                 3.3026                3.
22          90.439         3.3366                  3.3386                 3.3415                3.
23          103.98        3.3704                  3.3719                 3.3741                3.
24          118.82        3.3987                  3.3999                 3.4015                3.
25            135          3.4225                  3.4234                 3.4247                3.

% Aprime Choice
tb_az_ap = ff_summ_nd_array("MEAN(AP(A,Z))", ap_VFI, true, ["mean"], 4, 1, cl_mp_datasetdesc, ar_permute);

xxx MEAN(AP(A,Z)) xxxxxxxxxxxxxxxxxxxxxxxxx
group      savings      mean_Hshock__0_91976      mean_Hshock__0_45988      mean_Hshock_0      mean_Hsho
-----      -----
1           0           1.1204                  1.3194                 1.7407                2.4
2          0.0097656     1.1389                  1.3611                 1.787                 2.4
3          0.078125      1.8241                  1.9861                 2.3009                2.7
4          0.26367       2.912                   3.0509                 3.2315                3.5
```

5	0.625	3.9861	4.1435	4.2269	4.4
6	1.2207	5.0231	5.1806	5.2407	5.3
7	2.1094	6.0741	6.1806	6.2037	6.2
8	3.3496	7.0463	7.1157	7.1528	7.1
9	5	7.9537	7.9954	8.0509	8.0
10	7.1191	8.8657	8.9028	8.9398	8.9
11	9.7656	9.787	9.787	9.8426	9.
12	12.998	10.606	10.63	10.639	10.
13	16.875	11.481	11.495	11.532	11.
14	21.455	12.407	12.407	12.421	12.
15	26.797	13.259	13.287	13.296	13.
16	32.959	14.093	14.102	14.125	14.
17	40	14.972	14.977	14.986	15.
18	47.979	15.843	15.866	15.87	15.
19	56.953	16.75	16.75	16.773	16.
20	66.982	17.653	17.657	17.667	17.
21	78.125	18.477	18.486	18.495	18.
22	90.439	19.315	19.319	19.329	19.
23	103.98	20.218	20.222	20.227	20.
24	118.82	21.083	21.083	21.083	21.
25	135	21.944	21.949	21.954	21.

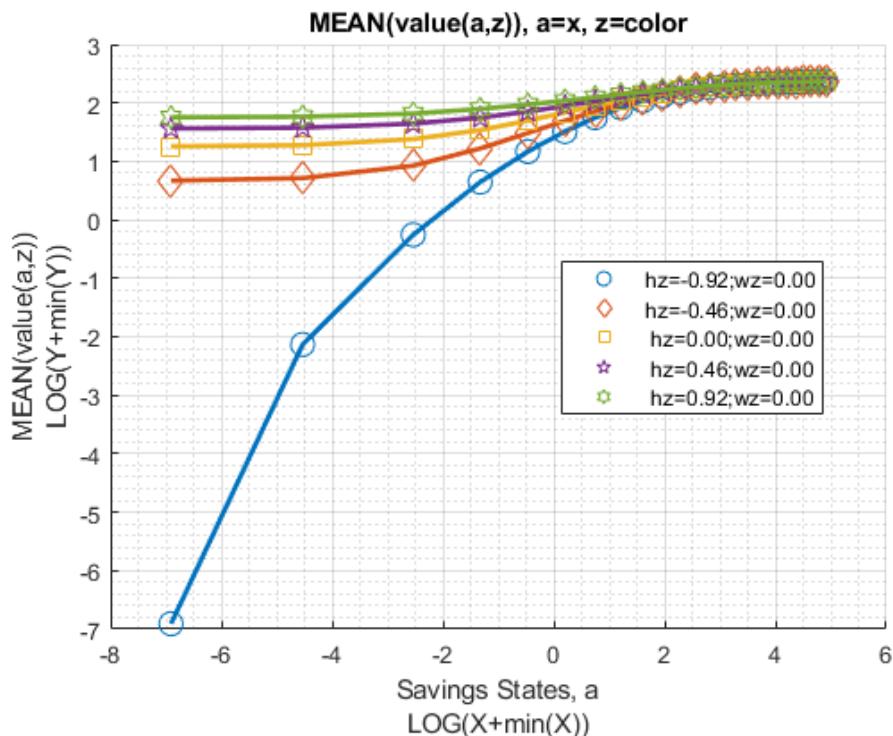
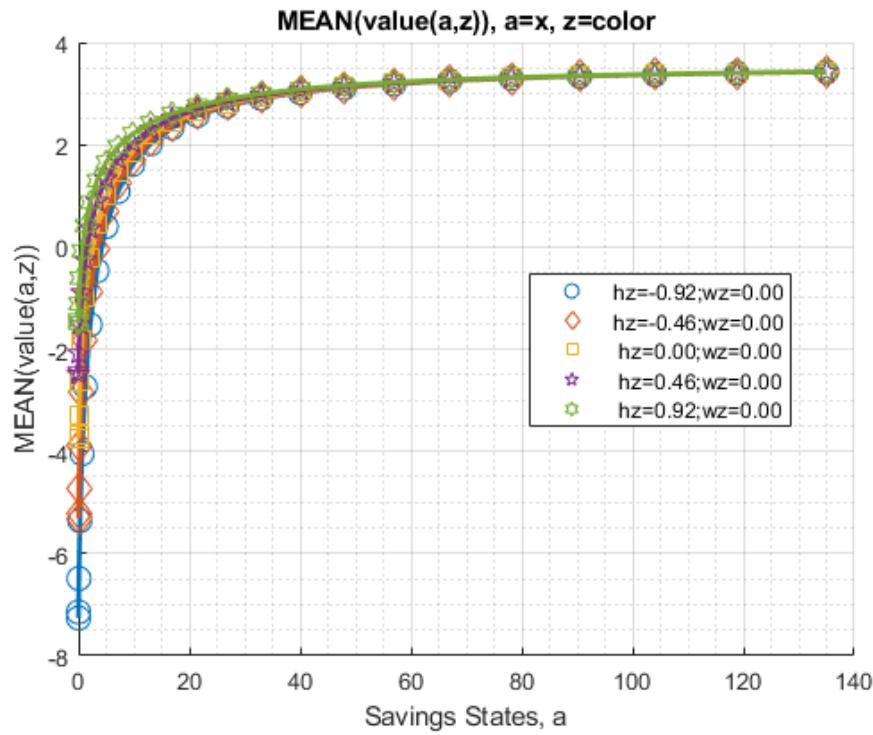
```
% Consumption Choices tb_az_c = ff_summ_nd_array("MEAN(C(A,Z))", cons_VFI, true, ["mean"], 4, 1, cl_mp_datasetdesc, ar_permute);
```

xxx MEAN(C(A,Z)) xxxxxxxxxxxxxxxxxxxxxxxxx		mean_Hshock__0_91976	mean_Hshock__0_45988	mean_Hshock_0	mean_Hsho
group	savings	-----	-----	-----	-----
1	0	0.47561	0.60477	0.78755	1.0
2	0.0097656	0.48688	0.61444	0.79661	1.0
3	0.078125	0.55276	0.67316	0.84544	1.0
4	0.26367	0.68068	0.79387	0.9582	1.1
5	0.625	0.87413	0.95556	1.1377	1.3
6	1.2207	1.1386	1.1823	1.359	1.6
7	2.1094	1.4348	1.4767	1.6678	1.9
8	3.3496	1.8593	1.9088	2.0737	2.3
9	5	2.4822	2.5483	2.6665	2.9
10	7.1191	3.276	3.3318	3.4625	3.6
11	9.7656	4.2223	4.356	4.4176	4.6
12	12.998	5.5639	5.6224	5.8007	5.9
13	16.875	7.1191	7.1983	7.2626	7.4
14	21.455	8.7496	8.8825	9.0265	9.1
15	26.797	10.88	10.865	11.023	11.
16	32.959	13.483	13.559	13.624	13.
17	40	16.255	16.355	16.497	16.
18	47.979	19.414	19.362	19.532	19.
19	56.953	22.728	22.861	22.86	23.
20	66.982	26.496	26.587	26.701	26.
21	78.125	31.189	31.223	31.332	31.
22	90.439	36.369	36.444	36.537	36.
23	103.98	41.558	41.627	41.772	41.
24	118.82	47.433	47.565	47.772	47.
25	135	53.934	53.998	54.13	54.

Graph Mean Values:

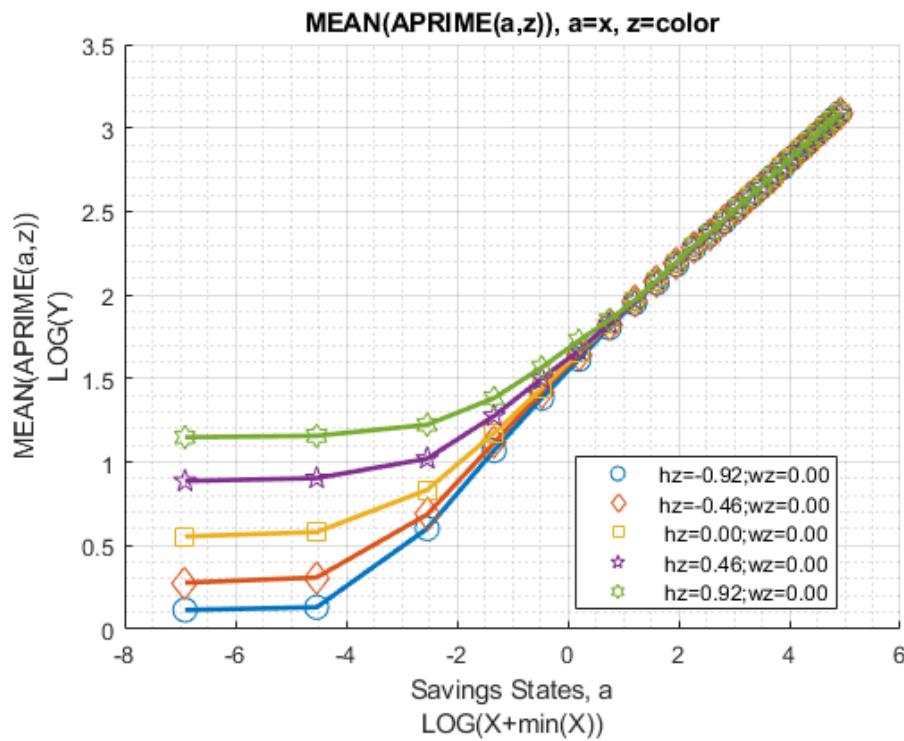
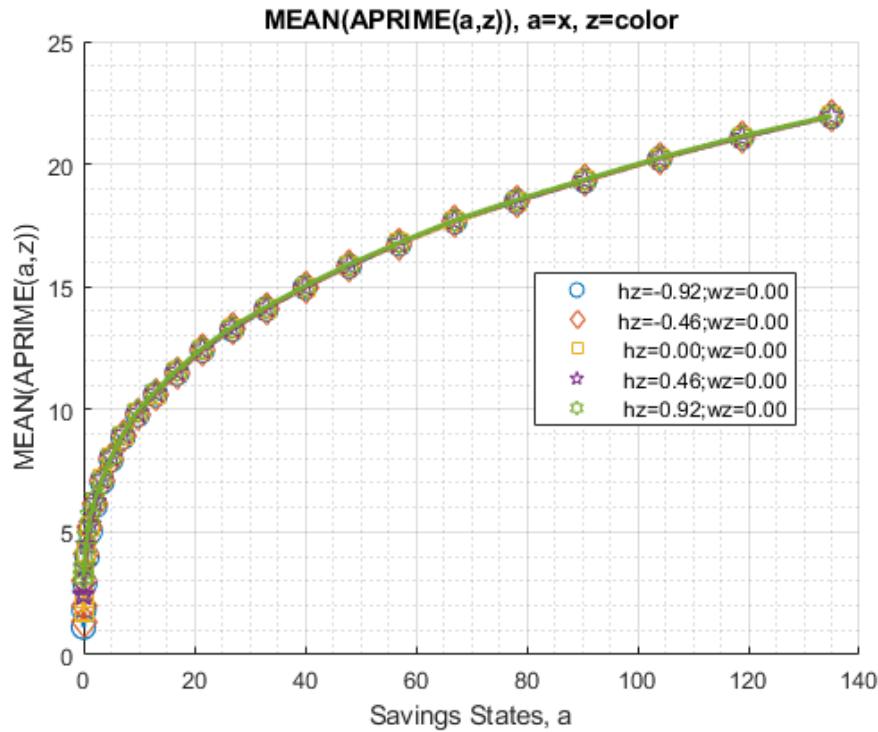
```
mp_support_graph('cl_st_graph_title') = {'MEAN(value(a,z)), a=x, z=color'};
mp_support_graph('cl_st_ytitle') = {'MEAN(value(a,z))'};
```

```
ff_graph_grid((tb_az_v{1:end, 3:end})', ar_st_eta_HS_grid, agrid, mp_support_graph);
```



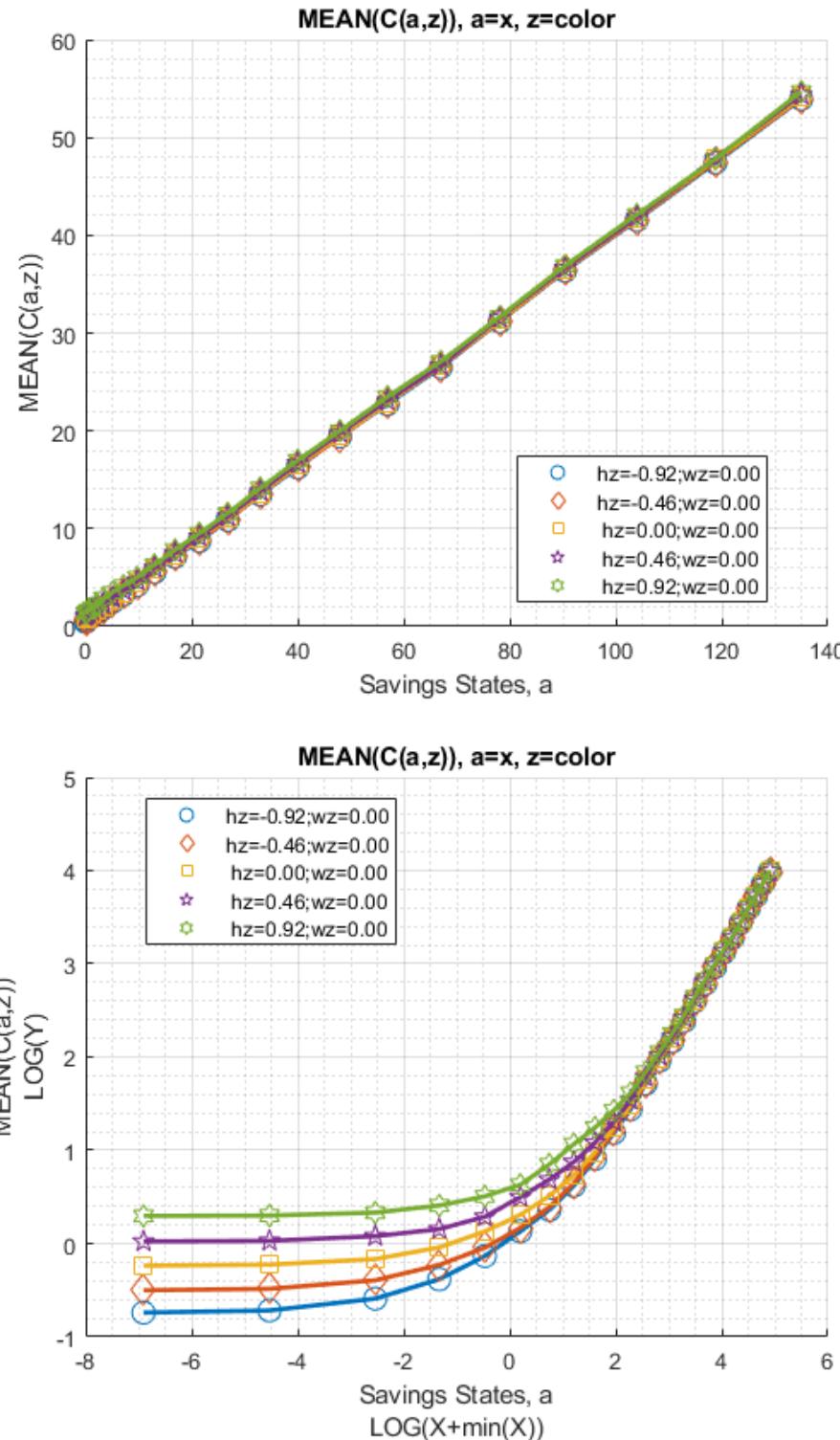
Graph Mean Savings Choices:

```
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);
```



### 3.2.4 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)) xxxxxxxxxxxxxxxxxxxxxxxxx
group kids marry mean_age_19 mean_age_22 mean_age_27 mean_age_32 mean_age_3
-----
1 1 0 2.5769 2.726 2.8073 2.7855 2.6939
2 2 0 1.5197 1.8098 2.0206 2.1004 2.0952
3 3 0 0.9869 1.2649 1.4811 1.5698 1.5738
4 1 1 2.3544 2.5201 2.6205 2.6297 2.5748
5 2 1 1.564 1.8114 1.9978 2.0809 2.0936
6 3 1 1.2123 1.4401 1.6171 1.6965 1.7071

% 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)) xxxxxxxxxxxxxxxxxxxxxxxxx
group kids marry mean_age_19 mean_age_22 mean_age_27 mean_age_32 mean_age_3
-----
1 1 0 12.876 12.86 12.976 13.068 13.14
2 2 0 12.86 12.84 12.916 13.016 13.06
3 3 0 12.824 12.792 12.884 12.988 12.94
4 1 1 12.832 12.796 12.892 12.98 13.052
5 2 1 12.824 12.788 12.856 12.94 13.004
6 3 1 12.768 12.724 12.828 12.904 12.972

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

xxx MEAN(C(KM,J)) xxxxxxxxxxxxxxxxxxxxxxxxx
group kids marry mean_age_19 mean_age_22 mean_age_27 mean_age_32 mean_age_3
-----
1 1 0 6.3895 6.4629 6.6288 6.7554 6.8327
2 2 0 6.4025 6.4709 6.6411 6.7667 7.2326
3 3 0 6.4139 6.4906 6.6473 6.7745 8.3105
4 1 1 6.6365 6.7334 6.9186 7.0691 7.1681
5 2 1 6.6219 6.7043 6.8923 7.0386 7.1354
6 3 1 6.6135 6.7111 6.8733 7.0145 7.1123

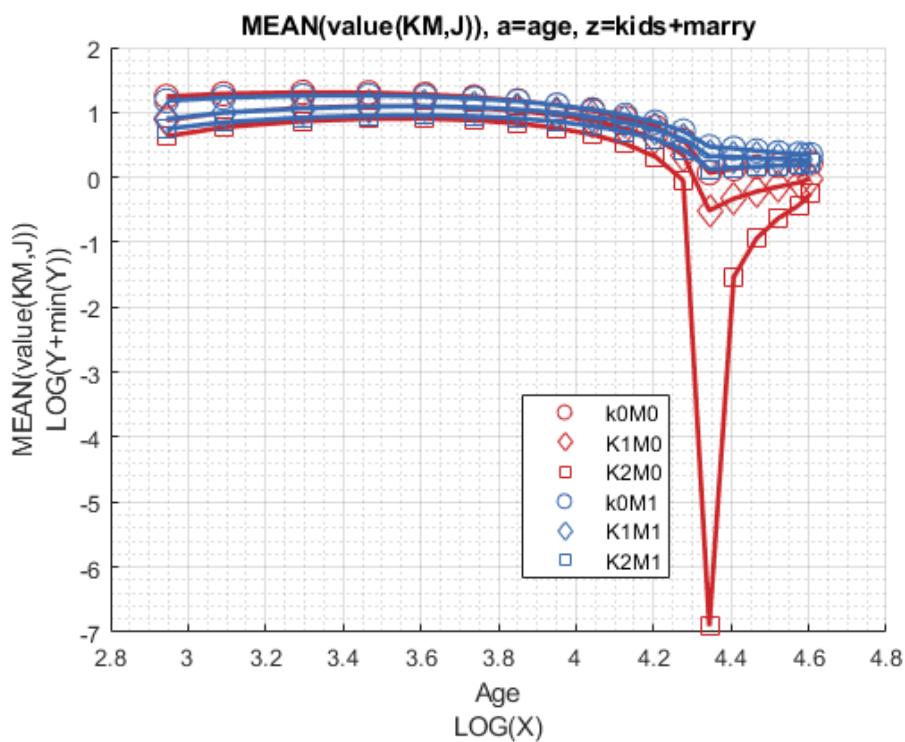
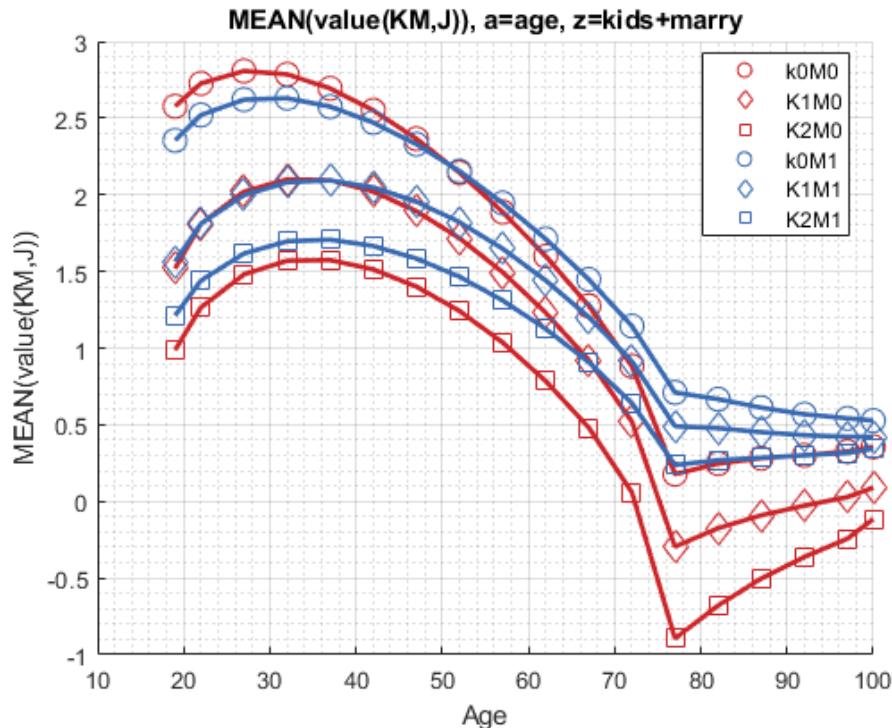
```

Graph Mean Values:

```

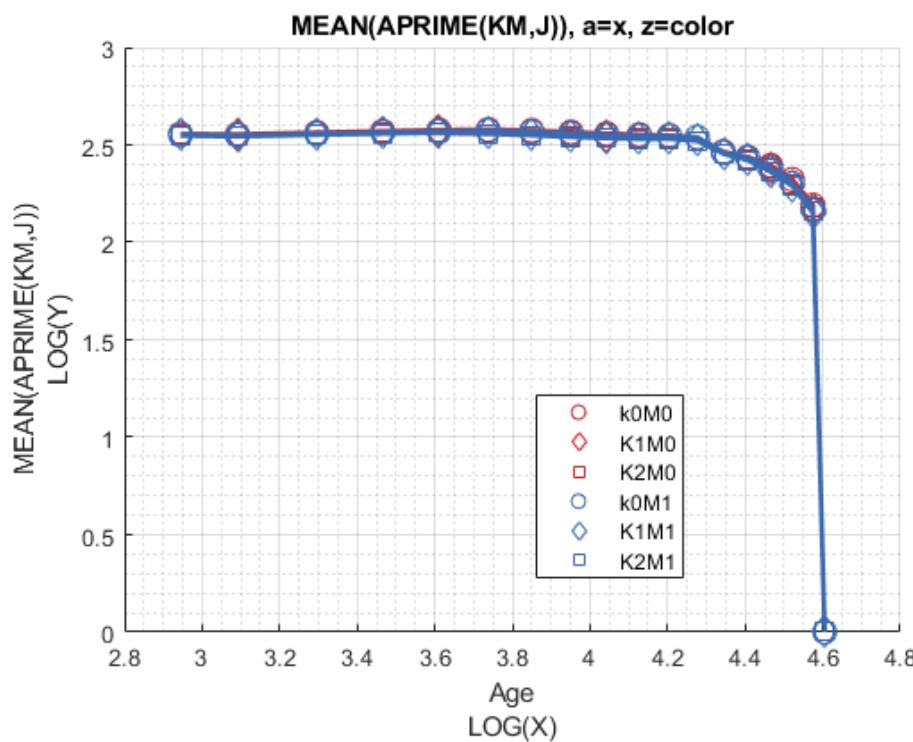
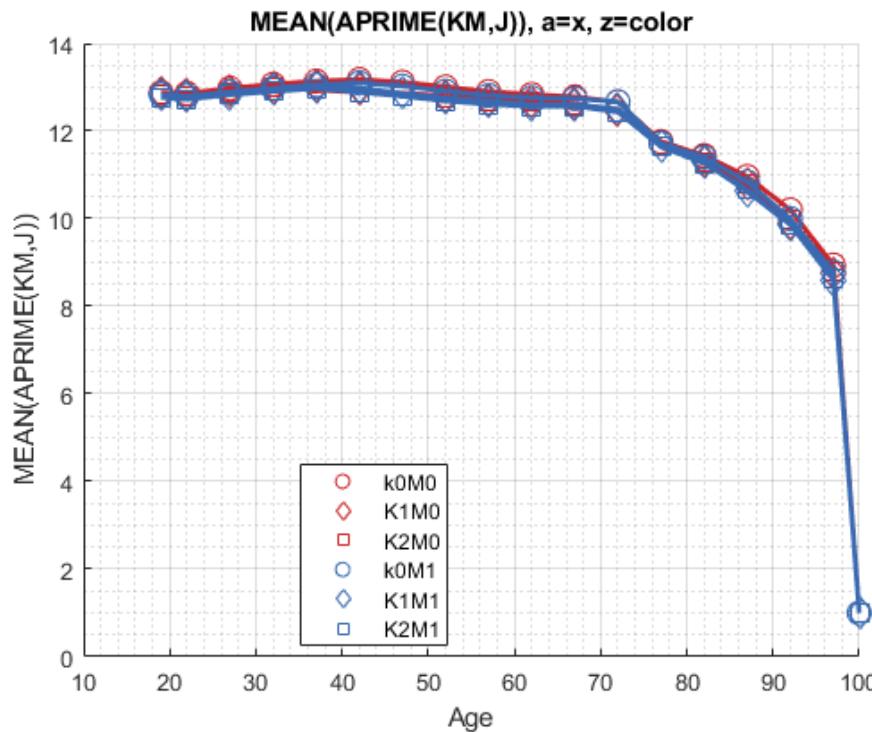
mp_support_graph('cl_st_graph_title') = {'MEAN(value(KM,J)), a=age, z=kids+marry'};
mp_support_graph('cl_st_ytitle') = {'MEAN(value(KM,J))'};
ff_graph_grid((tb_az_v{1:end, 4:end}), ar_row_grid, age_grid, mp_support_graph);

```



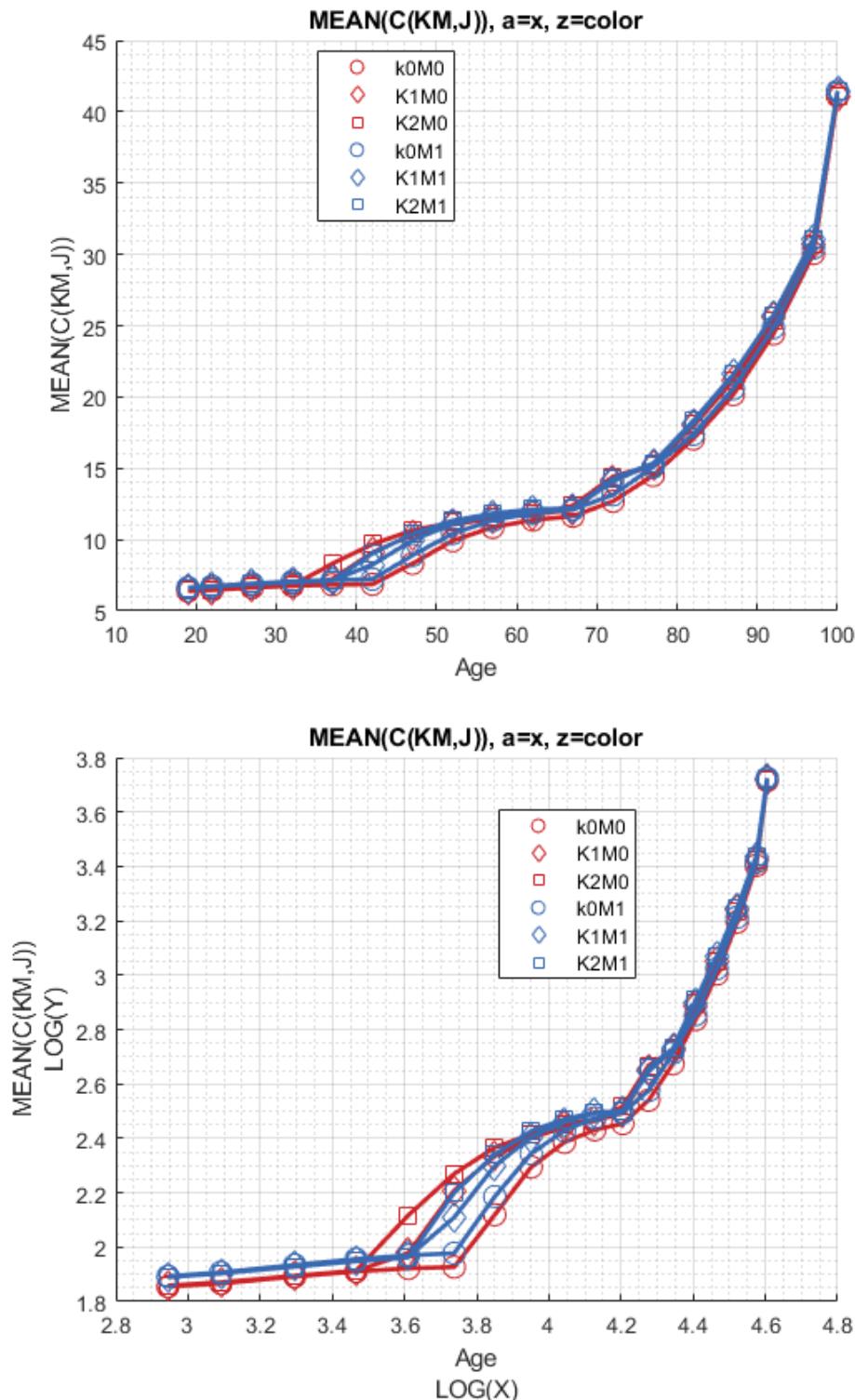
Graph Mean Savings Choices:

```
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);
```



### 3.2.5 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 = ["EOM0", "E1M0", "EOM1", "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)) xxxxxxxxxxxxxxxxxxxxxxxxx
group edu marry mean_age_19 mean_age_22 mean_age_27 mean_age_32 mean_age_37
---- --- ---- -----
1 0 0 1.397 1.5992 1.7503 1.807 1.7952
2 1 0 1.9919 2.268 2.4556 2.4968 2.4467
3 0 1 1.3943 1.589 1.7371 1.8066 1.8173
4 1 1 2.0262 2.2588 2.4199 2.4648 2.4331

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

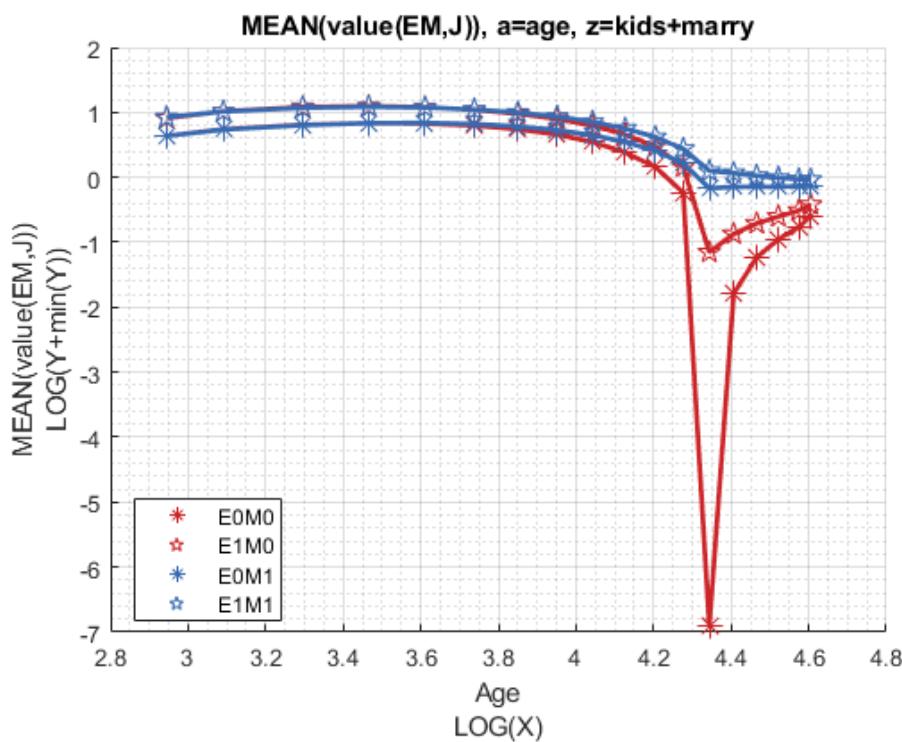
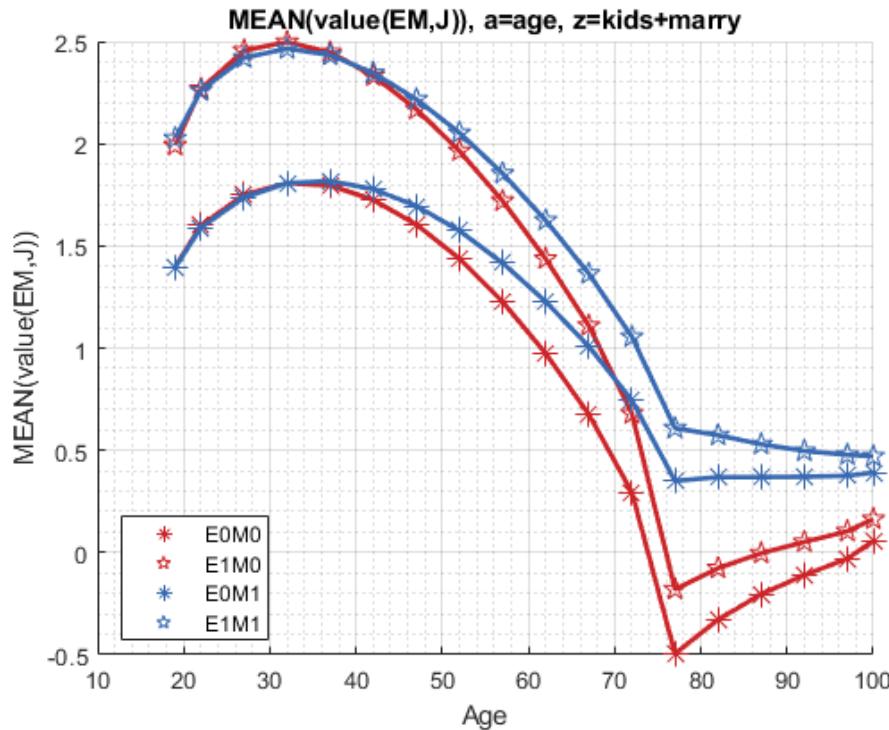
xxx MEAN(AP(EKM,J)) xxxxxxxxxxxxxxxxxxxxxxxxx
group edu marry mean_age_19 mean_age_22 mean_age_27 mean_age_32 mean_age_37
---- --- ---- -----
1 0 0 12.923 12.909 12.957 13.011 13.016
2 1 0 12.784 12.752 12.893 13.037 13.077
3 0 1 12.883 12.837 12.899 12.949 12.987
4 1 1 12.733 12.701 12.819 12.933 13.032

% 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)) xxxxxxxxxxxxxxxxxxxxxxxxx
group edu marry mean_age_19 mean_age_22 mean_age_27 mean_age_32 mean_age_37
---- --- ---- -----
1 0 0 6.3781 6.4224 6.5232 6.6018 7.3509
2 1 0 6.4259 6.5271 6.7549 6.9292 7.5663
3 0 1 6.5686 6.6336 6.7481 6.8408 6.9145
4 1 1 6.6793 6.799 7.0414 7.2407 7.3627
```

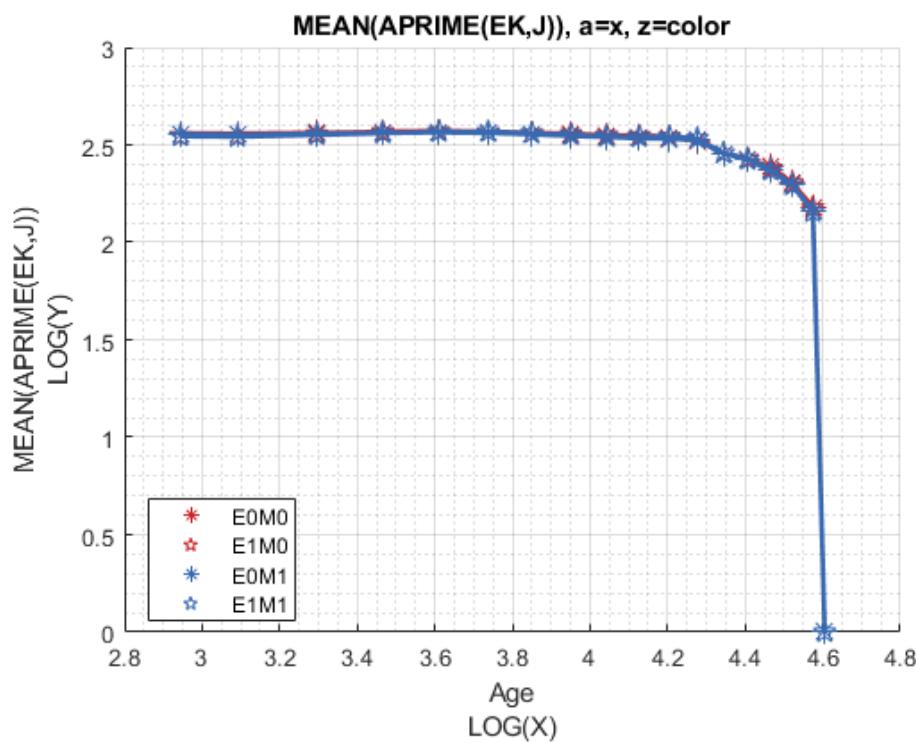
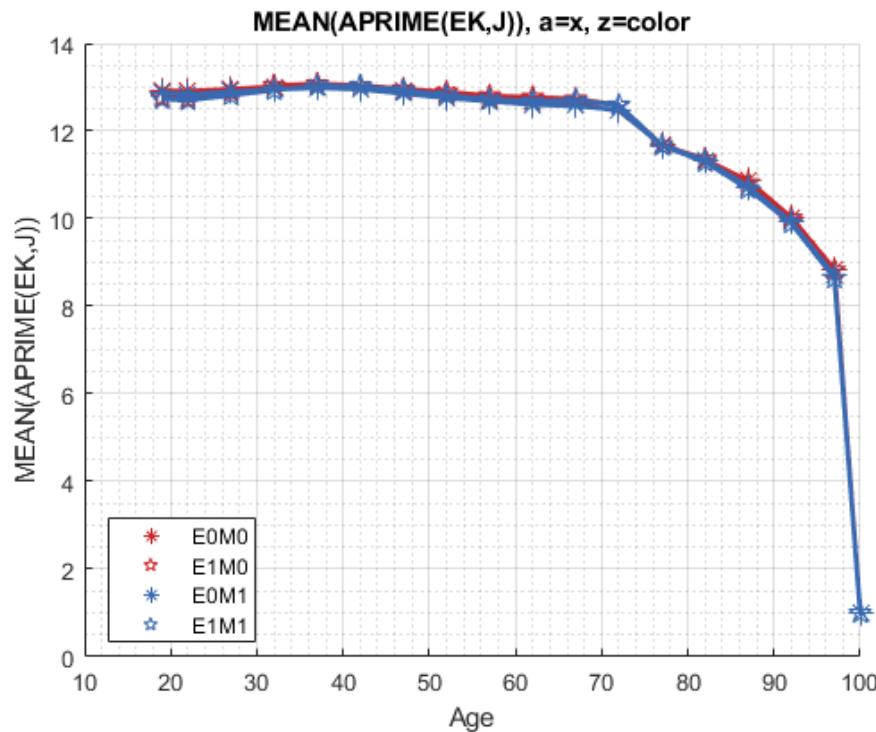
Graph Mean Values:

```
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);
```



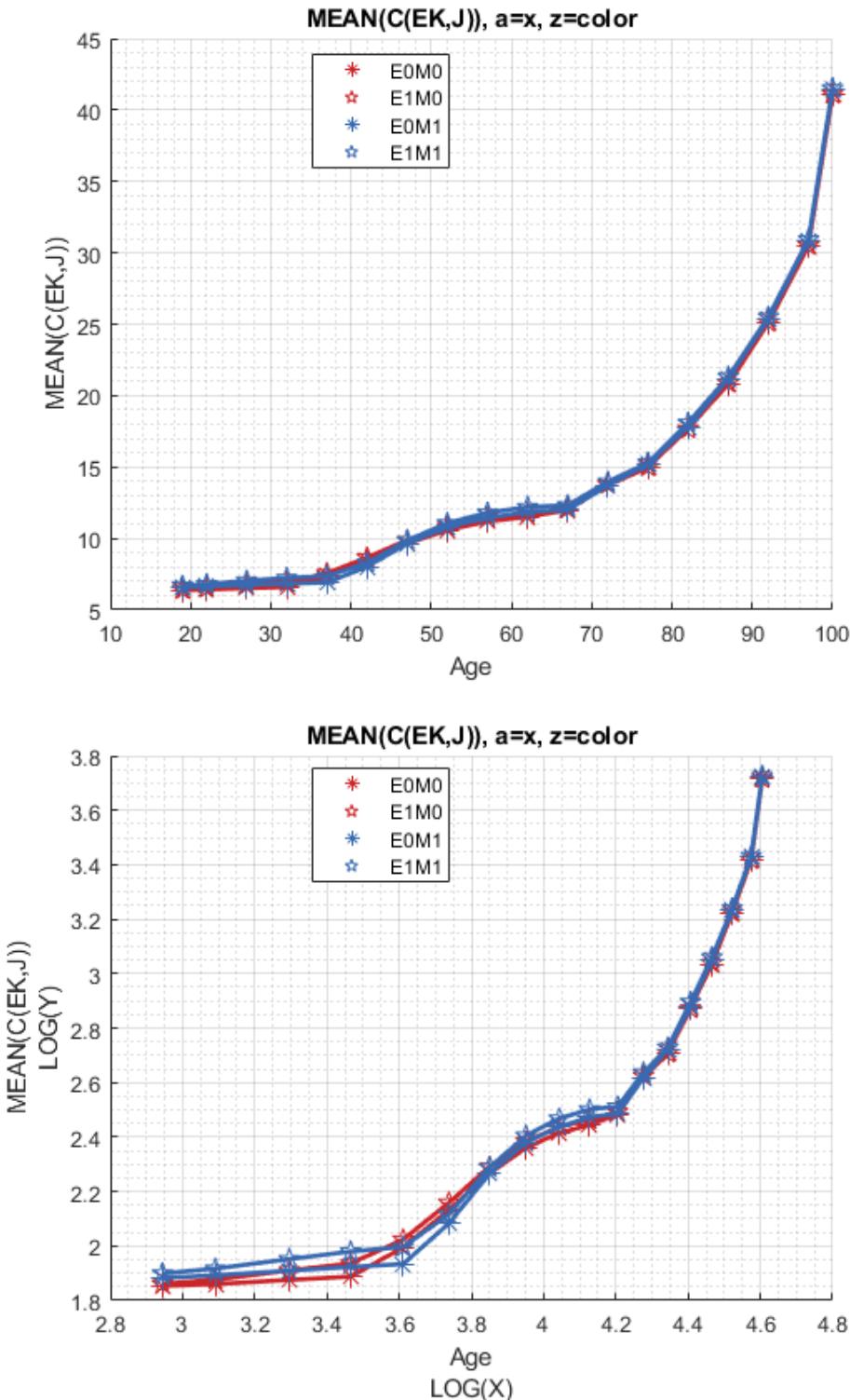
Graph Mean Savings Choices:

```
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);
```



### 3.3 SNW\_VFI\_PARAM Small Solution Analysis

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 1 shocks.

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

Call the function with defaults.

```

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: 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 0.300958 seconds.
Completed SNW_VFI_MAIN;SNW_MP_PARAM=default_small;SNW_MP_CONTROL=default_base

```

### 3.3.2 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});

```

### 3.3.3 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)) xxxxxxxxxxxxxxxxxxxxxxxxx
group      savings      mean_Hshock__0_91976      mean_Hshock__0_45988      mean_Hshock_0      mean_Hsho
-----      -----      -----      -----      -----      -----
1           0           -7.2503          -5.2835          -3.7134          -2.
2          0.0097656       -7.1324          -5.1969          -3.6417          -2.
3          0.078125        -6.4761          -4.7107          -3.2467          -2.
4          0.26367         -5.3284          -3.8496          -2.5707          -1.
5           0.625          -3.966           -2.8108          -1.7735          -0.8
6          1.2207          -2.597           -1.7598          -0.95324         -0.2
7          2.1094          -1.3566          -0.78465          -0.19312         0.3
8          3.3496          -0.30963          0.066182          0.47754          0.9
9           5             0.53291          0.7744           1.0517          1.
10         7.1191           1.1909           1.3448           1.5289          1.
11         9.7656           1.6974           1.7957           1.9172          2.
12         12.998            2.0855           2.1488           2.2293          2.
13         16.875            2.3829           2.4244           2.4781          2.
14         21.455            2.6121           2.6396           2.6759          2.
15         26.797             2.79           2.8086           2.8335          2.
16         32.959            2.9295           2.9423           2.9596          2.
17           40             3.0397           3.0487           3.061          3.
18         47.979            3.1277           3.1342           3.1429          3.
19         56.953            3.1987           3.2033           3.2097          3.
20         66.982            3.2563           3.2597           3.2645          3.
21         78.125            3.3036           3.3062           3.3097          3.
22         90.439            3.3427           3.3446           3.3473          3.
23        103.98             3.3753           3.3768           3.3788          3.
24        118.82             3.4026           3.4038           3.4054          3.
25           135             3.4257           3.4266           3.4279          3.

% Aprime Choice
tb_az_ap = ff_summ_nd_array("MEAN(AP(A,Z))", ap_VFI, true, ["mean"], 4, 1, cl_mp_datasetdesc, ar_permute);

xxx MEAN(AP(A,Z)) xxxxxxxxxxxxxxxxxxxxxxxxx
group      savings      mean_Hshock__0_91976      mean_Hshock__0_45988      mean_Hshock_0      mean_Hsho
-----      -----      -----      -----      -----      -----
1           0           0.0031715          0.018272          0.06218          0.1
2          0.0097656          0.0041856          0.02014          0.065449          0.
3          0.078125            0.0195          0.043246          0.094774          0.2
4          0.26367            0.11997          0.14608          0.20791          0.3
5           0.625            0.37091          0.40356          0.4536          0.5
6           1.2207            0.81324          0.85499          0.90105          1.
7           2.1094             1.495           1.5366           1.6037          1.
8           3.3496            2.4456           2.4842           2.56          2.
9           5                3.7173           3.7541           3.8276          3.
10          7.1191            5.3706           5.4067           5.4784          5.
11          9.7656            7.409            7.445           7.5165          7.
12          12.998            9.829           9.8609           9.9322          10.
13          16.875            12.836           12.867           12.93          13.
14          21.455            16.418           16.447           16.51          16.
15          26.797            20.467           20.493           20.551          2.
```

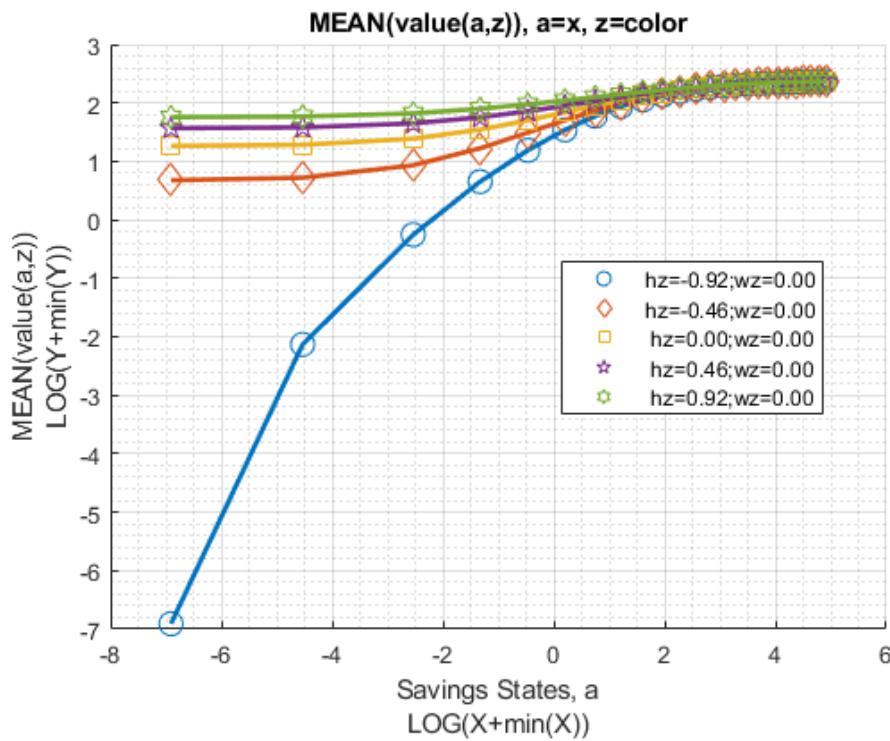
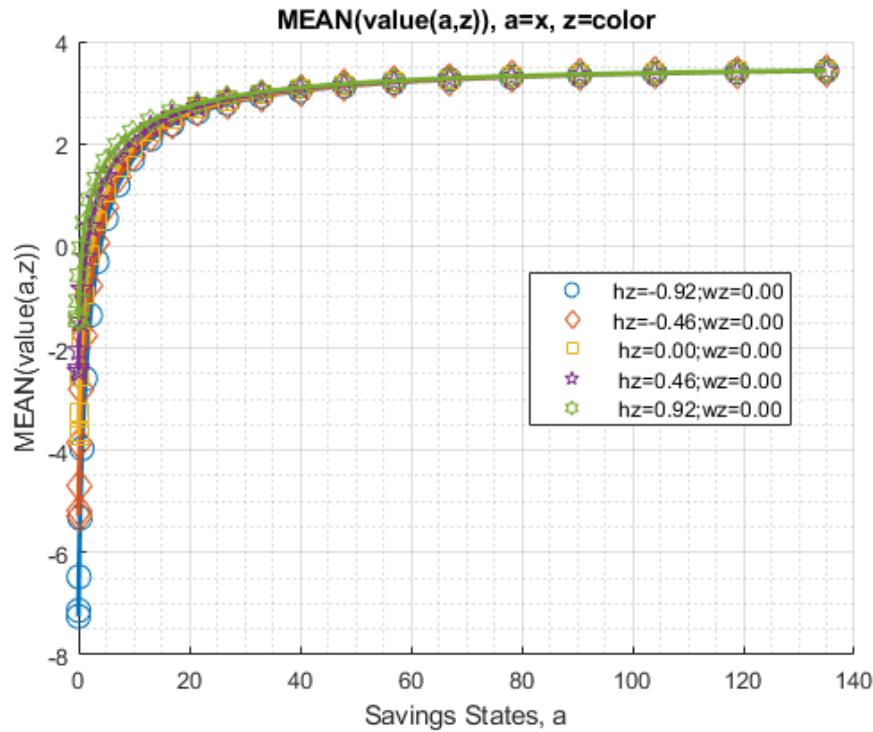
16	32.959	25.147	25.172	25.226	25.
17	40	30.496	30.527	30.586	30.
18	47.979	36.57	36.598	36.66	36.
19	56.953	43.556	43.586	43.646	43.
20	66.982	51.34	51.37	51.434	51.
21	78.125	59.622	59.655	59.719	59.
22	90.439	68.907	68.939	69.003	69.
23	103.98	79.38	79.41	79.47	79.
24	118.82	90.679	90.711	90.776	90.
25	135	102.99	103.02	103.08	10.

```
% Consumption Choices tb_az_c = ff_summ_nd_array("MEAN(C(A,Z))", cons_VFI, true, ["mean"], 4, 1, cl_mp_datasetdesc, ar_permute);
```

xxx	MEAN(C(A,Z))	xxxxxxxxxxxxxxxxxxxxxxxxxxxx	mean_Hshock_0_91976	mean_Hshock_0_45988	mean_Hshock_0	mean_Hsho
group	savings	-----	-----	-----	-----	-----
1	0	0.47551	0.59993	0.77031	1.0	
2	0.0097656	0.48595	0.60949	0.77845	1.0	
3	0.078125	0.5508	0.6664	0.82902	1.0	
4	0.26367	0.66781	0.78066	0.93266	1.1	
5	0.625	0.84	0.94566	1.1089	1.3	
6	1.2207	1.0944	1.1901	1.3565	1.	
7	2.1094	1.4504	1.5453	1.6898	1.9	
8	3.3496	1.9462	2.0432	2.1782	2.4	
9	5	2.597	2.695	2.8314	3.0	
10	7.1191	3.4097	3.5079	3.6454	3.8	
11	9.7656	4.449	4.5467	4.6839	4.8	
12	12.998	5.7861	5.8876	6.0245	6.2	
13	16.875	7.2831	7.3861	7.5301	7.7	
14	21.455	9.0219	9.1255	9.2698	9.4	
15	26.797	11.176	11.283	11.433	11.	
16	32.959	13.652	13.76	13.913	14.	
17	40	16.478	16.58	16.728	16.	
18	47.979	19.667	19.772	19.917	20.	
19	56.953	23.101	23.202	23.35	23.	
20	66.982	26.96	27.062	27.205	27	
21	78.125	31.613	31.712	31.855	32	
22	90.439	36.623	36.724	36.866	37.	
23	103.98	41.873	41.975	42.122	42.	
24	118.82	47.794	47.894	48.036	48.	
25	135	54.264	54.368	54.515	54.	

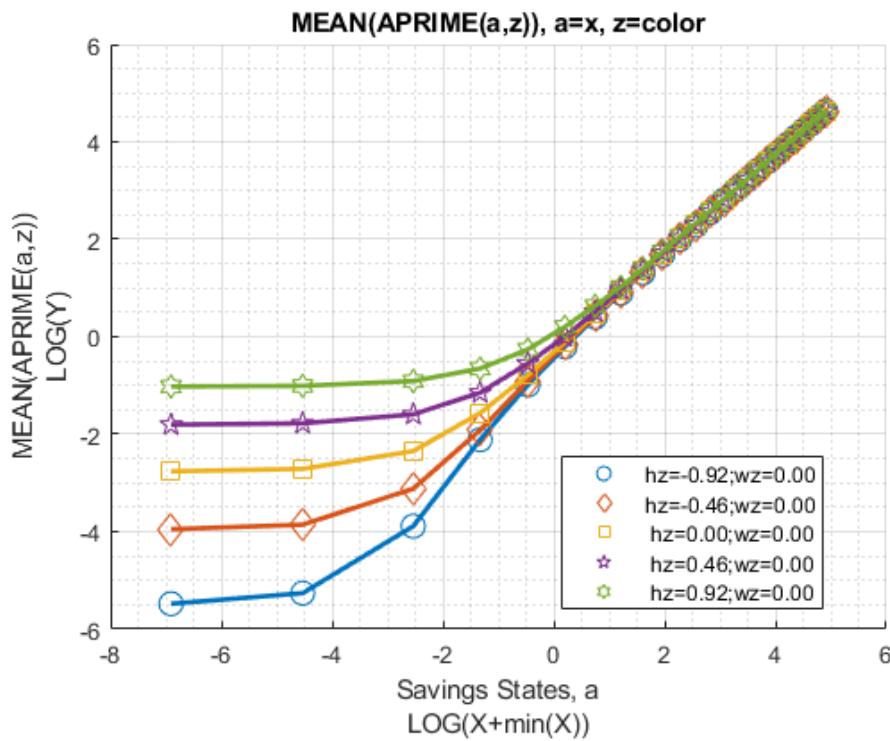
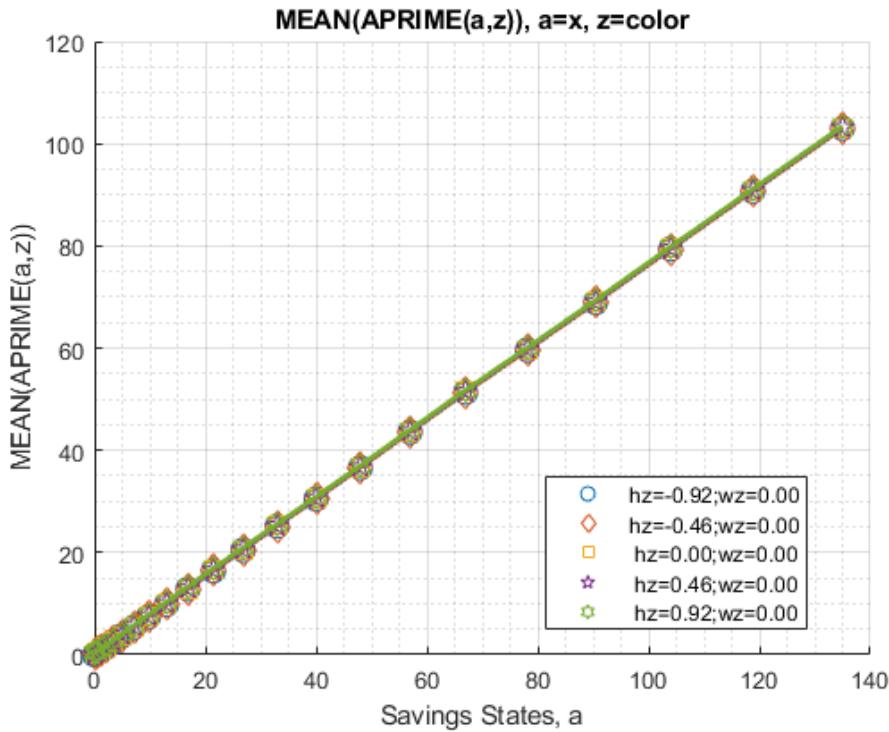
Graph Mean Values:

```
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);
```



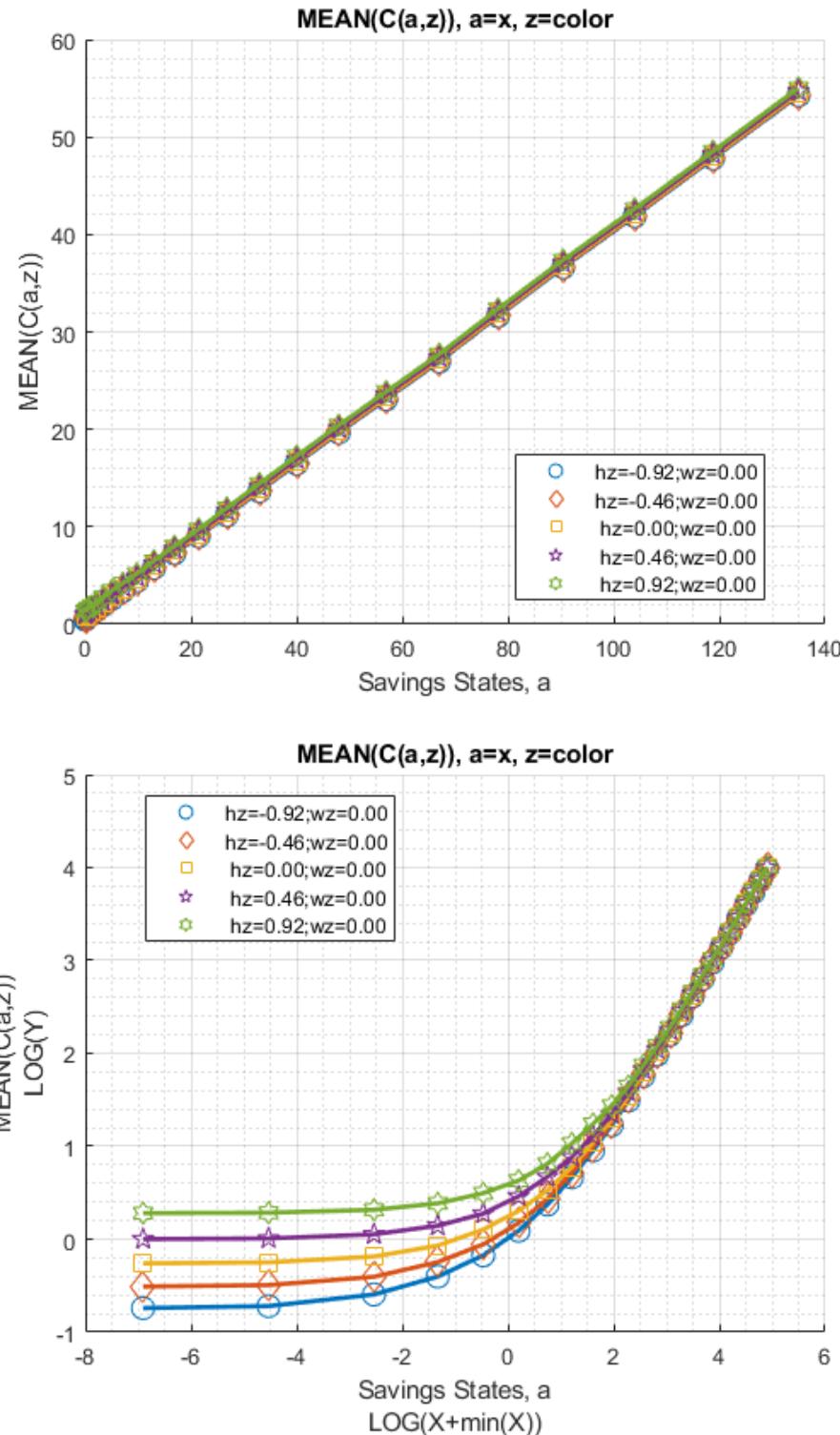
Graph Mean Savings Choices:

```
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);
```



### 3.3.4 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)) xxxxxxxxxxxxxxxxxxxxxxxxx
group kids marry mean_age_19 mean_age_22 mean_age_27 mean_age_32 mean_age_3
-----
1 1 0 2.6201 2.7665 2.8454 2.8242 2.7343
2 2 0 1.5887 1.8727 2.0791 2.1577 2.1527
3 3 0 1.0708 1.3439 1.5546 1.6415 1.6452
4 1 1 2.395 2.5572 2.6553 2.6638 2.609
5 2 1 1.6234 1.8656 2.0481 2.1297 2.1416
6 3 1 1.2806 1.5046 1.6784 1.7562 1.766

% 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)) xxxxxxxxxxxxxxxxxxxxxxxxx
group kids marry mean_age_19 mean_age_22 mean_age_27 mean_age_32 mean_age_3
-----
1 1 0 34.74 34.523 34.415 34.265 34.042
2 2 0 34.413 34.138 33.952 33.709 33.376
3 3 0 34.001 33.777 33.635 33.423 33.115
4 1 1 34.621 34.408 34.308 34.16 33.941
5 2 1 34.473 34.246 34.109 33.911 33.625
6 3 1 34.106 33.916 33.813 33.643 33.381

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

xxx MEAN(C(KM,J)) xxxxxxxxxxxxxxxxxxxxxxxxx
group kids marry mean_age_19 mean_age_22 mean_age_27 mean_age_32 mean_age_3
-----
1 1 0 6.778 7.0757 7.3697 7.6652 7.9826
2 2 0 7.1055 7.4611 7.8334 8.2212 8.6487
3 3 0 7.5174 7.8216 8.1497 8.5069 8.91
4 1 1 7.1206 7.4352 7.7476 8.0644 8.4009
5 2 1 7.2345 7.5595 7.9048 8.2677 8.6677
6 3 1 7.5771 7.8633 8.1717 8.5043 8.8779

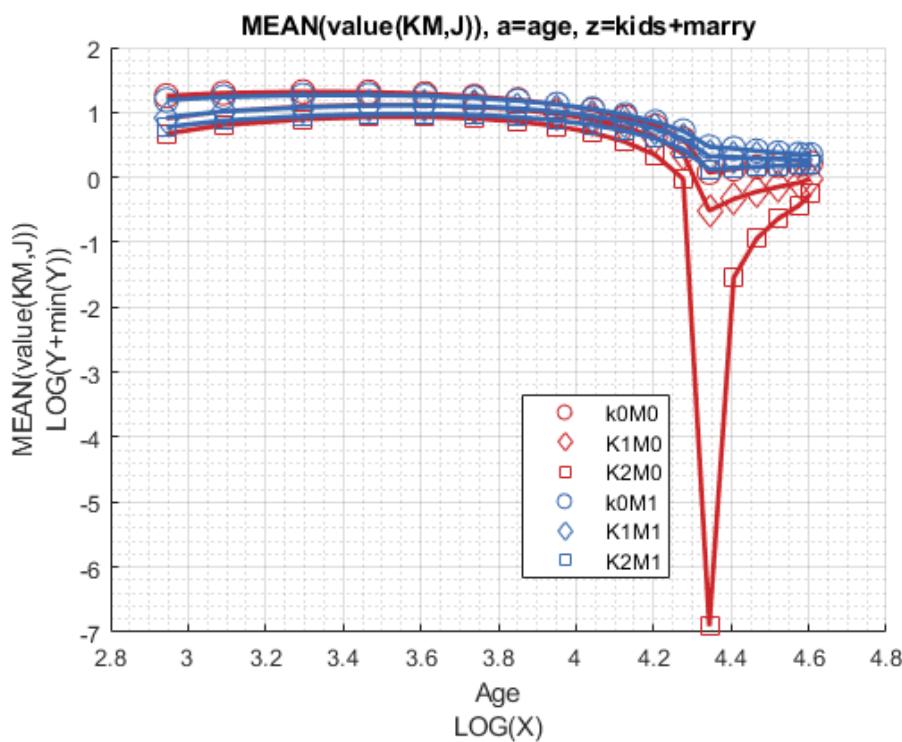
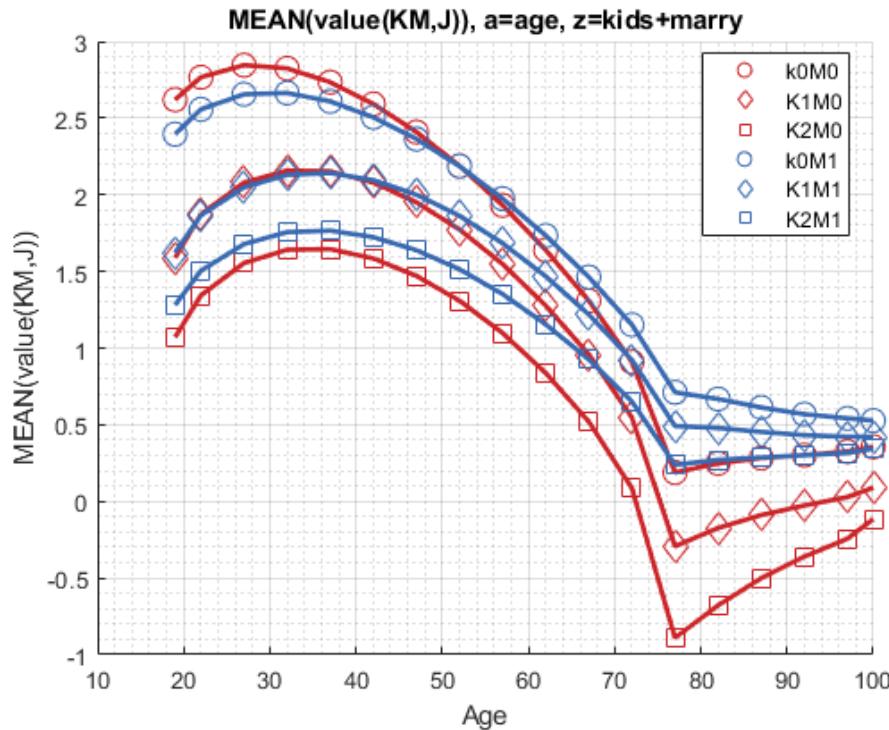
```

Graph Mean Values:

```

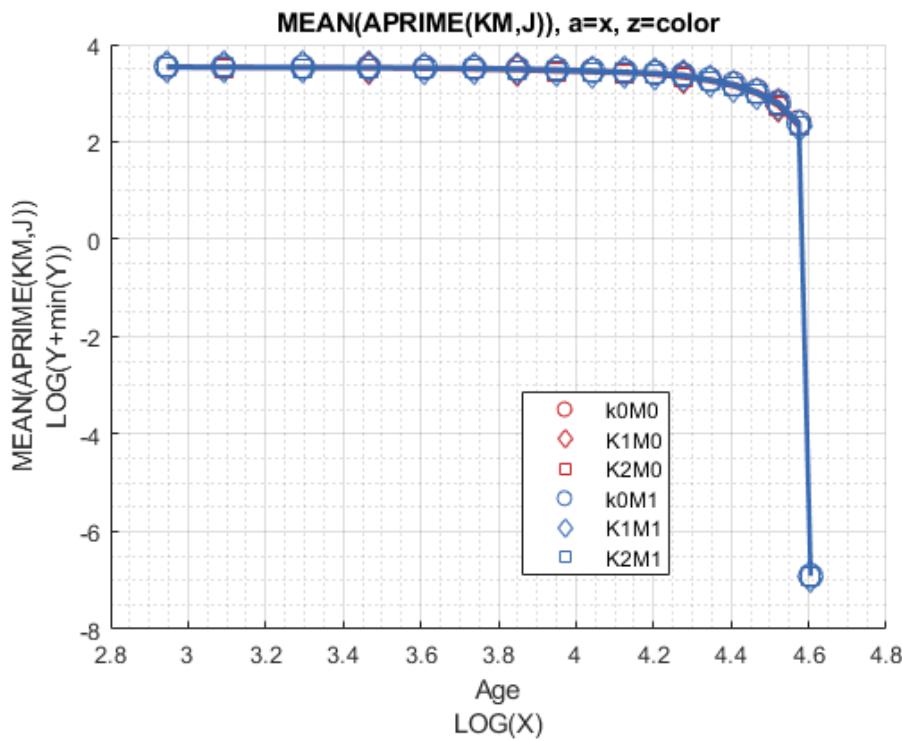
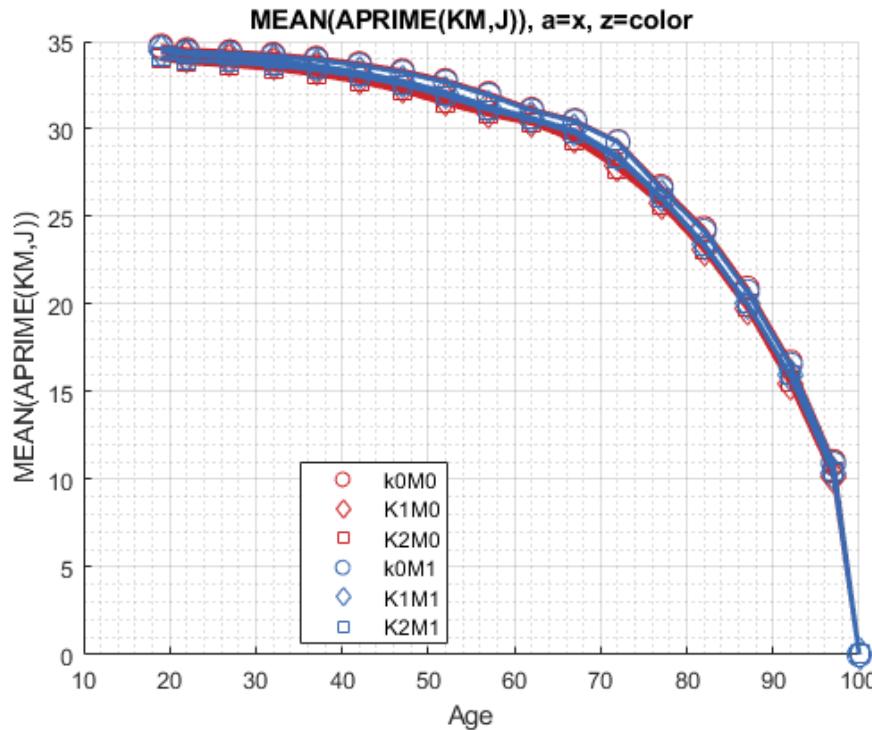
mp_support_graph('cl_st_graph_title') = {'MEAN(value(KM,J)), a=age, z=kids+marry'};
mp_support_graph('cl_st_ytitle') = {'MEAN(value(KM,J))'};
ff_graph_grid((tb_az_v{1:end, 4:end}), ar_row_grid, age_grid, mp_support_graph);

```



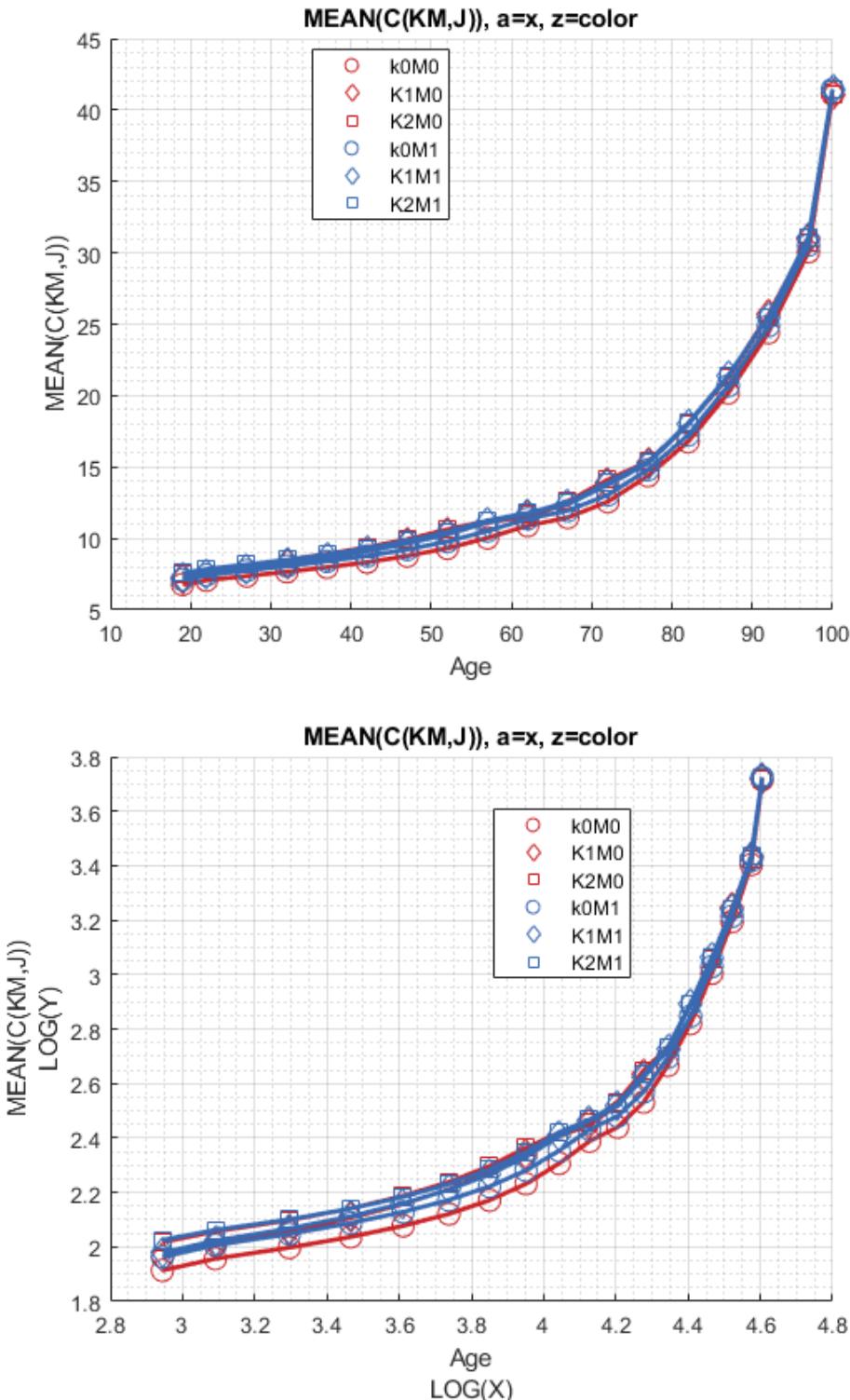
Graph Mean Savings Choices:

```
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);
```



### 3.3.5 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_pe

xxx MEAN(VAL(EKM,J)) xxxxxxxxxxxxxxxxxxxxxxxxx
group edu marry mean_age_19 mean_age_22 mean_age_27 mean_age_32 mean_age_37
---- --- ---- -----
1 0 0 1.4646 1.6636 1.8129 1.8698 1.8591
2 1 0 2.0551 2.3251 2.5065 2.5458 2.4958
3 0 1 1.4539 1.6452 1.7914 1.8602 1.8706
4 1 1 2.0788 2.3064 2.4632 2.5062 2.4738

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

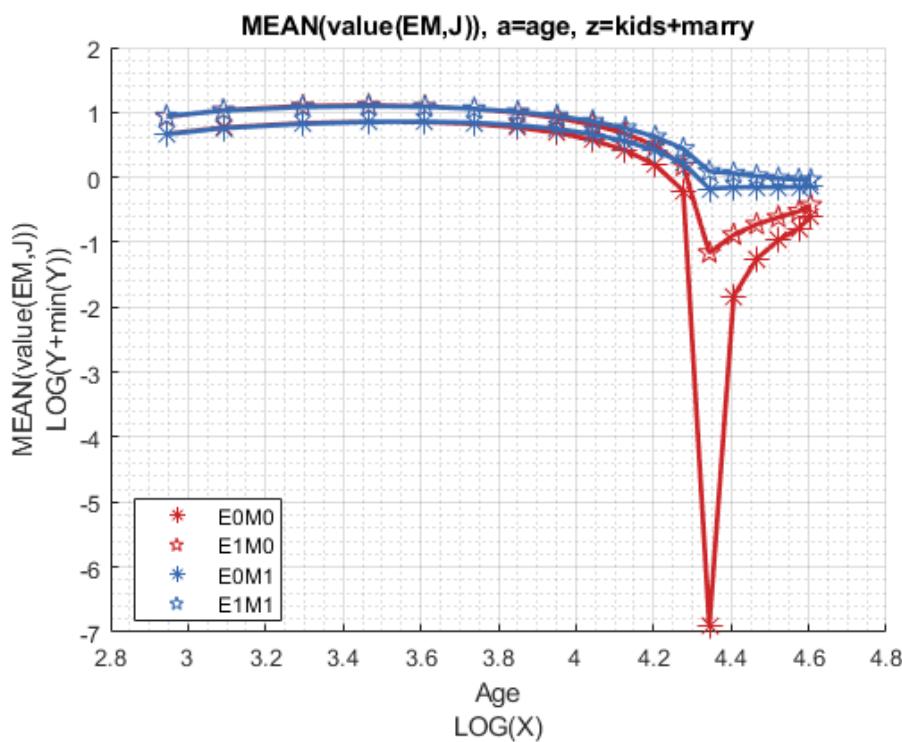
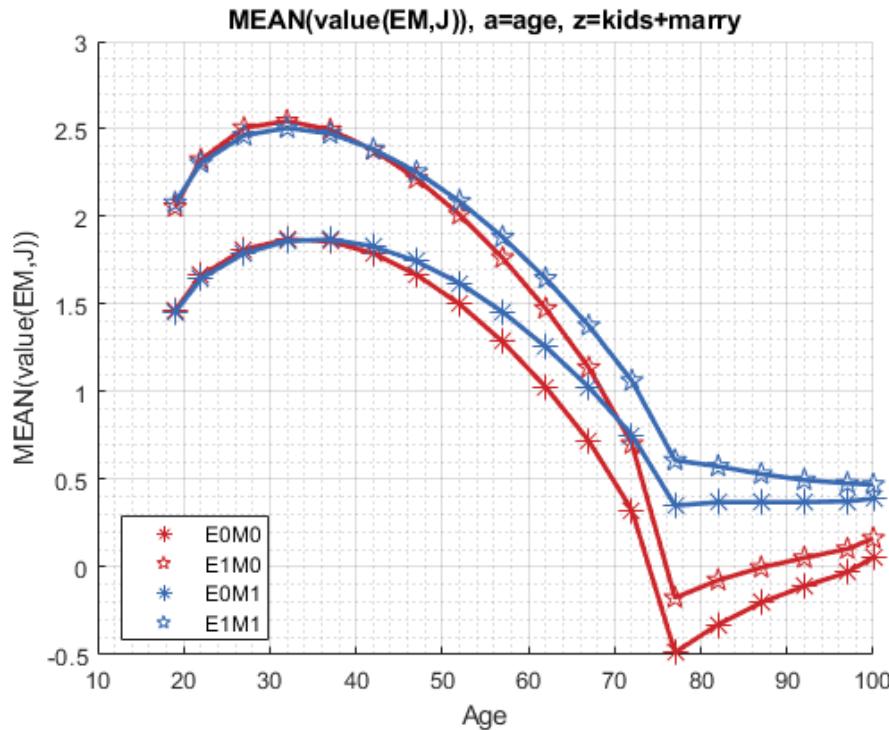
xxx MEAN(AP(EKM,J)) xxxxxxxxxxxxxxxxxxxxxxxxx
group edu marry mean_age_19 mean_age_22 mean_age_27 mean_age_32 mean_age_37
---- --- ---- -----
1 0 0 34.471 34.227 34.028 33.781 33.465
2 1 0 34.298 34.065 33.974 33.817 33.557
3 0 1 34.505 34.289 34.12 33.903 33.618
4 1 1 34.294 34.091 34.033 33.907 33.681

% 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)) xxxxxxxxxxxxxxxxxxxxxxxxx
group edu marry mean_age_19 mean_age_22 mean_age_27 mean_age_32 mean_age_37
---- --- ---- -----
1 0 0 7.047 7.3391 7.647 7.982 8.3628
2 1 0 7.2203 7.5665 7.9215 8.2802 8.6647
3 0 1 7.1855 7.465 7.7602 8.0826 8.4489
4 1 1 7.436 7.7737 8.1225 8.475 8.8488
```

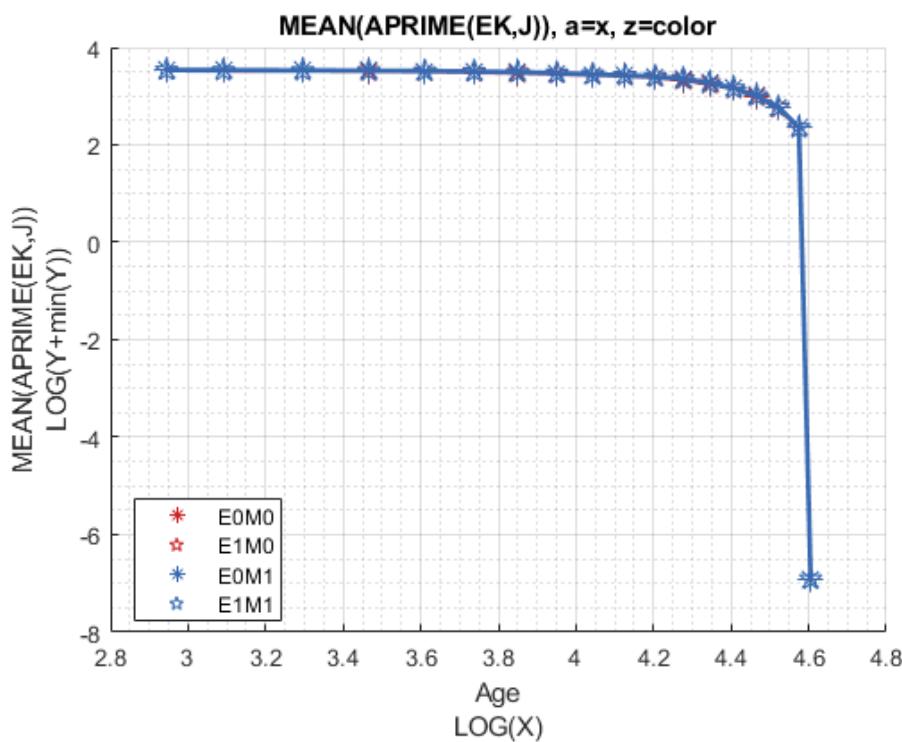
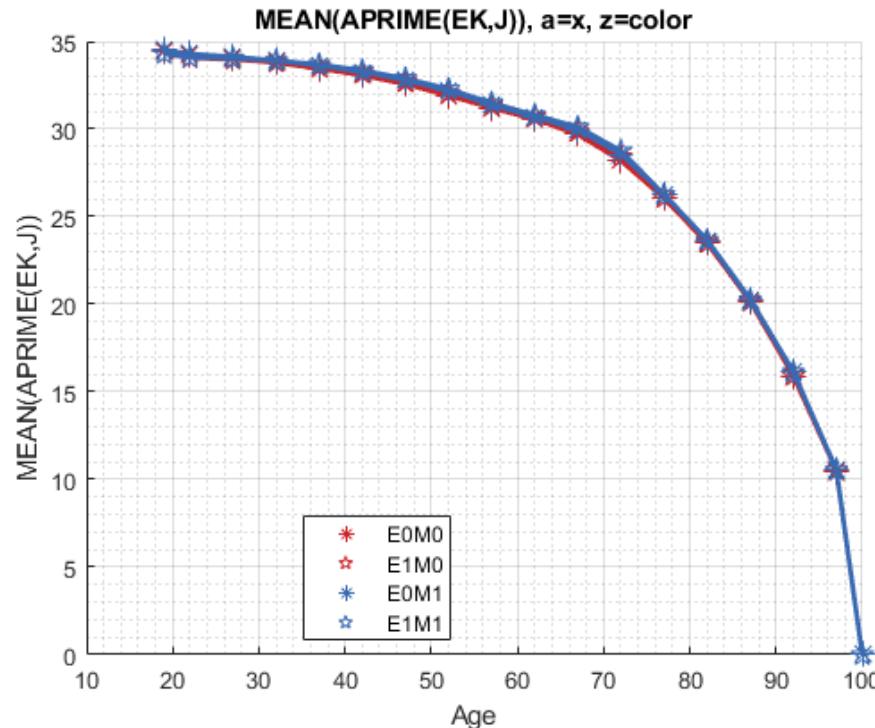
Graph Mean Values:

```
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);
```



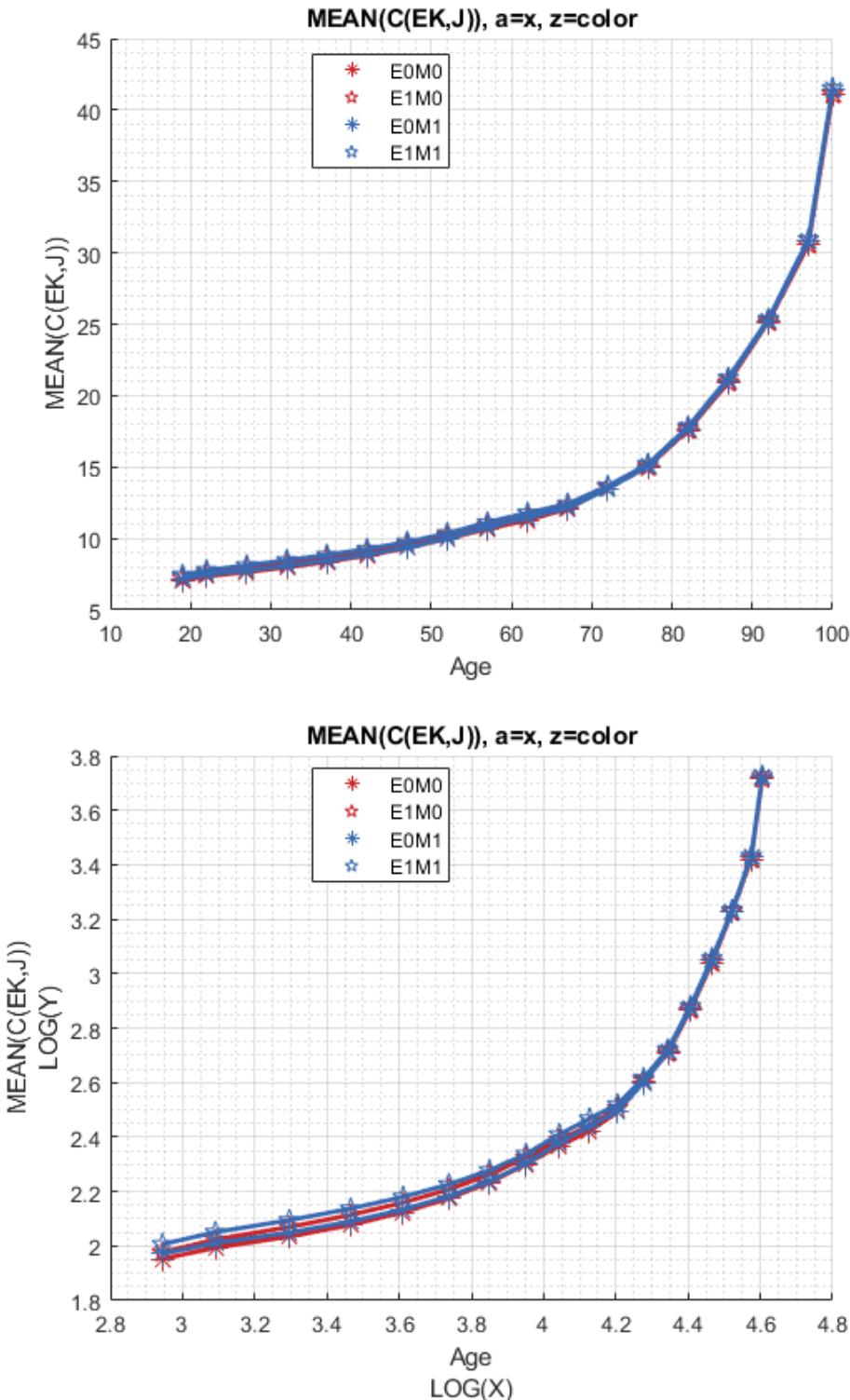
Graph Mean Savings Choices:

```
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);
```



## 3.4 SNW\_VFI\_PARAM Small 5/3 Solution Analysis

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.

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

Call the function with defaults.

```

mp_param = snw_mp_param('default_small53');
[V_VFI,ap_VFI,cons_VFI,mp_valpol_more] = snw_vfi_main_bisec_vec(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 4.405878 seconds.
Completed SNW_VFI_MAIN;SNW_MP_PARAM=default_small53;SNW_MP_CONTROL=default_base

```

### 3.4.2 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});

```

### 3.4.3 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)) xxxxxxxxxxxxxxxxxxxxxxxxx
group savings mean_eta_1 mean_eta_2 mean_eta_3 mean_eta_4 mean_eta_5 mean
-----
1 0 -7.882 -5.7348 -4.085 -2.8085 -1.8188 -7
2 0.0097656 -7.7212 -5.6181 -3.9885 -2.7215 -1.7365 -6
3 0.078125 -6.8428 -4.9741 -3.4642 -2.2559 -1.3014 -6
4 0.26367 -5.4385 -3.9243 -2.6322 -1.5472 -0.66003 -5
5 0.625 -3.9212 -2.7733 -1.7454 -0.83276 -0.049731 -3
6 1.2207 -2.4938 -1.6768 -0.89179 -0.17035 0.48277 -2
7 2.1094 -1.2492 -0.69701 -0.12719 0.42663 0.94331 -1
8 3.3496 -0.21896 0.14154 0.536 0.94666 1.3467 -0.
9 5 0.60263 0.83385 1.0995 1.3921 1.6958 0.
10 7.1191 1.242 1.3897 1.5663 1.7699 1.9935 1
11 9.7656 1.7339 1.8287 1.9458 2.086 2.247 1
12 12.998 2.1109 2.1725 2.2505 2.3468 2.4616 2
13 16.875 2.4005 2.4411 2.4935 2.5599 2.6414 2
14 21.455 2.6243 2.6513 2.687 2.733 2.7911 2
15 26.797 2.7986 2.817 2.8415 2.8737 2.9153 2
16 32.959 2.9355 2.9482 2.9654 2.9882 3.0181 2
17 40 3.0441 3.053 3.0651 3.0815 3.1033 3
18 47.979 3.1309 3.1373 3.146 3.1579 3.1739 3
19 56.953 3.201 3.2056 3.212 3.2207 3.2326 3
20 66.982 3.258 3.2614 3.2662 3.2727 3.2816 3
21 78.125 3.3049 3.3074 3.311 3.3159 3.3226 3
22 90.439 3.3437 3.3456 3.3483 3.352 3.3572 3
23 103.98 3.3761 3.3775 3.3796 3.3824 3.3864 3
24 118.82 3.4032 3.4044 3.4059 3.4082 3.4113 3
25 135 3.4262 3.4271 3.4283 3.4301 3.4325 3
```

```
% Aprime Choice
tb_az_ap = ff_summ_nd_array("MEAN(AP(A,Z))", ap_VFI, true, ["mean"], 4, 1, cl_mp_datasetdesc, ar_permute);

xxx MEAN(AP(A,Z)) xxxxxxxxxxxxxxxxxxxxxxxxx
group savings mean_eta_1 mean_eta_2 mean_eta_3 mean_eta_4 mean_eta_5 mean
-----
1 0 0.0019699 0.012569 0.042745 0.11279 0.27641 0.00
2 0.0097656 0.0026822 0.013934 0.045039 0.11613 0.28116 0.00
3 0.078125 0.012725 0.028983 0.063429 0.14286 0.31616 0.00
4 0.26367 0.086315 0.10163 0.14743 0.23696 0.42136 0.00
5 0.625 0.30688 0.32748 0.37158 0.48022 0.66179 0.00
6 1.2207 0.71364 0.74681 0.79866 0.90672 1.1008 0.00
7 2.1094 1.38 1.4122 1.473 1.5674 1.7516 1
8 3.3496 2.3237 2.3547 2.4215 2.5241 2.6817 2
9 5 3.5866 3.6174 3.6852 3.8049 3.9657 0
10 7.1191 5.2284 5.258 5.3256 5.4521 5.645 5
11 9.7656 7.2439 7.2717 7.3376 7.4667 7.6795 7
12 12.998 9.683 9.7074 9.7687 9.8969 10.122 1
13 16.875 12.69 12.713 12.768 12.888 13.118 1
14 21.455 16.245 16.267 16.322 16.434 16.656 1
```

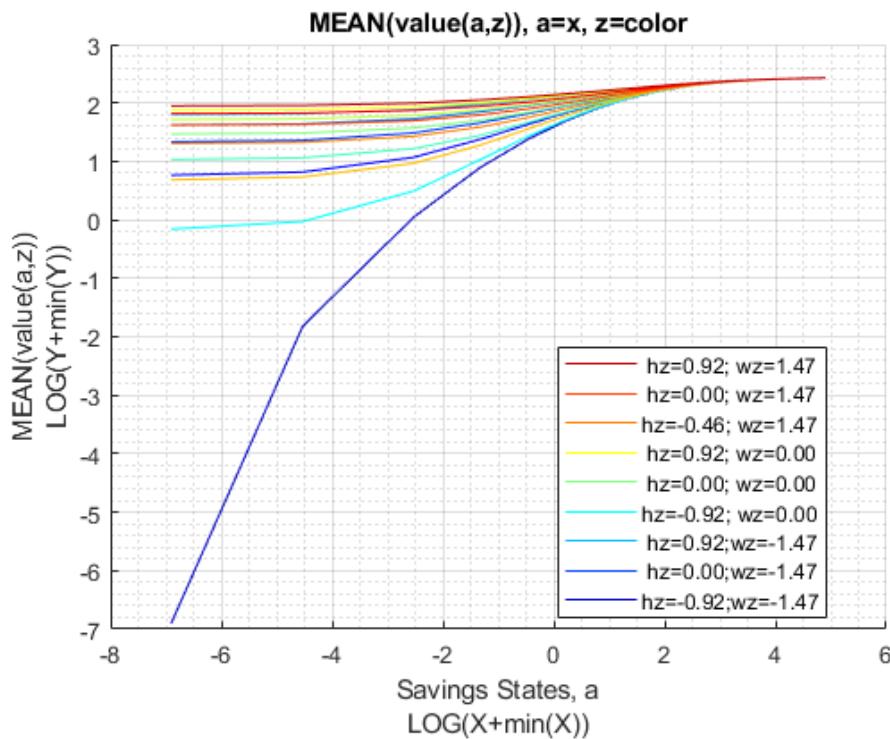
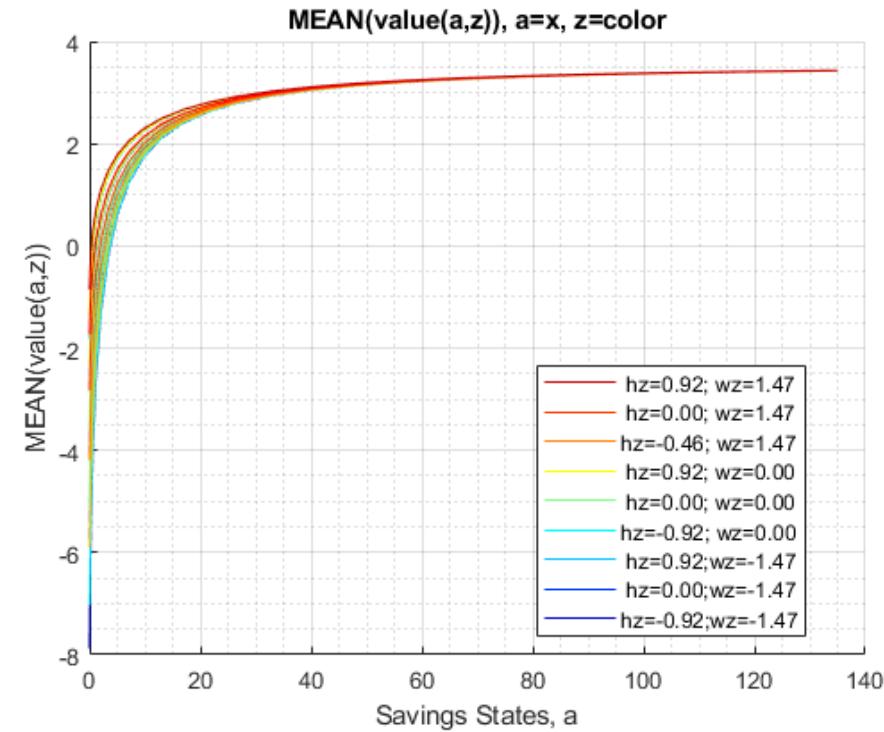
15	26.797	20.297	20.314	20.362	20.471	20.681	2
16	32.959	24.972	24.994	25.04	25.136	25.339	
17	40	30.336	30.36	30.416	30.523	30.708	3
18	47.979	36.418	36.442	36.497	36.607	36.811	3
19	56.953	43.405	43.428	43.48	43.586	43.789	4
20	66.982	51.176	51.202	51.26	51.37	51.568	5
21	78.125	59.419	59.447	59.507	59.624	59.834	5
22	90.439	68.737	68.762	68.819	68.932	69.146	6
23	103.98	79.211	79.236	79.291	79.402	79.606	7
24	118.82	90.517	90.543	90.601	90.715	90.921	9
25	135	102.82	102.85	102.9	103.01	103.22	

```
% Consumption Choices tb_az_c = ff_summ_nd_array("MEAN(C(A,Z))", cons_VFI, true, ["mean"], 4, 1, cl_mp_datasetdesc, ar_permute);
```

xxx	MEAN(C(A,Z))	xxxxxxxxxxxxxxxxxxxxxxxxxxxxxx	group	savings	mean_eta_1	mean_eta_2	mean_eta_3	mean_eta_4	mean_eta_5	mean
---	---	---	group	-----	-----	-----	-----	-----	-----	-----
1	0	0.36263	0.36263	0.48831	0.66884	0.92666	1.2761	1.2761	0.4	
2	0.0097656	0.37339	0.0097656	0.4984	0.67798	0.93473	1.2828	1.2828	0.	
3	0.078125	0.44367	0.078125	0.56349	0.73958	0.98789	1.3276	1.3276	0.5	
4	0.26367	0.58796	0.26367	0.70825	0.87262	1.1106	1.439	1.439	0.6	
5	0.625	0.7912	0.625	0.90541	1.0708	1.2892	1.6202	1.6202	0.8	
6	1.2207	1.082	1.2207	1.1826	1.3394	1.5577	1.8756	1.8756	1.	
7	2.1094	1.4544	2.1094	1.5549	1.7017	1.9328	2.26	2.26	1.	
8	3.3496	1.958	3.3496	2.0586	2.1984	2.4204	2.7735	2.7735		
9	5	2.6182	5	2.7182	2.8561	3.0601	3.4093	3.4093	2.	
10	7.1191	3.4432	7.1191	3.5437	3.6809	3.8773	4.1937	4.1937	3.	
11	9.7656	4.5057	9.7656	4.6075	4.7459	4.939	5.2349	5.2349	4.	
12	12.998	5.824	12.998	5.9289	6.0713	6.2649	6.5482	6.5482	5.	
13	16.875	7.322	16.875	7.4281	7.5761	7.7778	8.0549	8.0549	7	
14	21.455	9.0868	21.455	9.1934	9.342	9.5513	9.8361	9.8361	9.	
15	26.797	11.239	26.797	11.351	11.506	11.717	12.014	12.014	1	
16	32.959	13.72	32.959	13.826	13.983	14.207	14.511	14.511	13	
17	40	16.53	40	16.635	16.782	16.996	17.316	17.316	16	
18	47.979	19.712	47.979	19.817	19.964	20.174	20.477	20.477	19	
19	56.953	23.144	56.953	23.25	23.4	23.614	23.917	23.917	23	
20	66.982	27.016	66.982	27.118	27.263	27.473	27.781	27.781	27	
21	78.125	31.708	78.125	31.809	31.951	32.154	32.451	32.451	31	
22	90.439	36.685	90.439	36.789	36.934	37.141	37.433	37.433	36	
23	103.98	41.935	103.98	42.038	42.186	42.395	42.696	42.696	41	
24	118.82	47.848	118.82	47.951	48.095	48.301	48.601	48.601	47	
25	135	54.325	135	54.429	54.577	54.788	55.087	55.087	5	

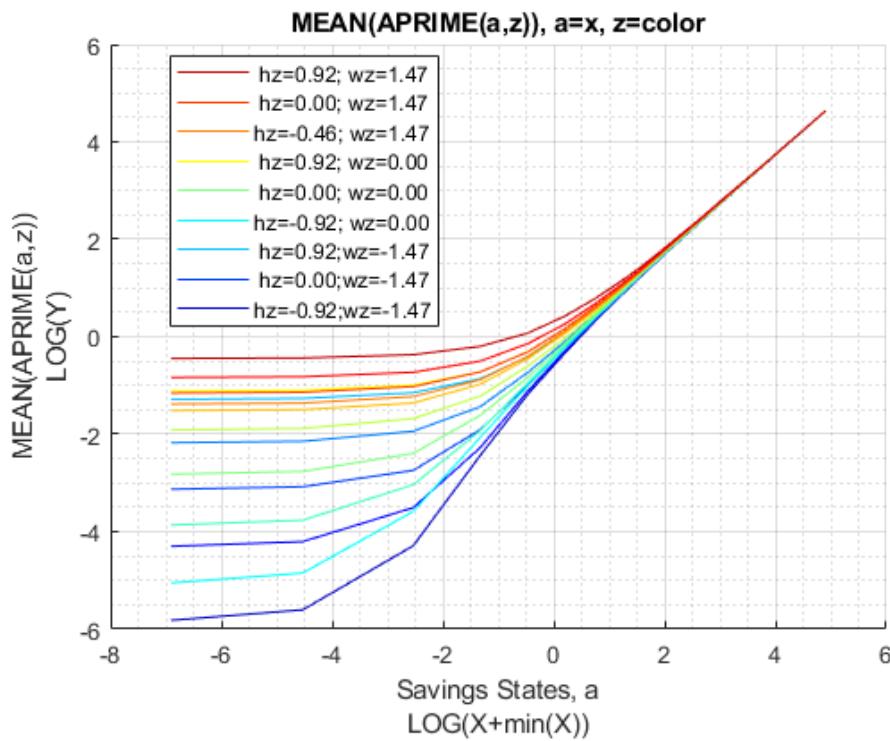
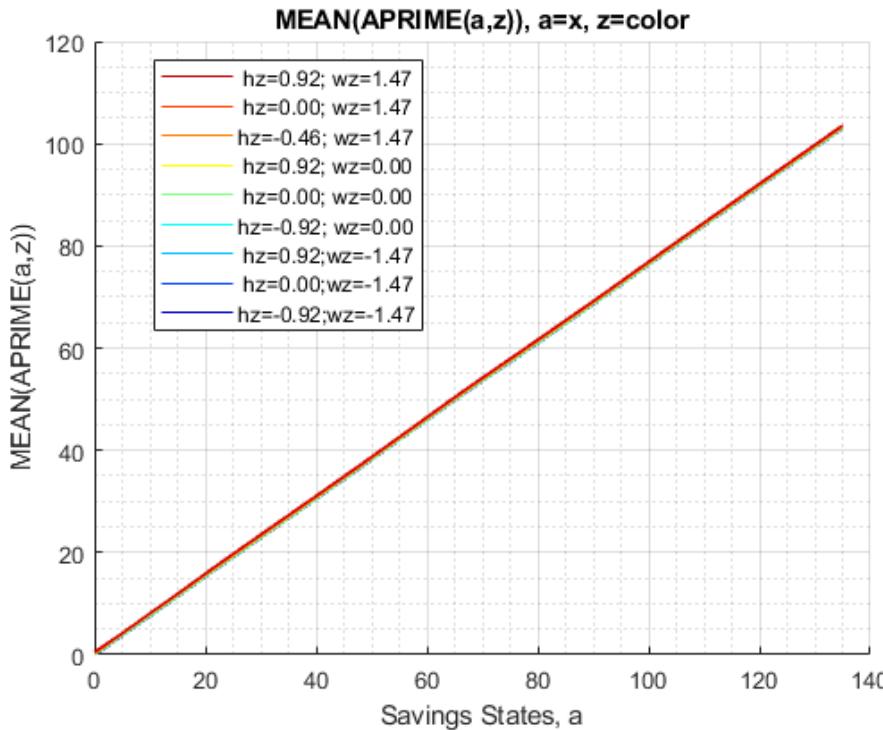
Graph Mean Values:

```
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);
```



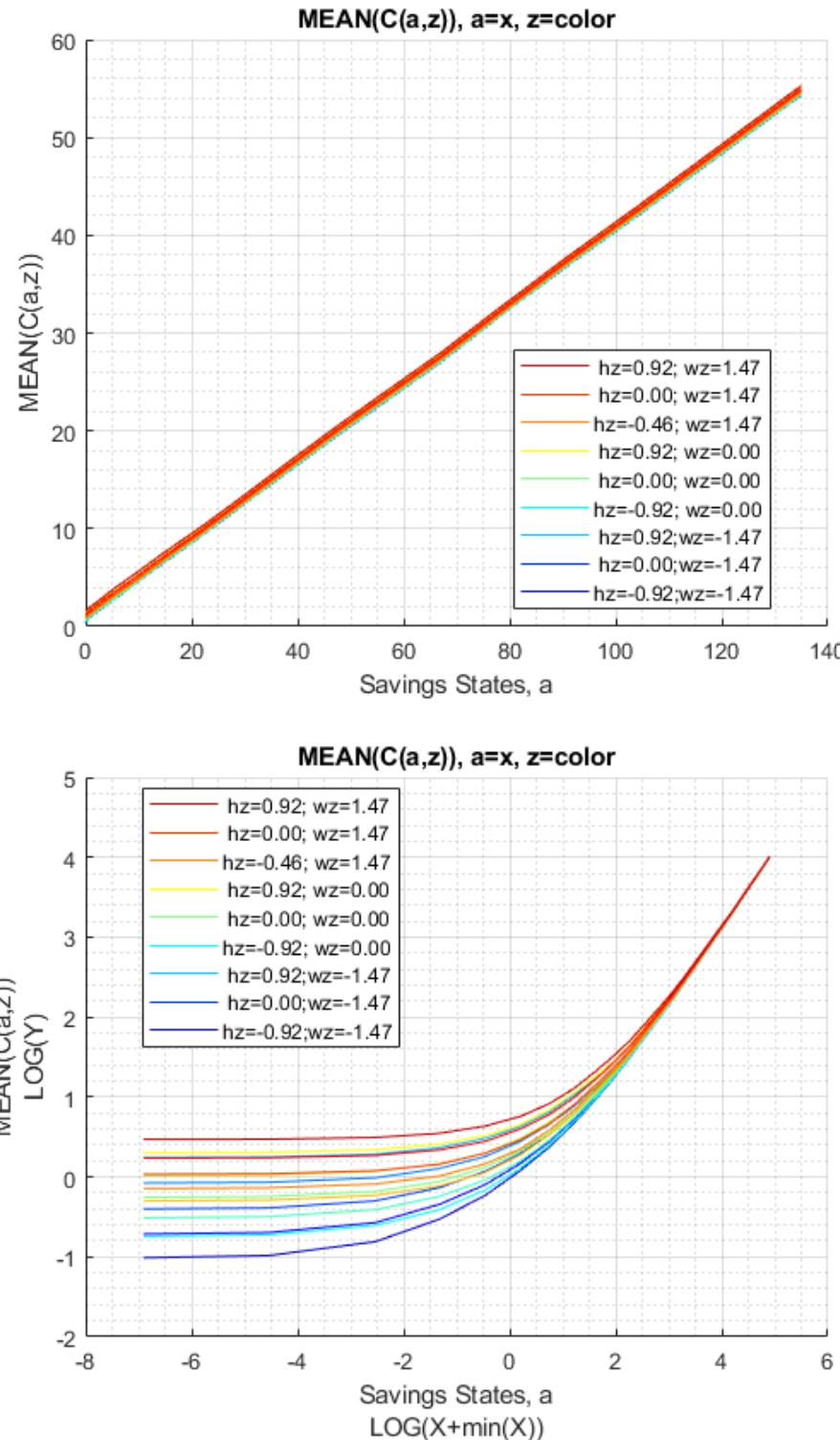
Graph Mean Savings Choices:

```
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);
```



### 3.4.4 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)) xxxxxxxxxxxxxxxxxxxxxxxxx
group kids marry mean_age_19 mean_age_22 mean_age_27 mean_age_32 mean_age_3
-----
1 1 0 2.6201 2.7665 2.8454 2.8242 2.7343
2 2 0 1.5887 1.8727 2.0791 2.1577 2.1527
3 3 0 1.0708 1.3439 1.5546 1.6415 1.6452
4 1 1 2.6802 2.8229 2.9077 2.9056 2.8417
5 2 1 1.9461 2.164 2.3286 2.3959 2.3955
6 3 1 1.615 1.8161 1.9731 2.0371 2.0352

% 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)) xxxxxxxxxxxxxxxxxxxxxxxxx
group kids marry mean_age_19 mean_age_22 mean_age_27 mean_age_32 mean_age_3
-----
1 1 0 34.74 34.523 34.415 34.265 34.042
2 2 0 34.413 34.138 33.952 33.709 33.376
3 3 0 34.001 33.777 33.635 33.423 33.115
4 1 1 34.626 34.419 34.323 34.185 33.976
5 2 1 34.477 34.253 34.116 33.923 33.642
6 3 1 34.101 33.913 33.809 33.641 33.384

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

xxx MEAN(C(KM,J)) xxxxxxxxxxxxxxxxxxxxxxxxx
group kids marry mean_age_19 mean_age_22 mean_age_27 mean_age_32 mean_age_3
-----
1 1 0 6.778 7.0757 7.3697 7.6652 7.9826
2 2 0 7.1055 7.4611 7.8334 8.2212 8.6487
3 3 0 7.5174 7.8216 8.1497 8.5069 8.91
4 1 1 7.3063 7.6329 7.9639 8.2916 8.638
5 2 1 7.3917 7.7297 8.0937 8.4696 8.8812
6 3 1 7.7233 8.0217 8.3477 8.6932 9.0766

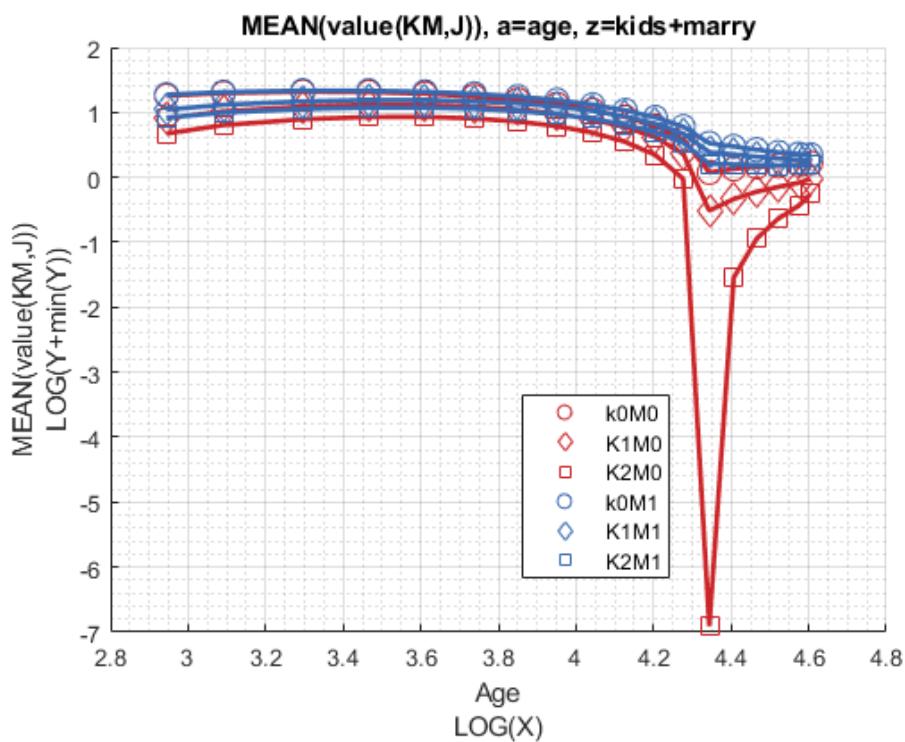
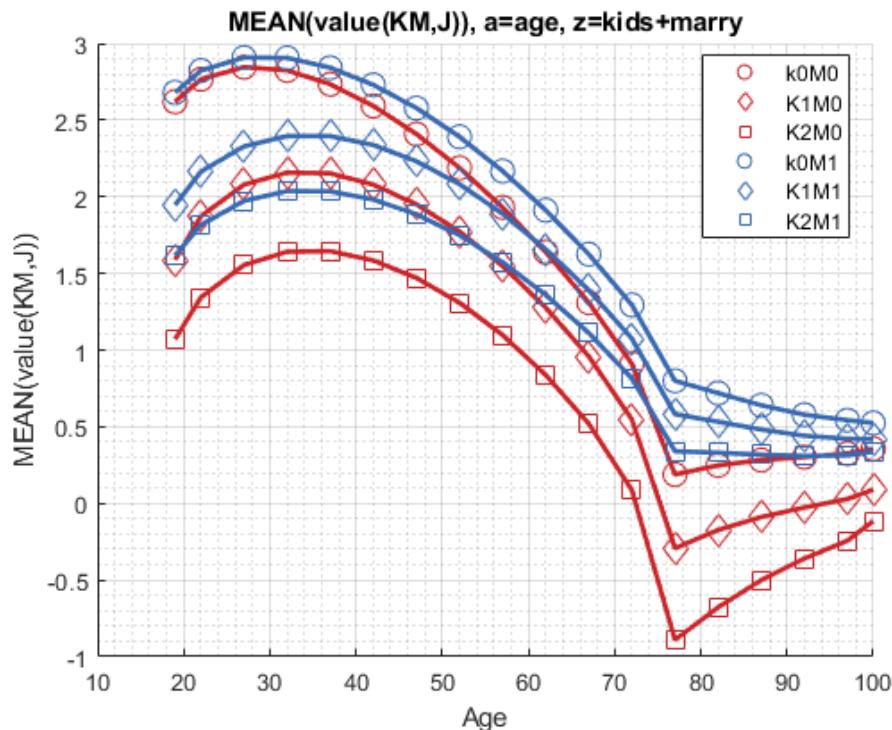
```

Graph Mean Values:

```

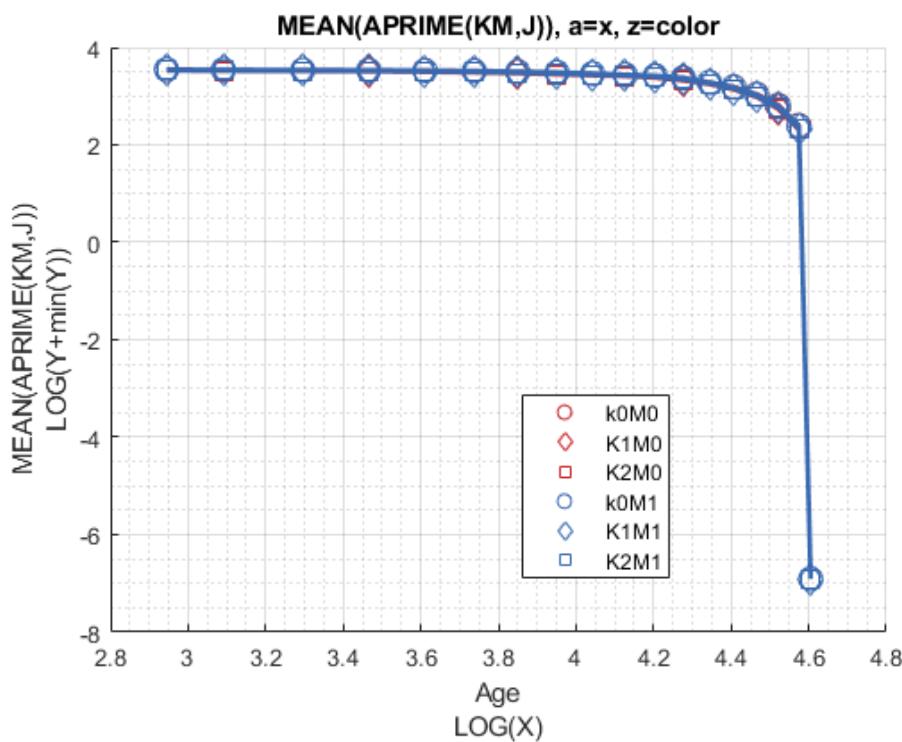
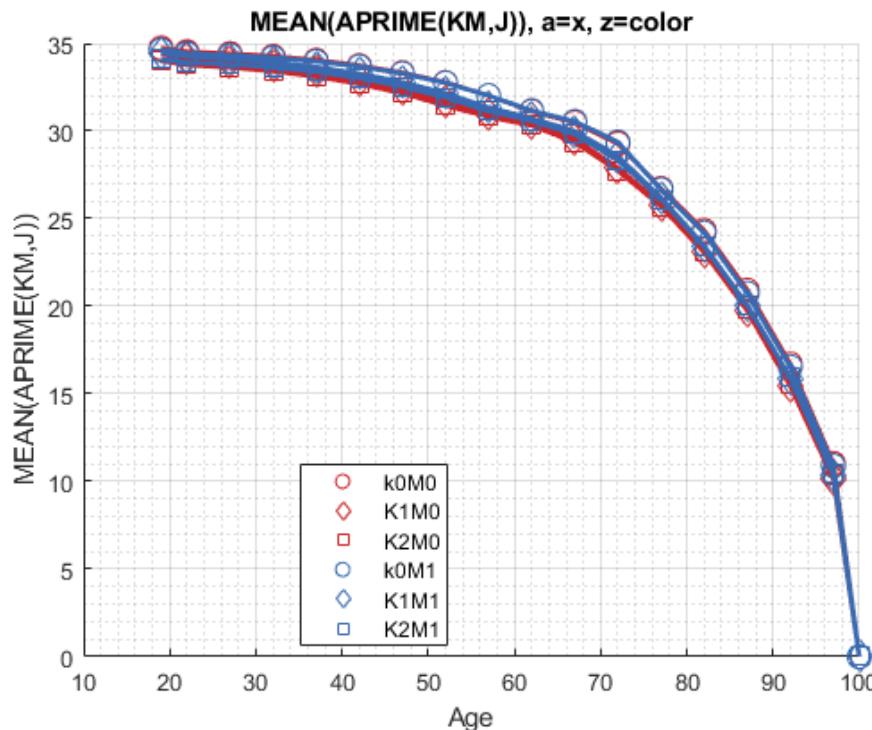
mp_support_graph('cl_st_graph_title') = {'MEAN(value(KM,J)), a=age, z=kids+marry'};
mp_support_graph('cl_st_ytitle') = {'MEAN(value(KM,J))'};
ff_graph_grid((tb_az_v{1:end, 4:end}), ar_row_grid, age_grid, mp_support_graph);

```



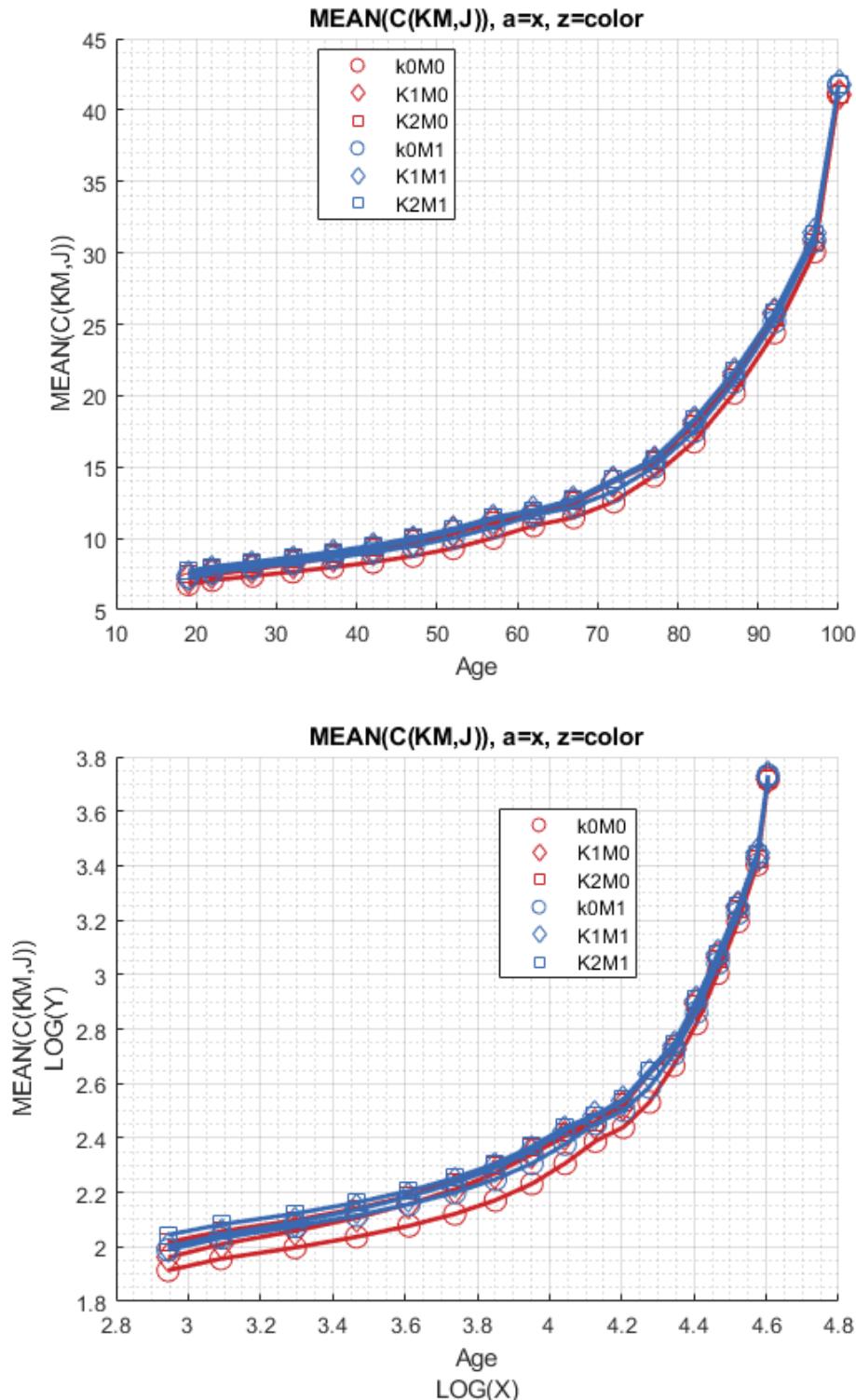
Graph Mean Savings Choices:

```
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);
```



### 3.4.5 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_pe

xxx MEAN(VAL(EKM,J)) xxxxxxxxxxxxxxxxxxxxxxxxx
group edu marry mean_age_19 mean_age_22 mean_age_27 mean_age_32 mean_age_37
---- --- ---- -----
1 0 0 1.4646 1.6636 1.8129 1.8698 1.8591
2 1 0 2.0551 2.3251 2.5065 2.5458 2.4958
3 0 1 1.795 1.9657 2.0955 2.1504 2.1481
4 1 1 2.3659 2.5697 2.7107 2.7421 2.7001

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

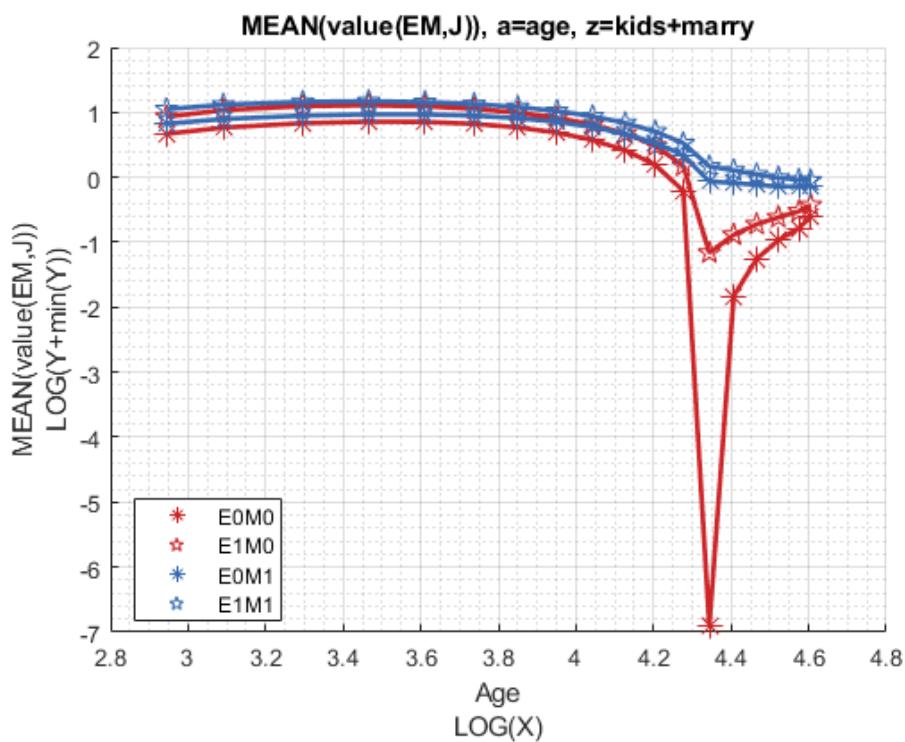
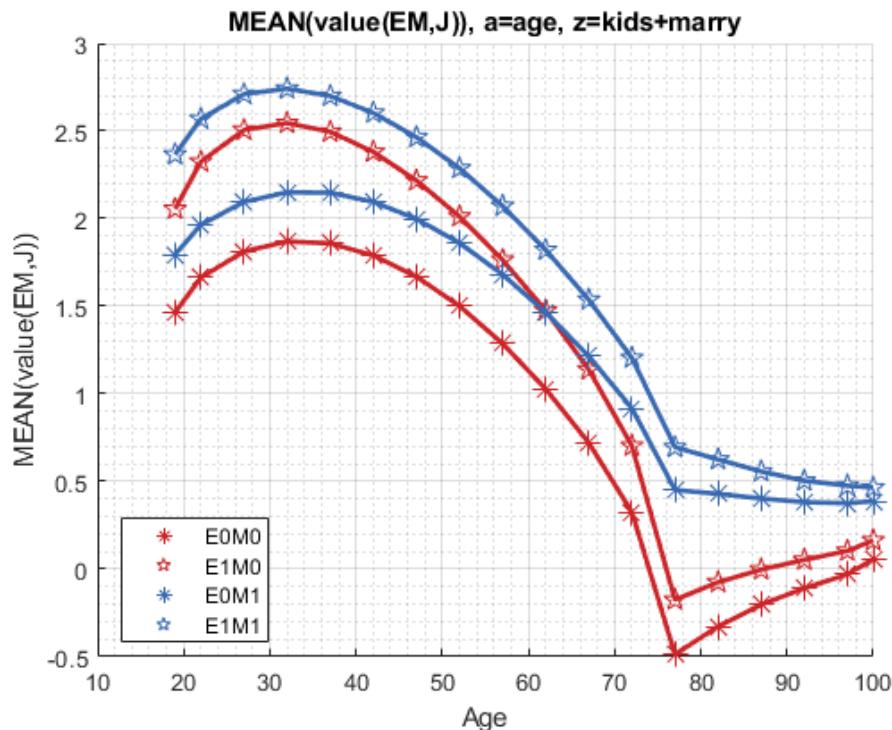
xxx MEAN(AP(EKM,J)) xxxxxxxxxxxxxxxxxxxxxxxxx
group edu marry mean_age_19 mean_age_22 mean_age_27 mean_age_32 mean_age_37
---- --- ---- -----
1 0 0 34.471 34.227 34.028 33.781 33.465
2 1 0 34.298 34.065 33.974 33.817 33.557
3 0 1 34.499 34.288 34.123 33.91 33.632
4 1 1 34.304 34.102 34.042 33.923 33.703

% 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)) xxxxxxxxxxxxxxxxxxxxxxxxx
group edu marry mean_age_19 mean_age_22 mean_age_27 mean_age_32 mean_age_37
---- --- ---- -----
1 0 0 7.047 7.3391 7.647 7.982 8.3628
2 1 0 7.2203 7.5665 7.9215 8.2802 8.6647
3 0 1 7.3401 7.6271 7.9338 8.2659 8.6401
4 1 1 7.6075 7.9624 8.3364 8.7038 9.0904
```

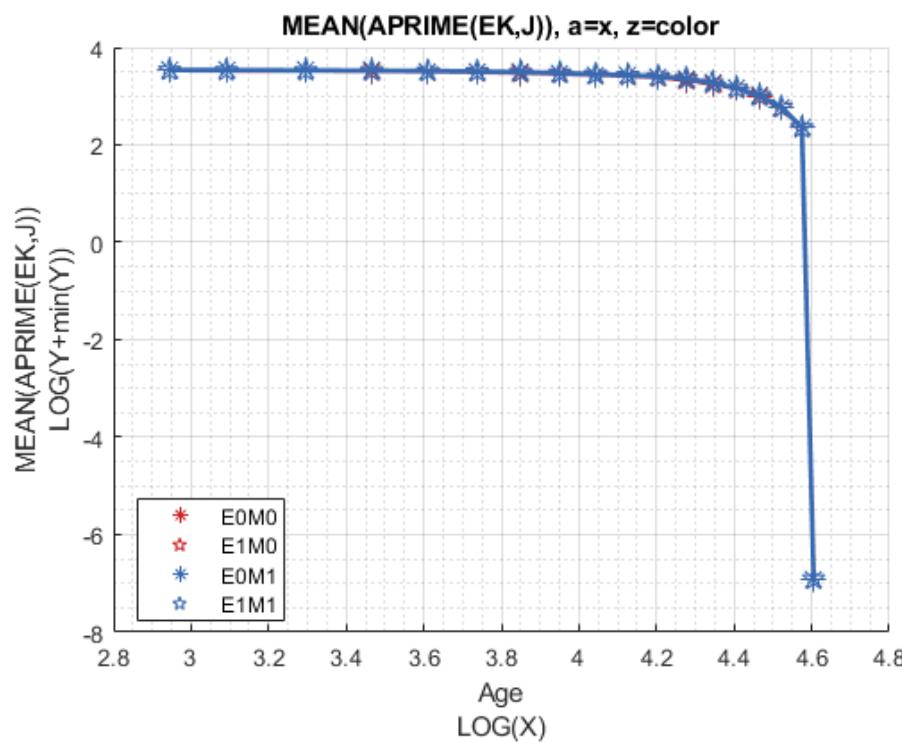
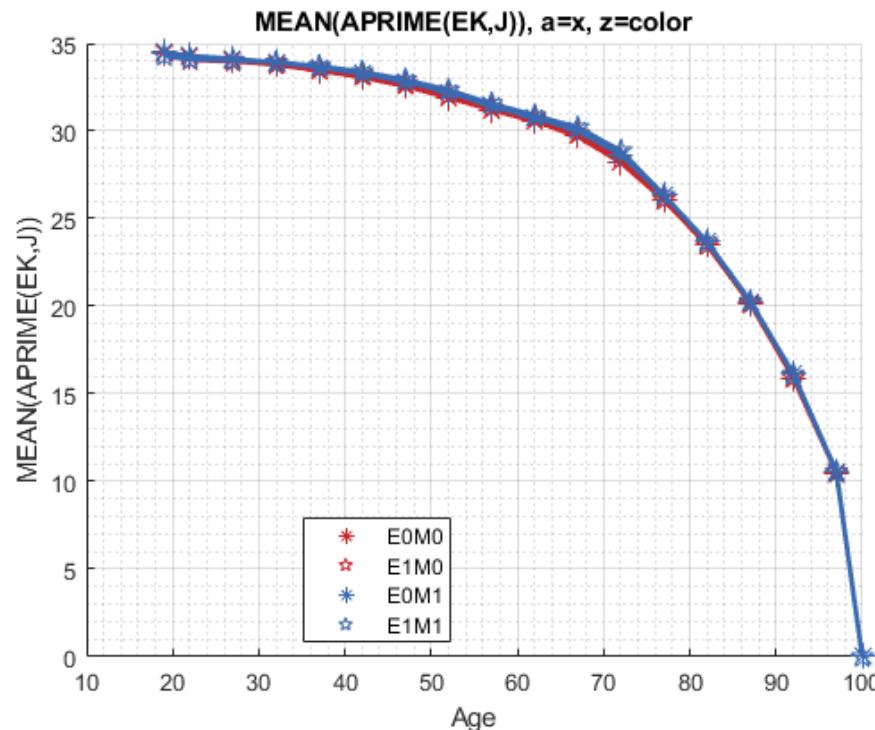
Graph Mean Values:

```
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);
```



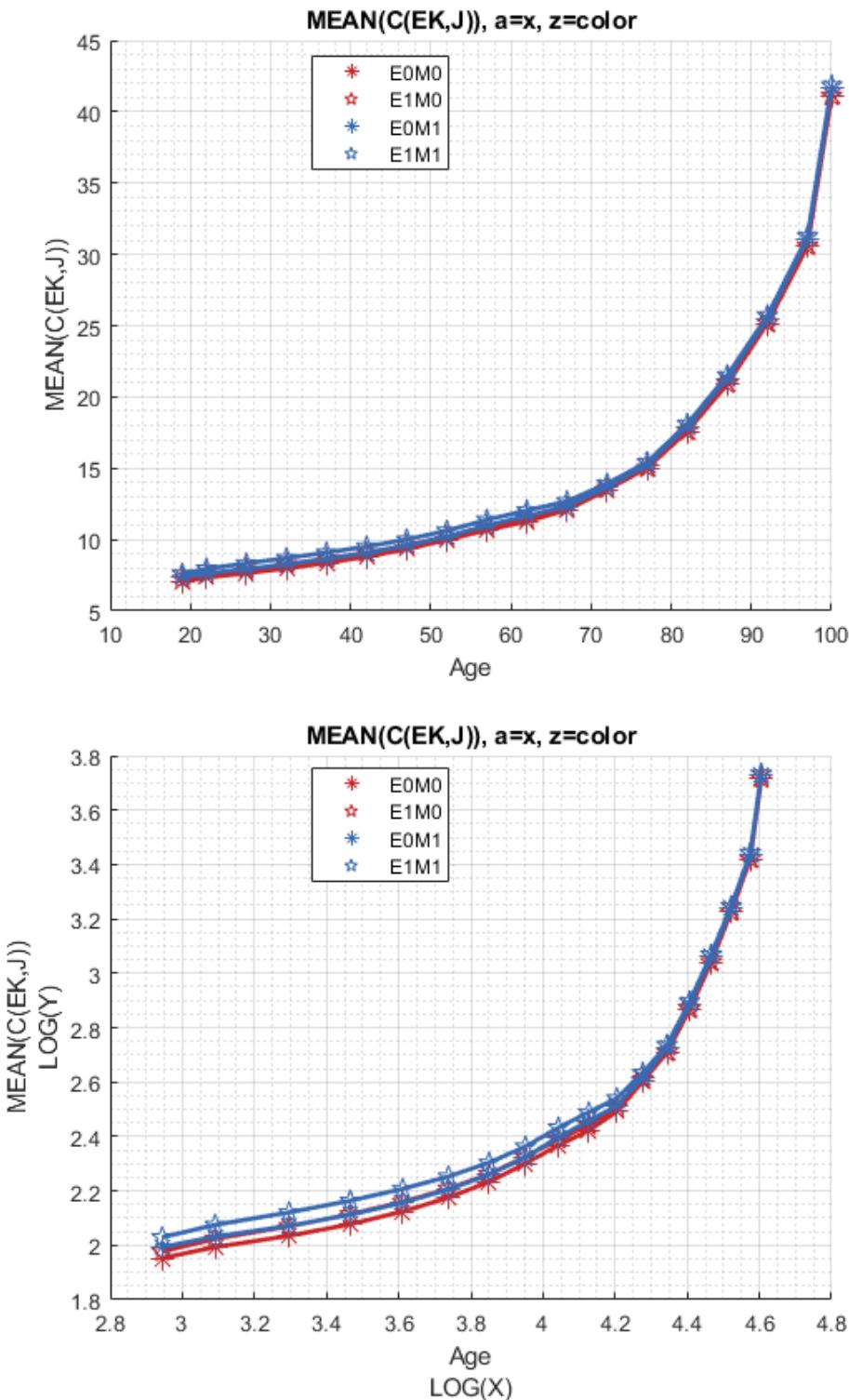
Graph Mean Savings Choices:

```
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

## Solution with Unemployment

### 4.1 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. Dense Solution Analysis. Unemployment Shock. 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).

#### 4.1.1 Test SNW\_VFI\_UNEMP Defaults Dense

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:1.8205
SNW_VFI_MAIN_BISEC_VEC: Finished Age Group:82 of 82, time-this-age:3.1788
SNW_VFI_MAIN_BISEC_VEC: Finished Age Group:81 of 82, time-this-age:3.0847
SNW_VFI_MAIN_BISEC_VEC: Finished Age Group:80 of 82, time-this-age:3.0421
SNW_VFI_MAIN_BISEC_VEC: Finished Age Group:79 of 82, time-this-age:3.0229
SNW_VFI_MAIN_BISEC_VEC: Finished Age Group:78 of 82, time-this-age:3.075
SNW_VFI_MAIN_BISEC_VEC: Finished Age Group:77 of 82, time-this-age:3.0089
SNW_VFI_MAIN_BISEC_VEC: Finished Age Group:76 of 82, time-this-age:3.0223
SNW_VFI_MAIN_BISEC_VEC: Finished Age Group:75 of 82, time-this-age:3.0628
SNW_VFI_MAIN_BISEC_VEC: Finished Age Group:74 of 82, time-this-age:2.9162
SNW_VFI_MAIN_BISEC_VEC: Finished Age Group:73 of 82, time-this-age:2.8128
SNW_VFI_MAIN_BISEC_VEC: Finished Age Group:72 of 82, time-this-age:2.8287
SNW_VFI_MAIN_BISEC_VEC: Finished Age Group:71 of 82, time-this-age:2.8302
SNW_VFI_MAIN_BISEC_VEC: Finished Age Group:70 of 82, time-this-age:2.8056
SNW_VFI_MAIN_BISEC_VEC: Finished Age Group:69 of 82, time-this-age:2.7875
SNW_VFI_MAIN_BISEC_VEC: Finished Age Group:68 of 82, time-this-age:2.9285
SNW_VFI_MAIN_BISEC_VEC: Finished Age Group:67 of 82, time-this-age:2.9005
SNW_VFI_MAIN_BISEC_VEC: Finished Age Group:66 of 82, time-this-age:2.8196
SNW_VFI_MAIN_BISEC_VEC: Finished Age Group:65 of 82, time-this-age:2.791
SNW_VFI_MAIN_BISEC_VEC: Finished Age Group:64 of 82, time-this-age:2.8039
SNW_VFI_MAIN_BISEC_VEC: Finished Age Group:63 of 82, time-this-age:2.7649
SNW_VFI_MAIN_BISEC_VEC: Finished Age Group:62 of 82, time-this-age:2.8592
SNW_VFI_MAIN_BISEC_VEC: Finished Age Group:61 of 82, time-this-age:2.7595
```

SNW\_VFI\_MAIN\_BISEC\_VEC: Finished Age Group:60 of 82, time-this-age:2.7984  
SNW\_VFI\_MAIN\_BISEC\_VEC: Finished Age Group:59 of 82, time-this-age:2.8238  
SNW\_VFI\_MAIN\_BISEC\_VEC: Finished Age Group:58 of 82, time-this-age:2.8372  
SNW\_VFI\_MAIN\_BISEC\_VEC: Finished Age Group:57 of 82, time-this-age:2.847  
SNW\_VFI\_MAIN\_BISEC\_VEC: Finished Age Group:56 of 82, time-this-age:2.8287  
SNW\_VFI\_MAIN\_BISEC\_VEC: Finished Age Group:55 of 82, time-this-age:2.8489  
SNW\_VFI\_MAIN\_BISEC\_VEC: Finished Age Group:54 of 82, time-this-age:2.8663  
SNW\_VFI\_MAIN\_BISEC\_VEC: Finished Age Group:53 of 82, time-this-age:2.8091  
SNW\_VFI\_MAIN\_BISEC\_VEC: Finished Age Group:52 of 82, time-this-age:2.8397  
SNW\_VFI\_MAIN\_BISEC\_VEC: Finished Age Group:51 of 82, time-this-age:2.8433  
SNW\_VFI\_MAIN\_BISEC\_VEC: Finished Age Group:50 of 82, time-this-age:2.8445  
SNW\_VFI\_MAIN\_BISEC\_VEC: Finished Age Group:49 of 82, time-this-age:2.7143  
SNW\_VFI\_MAIN\_BISEC\_VEC: Finished Age Group:48 of 82, time-this-age:2.6729  
SNW\_VFI\_MAIN\_BISEC\_VEC: Finished Age Group:47 of 82, time-this-age:2.9111  
SNW\_VFI\_MAIN\_BISEC\_VEC: Finished Age Group:46 of 82, time-this-age:2.8268  
SNW\_VFI\_MAIN\_BISEC\_VEC: Finished Age Group:45 of 82, time-this-age:2.8303  
SNW\_VFI\_MAIN\_BISEC\_VEC: Finished Age Group:44 of 82, time-this-age:2.8012  
SNW\_VFI\_MAIN\_BISEC\_VEC: Finished Age Group:43 of 82, time-this-age:2.7892  
SNW\_VFI\_MAIN\_BISEC\_VEC: Finished Age Group:42 of 82, time-this-age:2.8242  
SNW\_VFI\_MAIN\_BISEC\_VEC: Finished Age Group:41 of 82, time-this-age:2.9846  
SNW\_VFI\_MAIN\_BISEC\_VEC: Finished Age Group:40 of 82, time-this-age:2.8347  
SNW\_VFI\_MAIN\_BISEC\_VEC: Finished Age Group:39 of 82, time-this-age:2.8005  
SNW\_VFI\_MAIN\_BISEC\_VEC: Finished Age Group:38 of 82, time-this-age:2.7936  
SNW\_VFI\_MAIN\_BISEC\_VEC: Finished Age Group:37 of 82, time-this-age:2.8617  
SNW\_VFI\_MAIN\_BISEC\_VEC: Finished Age Group:36 of 82, time-this-age:2.8021  
SNW\_VFI\_MAIN\_BISEC\_VEC: Finished Age Group:35 of 82, time-this-age:2.821  
SNW\_VFI\_MAIN\_BISEC\_VEC: Finished Age Group:34 of 82, time-this-age:2.8082  
SNW\_VFI\_MAIN\_BISEC\_VEC: Finished Age Group:33 of 82, time-this-age:2.7967  
SNW\_VFI\_MAIN\_BISEC\_VEC: Finished Age Group:32 of 82, time-this-age:2.8976  
SNW\_VFI\_MAIN\_BISEC\_VEC: Finished Age Group:31 of 82, time-this-age:2.8975  
SNW\_VFI\_MAIN\_BISEC\_VEC: Finished Age Group:30 of 82, time-this-age:3.0965  
SNW\_VFI\_MAIN\_BISEC\_VEC: Finished Age Group:29 of 82, time-this-age:3.169  
SNW\_VFI\_MAIN\_BISEC\_VEC: Finished Age Group:28 of 82, time-this-age:3.148  
SNW\_VFI\_MAIN\_BISEC\_VEC: Finished Age Group:27 of 82, time-this-age:3.1235  
SNW\_VFI\_MAIN\_BISEC\_VEC: Finished Age Group:26 of 82, time-this-age:3.1654  
SNW\_VFI\_MAIN\_BISEC\_VEC: Finished Age Group:25 of 82, time-this-age:3.0846  
SNW\_VFI\_MAIN\_BISEC\_VEC: Finished Age Group:24 of 82, time-this-age:3.2605  
SNW\_VFI\_MAIN\_BISEC\_VEC: Finished Age Group:23 of 82, time-this-age:2.8673  
SNW\_VFI\_MAIN\_BISEC\_VEC: Finished Age Group:22 of 82, time-this-age:2.8366  
SNW\_VFI\_MAIN\_BISEC\_VEC: Finished Age Group:21 of 82, time-this-age:2.9026  
SNW\_VFI\_MAIN\_BISEC\_VEC: Finished Age Group:20 of 82, time-this-age:2.8865  
SNW\_VFI\_MAIN\_BISEC\_VEC: Finished Age Group:19 of 82, time-this-age:2.8479  
SNW\_VFI\_MAIN\_BISEC\_VEC: Finished Age Group:18 of 82, time-this-age:2.8406  
SNW\_VFI\_MAIN\_BISEC\_VEC: Finished Age Group:17 of 82, time-this-age:2.9797  
SNW\_VFI\_MAIN\_BISEC\_VEC: Finished Age Group:16 of 82, time-this-age:3.2286  
SNW\_VFI\_MAIN\_BISEC\_VEC: Finished Age Group:15 of 82, time-this-age:3.0905  
SNW\_VFI\_MAIN\_BISEC\_VEC: Finished Age Group:14 of 82, time-this-age:2.9062  
SNW\_VFI\_MAIN\_BISEC\_VEC: Finished Age Group:13 of 82, time-this-age:2.8862  
SNW\_VFI\_MAIN\_BISEC\_VEC: Finished Age Group:12 of 82, time-this-age:2.948  
SNW\_VFI\_MAIN\_BISEC\_VEC: Finished Age Group:11 of 82, time-this-age:2.9553  
SNW\_VFI\_MAIN\_BISEC\_VEC: Finished Age Group:10 of 82, time-this-age:2.9076  
SNW\_VFI\_MAIN\_BISEC\_VEC: Finished Age Group:9 of 82, time-this-age:2.9098  
SNW\_VFI\_MAIN\_BISEC\_VEC: Finished Age Group:8 of 82, time-this-age:2.8502  
SNW\_VFI\_MAIN\_BISEC\_VEC: Finished Age Group:7 of 82, time-this-age:2.8649  
SNW\_VFI\_MAIN\_BISEC\_VEC: Finished Age Group:6 of 82, time-this-age:2.8968  
SNW\_VFI\_MAIN\_BISEC\_VEC: Finished Age Group:5 of 82, time-this-age:2.8606  
SNW\_VFI\_MAIN\_BISEC\_VEC: Finished Age Group:4 of 82, time-this-age:2.835  
SNW\_VFI\_MAIN\_BISEC\_VEC: Finished Age Group:3 of 82, time-this-age:2.8988

SNW\_VFI\_MAIN\_BISEC\_VEC: Finished Age Group:2 of 82, time-this-age:2.8594

SNW\_VFI\_MAIN\_BISEC\_VEC: Finished Age Group:1 of 82, time-this-age:2.867

Completed SNW\_VFI\_MAIN\_BISEC\_VEC;SNW\_MP\_PARAM=default\_docdense;SNW\_MP\_CONTROL=default\_test;time=240.

xxxxxxxxxxxxxxxxxxxxxxxxxxxxxxxxxxxxxx

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

xxxxxxxxxxxxxxxxxxxxxxxxxxxxxxxxxxxxxx

	i	idx	ndim	numel	rowN	colN	sum	mean	std
	-	---	----	-----	---	-----	-----	-----	-----
V_VFI	1	1	6	4.37e+07	83	5.265e+05	-1.5339e+08	-3.5101	26.11
ap_VFI	2	2	6	4.37e+07	83	5.265e+05	1.4159e+09	32.402	36.79
cons_VFI	3	3	6	4.37e+07	83	5.265e+05	2.1402e+08	4.8975	8.329

xxx TABLE:V\_VFI xxxxxxxxxxxxxxxxxxxxxxxx

	c1	c2	c3	c4	c5	c526496	c526497	c526498	c
	-----	-----	-----	-----	-----	-----	-----	-----	-----
r1	-346.51	-346.12	-343.63	-337.86	-328.51	21.702	21.852	22.003	
r2	-334.38	-333.99	-331.51	-325.83	-316.83	21.724	21.869	22.015	
r3	-322.45	-322.06	-319.6	-314.14	-305.6	21.745	21.885	22.027	
r4	-310.63	-310.27	-307.99	-302.88	-294.87	21.767	21.903	22.041	
r5	-299.94	-299.6	-297.46	-292.67	-285.12	21.775	21.907	22.042	
r79	-9.9437	-9.9325	-9.8557	-9.6597	-9.3232	2.5394	2.5501	2.5602	
r80	-8.9023	-8.8911	-8.8143	-8.6183	-8.2818	2.3039	2.3121	2.3198	
r81	-7.6363	-7.6251	-7.5484	-7.3524	-7.0159	2.0068	2.0124	2.0176	
r82	-5.9673	-5.9561	-5.8793	-5.6833	-5.3468	1.5958	1.5989	1.6018	
r83	-3.5892	-3.578	-3.5012	-3.3052	-2.9687	0.97904	0.98004	0.98097	0

xxx TABLE:ap\_VFI xxxxxxxxxxxxxxxxxxxxxxxx

	c1	c2	c3	c4	c5	c526496	c526497	c526498	c5264
	--	--	-----	-----	-----	-----	-----	-----	-----
r1	0	0	0.0005656	0.0075134	0.022901	114.75	120.41	126.27	132.3
r2	0	0	0.00051498	0.0065334	0.021549	114.86	120.53	126.41	132.5
r3	0	0	0.00051498	0.0049294	0.019875	114.97	120.65	126.56	132.
r4	0	0	0.00051498	0.0047937	0.019672	115.73	121.42	127.34	133.5
r5	0	0	0.00048517	0.0046683	0.019484	116.5	122.21	128.15	134.3
r79	0	0	0	0	0	81.091	85.68	90.335	94.37
r80	0	0	0	0	0	76.669	80.563	84.304	88.0
r81	0	0	0	0	0	68.313	71.534	74.475	77.83
r82	0	0	0	0	0	50.126	53.467	56.953	58.74
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	0.040426	0.04363	0.048012	9.6491	9.817	9.9649
r2	0.036717	0.037251	0.040477	0.04461	0.049364	9.8118	9.9685	10.101
r3	0.036717	0.037251	0.040477	0.046214	0.051039	9.9779	10.12	10.234
r4	0.038144	0.038678	0.041903	0.047776	0.052666	10.131	10.258	10.354
r5	0.039534	0.040068	0.043323	0.04929	0.054241	10.272	10.384	10.463
r79	0.2179	0.21844	0.22216	0.23228	0.25197	35.858	37.092	38.455
r80	0.2179	0.21844	0.22216	0.23228	0.25197	40.253	42.183	44.459
r81	0.2179	0.21844	0.22216	0.23228	0.25197	48.587	51.19	54.266
r82	0.2179	0.21844	0.22216	0.23228	0.25197	66.755	69.238	71.77
r83	0.2179	0.21844	0.22216	0.23228	0.25197	116.87	122.69	128.71

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:

```

mp_params('xi') = 0.5;
mp_params('b') = 0;
[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:2.8563
SNW_VFI_MAIN_BISEC_VEC 1 Period Unemp Shock: Age 2 of 82, time-this-age:3.0648
SNW_VFI_MAIN_BISEC_VEC 1 Period Unemp Shock: Age 3 of 82, time-this-age:2.7929
SNW_VFI_MAIN_BISEC_VEC 1 Period Unemp Shock: Age 4 of 82, time-this-age:2.8051
SNW_VFI_MAIN_BISEC_VEC 1 Period Unemp Shock: Age 5 of 82, time-this-age:2.8264
SNW_VFI_MAIN_BISEC_VEC 1 Period Unemp Shock: Age 6 of 82, time-this-age:2.836
SNW_VFI_MAIN_BISEC_VEC 1 Period Unemp Shock: Age 7 of 82, time-this-age:2.8277
SNW_VFI_MAIN_BISEC_VEC 1 Period Unemp Shock: Age 8 of 82, time-this-age:2.7941
SNW_VFI_MAIN_BISEC_VEC 1 Period Unemp Shock: Age 9 of 82, time-this-age:2.8232
SNW_VFI_MAIN_BISEC_VEC 1 Period Unemp Shock: Age 10 of 82, time-this-age:2.7723
SNW_VFI_MAIN_BISEC_VEC 1 Period Unemp Shock: Age 11 of 82, time-this-age:2.8291
SNW_VFI_MAIN_BISEC_VEC 1 Period Unemp Shock: Age 12 of 82, time-this-age:2.7968
SNW_VFI_MAIN_BISEC_VEC 1 Period Unemp Shock: Age 13 of 82, time-this-age:2.848
SNW_VFI_MAIN_BISEC_VEC 1 Period Unemp Shock: Age 14 of 82, time-this-age:2.8093
SNW_VFI_MAIN_BISEC_VEC 1 Period Unemp Shock: Age 15 of 82, time-this-age:2.8312
SNW_VFI_MAIN_BISEC_VEC 1 Period Unemp Shock: Age 16 of 82, time-this-age:2.8063
SNW_VFI_MAIN_BISEC_VEC 1 Period Unemp Shock: Age 17 of 82, time-this-age:2.8041
SNW_VFI_MAIN_BISEC_VEC 1 Period Unemp Shock: Age 18 of 82, time-this-age:2.8034
SNW_VFI_MAIN_BISEC_VEC 1 Period Unemp Shock: Age 19 of 82, time-this-age:2.796
SNW_VFI_MAIN_BISEC_VEC 1 Period Unemp Shock: Age 20 of 82, time-this-age:2.8926
SNW_VFI_MAIN_BISEC_VEC 1 Period Unemp Shock: Age 21 of 82, time-this-age:3.4005
SNW_VFI_MAIN_BISEC_VEC 1 Period Unemp Shock: Age 22 of 82, time-this-age:3.0663
SNW_VFI_MAIN_BISEC_VEC 1 Period Unemp Shock: Age 23 of 82, time-this-age:2.839
SNW_VFI_MAIN_BISEC_VEC 1 Period Unemp Shock: Age 24 of 82, time-this-age:3.0613
SNW_VFI_MAIN_BISEC_VEC 1 Period Unemp Shock: Age 25 of 82, time-this-age:3.1482
SNW_VFI_MAIN_BISEC_VEC 1 Period Unemp Shock: Age 26 of 82, time-this-age:2.9432
SNW_VFI_MAIN_BISEC_VEC 1 Period Unemp Shock: Age 27 of 82, time-this-age:2.964
SNW_VFI_MAIN_BISEC_VEC 1 Period Unemp Shock: Age 28 of 82, time-this-age:2.9991
SNW_VFI_MAIN_BISEC_VEC 1 Period Unemp Shock: Age 29 of 82, time-this-age:2.7389
SNW_VFI_MAIN_BISEC_VEC 1 Period Unemp Shock: Age 30 of 82, time-this-age:2.8259
SNW_VFI_MAIN_BISEC_VEC 1 Period Unemp Shock: Age 31 of 82, time-this-age:2.7929
SNW_VFI_MAIN_BISEC_VEC 1 Period Unemp Shock: Age 32 of 82, time-this-age:2.7872
SNW_VFI_MAIN_BISEC_VEC 1 Period Unemp Shock: Age 33 of 82, time-this-age:2.8341
SNW_VFI_MAIN_BISEC_VEC 1 Period Unemp Shock: Age 34 of 82, time-this-age:2.9876
SNW_VFI_MAIN_BISEC_VEC 1 Period Unemp Shock: Age 35 of 82, time-this-age:3.0836
SNW_VFI_MAIN_BISEC_VEC 1 Period Unemp Shock: Age 36 of 82, time-this-age:2.7955
SNW_VFI_MAIN_BISEC_VEC 1 Period Unemp Shock: Age 37 of 82, time-this-age:2.9634
SNW_VFI_MAIN_BISEC_VEC 1 Period Unemp Shock: Age 38 of 82, time-this-age:2.7022
SNW_VFI_MAIN_BISEC_VEC 1 Period Unemp Shock: Age 39 of 82, time-this-age:2.6388
SNW_VFI_MAIN_BISEC_VEC 1 Period Unemp Shock: Age 40 of 82, time-this-age:2.6754
SNW_VFI_MAIN_BISEC_VEC 1 Period Unemp Shock: Age 41 of 82, time-this-age:2.6157
SNW_VFI_MAIN_BISEC_VEC 1 Period Unemp Shock: Age 42 of 82, time-this-age:2.7739
SNW_VFI_MAIN_BISEC_VEC 1 Period Unemp Shock: Age 43 of 82, time-this-age:3.0513
SNW_VFI_MAIN_BISEC_VEC 1 Period Unemp Shock: Age 44 of 82, time-this-age:2.6043
SNW_VFI_MAIN_BISEC_VEC 1 Period Unemp Shock: Age 45 of 82, time-this-age:2.6203
SNW_VFI_MAIN_BISEC_VEC 1 Period Unemp Shock: Age 46 of 82, time-this-age:2.9099
SNW_VFI_MAIN_BISEC_VEC 1 Period Unemp Shock: Age 47 of 82, time-this-age:2.8328
SNW_VFI_MAIN_BISEC_VEC 1 Period Unemp Shock: Age 48 of 82, time-this-age:2.5949
SNW_VFI_MAIN_BISEC_VEC 1 Period Unemp Shock: Age 49 of 82, time-this-age:2.5623
SNW_VFI_MAIN_BISEC_VEC 1 Period Unemp Shock: Age 50 of 82, time-this-age:2.4733
SNW_VFI_MAIN_BISEC_VEC 1 Period Unemp Shock: Age 51 of 82, time-this-age:2.4966

```

SNW\_VFI\_MAIN\_BISEC\_VEC 1 Period Unemp Shock: Age 52 of 82, time-this-age:2.4712  
 SNW\_VFI\_MAIN\_BISEC\_VEC 1 Period Unemp Shock: Age 53 of 82, time-this-age:2.5194  
 SNW\_VFI\_MAIN\_BISEC\_VEC 1 Period Unemp Shock: Age 54 of 82, time-this-age:2.5973  
 SNW\_VFI\_MAIN\_BISEC\_VEC 1 Period Unemp Shock: Age 55 of 82, time-this-age:2.6167  
 SNW\_VFI\_MAIN\_BISEC\_VEC 1 Period Unemp Shock: Age 56 of 82, time-this-age:2.8954  
 SNW\_VFI\_MAIN\_BISEC\_VEC 1 Period Unemp Shock: Age 57 of 82, time-this-age:2.6303  
 SNW\_VFI\_MAIN\_BISEC\_VEC 1 Period Unemp Shock: Age 58 of 82, time-this-age:2.5062  
 SNW\_VFI\_MAIN\_BISEC\_VEC 1 Period Unemp Shock: Age 59 of 82, time-this-age:2.8318  
 SNW\_VFI\_MAIN\_BISEC\_VEC 1 Period Unemp Shock: Age 60 of 82, time-this-age:3.1076  
 SNW\_VFI\_MAIN\_BISEC\_VEC 1 Period Unemp Shock: Age 61 of 82, time-this-age:2.4185  
 SNW\_VFI\_MAIN\_BISEC\_VEC 1 Period Unemp Shock: Age 62 of 82, time-this-age:2.5062  
 SNW\_VFI\_MAIN\_BISEC\_VEC 1 Period Unemp Shock: Age 63 of 82, time-this-age:3.0883  
 SNW\_VFI\_MAIN\_BISEC\_VEC 1 Period Unemp Shock: Age 64 of 82, time-this-age:2.715  
 SNW\_VFI\_MAIN\_BISEC\_VEC 1 Period Unemp Shock: Age 65 of 82, time-this-age:2.5774  
 SNW\_VFI\_MAIN\_BISEC\_VEC 1 Period Unemp Shock: Age 66 of 82, time-this-age:2.6634  
 SNW\_VFI\_MAIN\_BISEC\_VEC 1 Period Unemp Shock: Age 67 of 82, time-this-age:2.4816  
 SNW\_VFI\_MAIN\_BISEC\_VEC 1 Period Unemp Shock: Age 68 of 82, time-this-age:2.4953  
 SNW\_VFI\_MAIN\_BISEC\_VEC 1 Period Unemp Shock: Age 69 of 82, time-this-age:2.7169  
 SNW\_VFI\_MAIN\_BISEC\_VEC 1 Period Unemp Shock: Age 70 of 82, time-this-age:2.5446  
 SNW\_VFI\_MAIN\_BISEC\_VEC 1 Period Unemp Shock: Age 71 of 82, time-this-age:2.6734  
 SNW\_VFI\_MAIN\_BISEC\_VEC 1 Period Unemp Shock: Age 72 of 82, time-this-age:2.5802  
 SNW\_VFI\_MAIN\_BISEC\_VEC 1 Period Unemp Shock: Age 73 of 82, time-this-age:2.5602  
 SNW\_VFI\_MAIN\_BISEC\_VEC 1 Period Unemp Shock: Age 74 of 82, time-this-age:2.5524  
 SNW\_VFI\_MAIN\_BISEC\_VEC 1 Period Unemp Shock: Age 75 of 82, time-this-age:2.5331  
 SNW\_VFI\_MAIN\_BISEC\_VEC 1 Period Unemp Shock: Age 76 of 82, time-this-age:2.5831  
 SNW\_VFI\_MAIN\_BISEC\_VEC 1 Period Unemp Shock: Age 77 of 82, time-this-age:2.5422  
 SNW\_VFI\_MAIN\_BISEC\_VEC 1 Period Unemp Shock: Age 78 of 82, time-this-age:2.5236  
 SNW\_VFI\_MAIN\_BISEC\_VEC 1 Period Unemp Shock: Age 79 of 82, time-this-age:2.5017  
 SNW\_VFI\_MAIN\_BISEC\_VEC 1 Period Unemp Shock: Age 80 of 82, time-this-age:2.4577  
 SNW\_VFI\_MAIN\_BISEC\_VEC 1 Period Unemp Shock: Age 81 of 82, time-this-age:2.7372  
 SNW\_VFI\_MAIN\_BISEC\_VEC 1 Period Unemp Shock: Age 82 of 82, time-this-age:2.71  
 SNW\_VFI\_MAIN\_BISEC\_VEC 1 Period Unemp Shock: Age 83 of 82, time-this-age:1.6049  
 Completed SNW\_VFI\_MAIN\_BISEC\_VEC 1 Period Unemp Shock;SNW\_MP\_PARAM=default\_docdense;SNW\_MP\_CONTROL=d  
 -----

xxxxxxxxxxxxxxxxxxxxxxxxxxxxxxxxxxxxxx

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

xxxxxxxxxxxxxxxxxxxxxxxxxxxxxxxxxxxxxx

	i	idx	ndim	numel	rowN	colN	sum	mean	std
	-	---	----	-----	----	-----	-----	-----	-----
V_VFI	1	1	6	4.37e+07	83	5.265e+05	-1.7805e+08	-4.0743	27.11
ap_VFI	2	2	6	4.37e+07	83	5.265e+05	1.3789e+09	31.553	36.67
cons_VFI	3	3	6	4.37e+07	83	5.265e+05	2.1097e+08	4.8277	8.328

xxx TABLE:V\_VFI xxxxxxxxxxxxxxxxxxxxxxxx

	c1	c2	c3	c4	c5	c526496	c526497	c526498	c
	-----	-----	-----	-----	-----	-----	-----	-----	-----
r1	-372.97	-371.47	-362.94	-349.52	-336.96	21.573	21.728	21.882	
r2	-360.84	-359.34	-350.81	-337.39	-324.98	21.595	21.745	21.894	
r3	-348.91	-347.41	-338.88	-325.46	-313.34	21.617	21.762	21.906	
r4	-336.09	-334.7	-326.73	-314.01	-302.44	21.633	21.772	21.913	
r5	-324.48	-323.18	-315.72	-303.62	-292.54	21.634	21.77	21.907	
r79	-9.9437	-9.9325	-9.8557	-9.6597	-9.3232	2.5374	2.5482	2.5584	
r80	-8.9023	-8.8911	-8.8143	-8.6183	-8.2818	2.3024	2.3107	2.3185	
r81	-7.6363	-7.6251	-7.5484	-7.3524	-7.0159	2.0057	2.0114	2.0168	
r82	-5.9673	-5.9561	-5.8793	-5.6833	-5.3468	1.5952	1.5984	1.6014	
r83	-3.5892	-3.578	-3.5012	-3.3052	-2.9687	0.97886	0.97987	0.98082	0

xxx TABLE:ap\_VFI xxxxxxxxxxxxxxxxxxxxxxx

	c1	c2	c3	c4	c5	c526496	c526497	c526498	c526499	c526500
	--	--	--	--	-----	-----	-----	-----	-----	-----
r1	0	0	0	0	0.0092181	110.06	115.71	121.55	127.62	133.93
r2	0	0	0	0	0.008238	110.03	115.68	121.54	127.62	133.95
r3	0	0	0	0	0.0066341	109.99	115.65	121.53	127.63	133.97
r4	0	0	0	0	0.0058019	110.28	115.95	121.84	127.96	134.33
r5	0	0	0	0	0.004998	110.58	116.27	122.17	128.31	134.69
r79	0	0	0	0	0	81.091	85.229	89.297	93.341	97.382
r80	0	0	0	0	0	75.865	79.539	83.28	87.016	90.669
r81	0	0	0	0	0	67.781	70.521	73.462	76.819	81.091
r82	0	0	0	0	0	50.126	53.467	56.108	57.742	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	0.04363	9.4708	9.6491	9.817
r2	0.018623	0.019158	0.022901	0.033062	0.04461	9.6414	9.8118	9.9685
r3	0.018623	0.019158	0.022901	0.033062	0.046214	9.8179	9.9779	10.12
r4	0.019354	0.019888	0.023632	0.033792	0.047776	9.9825	10.131	10.258
r5	0.020066	0.020601	0.024344	0.034504	0.04929	10.135	10.272	10.384
r79	0.2179	0.21844	0.22216	0.23228	0.25197	34.82	36.506	38.455
r80	0.2179	0.21844	0.22216	0.23228	0.25197	40.033	42.183	44.459
r81	0.2179	0.21844	0.22216	0.23228	0.25197	48.106	51.19	54.266
r82	0.2179	0.21844	0.22216	0.23228	0.25197	65.751	68.234	71.611
r83	0.2179	0.21844	0.22216	0.23228	0.25197	115.87	121.69	127.71

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;
```

#### 4.1.2 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});
```

### 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') = '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:

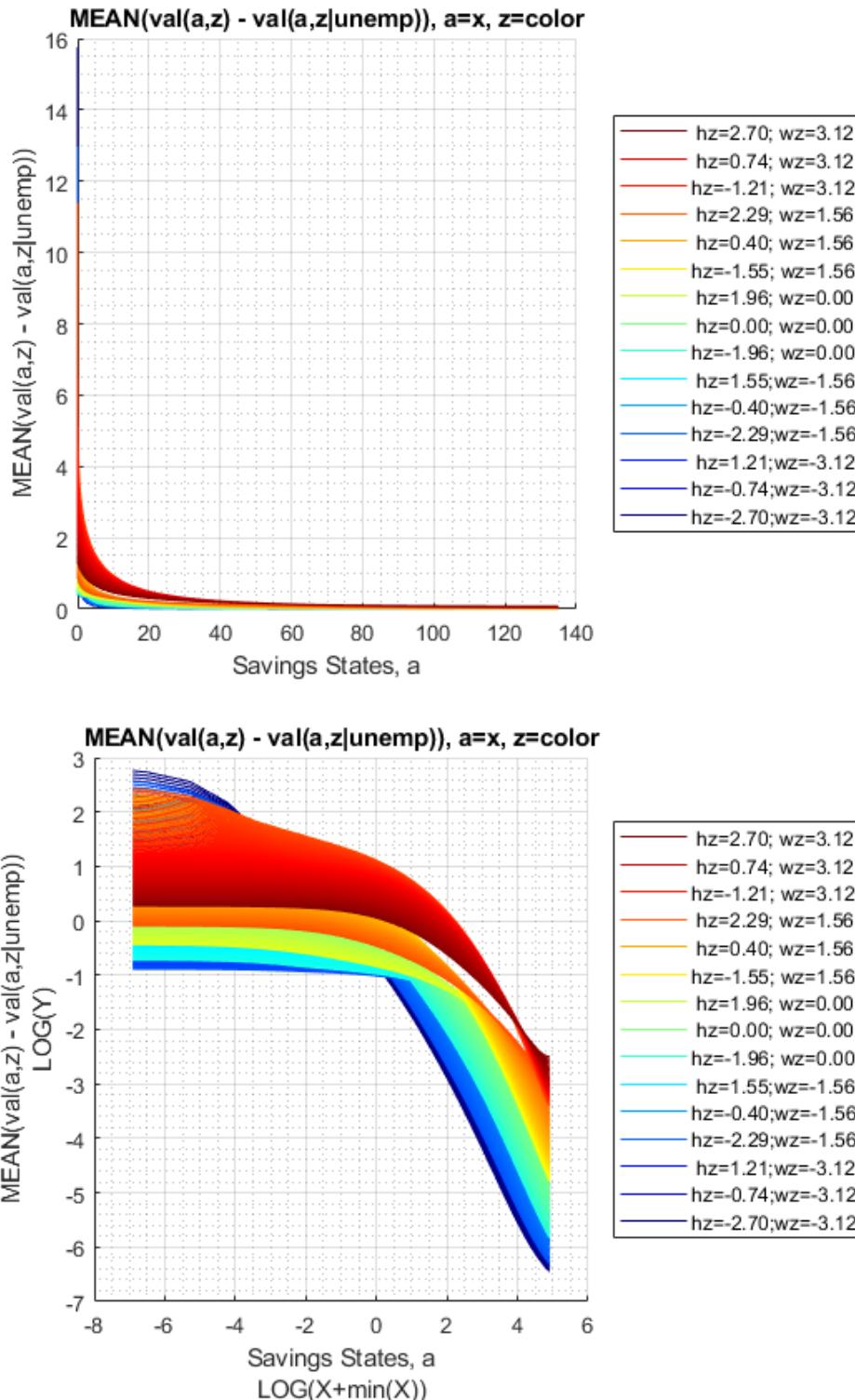
```
% Set
% NaN(n_jgrid,n_agrid,n_etagrid,n_educgrid,n_marriedgrid,n_kidsgrid);
ar_permute = [1,4,5,6,3,2];
% Value Function
tb_az_v = ff_summ_nd_array("MEAN(v(A,Z) - v(A,Z|unemp))", V_VFI_unemp_drop, true, ["mean"], 4, 1, cl

xxx MEAN(v(A,Z) - v(A,Z|unemp)) xxxxxxxxxxxxxxxxxxxxxxxx
group      savings      mean_eta_1      mean_eta_2      mean_eta_3      mean_eta_4      mean_eta_5      mea
-----
1           0            15.753        14.805        13.912        13.072        12.281
```

```
xxx MEAN(C(A,Z) - C(A,Z|unemp)) xxxxxxxxxxxxxxxxxxxxxxxx
group      savings      mean_eta_1      mean_eta_2      mean_eta_3      mean_eta_4      mean_eta_5      mea
-----
1           0            0.019317       0.020449       0.021654       0.022935       0.024299
```

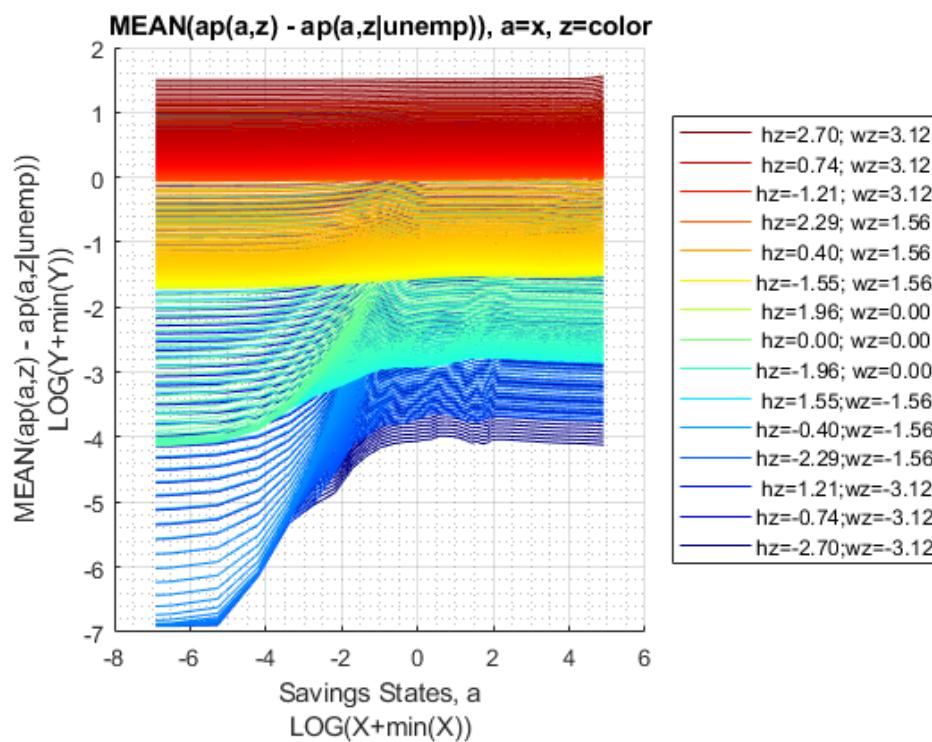
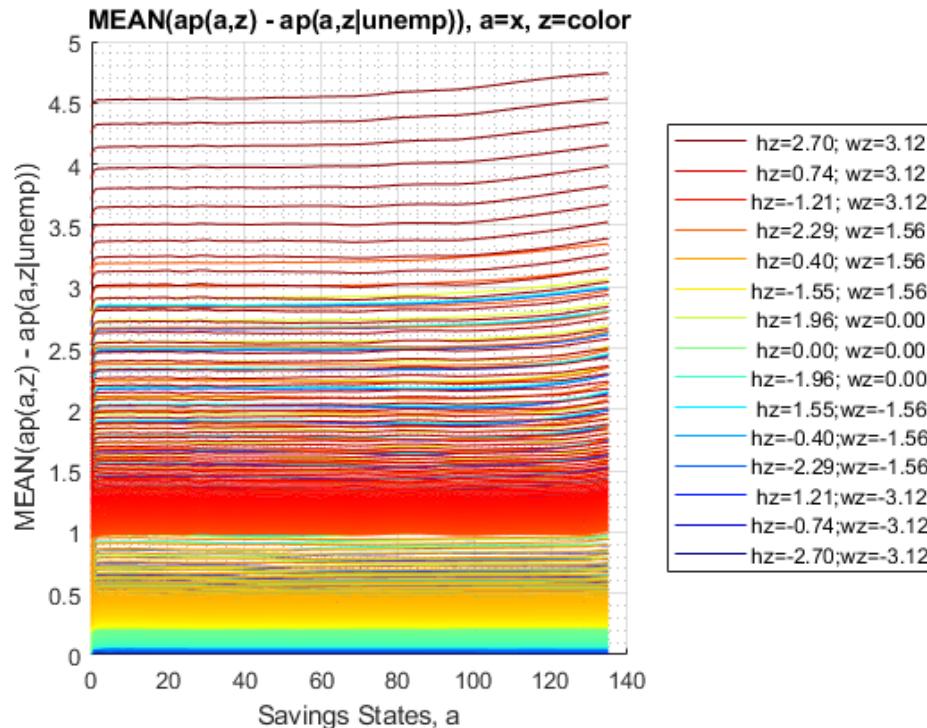
Graph Mean Values Change:

```
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);
```



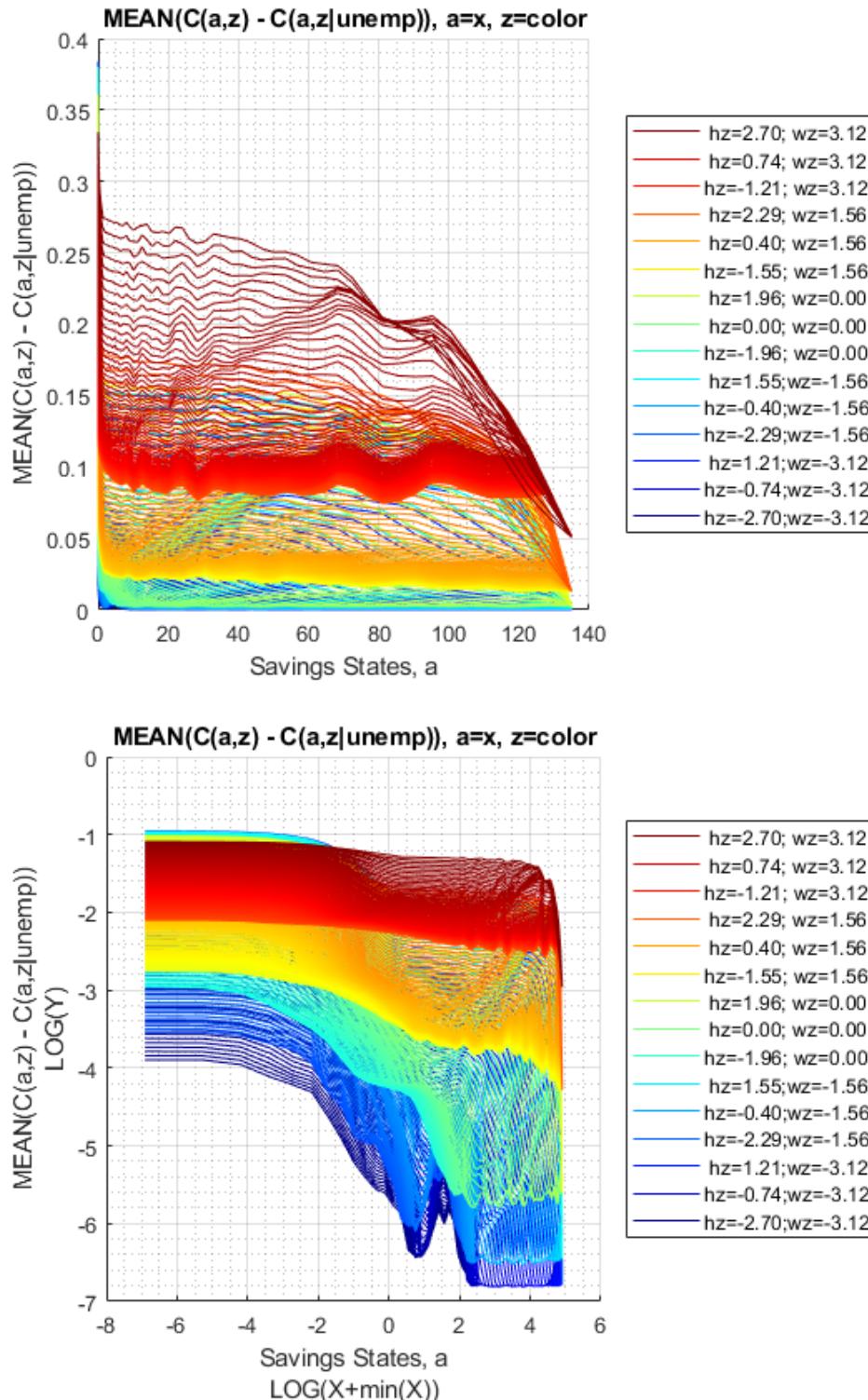
Graph Mean Savings Choices Change:

```
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);
```



#### 4.1.4 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)
```

xxx MEAN(V(KM,J) - V(KM,J | unemp)) xxxxxxxxxxxxxxxxxxxxxxxxx

group	kids	marry	mean_age_18	mean_age_19	mean_age_20	mean_age_21	mean_age_22
1	1	0	0.61637	0.59885	0.58106	0.56498	0.55117
2	2	0	0.82734	0.80489	0.78136	0.75704	0.73572
3	3	0	0.96755	0.94502	0.92045	0.89136	0.86587
4	4	0	1.0948	1.0713	1.045	1.0118	0.9827
5	5	0	1.2011	1.1779	1.151	1.1149	1.0833
6	1	1	0.76784	0.74924	0.73091	0.71544	0.70238
7	2	1	0.93021	0.90698	0.88323	0.86203	0.84347
8	3	1	1.0185	0.9941	0.96877	0.94495	0.92408
9	4	1	1.1171	1.0915	1.0645	1.0382	1.0151
10	5	1	1.1585	1.1346	1.1083	1.0807	1.0569

```
% Aprime Choice
```

```
tb_az_ap = ff_summ_nd_array("MEAN(ap(KM,J) - ap(KM,J | unemp))", ap_VFI_unemp_drop, true, ["mean"], 3, 1)
```

xxx MEAN(ap(KM,J) - ap(KM,J | unemp)) xxxxxxxxxxxxxxxxxxxxxxxxx

group	kids	marry	mean_age_18	mean_age_19	mean_age_20	mean_age_21	mean_age_22
1	1	0	0.54429	0.54157	0.53838	0.57688	0.61527
2	2	0	0.53828	0.53451	0.53011	0.56791	0.60562
3	3	0	0.53173	0.52734	0.52253	0.55991	0.59734
4	4	0	0.5276	0.523	0.51797	0.55513	0.59235
5	5	0	0.52354	0.51894	0.51381	0.55085	0.58805
6	1	1	1.1323	1.1757	1.2198	1.3119	1.4048
7	2	1	1.0396	1.0753	1.1115	1.1942	1.2777
8	3	1	0.97097	1.002	1.0331	1.1097	1.187
9	4	1	0.89591	0.92257	0.94909	1.0212	1.0937
10	5	1	0.78017	0.79798	0.81575	0.87811	0.94079

```
% Consumption Choices tb_az_c = ff_summ_nd_array("MEAN(c(KM,J) - c(KM,J | unemp))", cons_VFI_unemp_drop, true, ["mean"], 3, 1, cl_mp_datasetdesc, ar_permute);
```

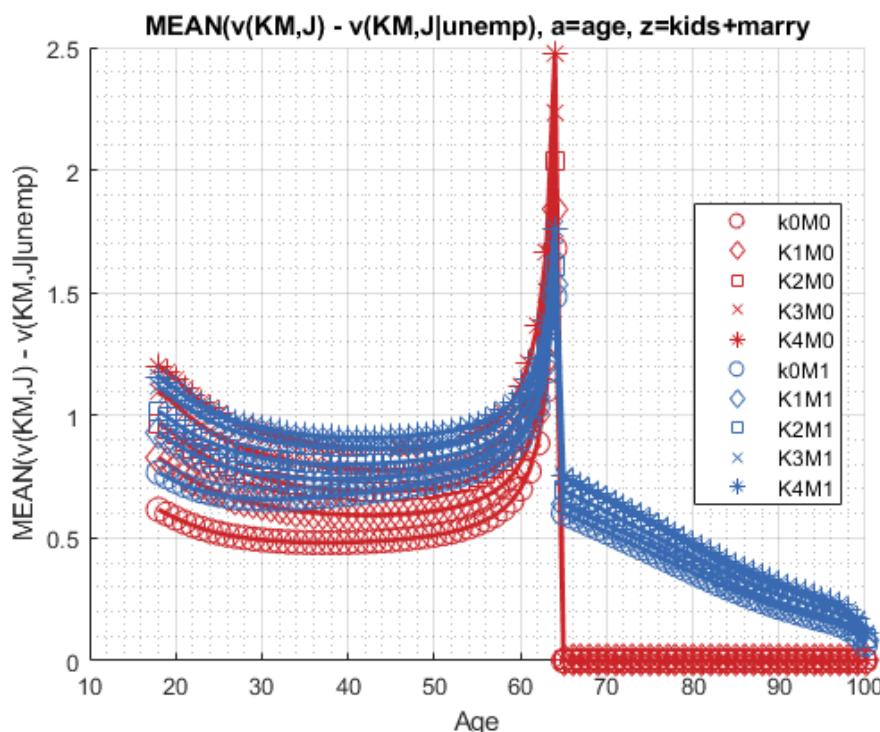
xxx MEAN(c(KM,J) - c(KM,J | unemp)) xxxxxxxxxxxxxxxxxxxxxxxxx

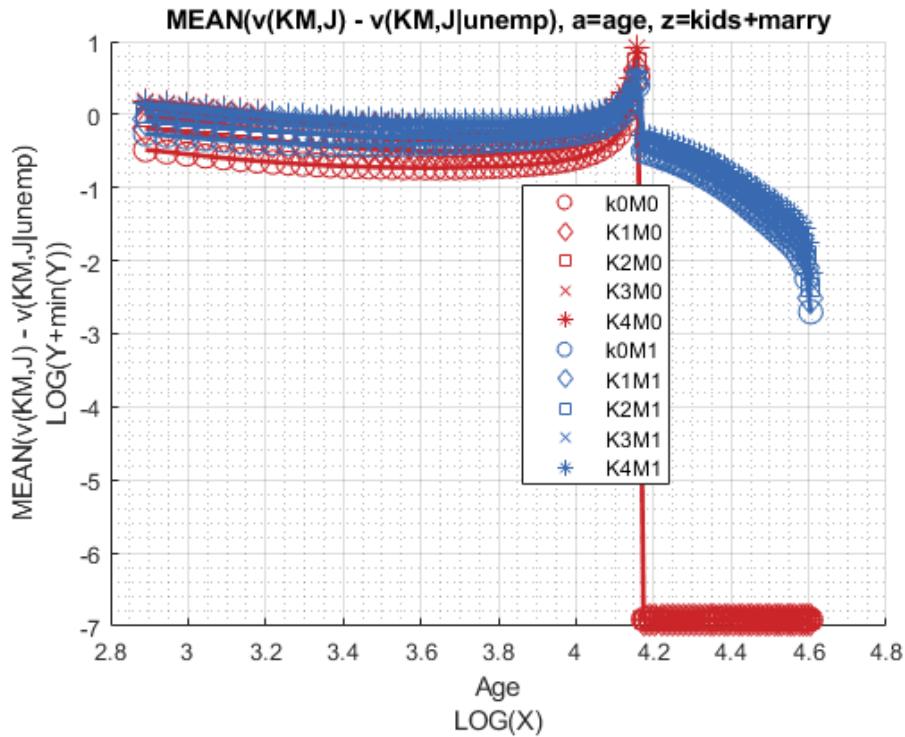
group	kids	marry	mean_age_18	mean_age_19	mean_age_20	mean_age_21	mean_age_22
1	1	0	0.54429	0.54157	0.53838	0.57688	0.61527

1	1	0	0.050084	0.052801	0.055995	0.056344	0.056497
2	2	0	0.056094	0.059866	0.064267	0.065317	0.06615
3	3	0	0.062643	0.067034	0.071841	0.073312	0.074434
4	4	0	0.06677	0.071371	0.076406	0.078097	0.079421
5	5	0	0.07083	0.075431	0.080561	0.082377	0.083719
6	1	1	0.091654	0.09722	0.1029	0.10693	0.11041
7	2	1	0.087426	0.093165	0.099035	0.10362	0.10765
8	3	1	0.089332	0.094467	0.10022	0.10478	0.10884
9	4	1	0.095488	0.099656	0.10451	0.10733	0.10981
10	5	1	0.1018	0.10631	0.11124	0.11381	0.11605

Graph Mean Values Change:

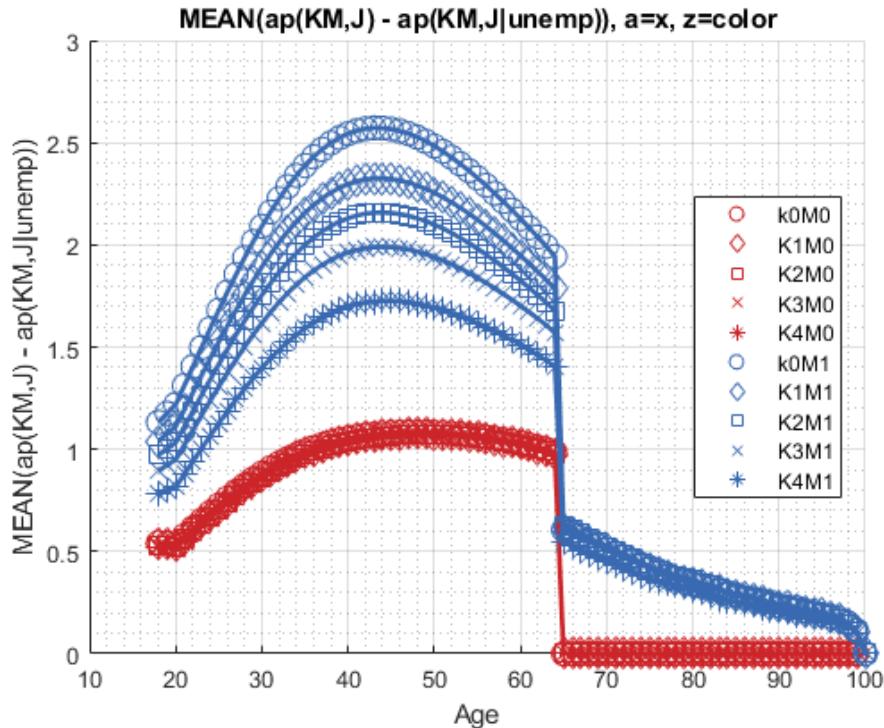
```
mp_support_graph('cl_st_graph_title') = {'MEAN(v(KM,J) - v(KM,J|unemp), a=age, z=kids+marry'};  
mp_support_graph('cl_st_ytitle') = {'MEAN(v(KM,J) - v(KM,J|unemp)'};  
ff_graph_grid((tb_az_v{1:end}, 4:end}), ar_row_grid, age_grid, mp_support_graph);
```

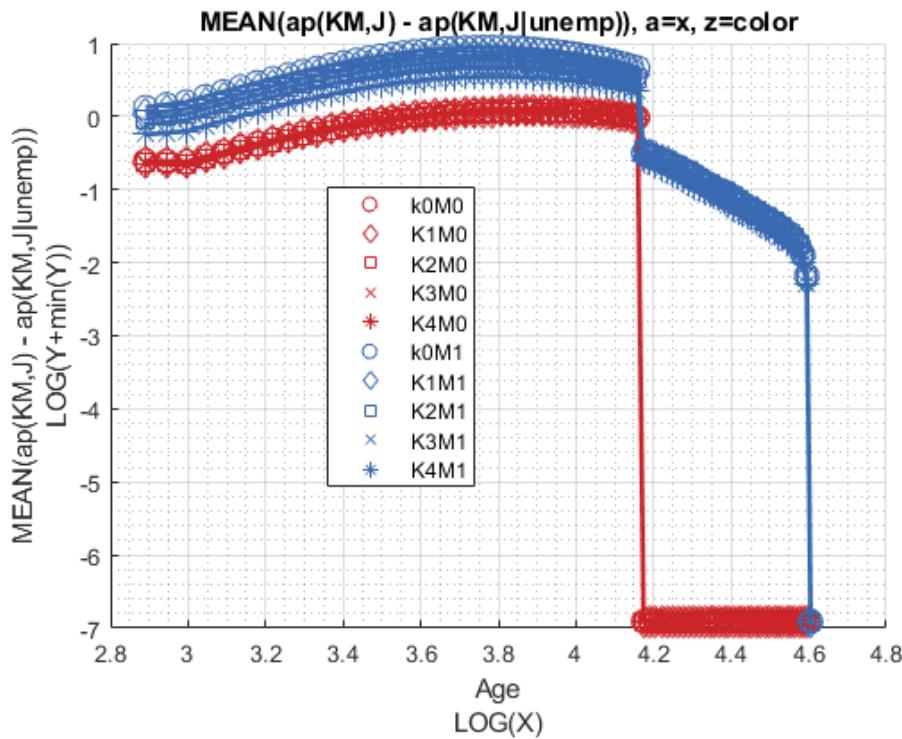




Graph Mean Savings Choices Change:

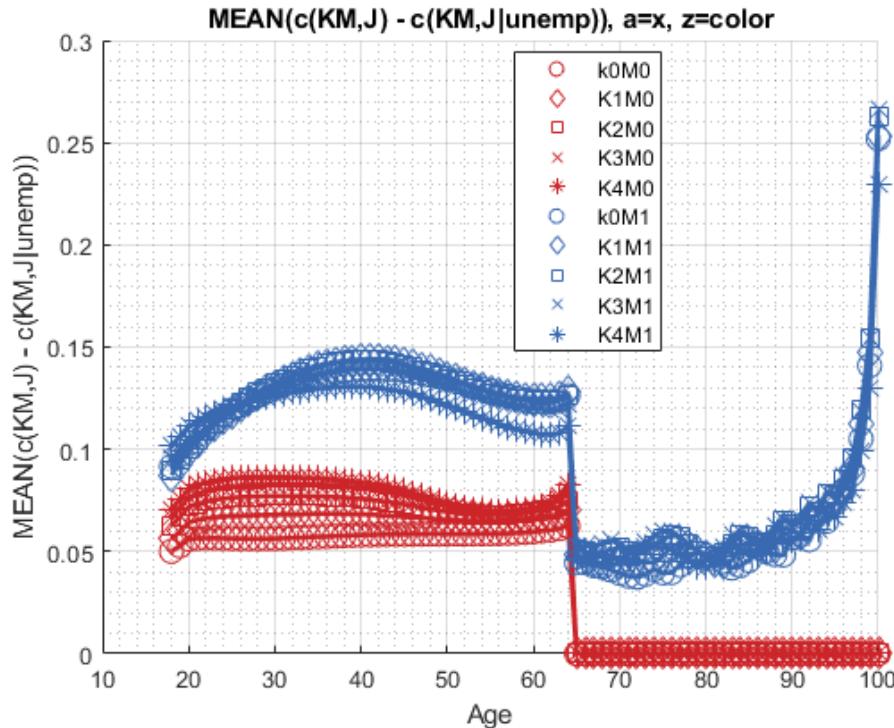
```
mp_support_graph('cl_st_graph_title') = {'MEAN(ap(KM,J) - ap(KM,J|unemp)), a=x, z=color'};
mp_support_graph('cl_st_ytitle') = {'MEAN(ap(KM,J) - ap(KM,J|unemp))'};
ff_graph_grid((tb_az_ap{1:end, 4:end}), ar_row_grid, age_grid, mp_support_graph);
```

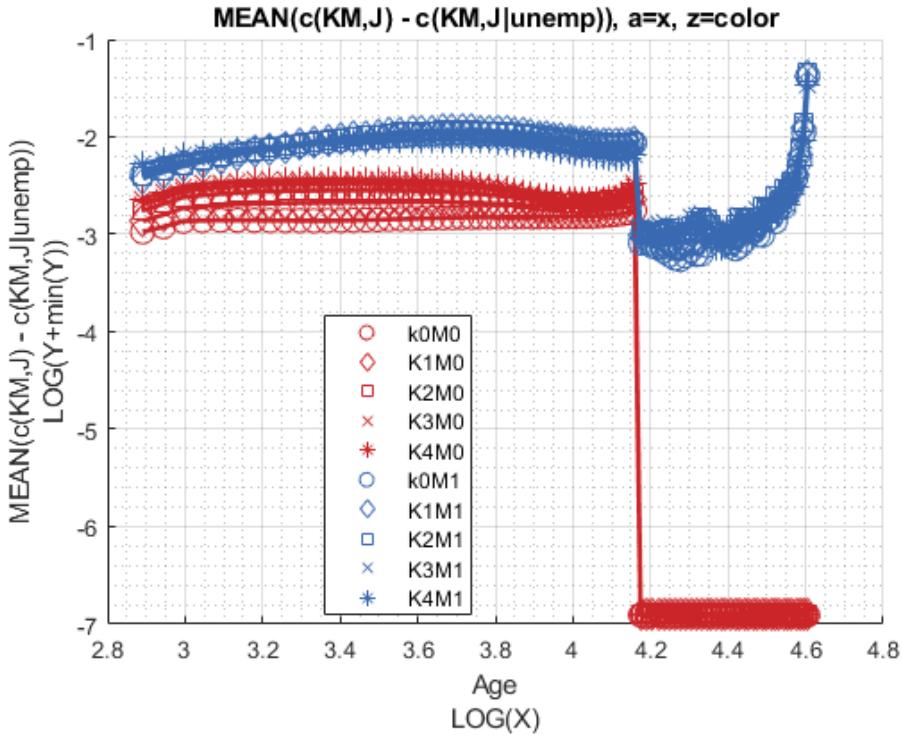




Graph Mean Consumption Change:

```
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);
```





#### 4.1.5 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)) xxxxxxxxxxxxxxxxxxxxxxxxx
group   edu    marry   mean_age_18   mean_age_19   mean_age_20   mean_age_21   mean_age_22
-----  ---  -----  -----  -----  -----  -----  -----
1       0      0      0.98303     0.96405     0.94385     0.92458     0.90689
2       1      0      0.89982     0.87513     0.84768     0.81144     0.78062
3       0      1      1.0503      1.0306      1.0104      0.99222     0.97585
4       1      1      0.94657     0.91993     0.89191     0.86431     0.84092
```

% 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)) xxxxxxxxxxxxxxxxxxxxxxxxx
group   edu    marry   mean_age_18   mean_age_19   mean_age_20   mean_age_21   mean_age_22
-----  ---  -----  -----  -----  -----  -----  -----
1       0      0      0.54395     0.54191     0.53951     0.56214     0.58423
2       1      0      0.52222     0.51623     0.50961     0.56213     0.61523
3       0      1      0.93033     0.95904     0.98801     1.0446      1.10111
4       1      1      0.99726     1.0304      1.0637      1.1614      1.2605
% 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)) xxxxxxxxxxxxxxxxxxxxxxxxx
group   edu    marry   mean_age_18   mean_age_19   mean_age_20   mean_age_21   mean_age_22
-----  ---  -----  -----  -----  -----  -----  -----
1       0      0      0.05042     0.052463    0.054861    0.055684    0.056488
2       1      0      0.072148    0.078138    0.084767    0.086495    0.0876
3       0      1      0.079245    0.082789    0.086633    0.089336    0.091941
4       1      1      0.10704     0.11354     0.12053     0.12525     0.12917

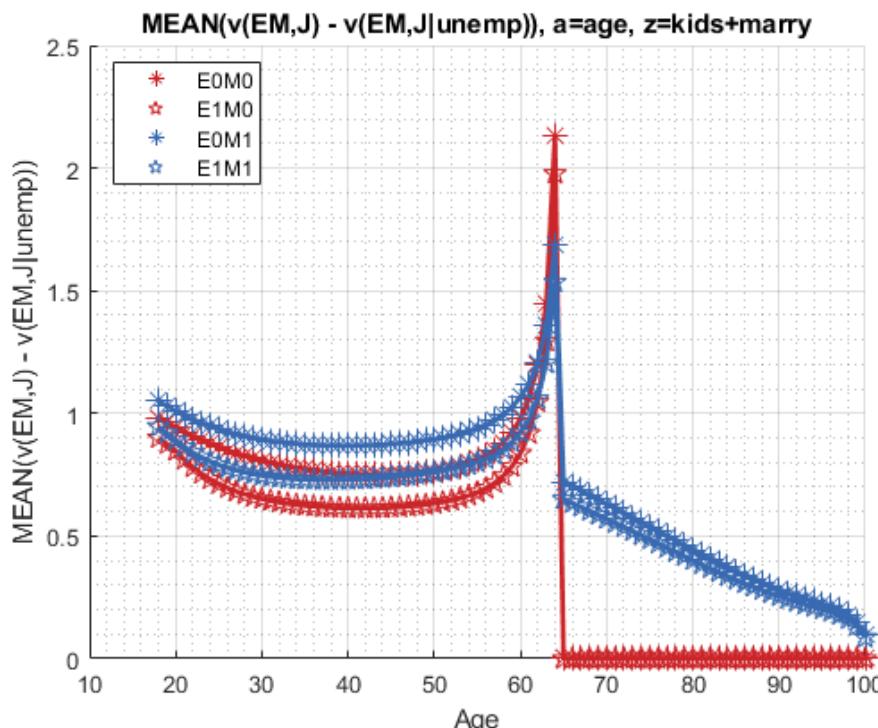
```

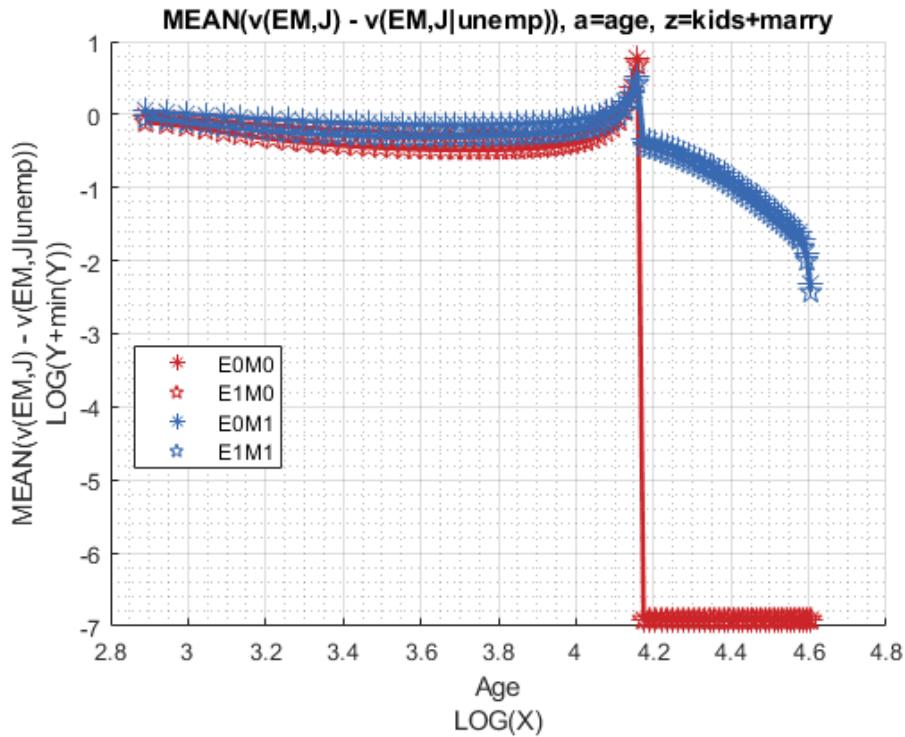
Graph Mean Values Change:

```

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);

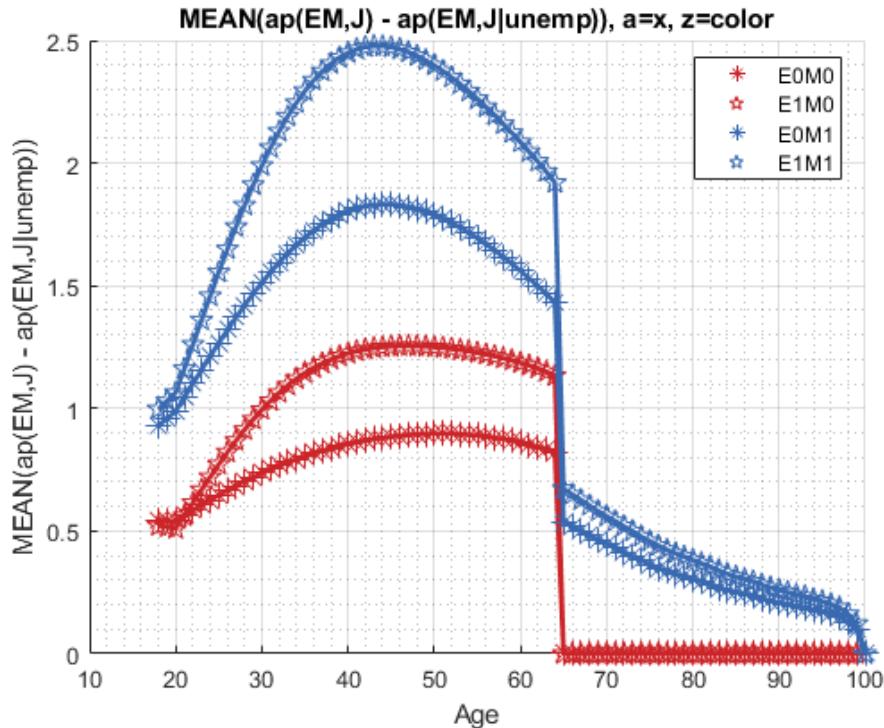
```

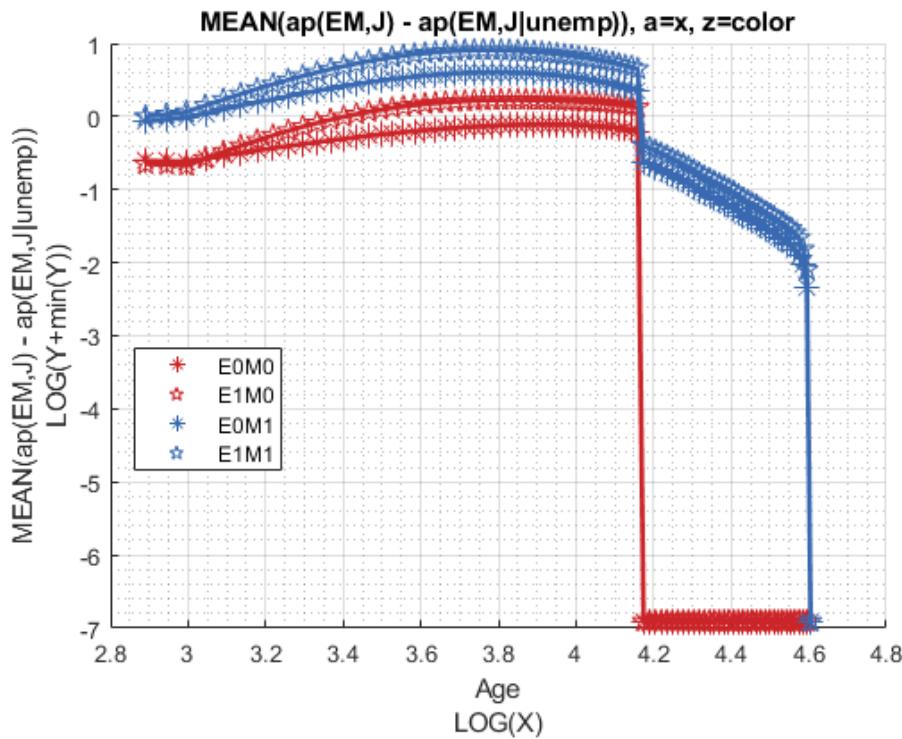




Graph Mean Savings Choices Change:

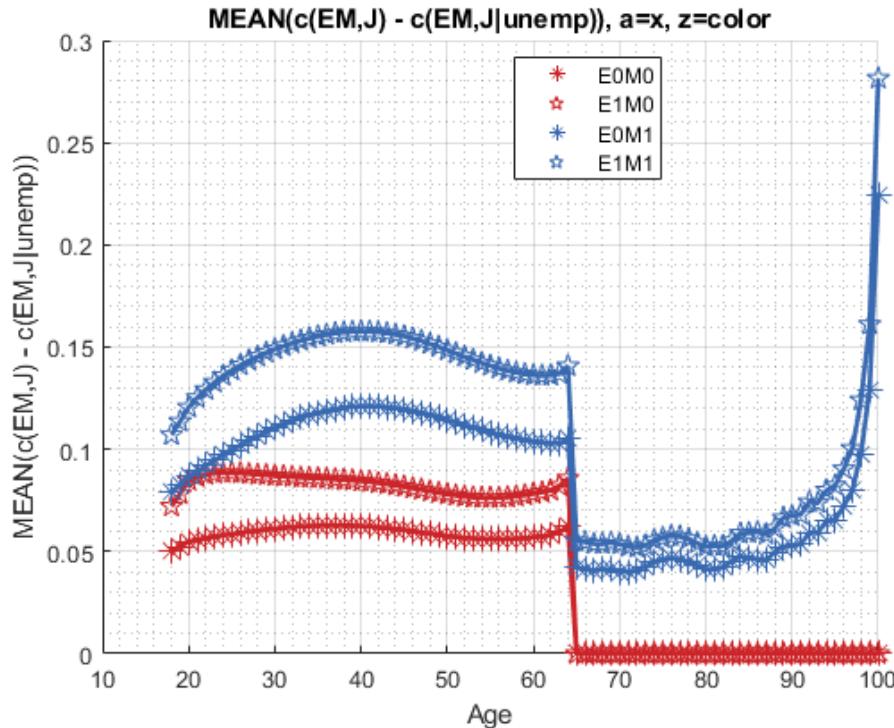
```
mp_support_graph('cl_st_graph_title') = {'MEAN(ap(EM,J) - ap(EM,J|unemp)), a=x, z=color'};
mp_support_graph('cl_st_ytitle') = {'MEAN(ap(EM,J) - ap(EM,J|unemp))'};
ff_graph_grid((tb_az_ap{1:end, 4:end}), ar_row_grid, age_grid, mp_support_graph);
```

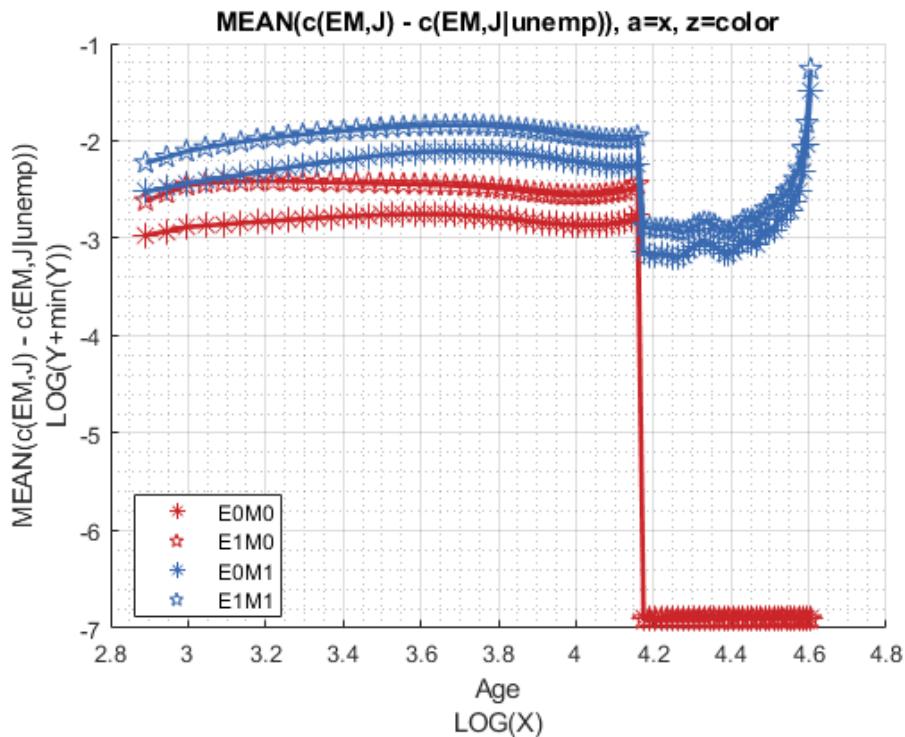




Graph Mean Consumption Change:

```
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);
```







# Chapter 5

## Household Life Cycle Distribution

### 5.1 Distribution Exact Savings Choices

This is the example vignette for function: `snw_ds_main` from the [PrjOptiSNW Package](#). This function solves for vfi and gets distribution induced by policy functions and exogenous distributions. More Dense Simulation. **Looped** to get distribution, but uses **bisect vec** for VFI.

#### 5.1.1 Test SNW\_DS\_MAIN Defaults Dense

Call the function with testing defaults.

```
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') = false;
mp_controls('bl_print_ds_verbose') = false;
[Phi_true,Phi_adj,A_agg,Y_inc_agg,it,mp_dsvfi_results] = snw_ds_main(mp_params, mp_controls);

Completed SNW_VFI_MAIN_BISEC_VEC;SNW_MP_PARAM=default_docdense;SNW_MP_CONTROL=default_test;time=253.
-----
xxxxxxxxxxxxxxxxxxxxxxxxxxxxxxxxxxxxxx
CONTAINER NAME: mp_outcomes ND Array (Matrix etc)
xxxxxxxxxxxxxxxxxxxxxxxxxxxxxxxxxxxxx
      i      idx     ndim    numel      rowN      colN        sum      mean      std
      -      ---     ----  -----      ---      -----  -----  -----
V_VFI    1       1       6   4.37e+07     83   5.265e+05 -1.5339e+08 -3.5101   26.11
ap_VFI   2       2       6   4.37e+07     83   5.265e+05  1.4159e+09  32.402   36.79
cons_VFI 3       3       6   4.37e+07     83   5.265e+05  2.1402e+08  4.8975   8.329

xxx TABLE:V_VFI xxxxxxxxxxxxxxxxxxxx
      c1      c2      c3      c4      c5      c526496    c526497    c526498    c
      ----  -----  -----  -----  -----  -----  -----
r1 -346.51 -346.12 -343.63 -337.86 -328.51    21.702    21.852   22.003
r2 -334.38 -333.99 -331.51 -325.83 -316.83    21.724    21.869   22.015
r3 -322.45 -322.06 -319.6  -314.14 -305.6    21.745    21.885   22.027
r4 -310.63 -310.27 -307.99 -302.88 -294.87    21.767    21.903   22.041
r5 -299.94 -299.6  -297.46 -292.67 -285.12    21.775    21.907   22.042
r79 -9.9437 -9.9325 -9.8557 -9.6597 -9.3232    2.5394    2.5501   2.5602
r80 -8.9023 -8.8911 -8.8143 -8.6183 -8.2818    2.3039    2.3121   2.3198
r81 -7.6363 -7.6251 -7.5484 -7.3524 -7.0159    2.0068    2.0124   2.0176
r82 -5.9673 -5.9561 -5.8793 -5.6833 -5.3468    1.5958    1.5989   1.6018
```

r83	-3.5892	-3.578	-3.5012	-3.3052	-2.9687	0.97904	0.98004	0.98097	0
<b>xxx TABLE:ap_VFI xxxxxxxxxxxxxxxxxxxxxxxx</b>									
c1	c2	c3	c4	c5	c526496	c526497	c526498	c5264	
--	--	-----	-----	-----	-----	-----	-----	-----	-----
r1	0	0	0.0005656	0.0075134	0.022901	114.75	120.41	126.27	132.3
r2	0	0	0.00051498	0.0065334	0.021549	114.86	120.53	126.41	132.5
r3	0	0	0.00051498	0.0049294	0.019875	114.97	120.65	126.56	132.
r4	0	0	0.00051498	0.0047937	0.019672	115.73	121.42	127.34	133.5
r5	0	0	0.00048517	0.0046683	0.019484	116.5	122.21	128.15	134.3
r79	0	0	0	0	0	81.091	85.68	90.335	94.37
r80	0	0	0	0	0	76.669	80.563	84.304	88.0
r81	0	0	0	0	0	68.313	71.534	74.475	77.83
r82	0	0	0	0	0	50.126	53.467	56.953	58.74
r83	0	0	0	0	0	0	0	0	0
<b>xxx TABLE:cons_VFI xxxxxxxxxxxxxxxxxxxxxxxx</b>									
c1	c2	c3	c4	c5	c526496	c526497	c526498		
-----	-----	-----	-----	-----	-----	-----	-----	-----	-----
r1	0.036717	0.037251	0.040426	0.04363	0.048012	9.6491	9.817	9.9649	
r2	0.036717	0.037251	0.040477	0.04461	0.049364	9.8118	9.9685	10.101	
r3	0.036717	0.037251	0.040477	0.046214	0.051039	9.9779	10.12	10.234	
r4	0.038144	0.038678	0.041903	0.047776	0.052666	10.131	10.258	10.354	
r5	0.039534	0.040068	0.043323	0.04929	0.054241	10.272	10.384	10.463	
r79	0.2179	0.21844	0.22216	0.23228	0.25197	35.858	37.092	38.455	
r80	0.2179	0.21844	0.22216	0.23228	0.25197	40.253	42.183	44.459	
r81	0.2179	0.21844	0.22216	0.23228	0.25197	48.587	51.19	54.266	
r82	0.2179	0.21844	0.22216	0.23228	0.25197	66.755	69.238	71.77	
r83	0.2179	0.21844	0.22216	0.23228	0.25197	116.87	122.69	128.71	

Completed SNW\_DS\_MAIN;SNW\_MP\_PARAM=default\_docdense;SNW\_MP\_CONTROL=default\_test;time=1804.8494

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

### 5.1.2 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	sd	coefofvar	min	max	pYis0	pYls0
a_ss	4.2486	6.7963	1.5996	0	135	0.1223	0
ap_ss	4.3473	6.834	1.572	0	163.7	0.10225	0
cons_ss	1.0676	0.69454	0.65055	0.036717	141.66	0	0
v_ss	-15.745	21.68	-1.3769	-586.22	24.63	0	0.8122
n_ss	2.3554	1.4375	0.61029	1	6	0	0
y_all	1.415	1.4926	1.0548	0	50.873	0.0072908	0
y_head_inc	1.1087	1.0092	0.91029	0.038108	24.357	0	0
y_head_earn	0.88655	0.92804	1.0468	0	18.957	0.2016	0
y_spouse_inc	0.35849	0.95494	2.6638	0	26.627	0.52499	0
yshr_interest	0.12214	0.16806	1.3759	0	0.99299	0.1223	0
yshr_wage	0.77513	0.33759	0.43553	0	1	0.10584	0
yshr_SS	0.10273	0.23637	2.3009	0	1	0.7984	0
yshr_tax	0.17862	0.03519	0.19701	0.036506	0.2552	0	0

yshr_nttxss	0.075896	0.25563	3.3681	-0.89184	0.2552	0	0.17845
-------------	----------	---------	--------	----------	--------	---	---------

### 5.1.3 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});
```

### 5.1.4 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_datasetde
```

xxx P(Age, EDU, MARRY))		xxxxxxxxxxxxxxxxxxxxxxxxxxxxxx						
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	0.002827	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 = ["MOE0", "M1E0", "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);
```



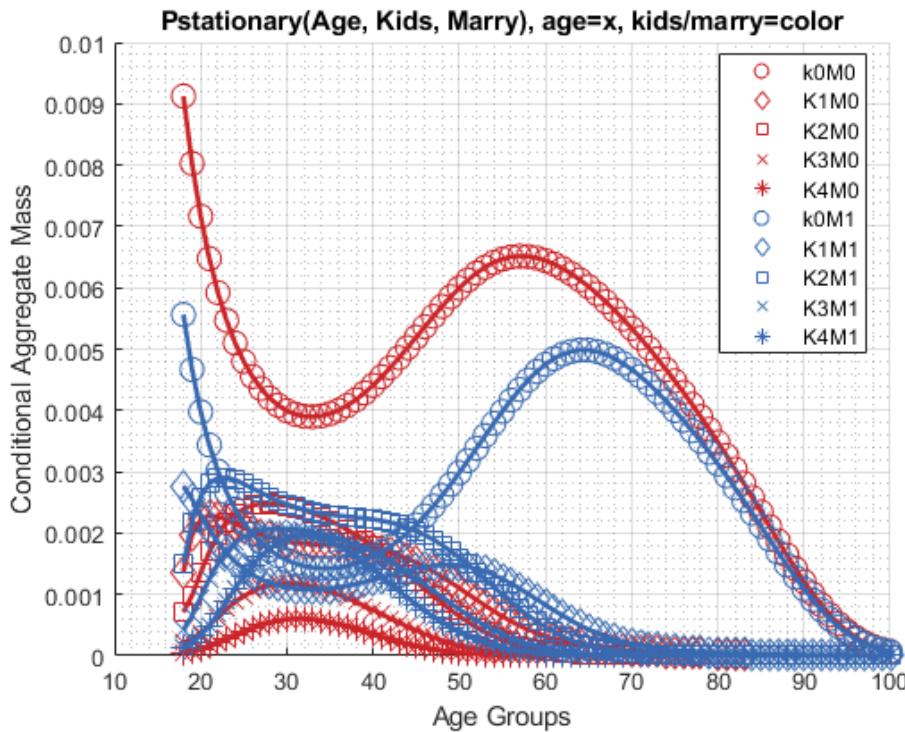
Kids and Marry By Age Mass

```
% 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) xxxxxxxxxxxxxxxxxxxxxxxxx
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);
```



### 5.1.5 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
```

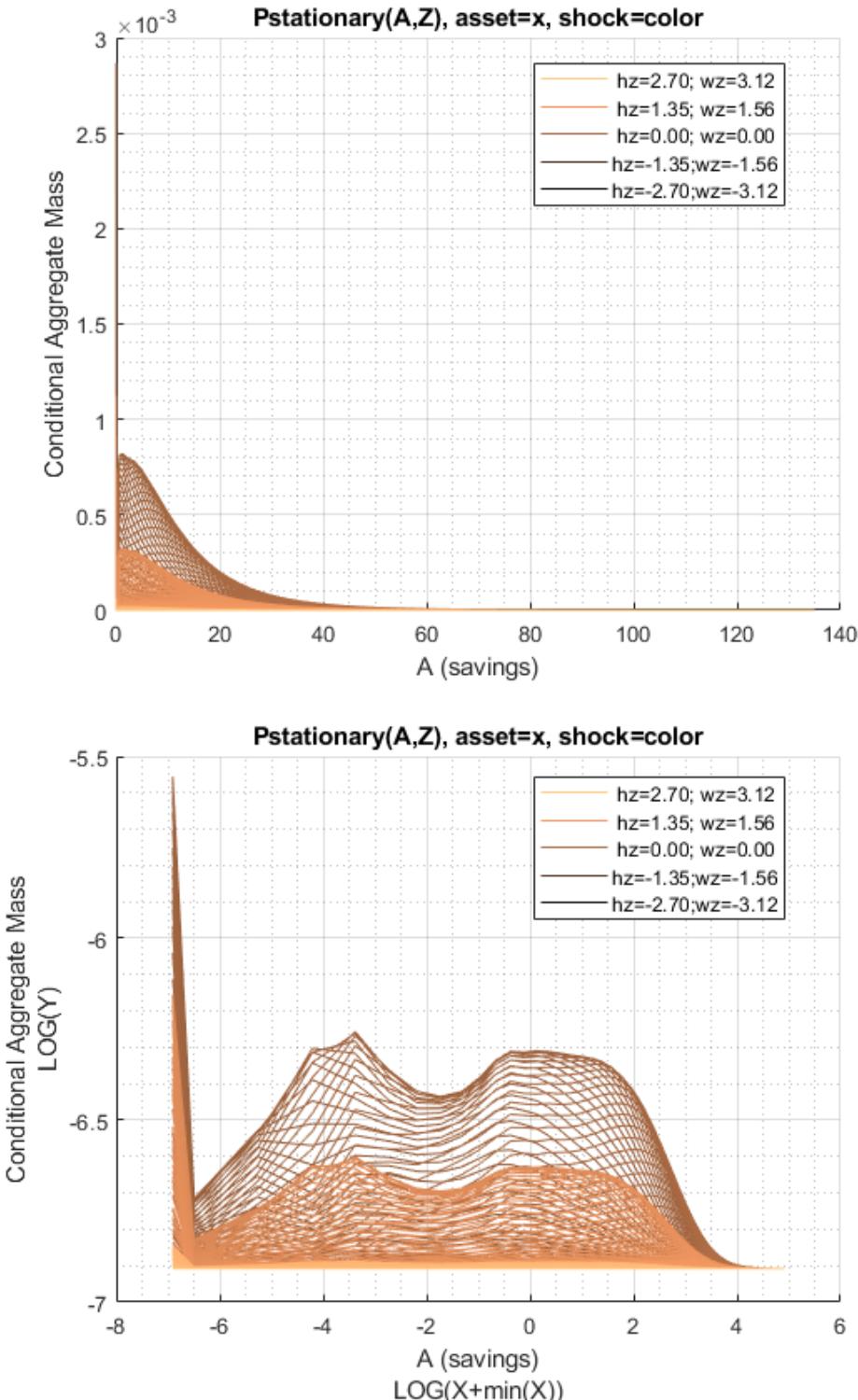
xxx P(A,Z))		xxxxxxxxxxxxxxxxxxxxxxxxxxxxxx					
group	savings	sum_eta_1	sum_eta_2	sum_eta_3	sum_eta_4	sum_eta_5	sum
1	0	1.6824e-07	1.4406e-07	2.1911e-07	3.1913e-07	4.5491e-07	6.4
2	0.00051498	3.4279e-10	3.2632e-10	5.6501e-10	1.0203e-09	1.9975e-09	4.1
3	0.0041199	7.1369e-10	6.2373e-10	9.7246e-10	1.4702e-09	2.2039e-09	3.2
4	0.013905	1.573e-09	1.3633e-09	2.1044e-09	3.1331e-09	4.6025e-09	6.7
5	0.032959	5.494e-09	4.7235e-09	7.23e-09	1.0641e-08	1.5401e-08	2.
6	0.064373	6.5788e-09	5.6779e-09	8.702e-09	1.2804e-08	1.8492e-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_aage = ff_summ_nd_array("P(A,Z)", Phi_true, true, ["sum"], 4, 1, cl_mp_datasetdesc, ar_permute);

```

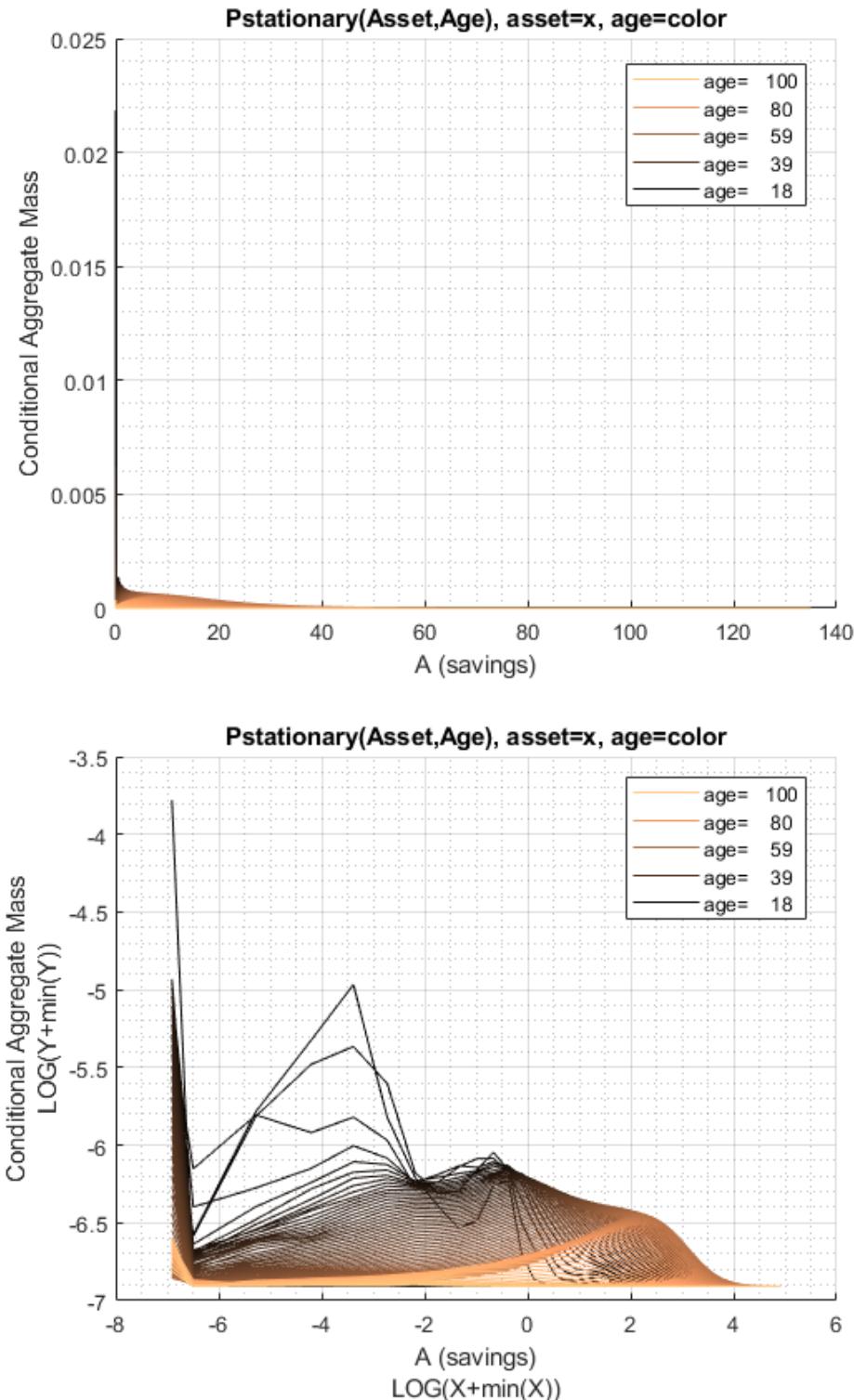
xxx	P(A,Z))	xxxxxxxxxxxxxxxxxxxxxxxxxxxxxx						
group	savings	sum_age_18	sum_age_19	sum_age_20	sum_age_21	sum_age_22	sum	
1	0	0.021837	0.0023507	0.0017993	0.0039371	0.0058435	0.	
2	0.00051498	0	0.00039608	0.00037932	0.0011301	0.00066626	0.0	
3	0.0041199	0	0.0020816	0.0019888	0.002009	0.00088325	0.0	
4	0.013905	0	0.0038656	0.0031682	0.001688	0.0011334	0.0	
5	0.032959	0	0.0059678	0.0036757	0.0019686	0.0014691	0.	
6	0.064373	0	0.001968	0.0026857	0.0015598	0.0012805	0.	
7	0.11124	0	0.0010155	0.0010772	0.00089495	0.00094737	0.0	
8	0.17664	0	0.00066497	0.00081578	0.0009608	0.0010548	0.	
9	0.26367	0	0.00045021	0.00085579	0.0011593	0.0011712	0.	
10	0.37542	0	0.00053095	0.0011218	0.0012745	0.0011467	0.	
11	0.51498	0	0.00090691	0.0013663	0.0012758	0.0012278	0.	
12	0.68544	0	0.00097523	0.0011111	0.0010957	0.0011325	0.	
13	0.88989	0	0.00023441	0.00050314	0.00074645	0.0009432	0.	
14	1.1314	0	4.5279e-05	0.00027467	0.00049029	0.00060869	0.0	
15	1.4131	0	1.7339e-05	0.00019476	0.00030104	0.00040391	0.0	
16	1.7381	0	8.1464e-06	6.6555e-05	0.00014925	0.00025602	0.0	
17	2.1094	0	6.1188e-06	3.5994e-05	9.5417e-05	0.000162	0.0	
18	2.5301	0	1.3448e-05	3.7101e-05	7.3464e-05	0.00012006	0.0	
19	3.0034	0	2.2537e-05	4.8195e-05	7.7883e-05	0.00011025	0.0	
20	3.5323	0	2.9909e-05	5.5599e-05	8.0928e-05	0.00010452	0.0	
21	4.1199	0	3.0433e-05	5.458e-05	7.2693e-05	9.1664e-05	0.0	
22	4.7693	0	2.0391e-05	3.7793e-05	5.5429e-05	7.2296e-05	8.9	
23	5.4836	0	5.1199e-06	1.8361e-05	3.277e-05	4.8259e-05	6.4	
24	6.2658	0	7.2528e-07	5.2955e-06	1.4093e-05	2.6887e-05	4.	
25	7.1191	0	1.0524e-07	1.2817e-06	4.9228e-06	1.2149e-05	2.2	
26	8.0466	0	1.7628e-08	5.0295e-07	2.0294e-06	5.2782e-06	1.1	
27	9.0514	0	3.0056e-09	3.0395e-07	1.0911e-06	2.7755e-06	5.7	
28	10.136	0	1.1825e-10	1.6421e-07	5.5086e-07	1.5801e-06	3.2	
29	11.305	0	0	4.8037e-08	2.2122e-07	8.0726e-07	1.8	
30	12.56	0	0	9.2865e-09	6.9448e-08	3.1086e-07	1.0	
31	13.905	0	0	1.789e-09	2.077e-08	9.8086e-08	4.7	
32	15.342	0	0	4.0984e-10	6.2012e-09	3.4485e-08	1.8	
33	16.875	0	0	9.8855e-11	1.6718e-09	1.2956e-08	6.	
34	18.507	0	0	2.1171e-11	4.7002e-10	4.2475e-09	2.1	
35	20.241	0	0	8.4937e-13	1.3772e-10	1.2013e-09	8.	
36	22.08	0	0	0	2.9206e-11	3.623e-10	2.7	
37	24.027	0	0	0	3.6378e-12	1.1269e-10	8.3	
38	26.085	0	0	0	7.7367e-13	2.3608e-11	2.7	
39	28.258	0	0	0	1.7753e-13	3.9993e-12	8.0	
40	30.548	0	0	0	8.3602e-15	1.0518e-12	1.7	
41	32.959	0	0	0	0	1.9415e-13	3.6	
42	35.493	0	0	0	0	1.4615e-14	9.1	
43	38.154	0	0	0	0	2.3455e-15	1.4	
44	40.945	0	0	0	0	2.9499e-16	1.7	
45	43.868	0	0	0	0	6.0398e-18	3.2	
46	46.928	0	0	0	0	0	0	3.3
47	50.126	0	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_aage{1:end, 3:end})', age_grid, agrid, mp_support_graph);% Consumption Choice
```



### 5.1.6 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'}	}	0.13166	0.63405	-31.11	1.9854	0.71265
{'sd'}	}	0.34823	0.37905	29.813	1.0848	0.54567
{'coefofvar'}	}	2.645	0.59783	-0.95831	0.54639	0.76569
{'min'}	}	0	0.036717	-586.22	1	0.038108
{'max'}	}	145.07	10.212	24.63	6	13.784
{'pYis0'}	}	0.10805	0	0	0	0
{'pYls0'}	}	0	0	0.93414	0	0
{'pYgr0'}	}	0.89195	1	0.065859	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	-322.58	1	0.046651
{'p10'}	}	0	0.24819	-67.491	1	0.23528
{'p25'}	}	0.012186	0.36957	-41.871	1	0.35258
{'p50'}	}	0.032959	0.55272	-24.354	2	0.56523
{'p75'}	}	0.07477	0.80089	-11.18	3	0.90612
{'p90'}	}	0.47812	1.1198	-2.6906	4	1.3579
{'p99_99'}	}	5.4504	3.6593	17.393	6	6.8484
{'fl_cov_ap_ss'}	}	0.12126	0.055072	2.4507	0.026881	0.05
{'fl_cor_ap_ss'}	}	1	0.41721	0.23606	0.071158	0.26313
{'fl_cov_c_ss'}	}	0.055072	0.14368	8.0391	0.07643	0.18689
{'fl_cor_c_ss'}	}	0.41721	1	0.71138	0.18587	0.90355
{'fl_cov_v_ss'}	}	2.4507	8.0391	888.8	0.38384	10.004
{'fl_cor_v_ss'}	}	0.23606	0.71138	1	0.011868	0.61498
{'fl_cov_n_ss'}	}	0.026881	0.07643	0.38384	1.1768	-8.185e-18
{'fl_cor_n_ss'}	}	0.071158	0.18587	0.011868	1	-1.3827e-17
{'fl_cov_y_head_inc'}	}	0.05	0.18689	10.004	-8.185e-18	0.29776
{'fl_cor_y_head_inc'}	}	0.26313	0.90355	0.61498	-1.3827e-17	1
{'fl_cov_y_spouse'}	}	0.18249	0.071644	3.4658	0.13323	0.010455
{'fl_cor_y_spouse'}	}	0.92021	0.33189	0.20413	0.21565	0.033645
{'fl_cov_yshr_wage'}	}	3.6882e-32	2.4079e-31	-9.3307e-30	1.6917e-30	1.2042e-31
{'fl_cor_yshr_wage'}	}	2.3849e-16	1.4304e-15	-7.0476e-16	3.5116e-15	4.9692e-16
{'fl_cov_yshr_SS'}	}	0	0	0	0	0
{'fl_cor_yshr_SS'}	}	NaN	NaN	NaN	NaN	NaN
{'fl_cov_yshr_nttxss'}		0.0057457	0.011176	0.85848	0.007516	0.01319
{'fl_cor_yshr_nttxss'}		0.48632	0.86907	0.84874	0.20421	0.71249
{'fracByP0_01'}	}	0	7.1684e-06	0.0013012	0.21046	7.788e-06
{'fracByP10'}	}	0	0.030643	0.32088	0.21046	0.027495
{'fracByP25'}	}	0.0067356	0.10365	0.58193	0.21046	0.092606
{'fracByP50'}	}	0.04689	0.29058	0.83099	0.53024	0.26377
{'fracByP75'}	}	0.13162	0.54875	0.97426	0.77109	0.5245
{'fracByP90'}	}	0.35822	0.76944	1.0077	0.92834	0.74403
{'fracByP99_99'}	}	0.99575	0.99938	1.0001	1	0.99912
age =59						
xxx tb_outcomes: all stats xxx						
OriginalVariableNames		ap_ss	c_ss	v_ss	n_ss	y_head_inc
-----	-----	-----	-----	-----	-----	-----
{'mean'}	}	9.4506	1.2067	-9.9431	1.7239	1.6033
{'sd'}	}	9.4598	0.76797	14.834	0.90777	1.2742
{'coefofvar'}	}	1.001	0.63643	-1.4919	0.52659	0.79474
{'min'}	}	0	0.05663	-208.18	1	0.059541
{'max'}	}	158.43	12.311	14.965	6	23.47
{'pYis0'}	}	0.0059691	0	0	0	0
{'pYls0'}	}	0	0	0.73383	0	0
{'pYgr0'}	}	0.99403	1	0.26617	1	1
{'pYisMINY'}	}	0.0059691	9.8324e-06	2.9687e-09	0.48835	9.8989e-06
{'pYisMAXY'}	}	9.0457e-09	3.8325e-11	5.2662e-07	0.0036816	1.4683e-06

{'p0_01'}	}	0	0.07838	-101	1	0.08341
{'p10'}	}	1.0833	0.41297	-30.14	1	0.49019
{'p25'}	}	3.0034	0.65765	-16.23	1	0.7717
{'p50'}	}	6.7818	1.0568	-6.363	2	1.2612
{'p75'}	}	12.812	1.5534	0.45344	2	2.0256
{'p90'}	}	20.8	2.1542	4.9139	3	3.0996
{'p99_99'}	}	112.23	8.4857	13.926	6	15.937
{'fl_cov_ap_ss'}	}	89.487	6.8831	97.649	0.8159	10.409
{'fl_cor_ap_ss'}	}	1	0.94746	0.69588	0.095013	0.86354
{'fl_cov_c_ss'}	}	6.8831	0.58977	8.5503	0.23192	0.85197
{'fl_cor_c_ss'}	}	0.94746	1	0.75055	0.33267	0.87063
{'fl_cov_v_ss'}	}	97.649	8.5503	220.04	2.4373	12.623
{'fl_cor_v_ss'}	}	0.69588	0.75055	1	0.181	0.66782
{'fl_cov_n_ss'}	}	0.8159	0.23192	2.4373	0.82404	0.055267
{'fl_cor_n_ss'}	}	0.095013	0.33267	0.181	1	0.04778
{'fl_cov_y_head_inc'}	}	10.409	0.85197	12.623	0.055267	1.6237
{'fl_cor_y_head_inc'}	}	0.86354	0.87063	0.66782	0.04778	1
{'fl_cov_y_spouse'}	}	2.2143	0.24542	3.4887	0.27625	0.116
{'fl_cor_y_spouse'}	}	0.2103	0.28712	0.21131	0.27342	0.08179
{'fl_cov_yshr_wage'}	}	-0.54196	-0.036396	-0.86915	0.0011758	-0.038212
{'fl_cor_yshr_wage'}	}	-0.56735	-0.46933	-0.58024	0.012827	-0.29697
{'fl_cov_yshr_SS'}	}	0	0	0	0	0
{'fl_cor_yshr_SS'}	}	NaN	NaN	NaN	NaN	NaN
{'fl_cov_yshr_nttxss'}	}	0.19452	0.017952	0.42036	0.0075501	0.027003
{'fl_cor_yshr_nttxss'}	}	0.67266	0.7647	0.92699	0.27208	0.69323
{'fracByP0_01'}	}	0	6.8812e-06	0.0011212	0.28329	5.8341e-06
{'fracByP10'}	}	0.004897	0.026408	0.43931	0.28329	0.022426
{'fracByP25'}	}	0.037048	0.092569	0.77208	0.28329	0.081818
{'fracByP50'}	}	0.16368	0.27051	1.0414	0.72028	0.23952
{'fracByP75'}	}	0.41532	0.53706	1.1137	0.72028	0.48823
{'fracByP90'}	}	0.67288	0.76168	1.075	0.85389	0.72007
{'fracByP99_99'}	}	0.99866	0.99926	1.0001	1	0.99889

age =100

xxx tb\_outcomes: all stats xxx

OriginalVariableNames	ap_ss	c_ss	v_ss	n_ss	y_head_inc	y_sp
{'mean'}	0	0.34868	-3.0033	1.4797	0.2604	0.
{'sd'}	0	0.23392	1.043	0.50567	0.02289	0.
{'coefofvar'}	NaN	0.67088	-0.34728	0.34173	0.087904	2
{'min'}	0	0.2179	-10.065	1	0.24433	
{'max'}	0	141.66	0.99282	6	5.6926	
{'pYis0'}	1	0	0	0	0	0.
{'pYls0'}	0	0	0.99285	0	0	
{'pYgro'}	0	1	0.0071501	1	1	0.
{'pYisMINY'}	1	0.36483	1.5455e-10	0.5232	0.52813	0.
{'pYisMAXY'}	1	0	0	4.2206e-08	0	1.033
{'p0_01'}	0	0.2179	-6.3349	1	0.24433	
{'p10'}	0	0.2179	-3.6603	1	0.24433	
{'p25'}	0	0.2179	-3.5892	1	0.24433	
{'p50'}	0	0.25824	-3.5892	1	0.24433	
{'p75'}	0	0.36458	-2.8095	2	0.29263	0.
{'p90'}	0	0.6134	-1.3055	2	0.29279	0.
{'p99_99'}	0	2.8989	0.51215	4	0.33789	2
{'fl_cov_ap_ss'}	0	0	0	0	0	
{'fl_cor_ap_ss'}	NaN	NaN	NaN	NaN	NaN	
{'fl_cov_c_ss'}	0	0.054721	0.19746	0.059476	0.0015551	0.
{'fl_cor_c_ss'}	NaN	1	0.80934	0.50281	0.29042	0.

{'fl_cov_v_ss'}	0	0.19746	1.0878	0.16711	0.01031	0.
{'fl_cor_v_ss'}	NaN	0.80934	1	0.31686	0.43183	0.
{'fl_cov_n_ss'}	0	0.059476	0.16711	0.2557	0.0019105	0.
{'fl_cor_n_ss'}	NaN	0.50281	0.31686	1	0.16506	0.
{'fl_cov_y_head_inc'}	0	0.0015551	0.01031	0.0019105	0.00052397	0.000
{'fl_cor_y_head_inc'}	NaN	0.29042	0.43183	0.16506	1	0.
{'fl_cov_y_spouse'}	0	0.05178	0.1649	0.0533	0.00067518	0.0
{'fl_cor_y_spouse'}	NaN	0.89356	0.63823	0.4255	0.11907	0.
{'fl_cov_yshr_wage'}	0	0.039513	0.15927	0.083913	0.00067571	0.0
{'fl_cor_yshr_wage'}	NaN	0.7643	0.69097	0.75087	0.13357	0.
{'fl_cov_yshr_SS'}	0	-0.040547	-0.16461	-0.085285	-0.00072523	-0.0
{'fl_cor_yshr_SS'}	NaN	-0.77966	-0.70991	-0.75864	-0.14251	-0.
{'fl_cov_yshr_nttxss'}	0	0.044511	0.18091	0.091879	0.00087698	0.0
{'fl_cor_yshr_nttxss'}	NaN	0.78763	0.71798	0.75212	0.15859	0.
{'fracByP0_01'}	NaN	0.22799	0.00053042	0.35357	0.49553	0.
{'fracByP10'}	NaN	0.22799	0.22059	0.35357	0.49553	0.
{'fracByP25'}	NaN	0.22799	0.6552	0.35357	0.49553	0.
{'fracByP50'}	NaN	0.35394	0.6552	0.35357	0.49553	0.
{'fracByP75'}	NaN	0.55083	0.87677	0.99419	0.88359	0.
{'fracByP90'}	NaN	0.7612	0.97549	0.99419	0.89158	0.
{'fracByP99_99'}	NaN	0.99927	1	0.99999	0.99991	0.

## 5.2 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.

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

Due to the speed of running this, the example below only uses dense grid

```
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 6514.834013 seconds.

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

Elapsed time is 8310.394598 seconds.

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

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

### 5.2.2 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	sd	coeofvar	min	max	pYls0	pYls0
	-----	-----	-----	-----	-----	-----	-----
a_ss	3.6126	6.4914	1.7969	0	135	0.17087	0
ap_ss	12.366	8.591	0.69474	1	55	0	0

cons_ss	1.1622	0.80935	0.69639	0.036857	140.65	0	0
v_ss	-15.043	17.999	-1.1965	-597.7	23.892	0	0.8378
n_ss	2.3554	1.4375	0.61029	1	6	0	0
y_all	1.5684	1.4453	0.92149	0.038325	47.427	0	0
y_head_inc	1.2411	1.1553	0.9309	0.038325	31.844	0	0
y_head_earn	1.0444	1.0725	1.0269	0	26.444	0.2016	0
y_spouse_inc	0.32734	0.73631	2.2494	0	15.702	0.52499	0
yshr_interest	0.096139	0.15385	1.6002	0	0.99295	0.17087	0
yshr_wage	0.79228	0.33742	0.42588	0	1	0.10584	0
yshr_SS	0.11158	0.25418	2.278	0	1	0.7984	0
yshr_tax	0.18447	0.034469	0.18686	0.038299	0.25519	0	0
yshr_nttxss	0.072887	0.27591	3.7854	-0.88844	0.25519	0	0.18437

### 5.2.3 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});
```

### 5.2.4 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)			xxxxxxxxxxxxxxxxxxxxxxxxxxxx	sum_age_18	sum_age_19	sum_age_20	sum_age_21	sum_age_22	s
group	marry	edu	-----	-----	-----	-----	-----	-----	-----
1	0	0	0.0085768	0.0084866	0.0083969	0.0083078	0.0082194	0.0081669	0
2	1	0	0.0066438	0.0065739	0.0065044	0.0064354	0.0063669	0.0063078	0

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 = ["MOE0", "M1E0", "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

```

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

```

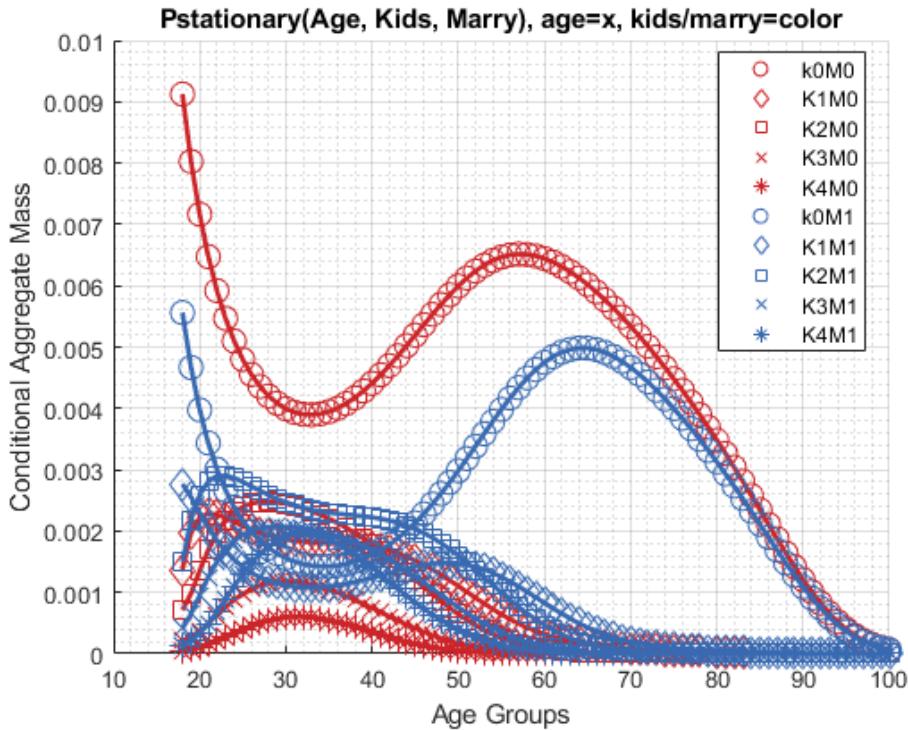
mp_support_graph('cl_st_graph_title') = {'Pstationary(Age, Kids, Marry), age=x, kids/marry=color'};
mp_support_graph('cl_st_ytitle') = {'Conditional Aggregate Mass'};

```

```

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);

```



### 5.2.5 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_permut

```

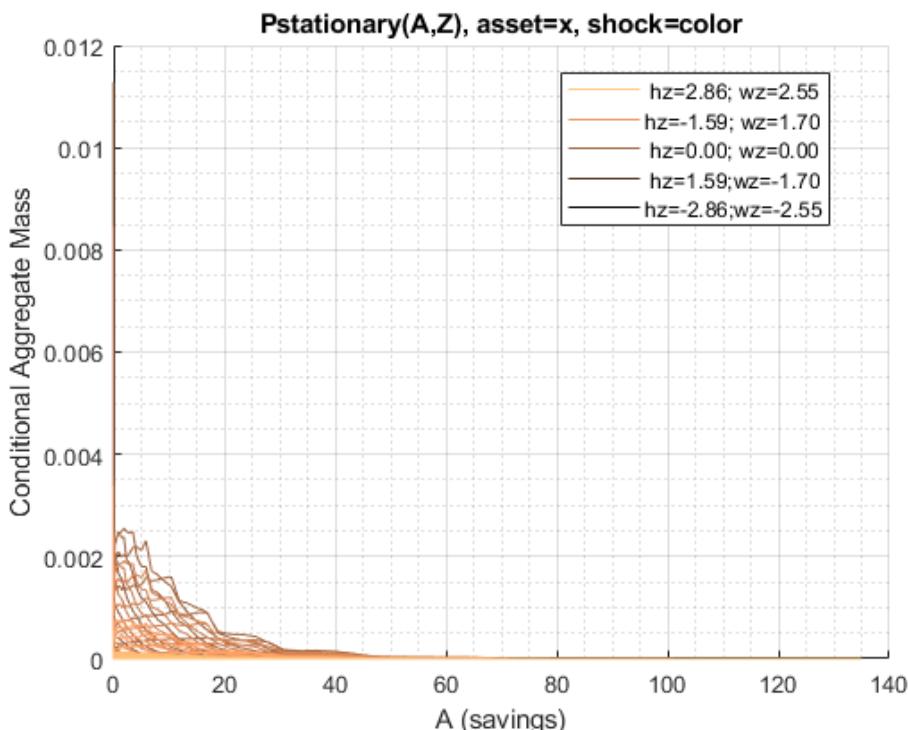
xxx	P(A,Z))	xxxxxxxxxxxxxxxxxxxxxxxxxxxxxx						
group	savings	sum_eta_1	sum_eta_2	sum_eta_3	sum_eta_4	sum_eta_5	sum	
---	-----	-----	-----	-----	-----	-----	-----	-----
1	0	3.3248e-08	5.983e-07	5.0468e-06	2.6071e-05	8.9773e-05	0.0	
2	0.00085734	1.0185e-10	1.5738e-09	3.3484e-08	6.0665e-07	5.2814e-06	1.7	
3	0.0068587	3.5085e-10	6.5198e-09	4.9979e-08	3.1065e-07	2.0919e-06	1.2	

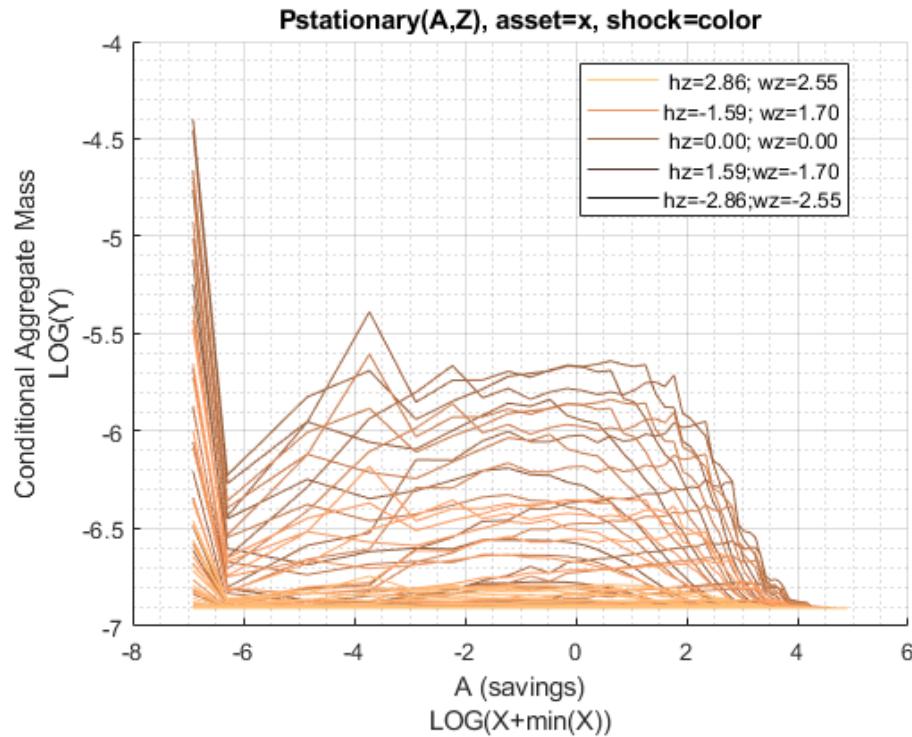
4	0.023148	9.1216e-10	1.727e-08	1.5853e-07	9.1924e-07	4.228e-06	1.6
5	0.05487	1.4512e-09	2.6722e-08	2.3417e-07	1.3076e-06	5.2407e-06	1.8
6	0.10717	1.6379e-09	2.9149e-08	2.4125e-07	1.2884e-06	5.1297e-06	1.7
7	0.18519	2.294e-09	4.0502e-08	3.4422e-07	1.7987e-06	6.7964e-06	2.0
8	0.29407	2.7467e-09	4.5812e-08	3.5554e-07	1.8118e-06	6.8723e-06	2.0
9	0.43896	2.8104e-09	4.8243e-08	3.9121e-07	1.9756e-06	7.1951e-06	2.0
10	0.625	2.7355e-09	4.7422e-08	3.8625e-07	1.9709e-06	7.2487e-06	2.0
11	0.85734	2.6045e-09	4.5648e-08	3.7801e-07	1.9446e-06	7.1135e-06	2.0
12	1.1411	2.3091e-09	4.118e-08	3.427e-07	1.7857e-06	6.6881e-06	1.9
13	1.4815	1.8391e-09	3.3807e-08	2.9225e-07	1.5886e-06	6.0926e-06	1.7
14	1.8836	1.4638e-09	2.7339e-08	2.4063e-07	1.3481e-06	5.3035e-06	1.5
15	2.3525	1.0398e-09	2.042e-08	1.9039e-07	1.1046e-06	4.5148e-06	1.3
16	2.8935	7.6831e-10	1.5168e-08	1.4306e-07	8.5678e-07	3.6129e-06	1.1
17	3.5117	5.0779e-10	1.0306e-08	1.0222e-07	6.4935e-07	2.7868e-06	9.0
18	4.2121	3.3725e-10	7.1325e-09	7.2301e-08	4.5701e-07	2.0605e-06	7.
19	5	2.0339e-10	4.5055e-09	4.7886e-08	3.1798e-07	1.4784e-06	5.2
20	5.8805	1.1697e-10	2.6614e-09	2.899e-08	2.04e-07	1.0085e-06	3.8
21	6.8587	6.4191e-11	1.5386e-09	1.7458e-08	1.2852e-07	6.6971e-07	2.7
22	7.9398	3.223e-11	8.2009e-10	1.023e-08	7.992e-08	4.4241e-07	1.8
23	9.1289	1.5935e-11	4.2547e-10	5.5799e-09	4.7148e-08	2.8701e-07	1.3
24	10.431	7.6602e-12	2.1449e-10	3.021e-09	2.7923e-08	1.8511e-07	9.7
25	11.852	3.4707e-12	1.1014e-10	1.6503e-09	1.6439e-08	1.1882e-07	6.7
26	13.396	1.5171e-12	5.0241e-11	8.4768e-10	9.2919e-09	7.4842e-08	4.
27	15.069	6.5407e-13	2.3567e-11	4.244e-10	4.9998e-09	4.3238e-08	2.8

```

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

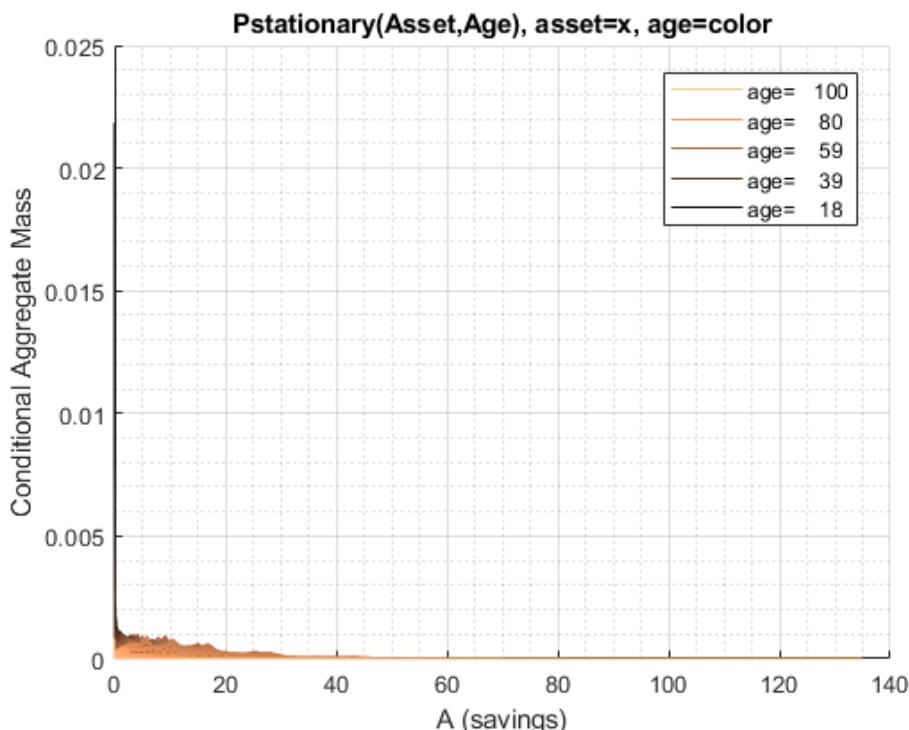
% NaN(n_jgrid,n_agrid,n_etagrid,n_educgrid,n_marriedgrid,n_kidsgrid);							
ar_permute = [3,4,5,6,1,2];							
% Value Function							
tb_prob_aage = ff_summ_nd_array("P(A,Z)", Phi_true, true, ["sum"], 4, 1, cl_mp_datasetdesc, ar_perm							
xxx	P(A,Z))	xxxxxxxxxxxxxxxxxxxxxxxxxxxx					
group	savings	sum_age_18	sum_age_19	sum_age_20	sum_age_21	sum_age_22	sum
-----	-----	-----	-----	-----	-----	-----	-----
1	0	0.021837	0.0034489	0.0022777	0.0051619	0.0070701	0.
2	0.00085734	0	0.00068848	0.00063521	0.0016036	0.0010378	0.0
3	0.0068587	0	0.0032017	0.0031082	0.0022491	0.0010432	0.0
4	0.023148	0	0.0058625	0.0047177	0.0019351	0.0014397	0.
5	0.05487	0	0.0024915	0.0022549	0.0014027	0.001227	0.
6	0.10717	0	0.0014086	0.0019373	0.0017422	0.0016421	
7	0.18519	0	0.0021091	0.0019779	0.0015628	0.0013724	0.
8	0.29407	0	0.00077614	0.0012753	0.0015936	0.0016414	0.
9	0.43896	0	0.00045252	0.001062	0.0009547	0.00098397	0.
10	0.625	0	0.00044667	0.0006628	0.0010416	0.00096275	0.0
11	0.85734	0	0.00047477	0.00074294	0.0006549	0.00088876	0.0
12	1.1411	0	5.5654e-05	0.00024727	0.00052409	0.00050156	0.0
13	1.4815	0	6.2855e-05	0.00019563	0.00024402	0.00047382	0.0
14	1.8836	0	5.9284e-05	0.00012121	0.00019477	0.00022476	0.0
15	2.3525	0	5.4786e-05	9.1062e-05	0.00015255	0.0001713	0.
16	2.8935	0	1.2562e-05	5.2495e-05	7.1526e-05	0.00013824	0.0
17	3.5117	0	1.3674e-06	1.1359e-05	3.0456e-05	4.9417e-05	0.0
18	4.2121	0	1.7163e-07	5.944e-06	2.1633e-05	2.4249e-05	3.9
19	5	0	7.8629e-08	1.35e-06	5.2915e-06	1.3252e-05	2.1
20	5.8805	0	6.0581e-09	7.6218e-07	4.4269e-06	1.3802e-05	1.2
21	6.8587	0	4.4396e-10	9.1165e-08	6.9508e-07	3.4569e-06	1.
22	7.9398	0	0	3.4291e-08	4.1481e-07	2.9624e-06	4.2
23	9.1289	0	0	2.5522e-08	3.1203e-07	5.0602e-07	2.4

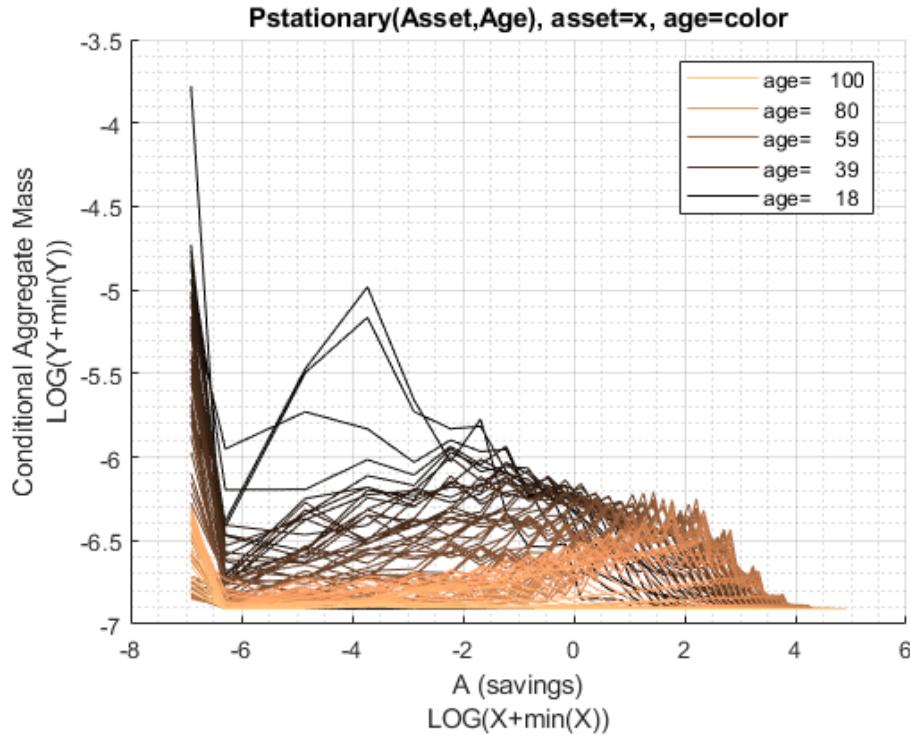
24	10.431	0	0	6.5868e-10	4.3387e-08	3.9922e-07	1.8
25	11.852	0	0	2.4326e-10	1.8803e-08	2.6275e-07	4.5
26	13.396	0	0	4.8838e-12	1.8589e-08	3.869e-08	2.8
27	15.069	0	0	1.813e-12	4.7634e-10	2.1906e-08	2.1
28	16.875	0	0	0	6.2066e-11	1.9079e-08	3.5
29	18.82	0	0	0	6.42e-12	6.8737e-10	2.0
30	20.91	0	0	0	1.6411e-13	9.995e-11	1.6
31	23.148	0	0	0	1.9878e-14	1.2652e-11	7.6
32	25.541	0	0	0	0	7.895e-13	1.3
33	28.093	0	0	0	0	1.2464e-14	1
34	30.81	0	0	0	0	2.5551e-16	5.
35	33.697	0	0	0	0	0	1.2
36	36.758	0	0	0	0	0	2.0
37	40	0	0	0	0	0	2.4
38	43.427	0	0	0	0	0	0
39	47.044	0	0	0	0	0	0
40	50.856	0	0	0	0	0	0
41	54.87	0	0	0	0	0	0
42	59.089	0	0	0	0	0	0
43	63.519	0	0	0	0	0	0
44	68.164	0	0	0	0	0	0
45	73.032	0	0	0	0	0	0
46	78.125	0	0	0	0	0	0
47	83.45	0	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_aage{1:end, 3:end}'), age_grid, agrid, mp_support_graph);% Consumption Choice

```





### 5.2.6 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');
    end
end

```

```

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'}              | 4.4841    | 0.73608    | -24.737    | 1.9854     | 0.83951    |
| {'sd'}                | 2.5942    | 0.43457    | 24.426     | 1.0848     | 0.62548    |
| {'coefofvar'}         | 0.57854   | 0.59038    | -0.98745   | 0.54639    | 0.74505    |
| {'min'}               | 1         | 0.036857   | -597.7     | 1          | 0.038325   |
| {'max'}               | 55        | 17.35      | 23.892     | 6          | 17.095     |
| {'pYiso'}             | 0         | 0          | 0          | 0          | 0          |
| {'pYls0'}             | 0         | 0          | 0.91009    | 0          | 0          |
| {'pYgr0'}             | 1         | 1          | 0.089914   | 1          | 1          |
| {'pYisMINY'}          | 0.15961   | 2.0027e-06 | 8.8672e-09 | 0.41786    | 3.8147e-06 |
| {'pYisMAXY'}          | 0         | 0          | 0          | 0.0060544  | 0          |
| {'p0_01'}             | 1         | 0.0682     | -251.7     | 1          | 0.072367   |
| {'p10'}               | 1         | 0.30119    | -51.639    | 1          | 0.25802    |
| {'p25'}               | 3         | 0.40819    | -36.859    | 1          | 0.4872     |
| {'p50'}               | 4         | 0.65163    | -19.949    | 2          | 0.66948    |
| {'p75'}               | 6         | 0.91178    | -7.7939    | 3          | 0.91995    |
| {'p90'}               | 8         | 1.2709     | -1.1471    | 4          | 1.7371     |
| {'p99_99'}            | 16        | 4.1437     | 17.666     | 6          | 6.1934     |
| {'fl_cov_ap_ss'}      | 6.73      | 0.61926    | 25.315     | -0.086009  | 0.71874    |
| {'fl_cor_ap_ss'}      | 1         | 0.5493     | 0.3995     | -0.030562  | 0.44295    |
| {'fl_cov_c_ss'}       | 0.61926   | 0.18885    | 7.7987     | 0.07295    | 0.25218    |
| {'fl_cor_c_ss'}       | 0.5493    | 1          | 0.7347     | 0.15474    | 0.92778    |
| {'fl_cov_v_ss'}       | 25.315    | 7.7987     | 596.64     | -1.0333    | 10.003     |
| {'fl_cor_v_ss'}       | 0.3995    | 0.7347     | 1          | -0.038995  | 0.65476    |
| {'fl_cov_n_ss'}       | -0.086009 | 0.07295    | -1.0333    | 1.1768     | 2.5745e-18 |
| {'fl_cor_n_ss'}       | -0.030562 | 0.15474    | -0.038995  | 1          | 3.7942e-18 |
| {'fl_cov_y_head_inc'} | 0.71874   | 0.25218    | 10.003     | 2.5745e-18 | 0.39122    |
| {'fl_cor_y_head_inc'} | 0.44295   | 0.92778    | 0.65476    | 3.7942e-18 | 1          |


```

{'fl_cov_y_spouse' }	0.77387	0.060176	2.2091	0.12195	0.010942
{'fl_cor_y_spouse' }	0.68113	0.31618	0.20651	0.25667	0.039945
{'fl_cov_yshr_wage' }	-1.9999e-30	-3.1429e-31	1.1155e-29	-5.0228e-31	-4.8634e-31
{'fl_cor_yshr_wage' }	-1.7359e-15	-1.6286e-15	1.0284e-15	-1.0426e-15	-1.7509e-15
{'fl_cov_yshr_SS' }	0	0	0	0	0
{'fl_cor_yshr_SS' }	NaN	NaN	NaN	NaN	NaN
{'fl_cov_yshr_nttxss'}	0.05377	0.011984	0.67106	0.0063843	0.014635
{'fl_cor_yshr_nttxss'}	0.65501	0.87148	0.8682	0.18598	0.73941
{'fracByP0_01' }	0.035596	3.1006e-05	0.0014244	0.21046	5.4793e-05
{'fracByP10' }	0.035596	0.046234	0.31706	0.21046	0.031399
{'fracByP25' }	0.14894	0.11395	0.58865	0.21046	0.17954
{'fracByP50' }	0.39097	0.28419	0.84937	0.53024	0.32745
{'fracByP75' }	0.60677	0.54782	0.99563	0.77109	0.51036
{'fracByP90' }	0.82323	0.77805	1.0163	0.92834	0.8397
{'fracByP99_99' }	0.99971	0.99944	1	1	0.99925
age =59					
xxx tb_outcomes: all stats xxx					
OriginalVariableNames	ap_ss	c_ss	v_ss	n_ss	y_head_inc
'mean'	19.816	1.359	-12.596	1.7239	1.7902
'sd'	7.5997	0.94263	14.529	0.90777	1.4384
'coefofvar'	0.3835	0.69362	-1.1534	0.52659	0.80349
'min'	1	0.056816	-211.91	1	0.05988
'max'	55	31.643	14.416	6	30.606
{'pYiso'}	0	0	0	0	0
{'pYls0'}	0	0	0.80596	0	0
{'pYgro'}	1	1	0.19404	1	1
{'pYisMINY'}	0.0097508	1.4955e-06	4.4767e-10	0.48835	1.5128e-06
{'pYisMAXY'}	3.9575e-05	3.6923e-09	2.35e-07	0.0036816	5.7591e-07
{'p0_01'}	1	0.1046	-83.156	1	0.11307
{'p10'}	10	0.4435	-33.387	1	0.56354
{'p25'}	15	0.68544	-20.857	1	0.82346
{'p50'}	20	1.1501	-9.5768	2	1.4112
{'p75'}	25	1.7983	-1.8874	2	2.3004
{'p90'}	29	2.5653	3.2283	3	3.3891
{'p99_99'}	52	10.514	13.528	6	17.142
{'fl_cov_ap_ss'}	57.755	5.9089	102.91	0.833	8.8962
{'fl_cor_ap_ss'}	1	0.82483	0.93205	0.12075	0.81382
{'fl_cov_c_ss'}	5.9089	0.88856	10.148	0.19066	1.1168
{'fl_cor_c_ss'}	0.82483	1	0.74094	0.22282	0.82371
{'fl_cov_v_ss'}	102.91	10.148	211.1	2.8206	14.8
{'fl_cor_v_ss'}	0.93205	0.74094	1	0.21386	0.70816
{'fl_cov_n_ss'}	0.833	0.19066	2.8206	0.82404	0.051157
{'fl_cor_n_ss'}	0.12075	0.22282	0.21386	1	0.039179
{'fl_cov_y_head_inc'}	8.8962	1.1168	14.8	0.051157	2.069
{'fl_cor_y_head_inc'}	0.81382	0.82371	0.70816	0.039179	1
{'fl_cov_y_spouse'}	1.5795	0.19114	3.2552	0.25285	0.10701
{'fl_cor_y_spouse'}	0.24292	0.23699	0.26185	0.32555	0.08695
{'fl_cov_yshr_wage'}	-0.49211	-0.043084	-0.82571	-0.0010612	-0.051178
{'fl_cor_yshr_wage'}	-0.75357	-0.53189	-0.66137	-0.013605	-0.41406
{'fl_cov_yshr_SS'}	0	0	0	0	0
{'fl_cor_yshr_SS'}	NaN	NaN	NaN	NaN	NaN
{'fl_cov_yshr_nttxss'}	0.18595	0.018907	0.38617	0.0064928	0.028554
{'fl_cor_yshr_nttxss'}	0.86513	0.70922	0.93979	0.2529	0.7019
{'fracByP0_01'}	0.00049206	1.8935e-05	0.0018764	0.28329	1.6223e-05
{'fracByP10'}	0.038429	0.027522	0.35161	0.28329	0.022756

{'fracByP25'}	}	0.15239	0.088557	0.65681	0.28329	0.081638
{'fracByP50'}	}	0.38532	0.25604	0.94508	0.72028	0.23879
{'fracByP75'}	}	0.65807	0.51752	1.0572	0.72028	0.4917
{'fracByP90'}	}	0.83502	0.75552	1.0505	0.85389	0.71833
{'fracByP99_99'}	}	0.99977	0.99911	1.0001	1	0.999
age =100						
xxx tb_outcomes: all stats xxx						
OriginalVariableNames		ap_ss	c_ss	v_ss	n_ss	y_head_inc
-----	-----	-----	-----	-----	-----	-----
{'mean'}	}	1	0.32267	-3.1409	1.4797	0.25976
{'sd'}	}	3.5527e-15	0.17242	0.94302	0.50567	0.022536
{'coefofvar'}	}	3.5527e-15	0.53435	-0.30024	0.34173	0.0867577
{'min'}	}	1	0.21707	-9.9745	1	0.24433
{'max'}	}	1	140.65	0.99282	6	5.6926
{'pYis0'}	}	0	0	0	0	0
{'pYls0'}	}	0	0	0.99701	0	0
{'pYgr0'}	}	1	1	0.0029896	1	1
{'pYisMINY'}	}	1	0.38656	2.0113e-10	0.5232	0.55431
{'pYisMAXY'}	}	1	0	0	4.2206e-08	0
{'p0_01'}	}	1	0.21707	-6.4374	1	0.24433
{'p10'}	}	1	0.21707	-3.6791	1	0.24433
{'p25'}	}	1	0.21707	-3.6067	1	0.24433
{'p50'}	}	1	0.25723	-3.6067	1	0.24433
{'p75'}	}	1	0.36309	-2.8876	2	0.29263
{'p90'}	}	1	0.50168	-1.819	2	0.29263
{'p99_99'}	}	1	1.8447	0.23336	4	0.31763
{'fl_cov_ap_ss'}	}	1.2622e-29	-6.2617e-30	6.0422e-29	-2.5736e-29	-5.0486e-30
{'fl_cor_ap_ss'}	}	1	-1.0222e-14	1.8035e-14	-1.4326e-14	-6.3058e-14
{'fl_cov_c_ss'}	}	-6.2617e-30	0.029727	0.1377	0.049528	0.0011258
{'fl_cor_c_ss'}	}	-1.0222e-14	1	0.8469	0.56809	0.28973
{'fl_cov_v_ss'}	}	6.0422e-29	0.1377	0.88928	0.13864	0.0090605
{'fl_cor_v_ss'}	}	1.8035e-14	0.8469	1	0.29075	0.42634
{'fl_cov_n_ss'}	}	-2.5736e-29	0.049528	0.13864	0.2557	0.0016977
{'fl_cor_n_ss'}	}	-1.4326e-14	0.56809	0.29075	1	0.14898
{'fl_cov_y_head_inc'}	}	-5.0486e-30	0.0011258	0.0090605	0.0016977	0.00050787
{'fl_cor_y_head_inc'}	}	-6.3058e-14	0.28973	0.42634	0.14898	1
{'fl_cov_y_spouse'}	}	-1.4744e-30	0.029696	0.12887	0.047692	0.0005624
{'fl_cor_y_spouse'}	}	-2.2307e-15	0.92578	0.73454	0.50696	0.13414
{'fl_cov_yshr_wage'}	}	-2.8197e-30	0.031233	0.14436	0.08326	0.00060599
{'fl_cor_yshr_wage'}	}	-3.6954e-15	0.84344	0.71277	0.76664	0.1252
{'fl_cov_yshr_SS'}	}	-1.9134e-29	-0.03166	-0.14677	-0.084206	-0.00062745
{'fl_cor_yshr_SS'}	}	-2.496e-14	-0.85097	-0.72129	-0.77173	-0.12903
{'fl_cov_yshr_nttxss'}	}	1.3054e-29	0.034596	0.16109	0.090587	0.00077099
{'fl_cor_yshr_nttxss'}	}	1.5717e-14	0.8583	0.7307	0.76628	0.14634
{'fracByP0_01'}	}	1	0.26006	0.00032592	0.35357	0.52138
{'fracByP10'}	}	1	0.26006	0.20378	0.35357	0.52138
{'fracByP25'}	}	1	0.26006	0.67085	0.35357	0.52138
{'fracByP50'}	}	1	0.41437	0.67085	0.35357	0.52138
{'fracByP75'}	}	1	0.59565	0.86725	0.99419	0.90276
{'fracByP90'}	}	1	0.77472	0.96654	0.99419	0.90276
{'fracByP99_99'}	}	1	0.99967	1	0.99999	0.99992

# Chapter 6

## Value of Each Check

### 6.1 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.

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

Call the function with defaults.

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

```
SNW_VFI_MAIN: Finished Age Group:83 of 83
SNW_VFI_MAIN: Finished Age Group:82 of 83
SNW_VFI_MAIN: Finished Age Group:81 of 83
SNW_VFI_MAIN: Finished Age Group:80 of 83
SNW_VFI_MAIN: Finished Age Group:79 of 83
SNW_VFI_MAIN: Finished Age Group:78 of 83
SNW_VFI_MAIN: Finished Age Group:77 of 83
SNW_VFI_MAIN: Finished Age Group:76 of 83
SNW_VFI_MAIN: Finished Age Group:75 of 83
SNW_VFI_MAIN: Finished Age Group:74 of 83
SNW_VFI_MAIN: Finished Age Group:73 of 83
SNW_VFI_MAIN: Finished Age Group:72 of 83
SNW_VFI_MAIN: Finished Age Group:71 of 83
SNW_VFI_MAIN: Finished Age Group:70 of 83
SNW_VFI_MAIN: Finished Age Group:69 of 83
SNW_VFI_MAIN: Finished Age Group:68 of 83
SNW_VFI_MAIN: Finished Age Group:67 of 83
SNW_VFI_MAIN: Finished Age Group:66 of 83
SNW_VFI_MAIN: Finished Age Group:65 of 83
SNW_VFI_MAIN: Finished Age Group:64 of 83
SNW_VFI_MAIN: Finished Age Group:63 of 83
SNW_VFI_MAIN: Finished Age Group:62 of 83
SNW_VFI_MAIN: Finished Age Group:61 of 83
SNW_VFI_MAIN: Finished Age Group:60 of 83
SNW_VFI_MAIN: Finished Age Group:59 of 83
```



```

Elapsed time is 139.984500 seconds.
Completed SNW_VFI_MAIN;SNW_MP_PARAM=default_dense;SNW_MP_CONTROL=default_test

welf_checks = 2;
[V_W, C_W] = snw_a4chk_wrk_bisec_vec(welf_checks, V_ss, cons_ss, mp_params, mp_controls);

Elapsed time is 76.079485 seconds.
Completed SNW_A4CHK_WRK_BISEC_VEC;welf_checks=2;TR=0.0017225;SNW_MP_PARAM=default_dense;SNW_MP_CONTR
-----
xxxxxxxxxxxxxxxxxxxxxxxxxxxxxxxxxxxxxx
CONTAINER NAME: mp_container_map ND Array (Matrix etc)
xxxxxxxxxxxxxxxxxxxxxxxxxxxxxxxxxxxxxx

      i    idx   ndim    numel    rowN    colN     sum     mean
      -    ---   ----   -----   ----   -----   -----   -----
C_W          1      1      6  1.9173e+06    83    23100  9.1863e+06   4.7913
C_W_minus_C_ss  2      2      6  1.9173e+06    83    23100    1018.4  0.00053118
V_W          3      3      6  1.9173e+06    83    23100 -4.2855e+06  -2.2352
V_W_minus_V_ss  4      4      6  1.9173e+06    83    23100    15640  0.0081571
mn_MPC        5      5      6  1.9173e+06    83    23100  2.9563e+05  0.15419

mn_V_W_gain_check = V_W - V_ss;
mn_MPC_W_gain_share_check = (C_W - cons_ss)./(welf_checks*mp_params('TR'));

```

### 6.1.2 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});

```

### 6.1.3 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 xxxxxxxxxxxxxxxxxxxxxxxxx
group   savings      mean_eta_1    mean_eta_2    mean_eta_3    mean_eta_4    mean_eta_5    mean_eta_6
-----  -----
1        0            0.1253       0.074981     0.055673     0.048117     0.044975     0.044975
2        0.00085734   0.12419      0.074491     0.055326     0.047802     0.044666     0.044666
3        0.0068587    0.1134       0.069223     0.051492     0.044298     0.041233     0.041233
4        0.023148     0.097789     0.061019     0.045415     0.038762     0.035824     0.035824
5        0.05487      0.080591     0.051512     0.038393     0.032456     0.029694     0.029694
6        0.10717      0.066209     0.04312      0.032206     0.026999     0.024439     0.024439
7        0.18519      0.055273     0.036722     0.027464     0.022816     0.020445     0.020445
8        0.29407      0.046205     0.031335     0.023475     0.019332     0.017115     0.017115
9        0.43896      0.038899     0.026901     0.020203     0.016487     0.014432     0.014432
10       0.625        0.032914     0.023206     0.01748      0.014151     0.012235     0.012235
11       0.85734      0.027964     0.020082     0.015185     0.012196     0.010425     0.010425
12       1.1411       0.023831     0.017415     0.013228     0.01055      0.0089155    0.0089155
13       1.4815       0.020354     0.015123     0.011544     0.009154     0.0076473    0.0076473
14       1.8836       0.017411     0.013142     0.010084     0.0079624    0.0065822    0.0065822
15       2.3525       0.01491      0.011422     0.0088155    0.0069411    0.0056799    0.0056799
16       2.8935       0.01278      0.0099292   0.0077111    0.0060627    0.0049139    0.0049139
17       3.5117       0.010963     0.0086325   0.006748      0.0053037    0.0042629    0.0042629
18       4.2121       0.0094097   0.0075049    0.0059067    0.0046452    0.003708     0.003708
19       5            0.0080801   0.0065236    0.0051712    0.0040728    0.0032336    0.0032336
20       5.8805       0.0069408   0.005669     0.0045263    0.0035738    0.0028265    0.0028265
21       6.8587       0.0059645   0.0049254    0.0039619    0.0031383    0.0024763    0.0024763
22       7.9398       0.0051283   0.0042793    0.0034693    0.0027581    0.0021743    0.0021743
23       9.1289       0.0044123   0.0037185    0.0030385    0.0024262    0.0019129    0.0019129
24       10.431       0.0037995   0.0032324    0.0026622    0.0021364    0.0016863    0.0016863
25       11.852       0.003275    0.0028112    0.002334     0.0018832    0.0014891    0.0014891
26       13.396       0.002826    0.0024466    0.0020476    0.0016617    0.0013172    0.0013172
27       15.069       0.0024417   0.002131     0.0017977    0.0014674    0.001167     0.001167
28       16.875       0.0021125   0.0018578    0.0015793    0.001297     0.0010354    0.0010354
29       18.82        0.0018302   0.0016212    0.0013885    0.0011478    0.00092002   0.00092002
30       20.91        0.0015879   0.0014162    0.0012217    0.0010167    0.00081861   0.00081861
31       23.148       0.0013798   0.0012385    0.0010759    0.0009012    0.00072932   0.00072932
32       25.541       0.0012009   0.0010843    0.0009484    0.00079962   0.00065056   0.00065056
33       28.093       0.0010468   0.0009506    0.00083682   0.00071027   0.00058112   0.00058112
34       30.81        0.00091399  0.00083444   0.00073914   0.00063151   0.00051959   0.00051959
35       33.697       0.00079937  0.00073346   0.00065356   0.000562     0.00046497   0.00046497
36       36.758       0.00070031  0.0006456    0.00057854   0.00050061   0.00041657   0.00041657
37       40           0.00061458  0.00056907   0.00051272   0.00044637   0.00037369   0.00037369
38       43.427       0.00054027  0.00050235   0.00045493   0.00039841   0.00033554   0.00033554
39       47.044       0.00047578  0.0004441    0.00040415   0.00035595   0.00030154   0.00030154
40       50.856       0.0004197   0.0003932    0.00035947   0.00031835   0.00027123   0.00027123
41       54.87        0.00037088  0.00034866   0.00032015   0.00028502   0.00024425   0.00024425
42       59.089       0.00032832  0.00030963   0.00028549   0.00025545   0.00022017   0.00022017
43       63.519       0.00029112  0.00027538   0.00025491   0.0002292    0.00019866   0.00019866
44       68.164       0.00025858  0.0002453    0.00022791   0.00020588   0.00017942   0.00017942
45       73.032       0.00023009  0.00021884   0.00020403   0.00018514   0.00016219   0.00016219
46       78.125       0.00020506  0.00019552   0.0001829    0.00016667   0.00014676   0.00014676
47       83.45        0.00018305  0.00017495   0.00016417   0.00015021   0.00013292   0.00013292
```

48	89.011	0.00016367	0.00015678	0.00014756	0.00013553	0.00012051	0.0
49	94.815	0.00014658	0.00014071	0.00013281	0.00012243	0.00010935	9.3
50	100.87	0.00013149	0.00012646	0.00011968	0.00011071	9.9328e-05	8.5
51	107.17	0.00011812	0.00011382	0.00010799	0.00010023	9.0308e-05	7.
52	113.73	0.00010628	0.00010259	9.756e-05	9.0844e-05	8.2186e-05	7.
53	120.55	9.5767e-05	9.2592e-05	8.8254e-05	8.2429e-05	7.4868e-05	6.
54	127.64	8.642e-05	8.3687e-05	7.9939e-05	7.4885e-05	6.8292e-05	6.0
55	135	8.642e-05	8.3687e-05	7.9939e-05	7.4886e-05	6.8293e-05	6.0

% Consumption

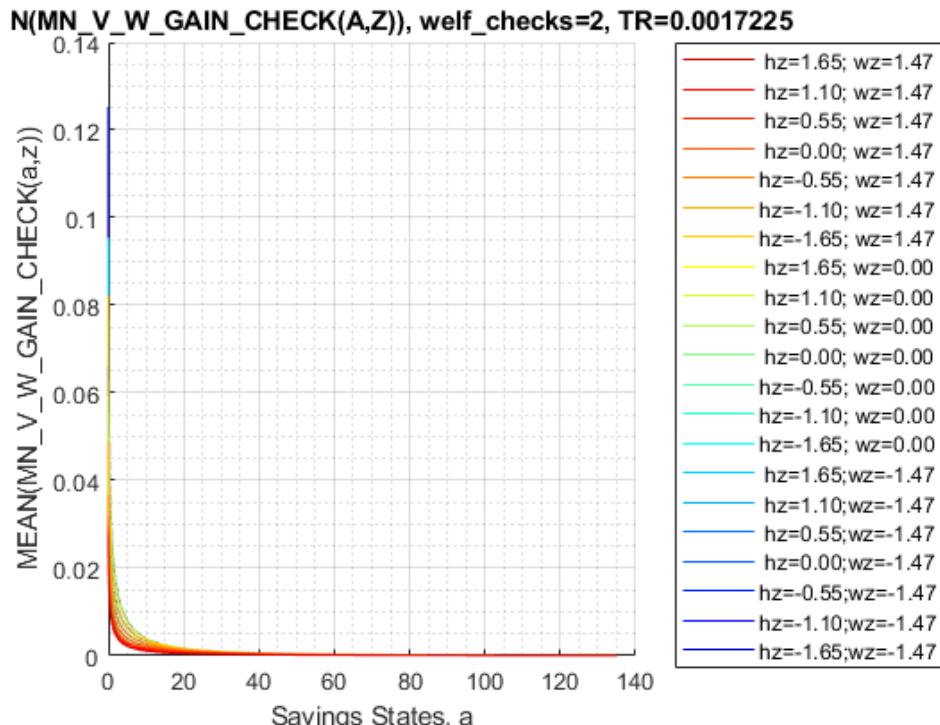
```
st_title = ['MEAN(MN_MPC_W_GAIN_CHECK(A,Z)), welf_checks=' num2str(welf_checks) ', TR=' num2str(mp_p
tb_az_c = ff_summ_nd_array(st_title, mn_MPC_W_gain_share_check, true, ["mean"], 4, 1, cl_mp_datasetd
```

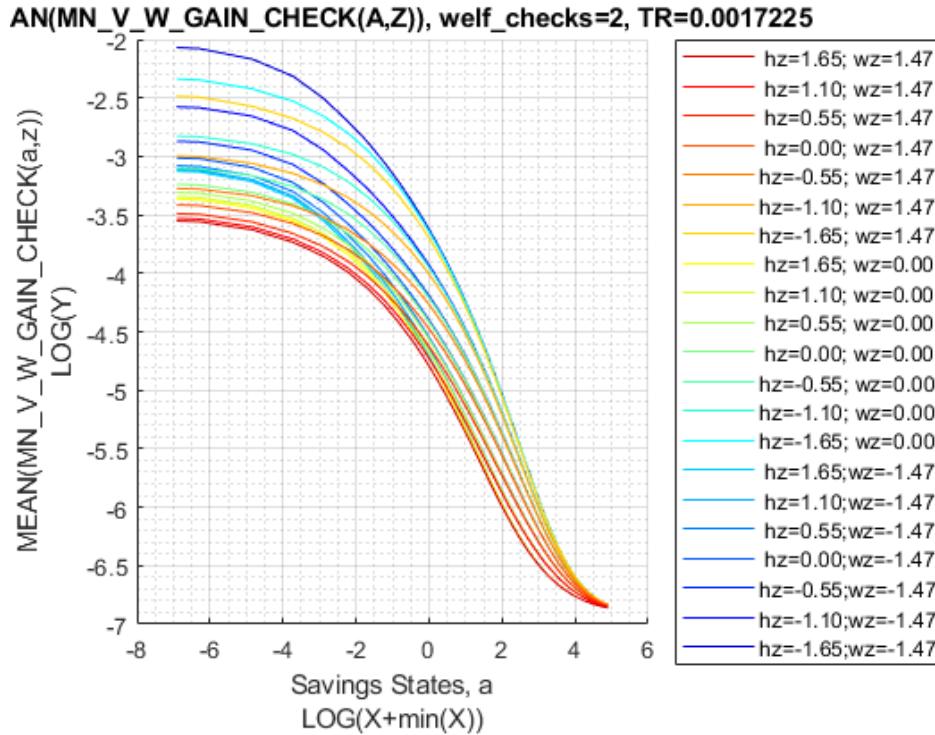
group	savings	mean_eta_1	mean_eta_2	mean_eta_3	mean_eta_4	mean_eta_5	mean
1	0	0.98526	0.94217	0.8526	0.74198	0.63783	0.
2	0.00085734	0.98083	0.93786	0.84881	0.73884	0.63523	0.
3	0.0068587	0.84368	0.82032	0.76961	0.69489	0.60245	0.
4	0.023148	0.74921	0.72805	0.68324	0.61779	0.54083	0.
5	0.05487	0.65324	0.6462	0.61132	0.55665	0.48187	0.
6	0.10717	0.44202	0.45645	0.45163	0.41094	0.33575	0.
7	0.18519	0.33034	0.32383	0.31456	0.29031	0.25187	0.
8	0.29407	0.2813	0.27271	0.25807	0.23769	0.21574	0.
9	0.43896	0.2249	0.21944	0.2088	0.19411	0.17106	0.
10	0.625	0.18874	0.18492	0.17862	0.16796	0.15453	0.
11	0.85734	0.16236	0.16065	0.15616	0.14905	0.14279	0.
12	1.1411	0.14885	0.14631	0.14134	0.13638	0.13247	0.
13	1.4815	0.14162	0.13888	0.13477	0.13128	0.12868	0.
14	1.8836	0.13892	0.1348	0.13159	0.12972	0.12474	0.
15	2.3525	0.1332	0.13062	0.12766	0.12451	0.12159	0.
16	2.8935	0.12454	0.12268	0.11998	0.1182	0.11676	0.
17	3.5117	0.11709	0.11733	0.11648	0.11442	0.11309	0.
18	4.2121	0.11435	0.11378	0.11298	0.11334	0.11262	0.
19	5	0.1145	0.11409	0.11341	0.11308	0.11352	0.
20	5.8805	0.11285	0.11256	0.11208	0.11172	0.11225	0.
21	6.8587	0.11083	0.11068	0.11047	0.10985	0.11078	0.
22	7.9398	0.10949	0.1094	0.10929	0.10873	0.10975	0.
23	9.1289	0.11049	0.11045	0.1103	0.11001	0.11084	0.
24	10.431	0.10943	0.10944	0.10941	0.10911	0.10976	0.
25	11.852	0.10714	0.10715	0.10724	0.10692	0.10733	0.
26	13.396	0.10662	0.10663	0.1067	0.10651	0.10659	0.
27	15.069	0.10898	0.10898	0.10905	0.10886	0.10872	0.
28	16.875	0.11044	0.11045	0.11051	0.11053	0.11005	0.
29	18.82	0.10911	0.10911	0.10917	0.10934	0.10873	0.
30	20.91	0.10635	0.10635	0.1064	0.10632	0.10602	0.
31	23.148	0.10594	0.10595	0.106	0.1059	0.10562	0.
32	25.541	0.10778	0.10778	0.10784	0.10792	0.10752	0.
33	28.093	0.10799	0.10799	0.10804	0.10814	0.10789	0.
34	30.81	0.10767	0.10768	0.10771	0.1078	0.1075	0.
35	33.697	0.10815	0.10815	0.10818	0.10827	0.1081	0.
36	36.758	0.10925	0.10926	0.10928	0.10937	0.10947	0.
37	40	0.10756	0.10757	0.10759	0.10766	0.10784	0.
38	43.427	0.1062	0.10621	0.10623	0.1063	0.10628	0.
39	47.044	0.10582	0.10583	0.10586	0.10592	0.1058	0.
40	50.856	0.10829	0.10831	0.10833	0.1084	0.1084	0.
41	54.87	0.10898	0.10899	0.10902	0.10908	0.10916	0.

42	59.089	0.10774	0.10775	0.10778	0.10783	0.10792	0.
43	63.519	0.10666	0.10668	0.1067	0.10674	0.10683	0.
44	68.164	0.1073	0.10732	0.10734	0.10738	0.10746	0.
45	73.032	0.1085	0.10851	0.10853	0.10857	0.10864	0.
46	78.125	0.10779	0.1078	0.10782	0.10785	0.10792	0.
47	83.45	0.10631	0.10632	0.10634	0.10637	0.10643	0.
48	89.011	0.10666	0.10667	0.10668	0.10671	0.10677	0.
49	94.815	0.10809	0.1081	0.10812	0.10814	0.1082	0.
50	100.87	0.10807	0.10808	0.10809	0.10811	0.10816	0.
51	107.17	0.10728	0.10729	0.1073	0.10732	0.10737	0.
52	113.73	0.10761	0.10762	0.10763	0.10764	0.10768	0.
53	120.55	0.10824	0.10825	0.10825	0.10827	0.10829	0.
54	127.64	0.10739	0.10738	0.10738	0.10736	0.10728	0.
55	135	0.10739	0.10738	0.10738	0.10736	0.10728	0.

Graph Mean Values:

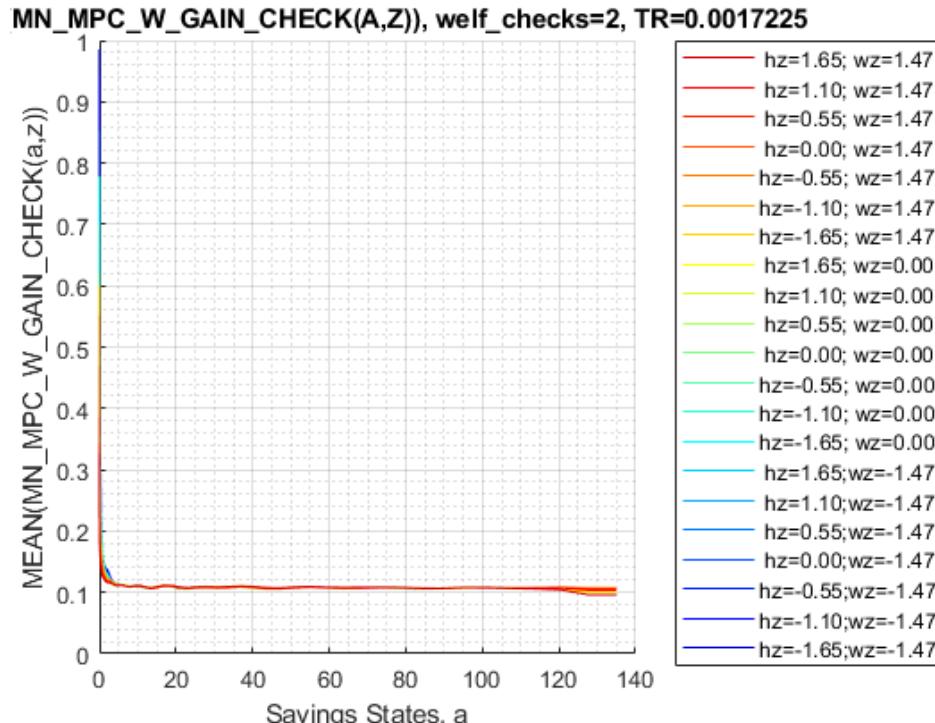
```
st_title = ['MEAN(MN\_V\_W\_GAIN\_CHECK(A,Z)), welf_checks=' num2str(welf_checks) ', TR=' num2str(mn
mp_support_graph('cl_st_graph_title') = {st_title};
mp_support_graph('cl_st_ytitle') = {'MEAN(MN\_V\_W\_GAIN\_CHECK(a,z))'};
ff_graph_grid((tb_az_v{1:end, 3:end})', ar_st_eta_HS_grid, agrid, mp_support_graph);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



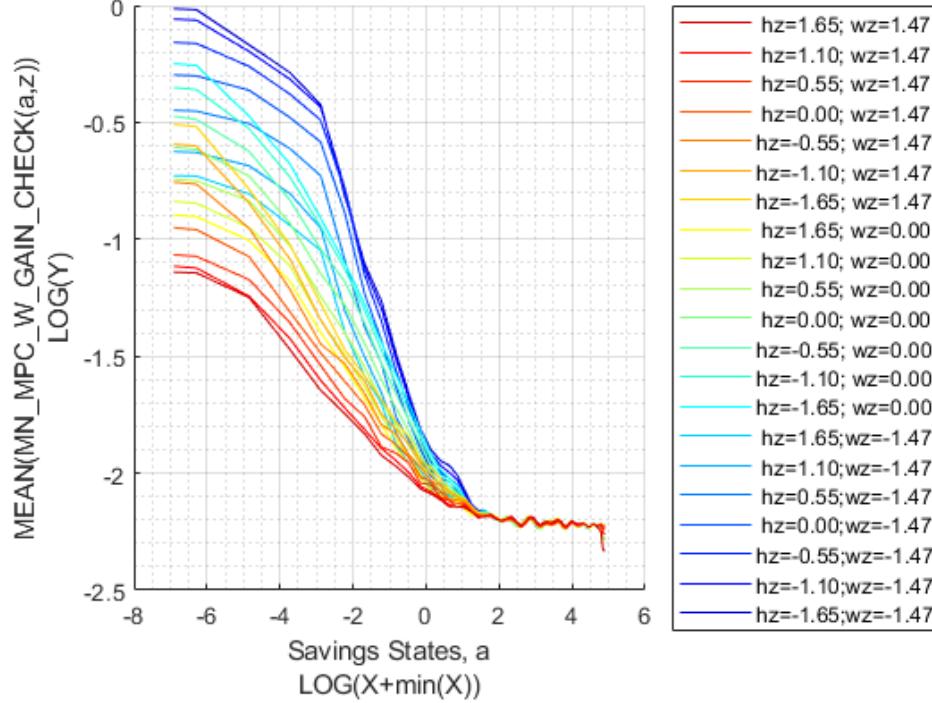


Graph Mean Consumption (*MPC: Share of Check Consumed*):

```
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);
```



N(MN\_MPC\_W\_GAIN\_CHECK(A,Z)), welf\_checks=2, TR=0.0017225



#### 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(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 xxxxxxxxxxxxxxxxxxxxxxxxx
group kids marry mean_age_18 mean_age_19 mean_age_20 mean_age_21 mean_age_22
----- ----- ----- ----- ----- ----- ----- -----
1 1 0 0.010124 0.0096664 0.0091647 0.0084563 0.007865
```

2	2	0	0.013555	0.012956	0.012265	0.01127	0.010434
3	3	0	0.015552	0.014968	0.014264	0.013108	0.012138
4	4	0	0.017504	0.016894	0.01613	0.014825	0.01373
5	5	0	0.019059	0.018461	0.017679	0.016263	0.015076
6	1	1	0.0042913	0.0040316	0.003771	0.0034429	0.003166
7	2	1	0.0057322	0.0053869	0.0050374	0.0045932	0.0042175
8	3	1	0.0067661	0.0063759	0.0059804	0.0054519	0.0050047
9	4	1	0.0080474	0.007599	0.0071398	0.0065203	0.0059876
10	5	1	0.0095567	0.0090861	0.0085927	0.0078601	0.0072337

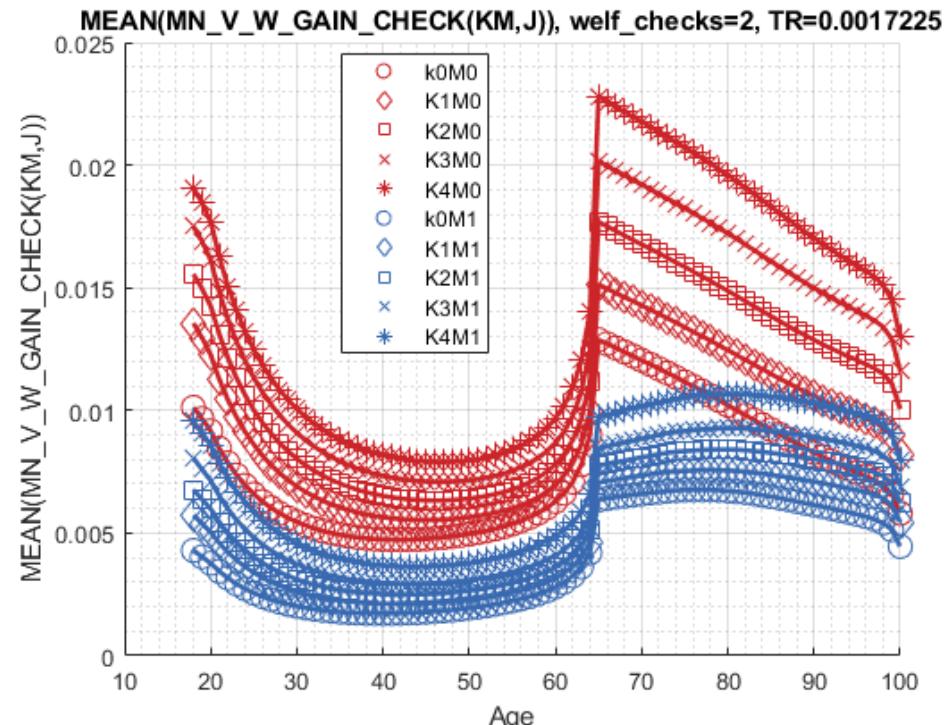
% Consumption Function

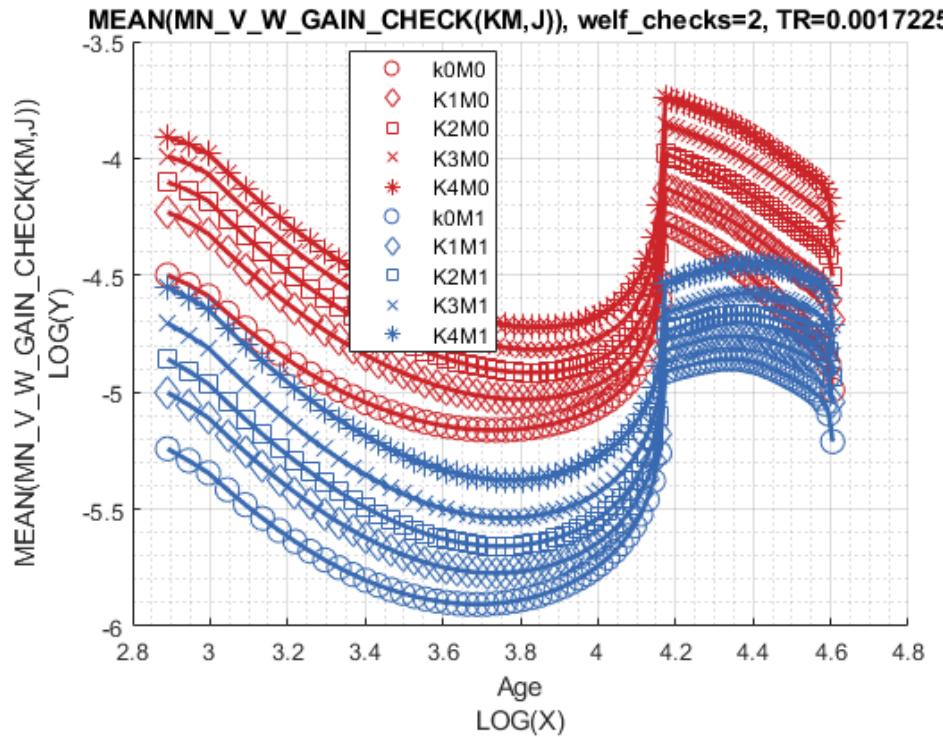
```
st_title = ['MEAN(MN_MPC_W_GAIN_CHECK(KM,J)), welf_checks=' num2str(welf_checks) ', TR=' num2str(mp_
```

group	kids	marry	mean_age_18	mean_age_19	mean_age_20	mean_age_21	mean_age_22
1	1	0	0.056055	0.062152	0.076579	0.072049	0.069081
2	2	0	0.062949	0.07061	0.08564	0.082109	0.080745
3	3	0	0.068855	0.079381	0.10061	0.099067	0.095297
4	4	0	0.073038	0.087775	0.10721	0.10193	0.10055
5	5	0	0.086493	0.089191	0.11627	0.10754	0.10561
6	1	1	0.087018	0.092174	0.10003	0.094839	0.091444
7	2	1	0.087939	0.094393	0.10299	0.10006	0.098626
8	3	1	0.10007	0.10127	0.11098	0.10622	0.10685
9	4	1	0.099978	0.1049	0.11207	0.11365	0.11202
10	5	1	0.10876	0.11206	0.12109	0.11868	0.1267

Graph Mean Values:

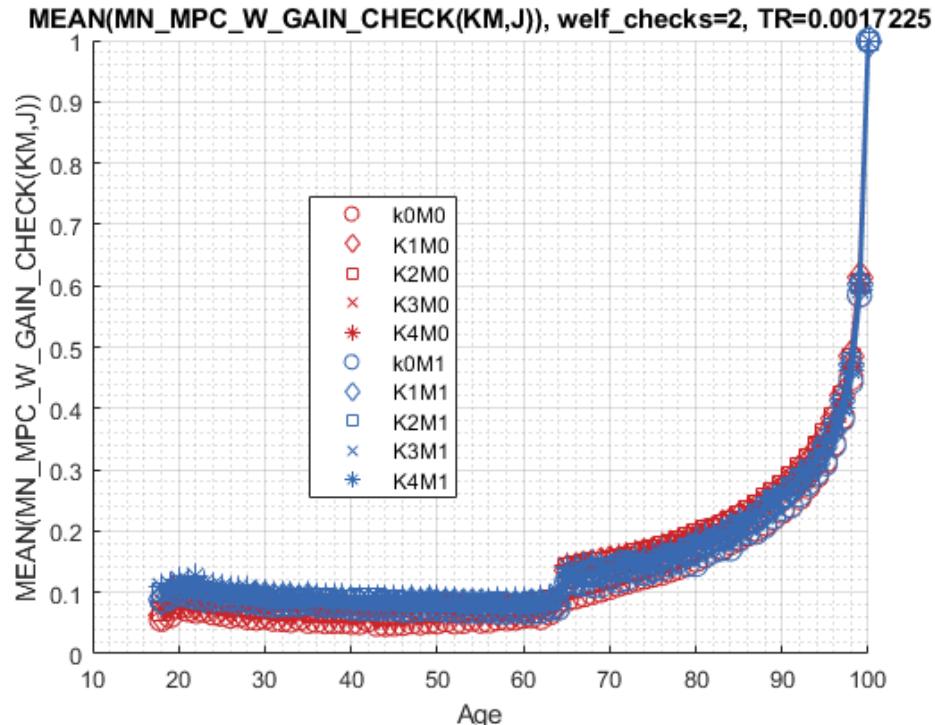
```
st_title = ['MEAN(MN_V_W_GAIN_CHECK(KM,J)), welf_checks=' num2str(welf_checks) ', TR=' num2str(mp_
```

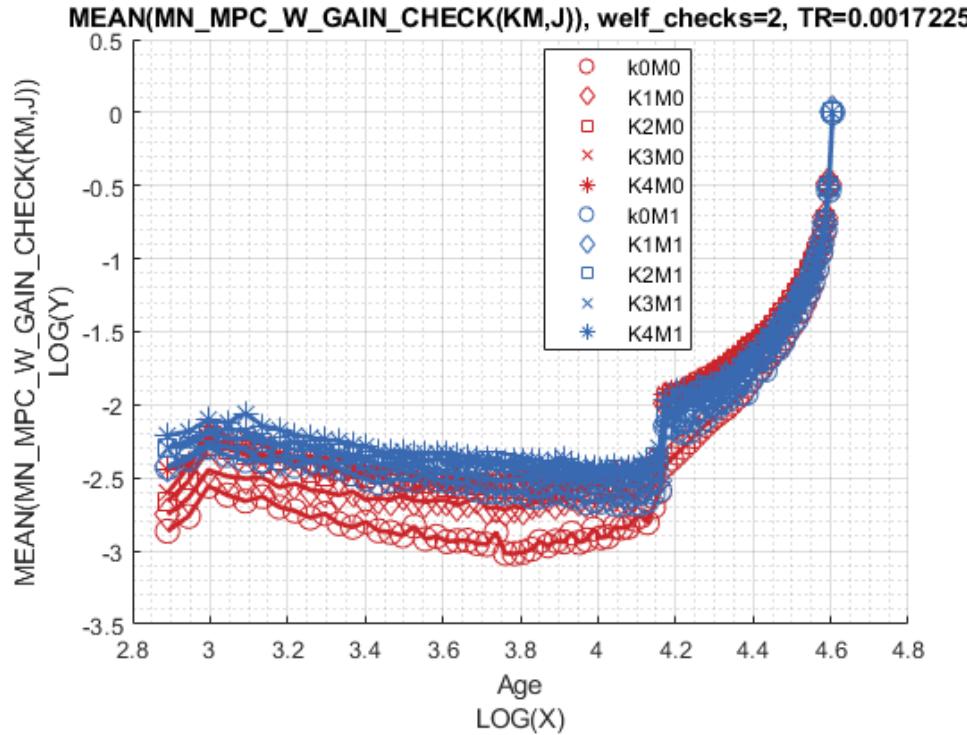




Graph Mean Consumption (*MPC: Share of Check Consumed*):

```
st_title = ['MEAN(MN\_MPC\_W\_GAIN\_CHECK(KM,J)), welf\_checks=' num2str(welf_checks) ', TR=' num2str(TR)];
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);
```





### 6.1.5 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(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_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_
```

group	edu	marry	mean_age_18	mean_age_19	mean_age_20	mean_age_21	mean_age_22
1	0	0	0.015898	0.015428	0.01488	0.014086	0.01338
2	1	0	0.01442	0.013751	0.012921	0.011482	0.010317
3	0	1	0.0074423	0.0070662	0.0066934	0.006237	0.0058341
4	1	1	0.0063152	0.0059256	0.005515	0.0049104	0.0044097

% 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 xxxxxxxxxxxxxxxxxxxxxxxxx
group   edu    marry   mean_age_18   mean_age_19   mean_age_20   mean_age_21   mean_age_22
-----  ---  -----  -----  -----  -----  -----  -----
1       0      0      0.059933  0.065486  0.078043  0.076386  0.076149
2       1      0      0.079022  0.090158  0.11648   0.10869   0.10436
3       0      1      0.088005  0.089818  0.094532  0.093334  0.094468
4       1      1      0.1055     0.1121     0.12433   0.12005   0.11979

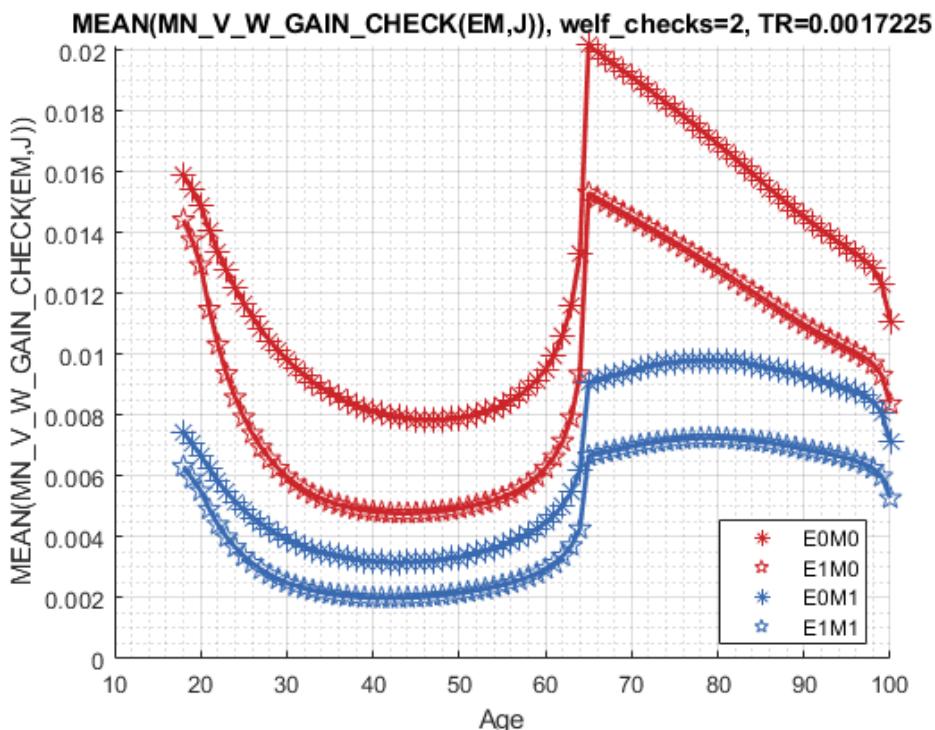
```

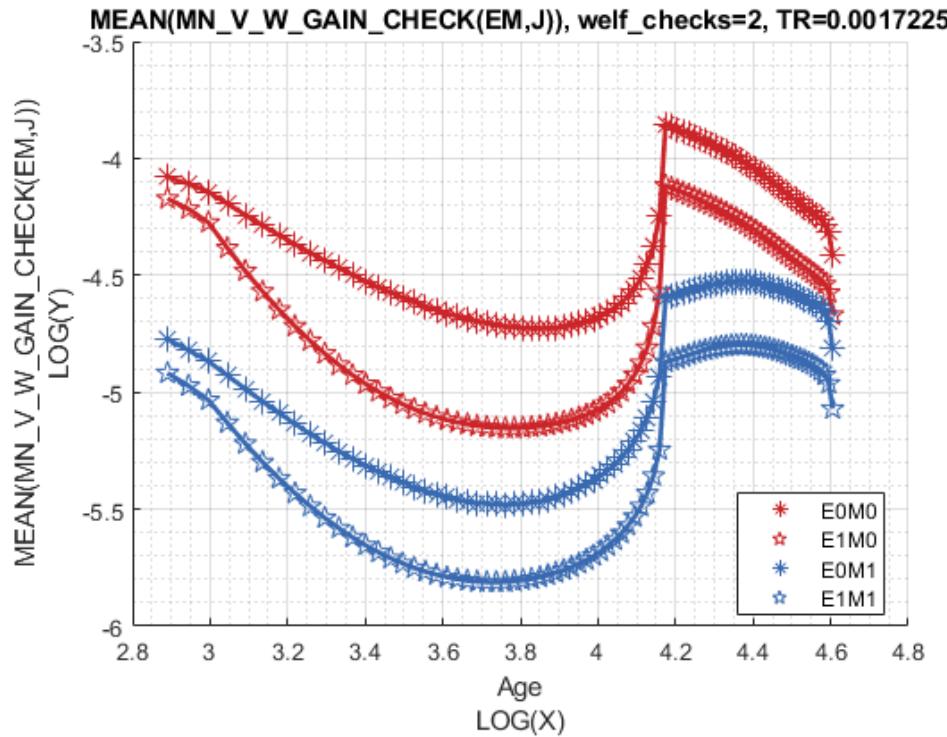
Graph Mean Values:

```

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);

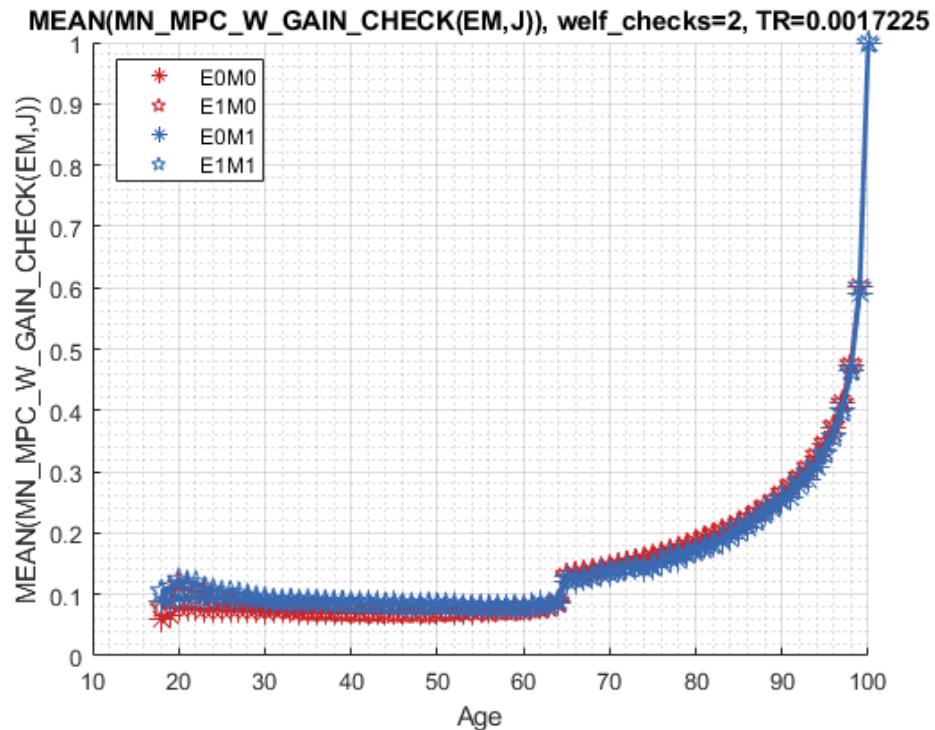
```

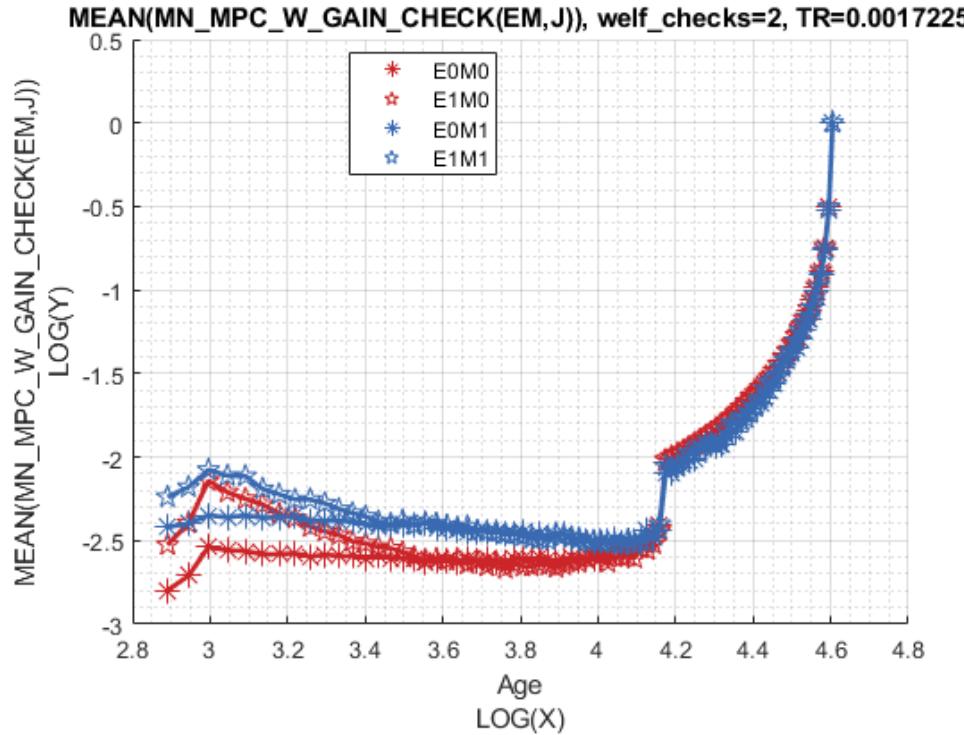




Graph Mean Consumption (*MPC: Share of Check Consumed*):

```
st_title = ['MEAN(MN\_MPC\_W\_GAIN\_CHECK(EM,J)), welf\_checks=' num2str(welf_checks) ', TR=' num2str(TR)];
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);
```





## 6.2 2020 V and C with Unemployment

This is the example vignette for function: [snw\\_a4chk\\_unemp\\_bisec\\_vec](#) from the [PrjOptiSNW Package](#). This function solves for the  $V(\text{states}, \text{check})$  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.

### 6.2.1 Test SNW\_A4CHK\_UNEMP\_BISEC\_VEC Defaults Dense

Call the function with defaults.

```
mp_params = snw_mp_param('default_docdense');
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);
```

Elapsed time is 117.306855 seconds.

Completed SNW\_VFI\_MAIN;SNW\_MP\_PARAM=default\_dense;SNW\_MP\_CONTROL=default\_test

```
welf_checks = 2;
xi=0.5;
b=0;
TR = 100/58056;
mp_params('TR') = TR;
mp_params('xi') = xi;
mp_params('b') = b;
[V_unemp,~,cons_unemp,~] = snw_vfi_main_bisec_vec(mp_params, mp_controls, V_ss);
```

Elapsed time is 118.125995 seconds.

Completed SNW\_VFI\_MAIN 1 PERIOD UNEMP SHK;SNW\_MP\_PARAM=default\_dense;SNW\_MP\_CONTROL=default\_test

```
[V_U, C_U] = snw_a4chk_unemp_bisec_vec(welf_checks, V_unemp, cons_unemp, mp_params, mp_controls);
```

```

Elapsed time is 65.195251 seconds.
Completed SNW_A4CHK_UNEMP_BISEC_VEC;welf_checks=2;TR=0.0017225;xi=0.5;b=0;SNW_MP_PARAM=default_dense
-----
xxxxxxxxxxxxxxxxxxxxxxxxxxxxxxxxxxxxxx
CONTAINER NAME: mp_container_map ND Array (Matrix etc)
xxxxxxxxxxxxxxxxxxxxxxxxxxxxxxxxxxxxxx
      i   idx  ndim    numel   rowN   colN     sum   mean
      -   ---  ----  -----  -----  -----  -----
C_U          1     1     6  1.9173e+06    83    23100  9.1143e+06  4.753
C_U_minus_C_unemp  2     2     6  1.9173e+06    83    23100  1264.8  0.0006596
V_U          3     3     6  1.9173e+06    83    23100 -4.8023e+06 -2.504
V_U_minus_V_unemp  4     4     6  1.9173e+06    83    23100  20117  0.01049
mn_MPC_unemp  5     5     6  1.9173e+06    83    23100  3.6714e+05  0.1914

mn_V_U_gain_check = V_U - V_unemp;
mn_MPC_U_gain_share_check = (C_U - cons_unemp)./(welf_checks*mp_params('TR'));

```

### 6.2.2 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});
```

### 6.2.3 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_par
```

tb_az_v = ff_summ_nd_array(st_title, mn_V_U_gain_check, true, ["mean"], 4, 1, cl_mp_datasetdesc, ar_							
group	savings	mean_eta_1	mean_eta_2	mean_eta_3	mean_eta_4	mean_eta_5	mean
1	0	0.30204	0.14591	0.083016	0.058265	0.048632	0
2	0.00085734	0.29687	0.14443	0.08243	0.057893	0.04831	0
3	0.0068587	0.24517	0.12826	0.075796	0.053707	0.044719	0
4	0.023148	0.17496	0.10278	0.064774	0.046886	0.039	0
5	0.05487	0.11411	0.075197	0.05168	0.038779	0.032381	0
6	0.10717	0.07945	0.053698	0.03981	0.031363	0.026553	0
7	0.18519	0.061381	0.041221	0.031035	0.025388	0.021951	0
8	0.29407	0.049672	0.033665	0.025164	0.020645	0.018059	0
9	0.43896	0.04097	0.028356	0.021184	0.017207	0.014985	0
10	0.625	0.03421	0.024175	0.018158	0.014629	0.012593	0
11	0.85734	0.028804	0.020748	0.015685	0.012564	0.010694	0
12	1.1411	0.024415	0.017898	0.013612	0.010849	0.0091391	0
13	1.4815	0.020781	0.015487	0.011845	0.009402	0.0078443	0
14	1.8836	0.017732	0.013429	0.01033	0.0081694	0.0067529	0
15	2.3525	0.015155	0.011653	0.0090184	0.0071161	0.005829	0
16	2.8935	0.012965	0.010113	0.0078806	0.0062113	0.0050446	0
17	3.5117	0.011102	0.0087778	0.0068893	0.0054304	0.0043768	0
18	4.2121	0.0095159	0.0076201	0.0060242	0.0047539	0.0038073	0
19	5	0.0081617	0.0066157	0.0052682	0.0041656	0.0033198	0
20	5.8805	0.0070048	0.0057428	0.0046071	0.003653	0.002901	0
21	6.8587	0.0060148	0.004985	0.0040287	0.0032059	0.0025406	0
22	7.9398	0.0051679	0.0043275	0.0035243	0.0028158	0.0022296	0
23	9.1289	0.0044436	0.0037576	0.0030842	0.0024752	0.0019606	0
24	10.431	0.0038243	0.0032641	0.0027001	0.002178	0.0017273	0
25	11.852	0.0032946	0.0028369	0.0023652	0.0019184	0.0015245	0
26	13.396	0.0028417	0.0024674	0.0020734	0.0016914	0.0013477	0
27	15.069	0.0024542	0.0021479	0.001819	0.0014925	0.0011933	0
28	16.875	0.0021225	0.0018716	0.0015969	0.0013182	0.0010581	0
29	18.82	0.0018382	0.0016324	0.0014031	0.0011655	0.00093959	0
30	20.91	0.0015944	0.0014253	0.0012338	0.0010316	0.00083546	0
31	23.148	0.001385	0.0012459	0.001086	0.00091386	0.00074382	0
32	25.541	0.0012051	0.0010904	0.00095674	0.00081028	0.00066306	0
33	28.093	0.0010502	0.00095561	0.00084375	0.00071923	0.0005918	0
34	30.81	0.00091678	0.00083855	0.00074491	0.00063906	0.00052877	0
35	33.697	0.00080165	0.00073685	0.00065837	0.00056838	0.00047287	0
36	36.758	0.00070216	0.0006484	0.00058255	0.000506	0.00042333	0
37	40	0.0006161	0.00057139	0.00051608	0.00045093	0.00037946	0
38	43.427	0.00054153	0.00050427	0.00045774	0.00040227	0.0003405	0
39	47.044	0.00047681	0.0004457	0.0004065	0.00035923	0.00030581	0
40	50.856	0.00042057	0.00039453	0.00036145	0.00032113	0.0002749	0
41	54.87	0.00037159	0.00034976	0.00032182	0.00028739	0.0002474	0
42	59.089	0.00032891	0.00031056	0.00028689	0.00025747	0.00022288	0
43	63.519	0.00029162	0.00027616	0.00025609	0.00023092	0.00020099	0
44	68.164	0.000259	0.00024595	0.00022891	0.00020735	0.00018142	0
45	73.032	0.00023043	0.0002194	0.00020489	0.00018639	0.00016392	0
46	78.125	0.00020535	0.00019599	0.00018363	0.00016774	0.00014826	0
47	83.45	0.0001833	0.00017535	0.00016479	0.00015113	0.00013422	0
48	89.011	0.00016388	0.00015711	0.00014808	0.00013632	0.00012163	0
49	94.815	0.00014675	0.00014099	0.00013325	0.00012311	0.00011033	9.5
50	100.87	0.00013164	0.00012671	0.00012006	0.00011113	0.00010017	8.6
51	107.17	0.00011825	0.00011403	0.00010832	0.00010074	9.1041e-05	7.9
52	113.73	0.00010639	0.00010277	9.7844e-05	9.1281e-05	8.2823e-05	7.2

53	120.55	9.586e-05	9.2745e-05	8.8498e-05	8.2806e-05	7.5422e-05	6.6
54	127.64	8.65e-05	8.3818e-05	8.0149e-05	7.5211e-05	6.877e-05	6.0
55	135	8.65e-05	8.3818e-05	8.0149e-05	7.5211e-05	6.877e-05	6.0

% Consumption

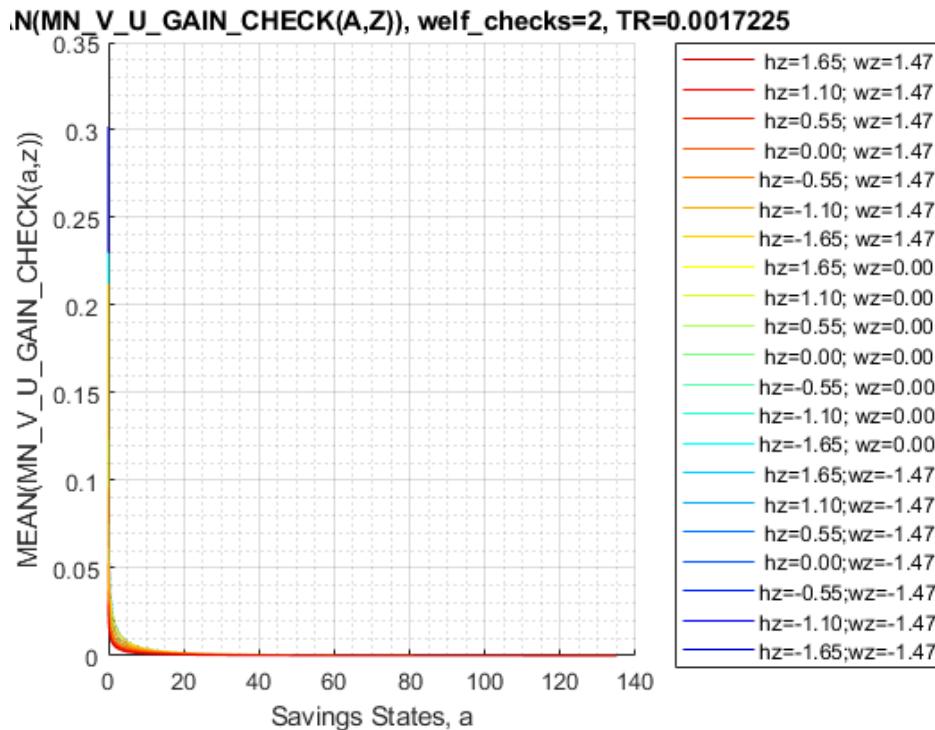
```
st_title = ['MEAN(MN_MPC_U_GAIN_CHECK(A,Z)), welf_checks=' num2str(welf_checks) ', TR=' num2str(mp_p
tb_az_c = ff_summ_nd_array(st_title, mn_MPC_U_gain_share_check, true, ["mean"], 4, 1, cl_mp_datasetd
```

xxx	MEAN(MN_MPC_U_GAIN_CHECK(A,Z)), welf_checks=2, TR=0.0017225	xxxxxxxxxxxxxxxxxxxxxxxxxxxxxx	group	savings	mean_eta_1	mean_eta_2	mean_eta_3	mean_eta_4	mean_eta_5	mean
1	0	0.99676	0.99676	0.98968	0.96861	0.936	0.	0.	0.	0.
2	0.00085734	0.99564	0.99564	0.9885	0.96775	0.93479	0.	0.	0.	0.
3	0.0068587	0.96608	0.96608	0.96111	0.93769	0.90391	0.	0.	0.	0.
4	0.023148	0.9144	0.91442	0.90273	0.87976	0.84669	0.	0.	0.	0.
5	0.05487	0.83014	0.8675	0.85172	0.82953	0.79856	0.	0.	0.	0.
6	0.10717	0.57928	0.6794	0.72166	0.70603	0.67574	0.	0.	0.	0.
7	0.18519	0.40677	0.4866	0.57883	0.62471	0.61322	0.	0.	0.	0.
8	0.29407	0.30075	0.32748	0.40471	0.48963	0.53386	0.	0.	0.	0.
9	0.43896	0.23989	0.24678	0.26581	0.32826	0.40159	0.	0.	0.	0.
10	0.625	0.20277	0.20016	0.20528	0.22484	0.27796	0.	0.	0.	0.
11	0.85734	0.17483	0.17446	0.16482	0.16705	0.18499	0.	0.	0.	0.
12	1.1411	0.15256	0.15408	0.15362	0.14656	0.14374	0.	0.	0.	0.
13	1.4815	0.13901	0.14193	0.1396	0.13759	0.13213	0.	0.	0.	0.
14	1.8836	0.13445	0.13173	0.13532	0.13183	0.12918	0.	0.	0.	0.
15	2.3525	0.13073	0.12804	0.12598	0.12513	0.12402	0.	0.	0.	0.
16	2.8935	0.12611	0.12259	0.11944	0.11919	0.11786	0.	0.	0.	0.
17	3.5117	0.11866	0.11921	0.11564	0.11369	0.11418	0.	0.	0.	0.
18	4.2121	0.11801	0.11572	0.11569	0.11296	0.11197	0.	0.	0.	0.
19	5	0.11495	0.1165	0.11547	0.11464	0.11333	0.	0.	0.	0.
20	5.8805	0.11283	0.11351	0.11397	0.11371	0.11268	0.	0.	0.	0.
21	6.8587	0.11082	0.11067	0.11238	0.11122	0.11137	0.	0.	0.	0.
22	7.9398	0.10947	0.10939	0.10939	0.11073	0.1094	0.	0.	0.	0.
23	9.1289	0.11048	0.11044	0.11055	0.11147	0.1111	0.	0.	0.	0.
24	10.431	0.10942	0.10943	0.10956	0.10966	0.1103	0.	0.	0.	0.
25	11.852	0.10713	0.10714	0.10723	0.1074	0.10779	0.	0.	0.	0.
26	13.396	0.10662	0.10662	0.10669	0.10689	0.10696	0.	0.	0.	0.
27	15.069	0.10897	0.10898	0.10904	0.10931	0.10944	0.	0.	0.	0.
28	16.875	0.11044	0.11044	0.1105	0.11079	0.11094	0.	0.	0.	0.
29	18.82	0.1091	0.10911	0.10916	0.10934	0.10959	0.	0.	0.	0.
30	20.91	0.10634	0.10635	0.10639	0.10655	0.10686	0.	0.	0.	0.
31	23.148	0.10594	0.10594	0.10599	0.10622	0.10646	0.	0.	0.	0.
32	25.541	0.10777	0.10778	0.10783	0.10802	0.10823	0.	0.	0.	0.
33	28.093	0.10798	0.10799	0.10803	0.10814	0.10838	0.	0.	0.	0.
34	30.81	0.10767	0.10768	0.10771	0.1078	0.10808	0.	0.	0.	0.
35	33.697	0.10814	0.10815	0.10818	0.10827	0.10861	0.	0.	0.	0.
36	36.758	0.10925	0.10925	0.10928	0.10936	0.10964	0.	0.	0.	0.
37	40	0.10756	0.10757	0.10759	0.10766	0.10783	0.	0.	0.	0.
38	43.427	0.1062	0.10621	0.10623	0.10629	0.10646	0.	0.	0.	0.
39	47.044	0.10582	0.10583	0.10586	0.10592	0.10616	0.	0.	0.	0.
40	50.856	0.10829	0.1083	0.10833	0.10839	0.10861	0.	0.	0.	0.
41	54.87	0.10898	0.10899	0.10902	0.10908	0.10921	0.	0.	0.	0.
42	59.089	0.10774	0.10775	0.10777	0.10782	0.10792	0.	0.	0.	0.
43	63.519	0.10666	0.10668	0.1067	0.10674	0.10683	0.	0.	0.	0.
44	68.164	0.1073	0.10731	0.10734	0.10738	0.10746	0.	0.	0.	0.
45	73.032	0.1085	0.10851	0.10853	0.10857	0.10864	0.	0.	0.	0.
46	78.125	0.10779	0.1078	0.10782	0.10785	0.10792	0.	0.	0.	0.

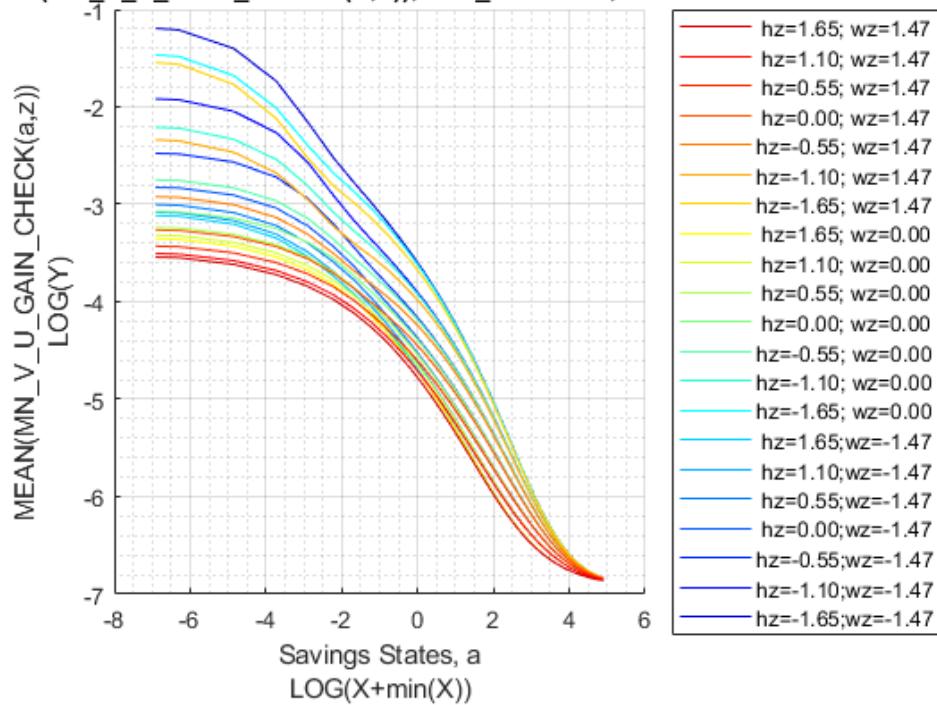
47	83.45	0.10631	0.10632	0.10634	0.10637	0.10643	0.
48	89.011	0.10666	0.10667	0.10668	0.10671	0.10677	0.
49	94.815	0.10809	0.1081	0.10811	0.10814	0.1082	0.
50	100.87	0.10807	0.10808	0.10809	0.10811	0.10816	0.
51	107.17	0.10728	0.10729	0.1073	0.10732	0.10737	0.
52	113.73	0.10761	0.10762	0.10763	0.10764	0.10768	0.
53	120.55	0.10824	0.10825	0.10825	0.10827	0.10829	0.
54	127.64	0.10739	0.10738	0.10738	0.10736	0.10728	0.
55	135	0.10739	0.10738	0.10738	0.10736	0.10728	0.

Graph Mean Values:

```
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);
```



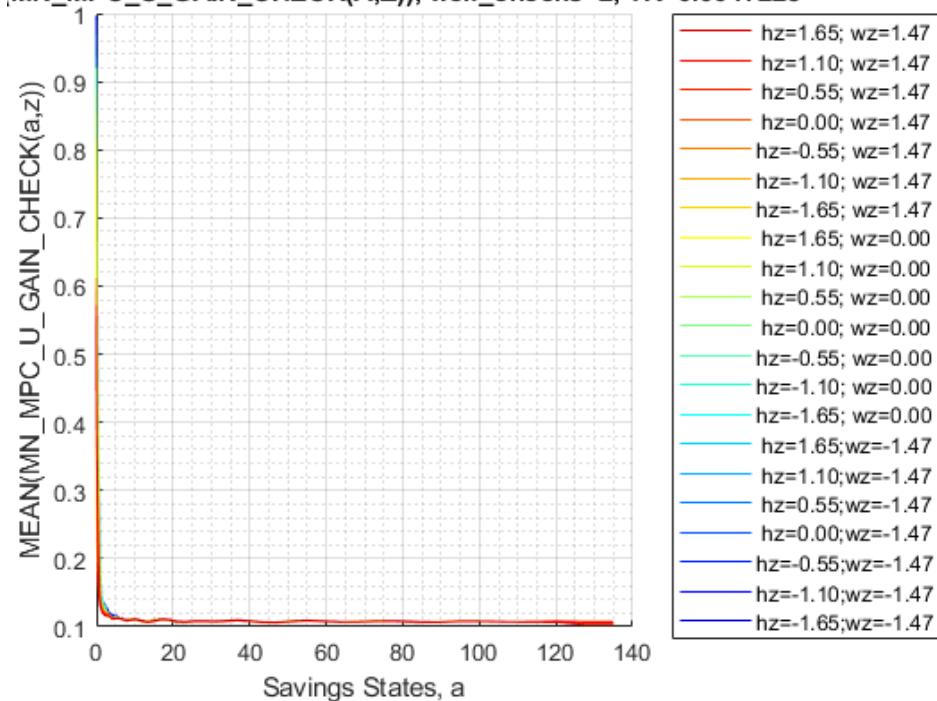
**AN(MN\_V\_U\_GAIN\_CHECK(A,Z)), welf\_checks=2, TR=0.0017225**

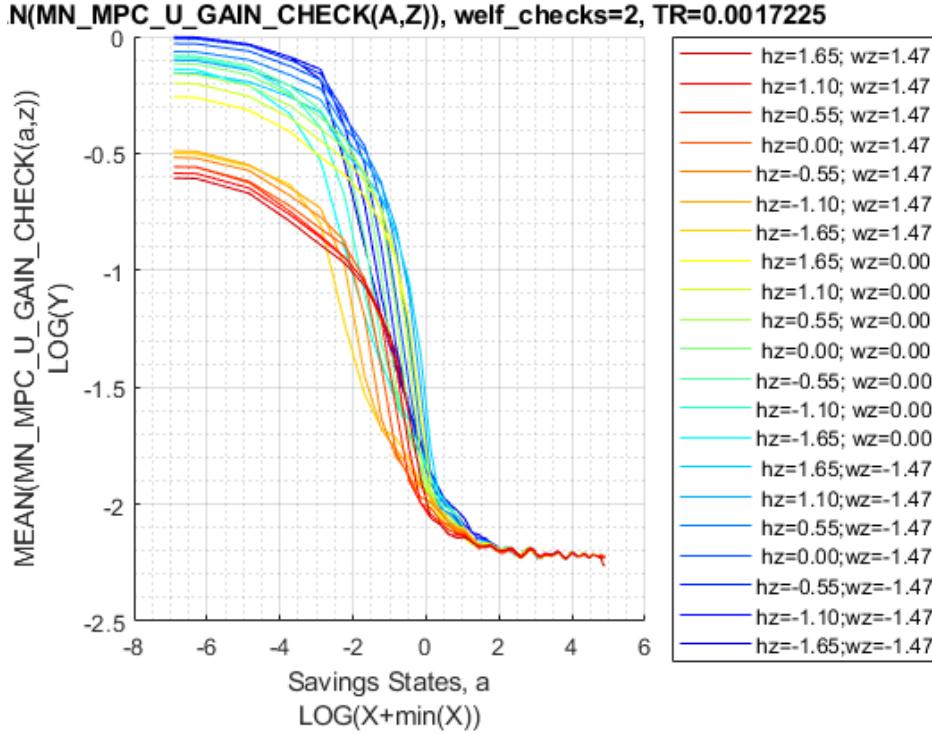


Graph Mean Consumption (*MPC: Share of Check Consumed*):

```
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);
```

**MN\_MPC\_U\_GAIN\_CHECK(A,Z)), welf\_checks=2, TR=0.0017225**





#### 6.2.4 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 xxxxxxxxxxxxxxxxxxxxxxxxx
group kids marry mean_age_18 mean_age_19 mean_age_20 mean_age_21 mean_age_22
----- ----- ----- ----- ----- ----- ----- -----
1 1 0 0.018051 0.017729 0.017395 0.015889 0.014636
```

2	2	0	0.024841	0.024418	0.023963	0.021844	0.020076
3	3	0	0.029625	0.029186	0.028697	0.026156	0.024037
4	4	0	0.033827	0.033361	0.03283	0.029923	0.0275
5	5	0	0.037408	0.03694	0.036392	0.033181	0.030504
6	1	1	0.0061332	0.0057595	0.0054053	0.0049063	0.0044877
7	2	1	0.0083066	0.0078178	0.007352	0.0066702	0.0060896
8	3	1	0.010082	0.0095157	0.0089749	0.0081404	0.007436
9	4	1	0.012214	0.011567	0.010941	0.0099258	0.0090678
10	5	1	0.015297	0.014584	0.013875	0.012596	0.011524

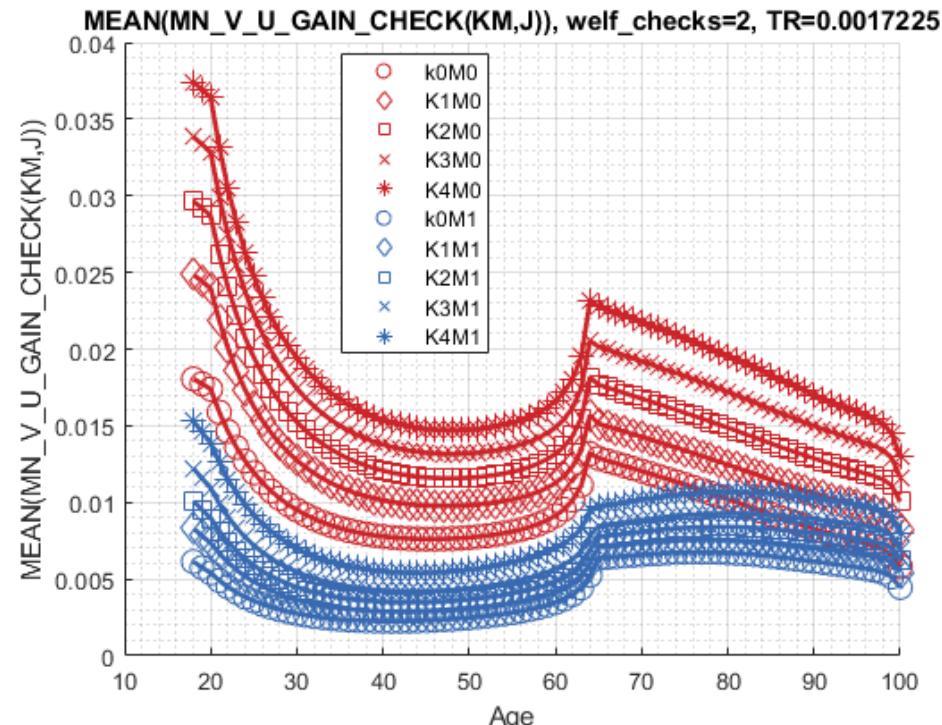
% Consumption Function

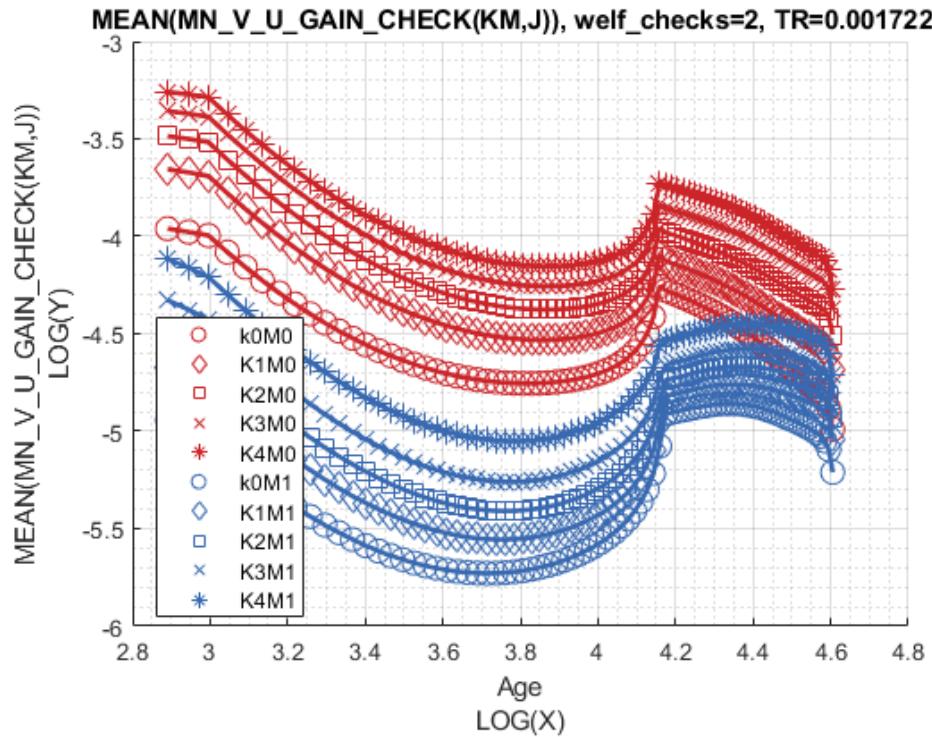
```
st_title = ['MEAN(MN_MPC_U_GAIN_CHECK(KM,J)), welf_checks=' num2str(welf_checks) ', TR=' num2str(mp_
```

group	kids	marry	mean_age_18	mean_age_19	mean_age_20	mean_age_21	mean_age_22
1	1	0	0.15281	0.15636	0.16001	0.16042	0.16057
2	2	0	0.16175	0.1653	0.16916	0.17012	0.17091
3	3	0	0.16911	0.17246	0.1763	0.17733	0.17815
4	4	0	0.17289	0.17613	0.17991	0.18092	0.18173
5	5	0	0.1764	0.17944	0.18311	0.18398	0.18469
6	1	1	0.13726	0.14236	0.14341	0.14404	0.14448
7	2	1	0.14642	0.14777	0.14963	0.15056	0.14937
8	3	1	0.15601	0.15841	0.1601	0.16253	0.15944
9	4	1	0.16238	0.1649	0.16712	0.16745	0.1673
10	5	1	0.17026	0.1742	0.17738	0.17809	0.17684

Graph Mean Values:

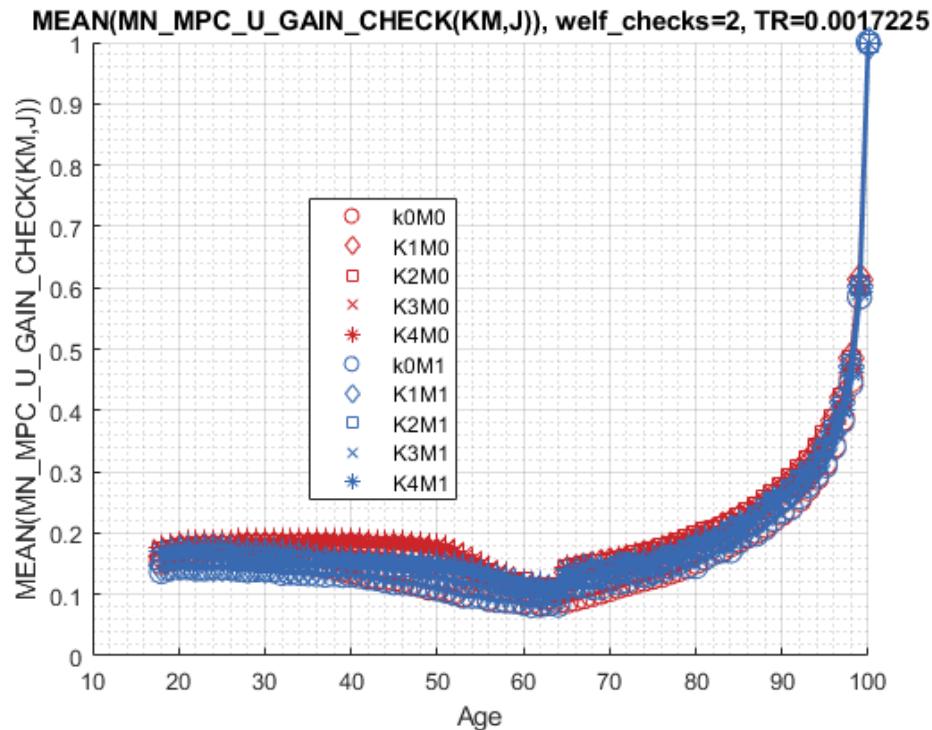
```
st_title = ['MEAN(MN_V_U_GAIN_CHECK(KM,J)), welf_checks=' num2str(welf_checks) ', TR=' num2str(mp_
```

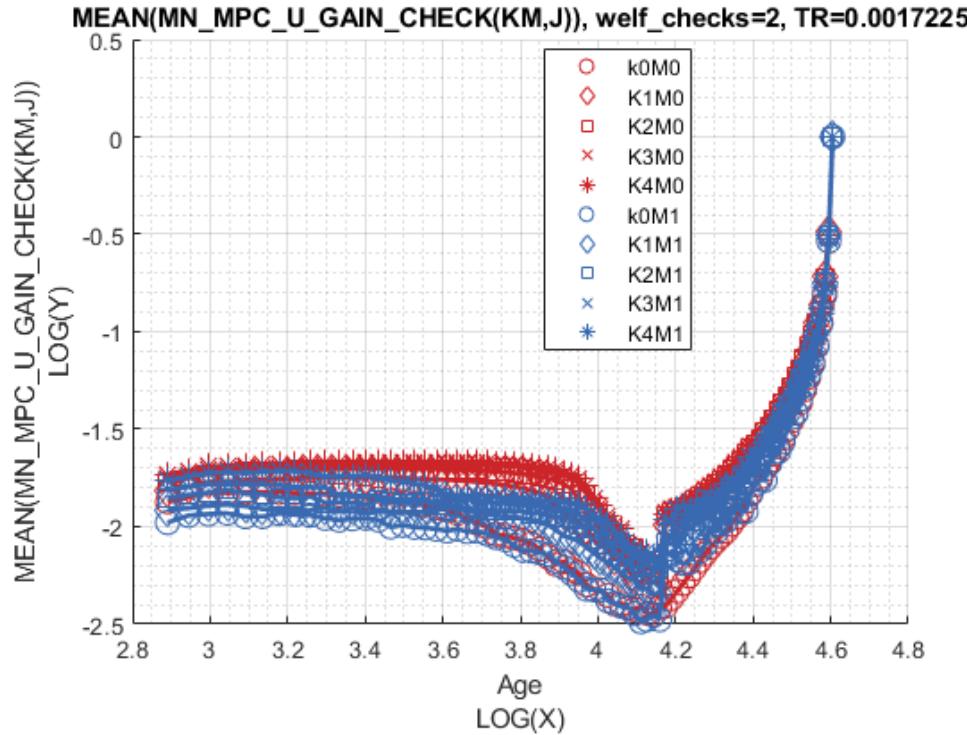




Graph Mean Consumption (*MPC: Share of Check Consumed*):

```
st_title = ['MEAN(MN\_MPC\_U\_GAIN\_CHECK(KM,J)), welf\_checks=' num2str(welf_checks) ', TR=' num2st
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);
```





### 6.2.5 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(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_
```

group	edu	marry	mean_age_18	mean_age_19	mean_age_20	mean_age_21	mean_age_22
1	0	0	0.029418	0.029071	0.028695	0.027067	0.025622
2	1	0	0.028083	0.027583	0.027015	0.02373	0.021079
3	0	1	0.011215	0.010661	0.010131	0.009383	0.0087272
4	1	1	0.0095983	0.0090363	0.0084881	0.0075126	0.0067144

% 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 xxxxxxxxxxxxxxxxxxxxxxxxx
group   edu    marry   mean_age_18   mean_age_19   mean_age_20   mean_age_21   mean_age_22
-----  ---  -----  -----  -----  -----  -----  -----
1       0      0      0.15946     0.16202     0.16481     0.16552     0.16614
2       1      0      0.17373     0.17785     0.18259     0.18359     0.18428
3       0      1      0.14851     0.15124     0.15155     0.15153     0.15098
4       1      1      0.16042     0.16382     0.16751     0.16954     0.16679

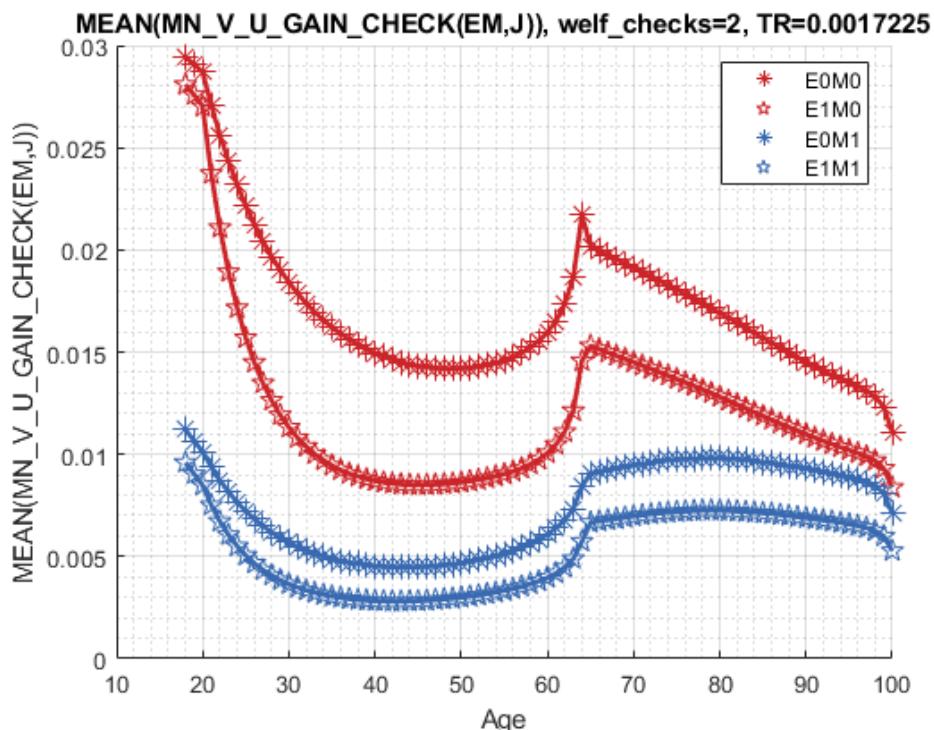
```

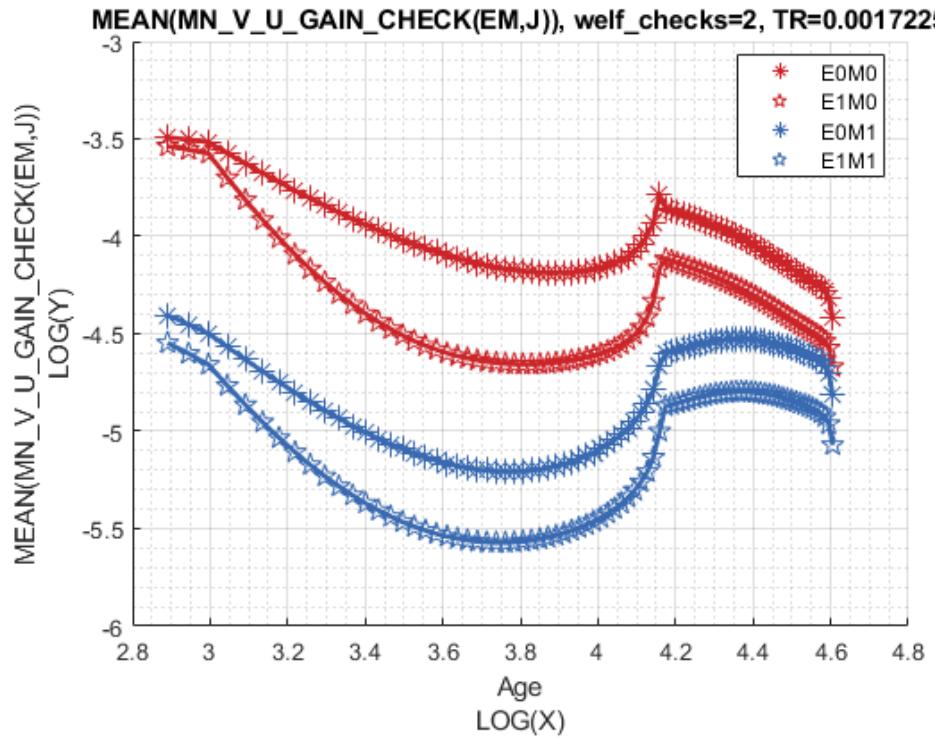
Graph Mean Values:

```

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);

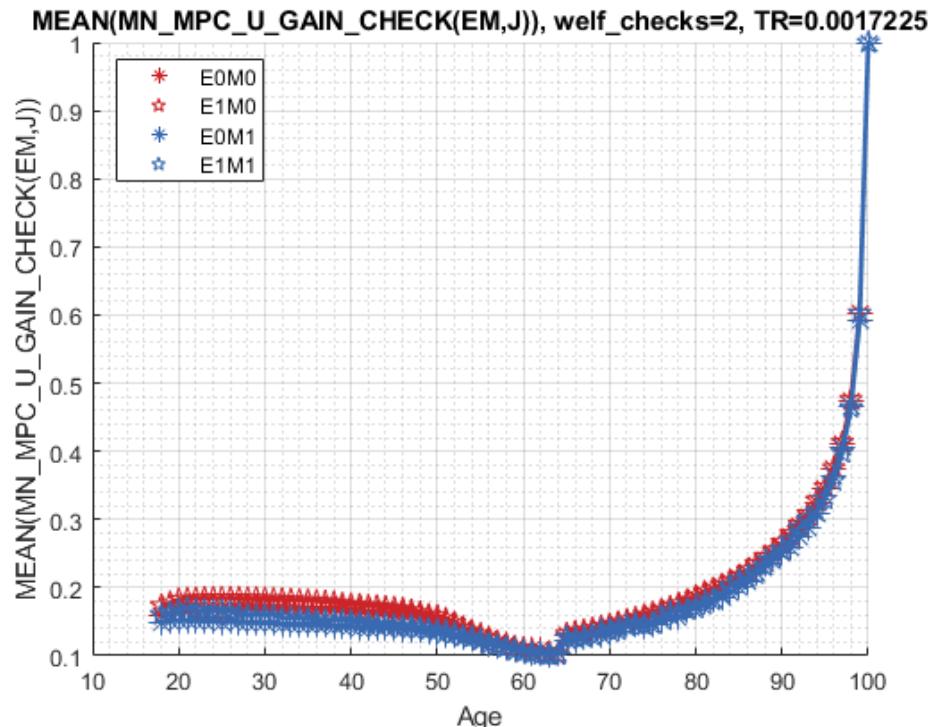
```

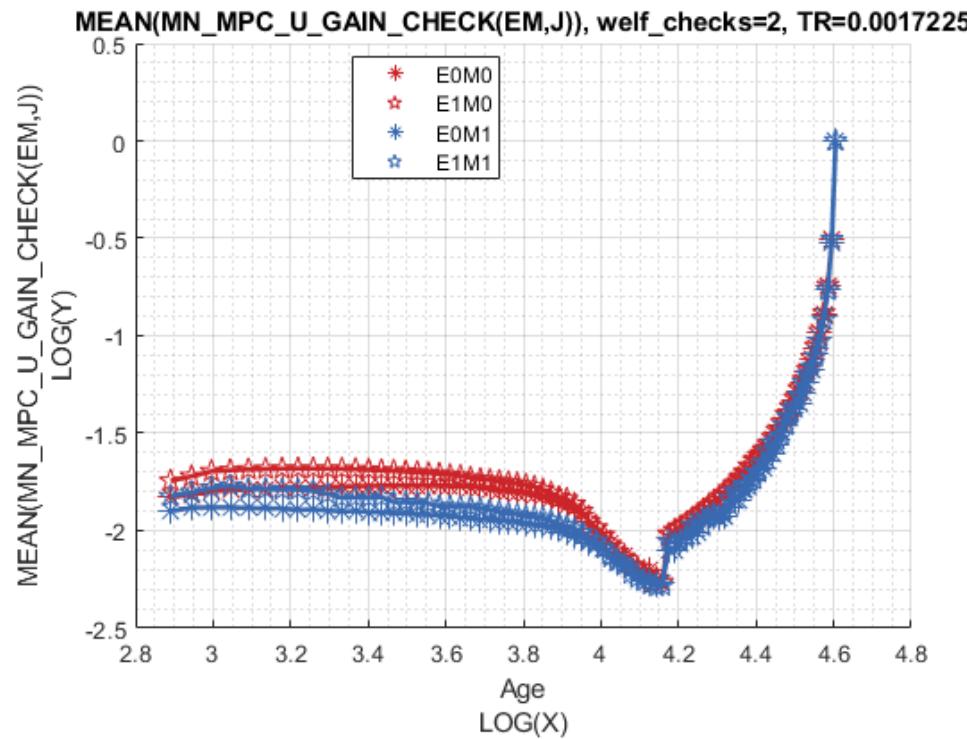




Graph Mean Consumption (*MPC: Share of Check Consumed*):

```
st_title = ['MEAN(MN\_MPC\_U\_GAIN\_CHECK(EM,J)), welf\_checks=' num2str(welf_checks) ', TR=' num2st
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 7

## 2020 Outcomes Full State Space with Savings, Shocks and Education

### 7.1 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

#### 7.1.1 Test SNW\_EVUVW20\_JAEEMK Defaults Dense

VFI and Distribution

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_docdense');
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 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_dense;SNW_MP_CONTROL=default_test;time=20.6119

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;
% 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_dense;SNW_MP_CONTROL=default_test;time=20.6119

[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_dense;SNW_MP_CONTROL=default_test;time=51.8429

% 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_true);

Wage quintile cutoffs=0.49295      0.79302      1.3138      2.1063
Completed SNW_HH_PRECOMPUTE;SNW_MP_PARAM=default_dense;SNW_MP_CONTROL=default_test;time cost=23.0315

```

### 7.1.2 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, cons_ss, V_unemp, cons_unemp, mp_precompute_res);

Completed SNW_A4CHK_UNEMP_BISEC_VEC;welf_checks=0;TR=0.0017225;xi=0.5;b=0;SNW_MP_PARAM=default_dense
Completed SNW_A4CHK_WRK_BISEC_VEC;welf_checks=0;TR=0.0017225;SNW_MP_PARAM=default_dense;SNW_MP_CONTROL=default_test;timeEUEC=0.64818
Completed SNW_EVUVW20_JAEEMK;SNW_MP_PARAM=default_dense;SNW_MP_CONTROL=default_test;timeEUEC=0.64818

% 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, cons_ss, V_unemp, cons_unemp, mp_precompute_res);

Completed SNW_A4CHK_UNEMP_BISEC_VEC;welf_checks=2;TR=0.0017225;xi=0.5;b=0;SNW_MP_PARAM=default_dense
Completed SNW_A4CHK_WRK_BISEC_VEC;welf_checks=2;TR=0.0017225;SNW_MP_PARAM=default_dense;SNW_MP_CONTROL=default_test;timeEUEC=0.44581
Completed SNW_EVUVW20_JAEEMK;SNW_MP_PARAM=default_dense;SNW_MP_CONTROL=default_test;timeEUEC=0.44581

```

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'))

```

### 7.1.3 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});

```

#### 7.1.4 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_

```

group	savings	mean_eta_1	mean_eta_2	mean_eta_3	mean_eta_4	mean_eta_5	mean_eta_6
1	0	0.27912	0.11616	0.067433	0.053393	0.049158	0
2	0.00085734	0.27485	0.11517	0.066984	0.053023	0.048799	0
3	0.0068587	0.23632	0.10481	0.062008	0.048905	0.044801	0
4	0.023148	0.1863	0.08898	0.054024	0.042348	0.038458	0
5	0.05487	0.14109	0.071528	0.044733	0.034862	0.031271	0
6	0.10717	0.10829	0.056442	0.036039	0.027915	0.024677	0
7	0.18519	0.087242	0.046352	0.02987	0.023041	0.020157	0
8	0.29407	0.072208	0.039367	0.025433	0.019424	0.016782	0
9	0.43896	0.060221	0.033761	0.021874	0.016469	0.014026	0
10	0.625	0.050442	0.029129	0.018949	0.014075	0.011802	0
11	0.85734	0.042316	0.025218	0.016484	0.012083	0.0099683	0
12	1.1411	0.035502	0.021857	0.014374	0.010409	0.0084519	0
13	1.4815	0.029772	0.01894	0.012549	0.0089945	0.0071841	0
14	1.8836	0.024956	0.016396	0.010963	0.0077932	0.0061208	0
15	2.3525	0.020913	0.014175	0.0095793	0.0067677	0.0052312	0
16	2.8935	0.01753	0.012238	0.008369	0.0058896	0.0044819	0
17	3.5117	0.014702	0.010552	0.0073101	0.0051351	0.0038505	0
18	4.2121	0.012342	0.0090878	0.006382	0.0044849	0.0033193	0
19	5	0.010373	0.0078203	0.0055676	0.0039231	0.0028711	0
20	5.8805	0.0087301	0.0067252	0.0048575	0.0034361	0.002492	0

21	6.8587	0.0073585	0.0057817	0.004238	0.0030132	0.0021701	0.
22	7.9398	0.0062131	0.0049708	0.0036966	0.0026454	0.001896	0.
23	9.1289	0.0052558	0.0042752	0.0032257	0.0023256	0.0016619	0.
24	10.431	0.0044552	0.0036794	0.0028167	0.002047	0.0014609	0.
25	11.852	0.0037847	0.0031694	0.0024609	0.0018039	0.0012875	0.
26	13.396	0.0032224	0.0027332	0.0021515	0.0015915	0.0011375	0.
27	15.069	0.0027501	0.00236	0.0018824	0.0014053	0.0010072	0.
28	16.875	0.0023527	0.0020407	0.0016483	0.001242	0.00089377	0.
29	18.82	0.0020176	0.0017673	0.0014445	0.0010993	0.0007946	0.
30	20.91	0.0017343	0.0015329	0.0012672	0.00097404	0.00070765	0.
31	23.148	0.0014944	0.0013318	0.0011128	0.00086375	0.00063126	0.
32	25.541	0.0012908	0.0011591	0.00097818	0.00076679	0.00056405	0.
33	28.093	0.0011176	0.0010105	0.0008609	0.00068159	0.00050477	0.
34	30.81	0.00096988	0.00088251	0.00075856	0.00060649	0.00045237	0.
35	33.697	0.0008436	0.00077212	0.00066925	0.00054025	0.00040595	0.
36	36.758	0.00073542	0.00067675	0.0005912	0.00048173	0.00036464	0.
37	40	0.00064253	0.00059424	0.00052296	0.00043001	0.00032792	0.
38	43.427	0.00056261	0.00052272	0.00046322	0.00038423	0.00029534	0.
39	47.044	0.00049368	0.00046065	0.00041086	0.00034368	0.00026633	0.
40	50.856	0.00043412	0.00040667	0.00036494	0.00030774	0.0002404	0.
41	54.87	0.00038251	0.00035966	0.00032459	0.00027584	0.00021718	0.
42	59.089	0.00033773	0.00031865	0.00028912	0.00024751	0.00019642	0.
43	63.519	0.00029877	0.00028279	0.00025789	0.00022233	0.00017785	0.
44	68.164	0.00026481	0.0002514	0.00023035	0.00019993	0.00016119	0.
45	73.032	0.00023517	0.00022388	0.00020604	0.00017998	0.00014624	0.
46	78.125	0.00020923	0.00019969	0.00018455	0.0001622	0.00013279	0.
47	83.45	0.00018648	0.00017841	0.00016553	0.00014633	0.00012068	9.11
48	89.011	0.00016649	0.00015965	0.00014868	0.00013216	0.00010978	8.4
49	94.815	0.00014891	0.0001431	0.00013373	0.00011949	9.995e-05	7.7
50	100.87	0.00013342	0.00012846	0.00012044	0.00010816	9.1084e-05	7.0
51	107.17	0.00011973	0.0001155	0.00010862	9.8007e-05	8.308e-05	6.5
52	113.73	0.00010762	0.000104	9.8089e-05	8.8914e-05	7.5856e-05	5.9
53	120.55	9.6907e-05	9.3809e-05	8.873e-05	8.0788e-05	6.9365e-05	5.5
54	127.64	8.7567e-05	8.4918e-05	8.0546e-05	7.3655e-05	6.364e-05	5.1
55	135	8.7567e-05	8.4918e-05	8.0546e-05	7.3655e-05	6.3641e-05	5.1

% Consumption

```
st_title = ['MEAN(MN_MPC_U_GAIN_CHECK(A,Z)), welf_checks=' num2str(welf_checks) ', TR=' num2str(mp_p
tb_az_c = ff_summ_nd_array(st_title, mn_MPC_U_gain_share_check, true, ["mean"], 4, 1, cl_mp_datasetd
```

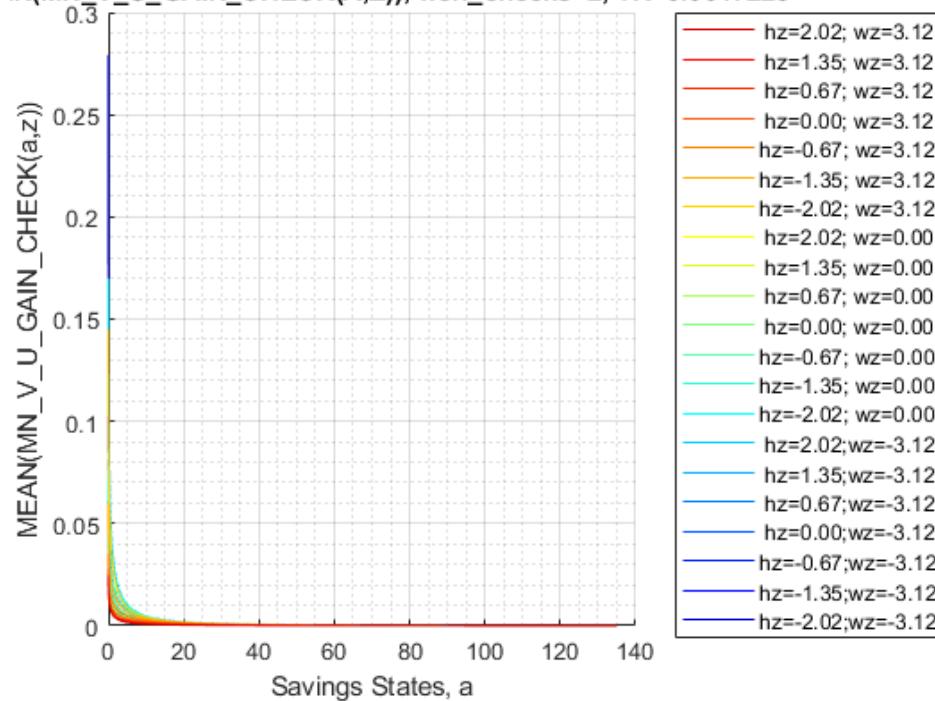
xxx	MEAN(MN_MPC_U_GAIN_CHECK(A,Z)), welf_checks=2, TR=0.0017225	xxxxxxxxxxxxxxxxxxxxxxxxxxxx	mean				
group	savings	mean_eta_1	mean_eta_2	mean_eta_3	mean_eta_4	mean_eta_5	mean
1	0	0.9469	0.94276	0.8717	0.79605	0.7222	0.
2	0.00085734	0.93411	0.9349	0.86947	0.79402	0.72155	0.
3	0.0068587	0.81862	0.82623	0.78945	0.74561	0.6858	0.
4	0.023148	0.71821	0.72464	0.70291	0.65987	0.61284	0.
5	0.05487	0.65702	0.66511	0.64788	0.60732	0.55769	0.
6	0.10717	0.54356	0.56685	0.56196	0.52654	0.48344	0.
7	0.18519	0.34762	0.37134	0.3935	0.38764	0.35935	0.
8	0.29407	0.27014	0.27012	0.26968	0.2781	0.27577	0.
9	0.43896	0.22635	0.22379	0.21808	0.21552	0.21153	0.
10	0.625	0.18643	0.18323	0.18257	0.18047	0.17918	0.
11	0.85734	0.16247	0.15989	0.15903	0.15917	0.1587	0.
12	1.1411	0.14602	0.14447	0.14433	0.1439	0.14242	0.
13	1.4815	0.13936	0.13684	0.13479	0.13517	0.13698	0.
14	1.8836	0.13686	0.13554	0.13207	0.13035	0.13296	0.

15	2.3525	0.13507	0.13247	0.12893	0.12723	0.12724	0.
16	2.8935	0.12673	0.12656	0.12382	0.12237	0.12168	0.
17	3.5117	0.12256	0.12043	0.11953	0.11889	0.11806	0.
18	4.2121	0.11793	0.11791	0.11793	0.11601	0.11689	0.
19	5	0.11739	0.11678	0.11684	0.11637	0.11577	0.
20	5.8805	0.11528	0.11487	0.11456	0.11528	0.11413	0.
21	6.8587	0.11285	0.11244	0.11208	0.11157	0.11191	0.
22	7.9398	0.11153	0.11118	0.11088	0.1103	0.11091	0.
23	9.1289	0.1122	0.11192	0.11174	0.11112	0.11192	0.
24	10.431	0.11098	0.11077	0.11058	0.11009	0.11068	0.
25	11.852	0.10854	0.10833	0.10817	0.10779	0.10805	0.
26	13.396	0.10801	0.10783	0.10765	0.10745	0.10738	0.
27	15.069	0.11027	0.11014	0.10997	0.10974	0.1096	0.
28	16.875	0.11158	0.11146	0.11134	0.11129	0.11095	0.
29	18.82	0.11001	0.1099	0.1098	0.10996	0.1093	0.
30	20.91	0.1067	0.10661	0.10651	0.10645	0.10603	0.
31	23.148	0.10684	0.10677	0.10669	0.10658	0.10631	0.
32	25.541	0.10847	0.10842	0.10835	0.1084	0.108	0.
33	28.093	0.1086	0.10855	0.10851	0.10857	0.10826	0.
34	30.81	0.10826	0.10822	0.10817	0.10821	0.10802	0.
35	33.697	0.10867	0.10864	0.1086	0.10861	0.10855	0.
36	36.758	0.10953	0.10951	0.10947	0.10947	0.10941	0.
37	40	0.10783	0.1078	0.10777	0.10776	0.10793	0.
38	43.427	0.10628	0.10627	0.10624	0.10623	0.1065	0.
39	47.044	0.10618	0.10618	0.10615	0.10614	0.1063	0.
40	50.856	0.10875	0.10873	0.10871	0.1087	0.10863	0.
41	54.87	0.1092	0.10918	0.10917	0.10916	0.10914	0.
42	59.089	0.10782	0.1078	0.10779	0.10778	0.10797	0.
43	63.519	0.10676	0.10675	0.10673	0.10673	0.10684	0.
44	68.164	0.10765	0.10764	0.10763	0.10762	0.1077	0.
45	73.032	0.10869	0.10868	0.10867	0.10866	0.10871	0.
46	78.125	0.10779	0.10778	0.10777	0.10776	0.1078	0.
47	83.45	0.10629	0.10629	0.10628	0.10627	0.1063	0.
48	89.011	0.10682	0.10682	0.10681	0.1068	0.10681	0.
49	94.815	0.10832	0.10832	0.10831	0.1083	0.1083	0.
50	100.87	0.10817	0.10817	0.10816	0.10815	0.10814	0.
51	107.17	0.10742	0.10742	0.10741	0.10739	0.10736	0.
52	113.73	0.10763	0.10763	0.10761	0.10757	0.1075	0.
53	120.55	0.10824	0.10821	0.10815	0.10805	0.10784	0.
54	127.64	0.10659	0.10646	0.10629	0.10605	0.10564	0.
55	135	0.10659	0.10646	0.10629	0.10605	0.10564	0.

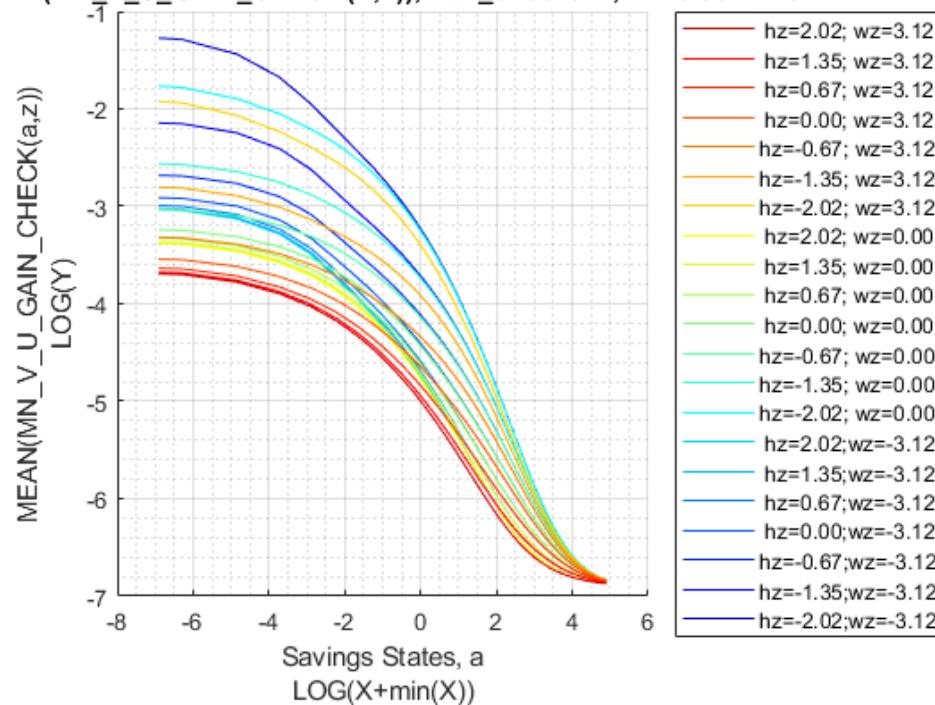
Graph Mean Values:

```
st_title = ['MEAN(MN\_V\_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\_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);
```

N(MN\_V\_U\_GAIN\_CHECK(A,Z)), welf\_checks=2, TR=0.0017225



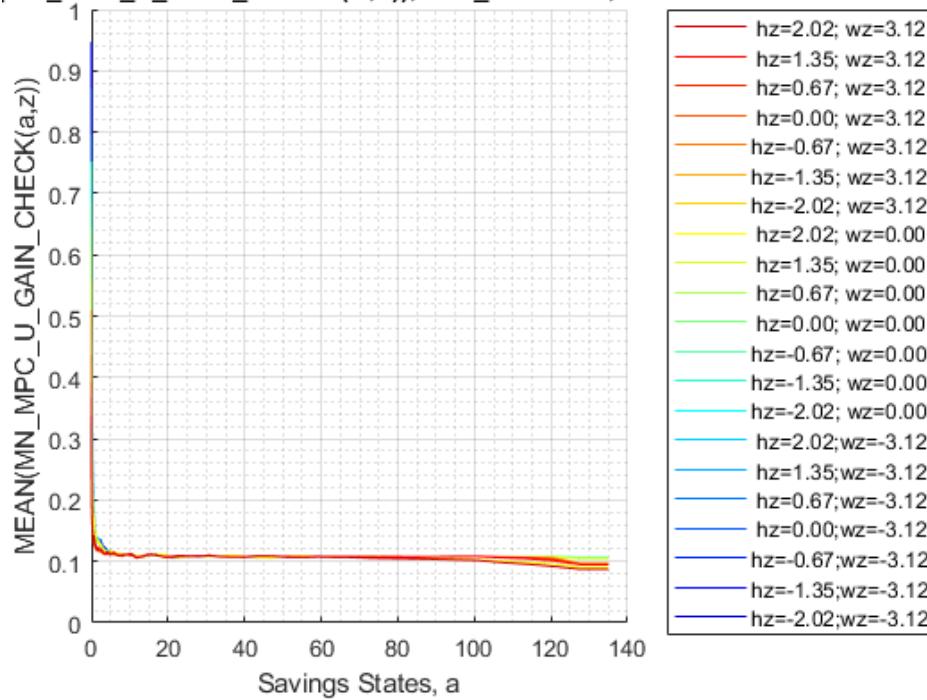
AN(MN\_V\_U\_GAIN\_CHECK(A,Z)), welf\_checks=2, TR=0.0017225



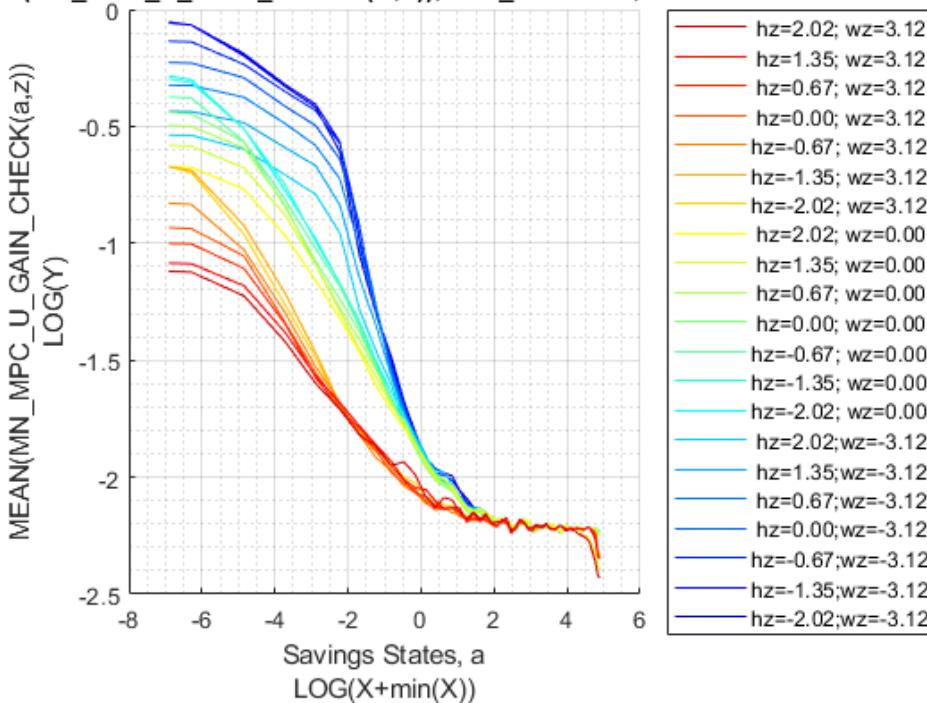
Graph Mean Consumption (MPC: Share of Check Consumed):

```
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);
```

'MN\_MPC\_U\_GAIN\_CHECK(A,Z)), welf\_checks=2, TR=0.0017225



N(MN\_MPC\_U\_GAIN\_CHECK(A,Z)), welf\_checks=2, TR=0.0017225



### 7.1.5 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 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;
```

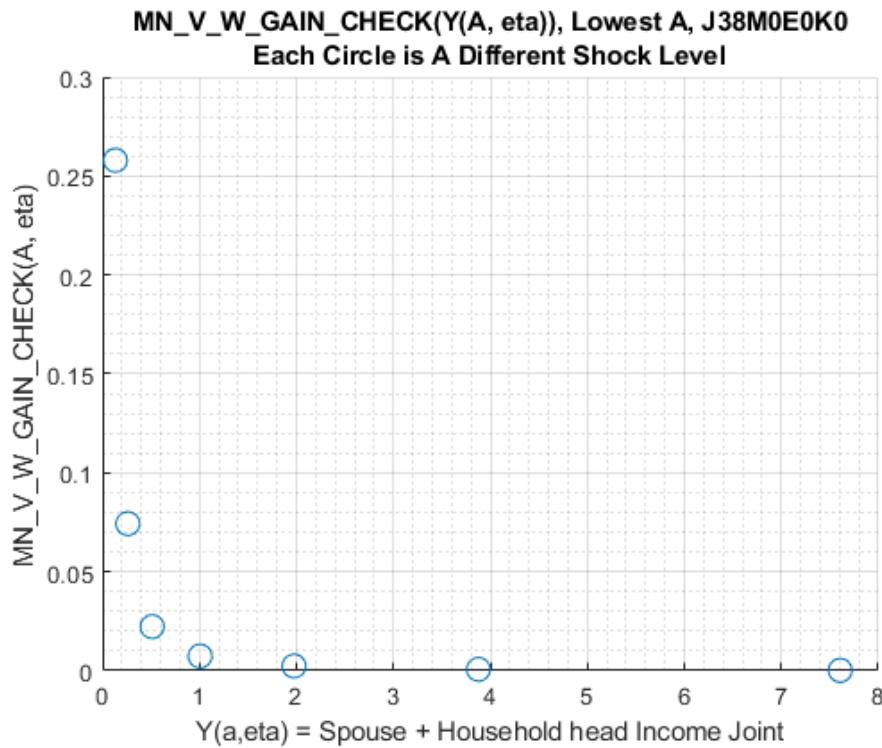
Select Age, Education, Marital, Kids Count:

```
% 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);
```

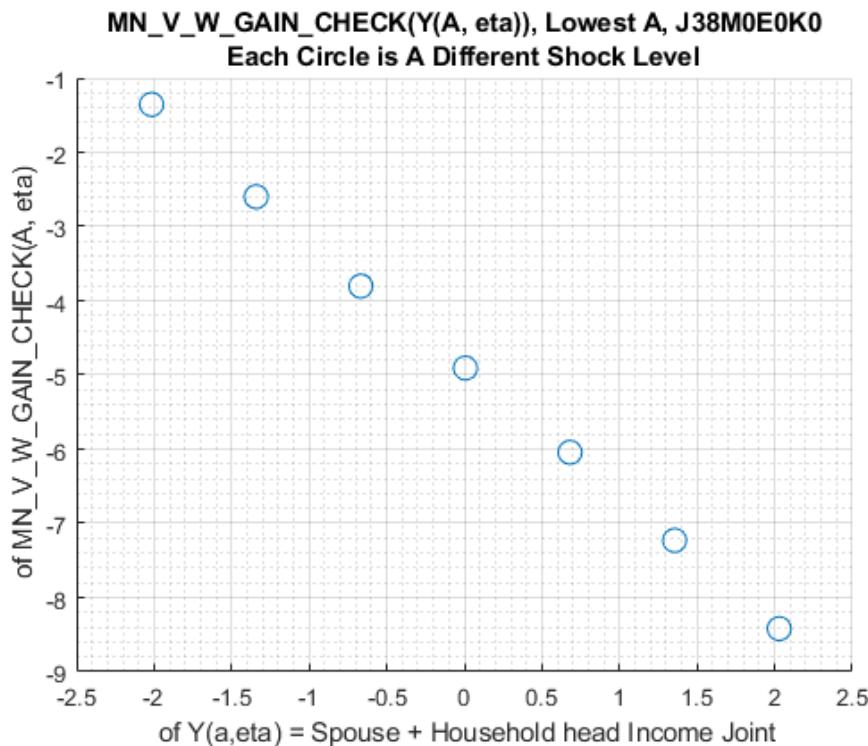
### 7.1.6 Marginal Value Gains, Color as Shock, Conditional on Age, Marital, Kids, and Education

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, J38M0EOK0', ...
'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;
```

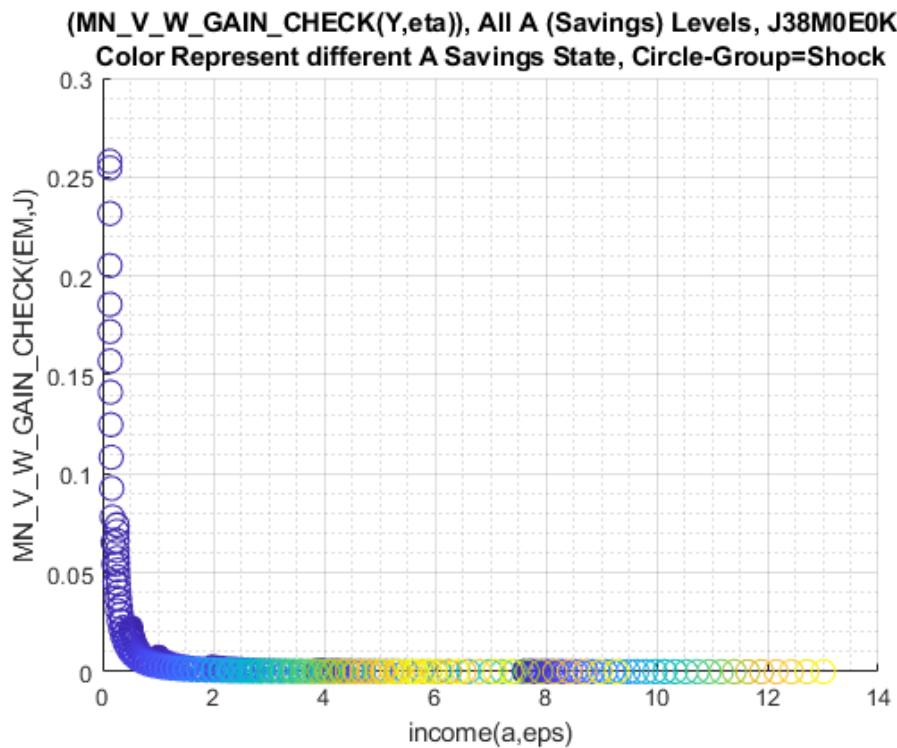


```
figure();
it_shock = 1;
scatter(log(mt_total_inc_jemk(:,it_a)), log(mt_V_W_gain_check_jemk(:,it_a)), 100);
title({'MN\_\V\_\W\_\GAIN\_\CHECK(Y(A, eta)), Lowest A, J38M0E0K0', ...
    'Each Circle is A Different Shock Level'});
xlabel(' of Y(a, eta) = Spouse + Household head Income Joint');
ylabel(' of MN\_\V\_\W\_\GAIN\_\CHECK(A, eta)');
grid on;
grid minor;
```

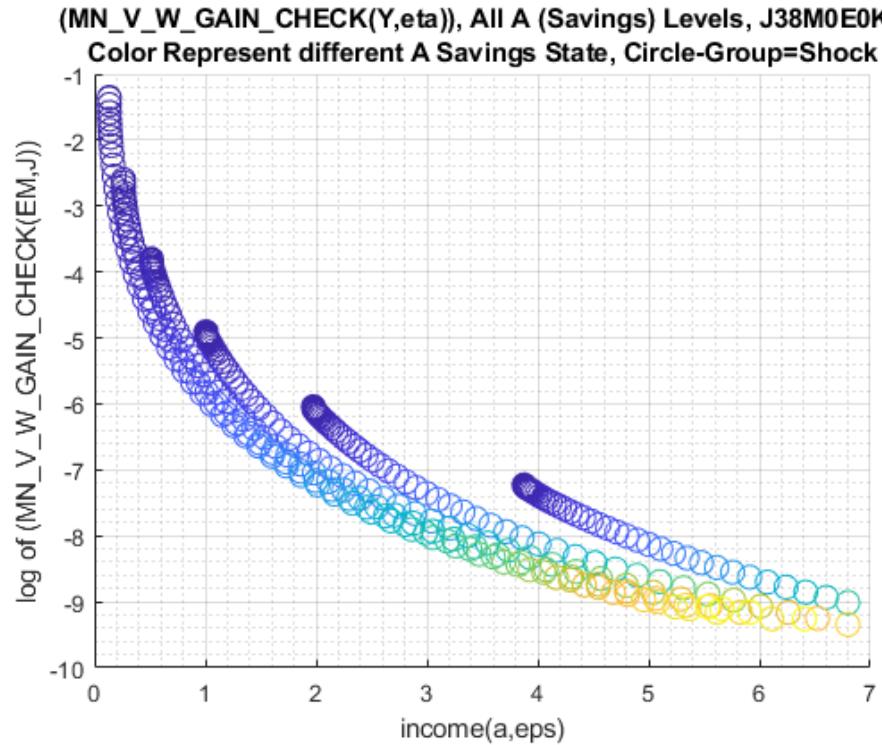


Plot all asset levels:

```
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;
```



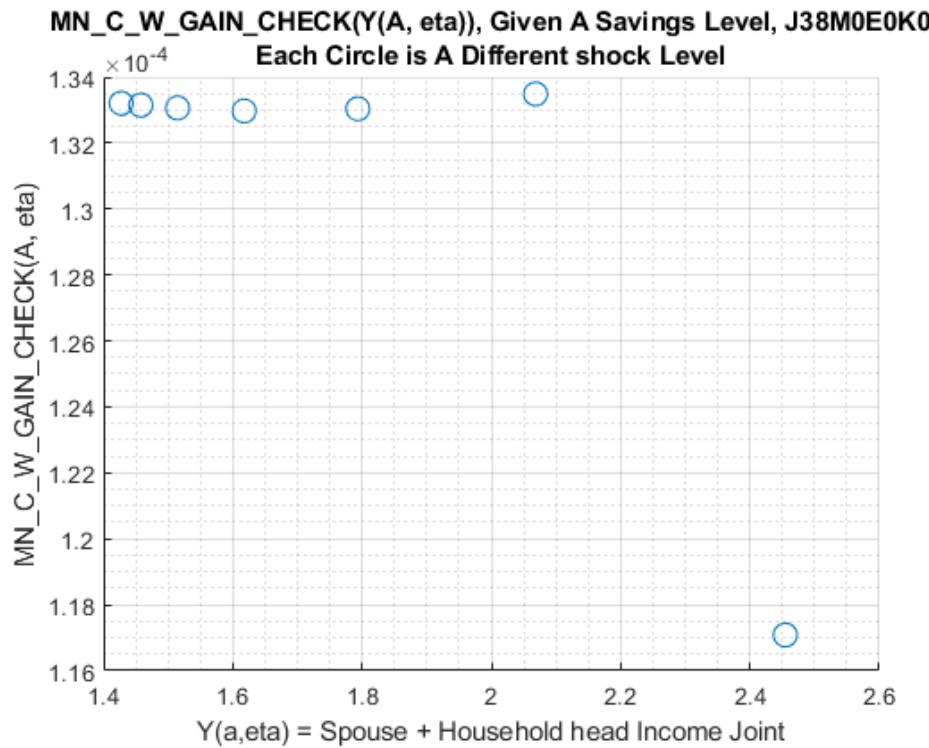
```
figure();
scatter((mt_total_inc_jemk(:)), log(mt_V_W_gain_check_jemk(:)), 100, mt_a(:));
title({'(MN\_V\_W\_GAIN\_CHECK(Y,eta)), All A (Savings) Levels, J38M0E0K0', ...
    'Color Represent different A Savings State, Circle-Group=Shock'});
xlabel('income(a,eps)');
ylabel('log of (MN\_V\_W\_GAIN\_CHECK(EM,J))');
xlim([0,7]);
grid on;
grid minor;
```



### 7.1.7 Marginal Consumption Gains, Color as Shock, Conditional on Age, Marital, Kids, and Education

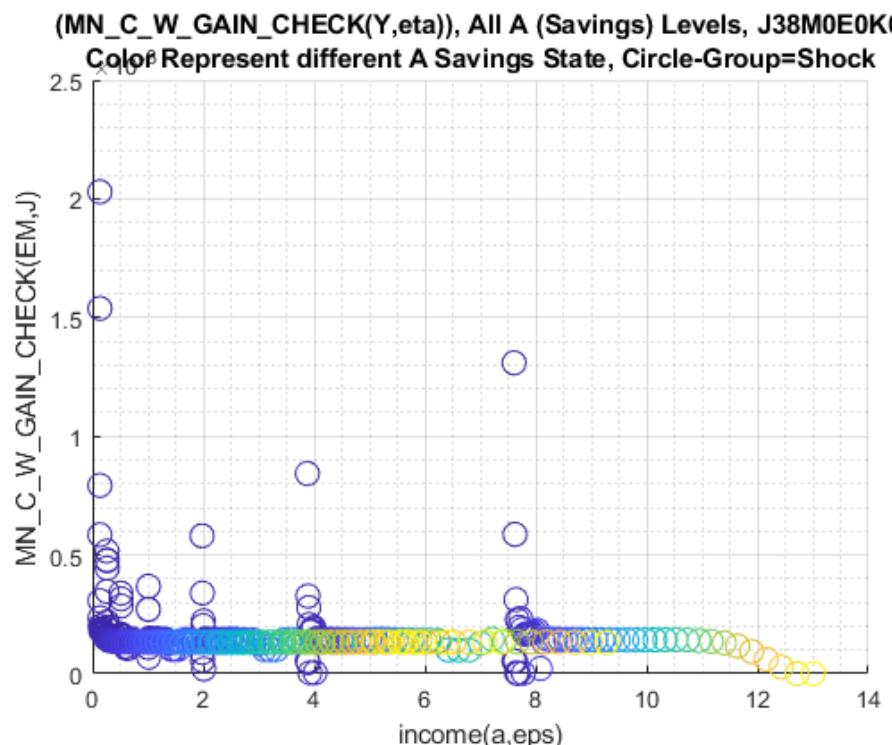
How do shocks and age impact marginal value. First plot one asset level, variation comes only from increasingly higher shocks:

```
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;
```

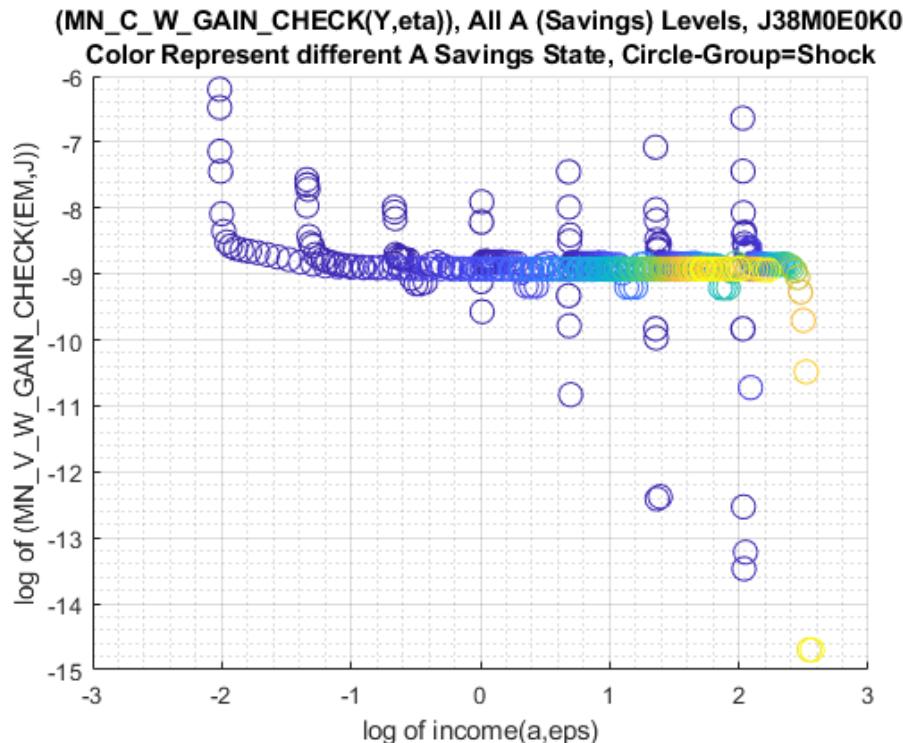


Plot all asset levels:

```
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;
```



### 7.1.8 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_
```

xxx MEAN(MN_V_U_GAIN_CHECK(KM,J)), welf_checks=2, TR=0.0017225 xxxxxxxxxxxxxxxxxxxxxxxxx							
group	kids	marry	mean_age_18	mean_age_19	mean_age_20	mean_age_21	mean_age_22
1	1	0	0.018089	0.017252	0.016367	0.015089	0.014021
2	2	0	0.024167	0.023077	0.021867	0.020077	0.018573
3	3	0	0.027732	0.026669	0.025441	0.023362	0.021616
4	4	0	0.031193	0.03009	0.028767	0.026421	0.024452
5	5	0	0.033947	0.032875	0.031534	0.02899	0.026856
6	1	1	0.0061943	0.0059191	0.0056503	0.0051336	0.0047002
7	2	1	0.0081386	0.0077695	0.007405	0.0067275	0.0061552
8	3	1	0.0095966	0.0091734	0.0087634	0.0079591	0.0072803
9	4	1	0.011304	0.010815	0.010337	0.0093981	0.0086038
10	5	1	0.013294	0.012771	0.012229	0.011142	0.010228

```
% Consumption Function
```

```
st_title = ['MEAN(MN_MPC_U_GAIN_CHECK(KM,J)), welf_checks=' num2str(welf_checks) ', TR=' num2str(mp_
```

xxx MEAN(MN_MPC_U_GAIN_CHECK(KM,J)), welf_checks=2, TR=0.0017225 xxxxxxxxxxxxxxxxxxxxxxxxx							
group	kids	marry	mean_age_18	mean_age_19	mean_age_20	mean_age_21	mean_age_22
1	1	0	0.064794	0.073581	0.10118	0.097925	0.093502
2	2	0	0.072702	0.085068	0.11591	0.11391	0.11124
3	3	0	0.087366	0.10442	0.13386	0.13266	0.1309
4	4	0	0.088926	0.10344	0.13895	0.138	0.13683
5	5	0	0.10276	0.11528	0.14404	0.14305	0.14187
6	1	1	0.098235	0.10626	0.11555	0.11505	0.11337
7	2	1	0.10346	0.10657	0.11743	0.11639	0.11571
8	3	1	0.10975	0.11642	0.12686	0.12437	0.12447
9	4	1	0.11043	0.11635	0.12843	0.12825	0.13154
10	5	1	0.12035	0.12608	0.13427	0.136	0.13418

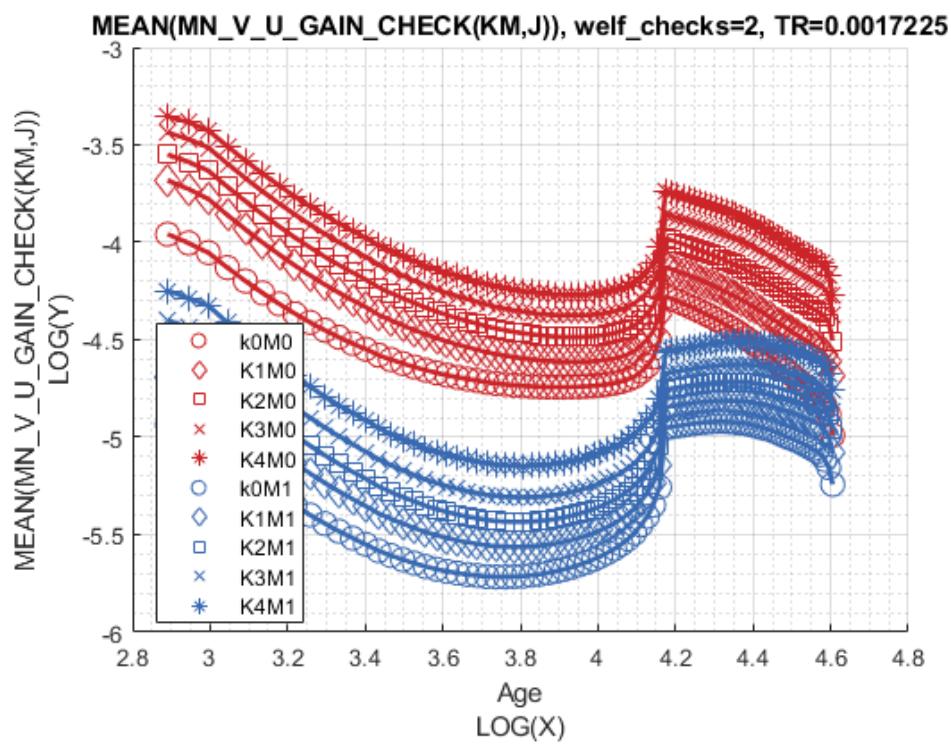
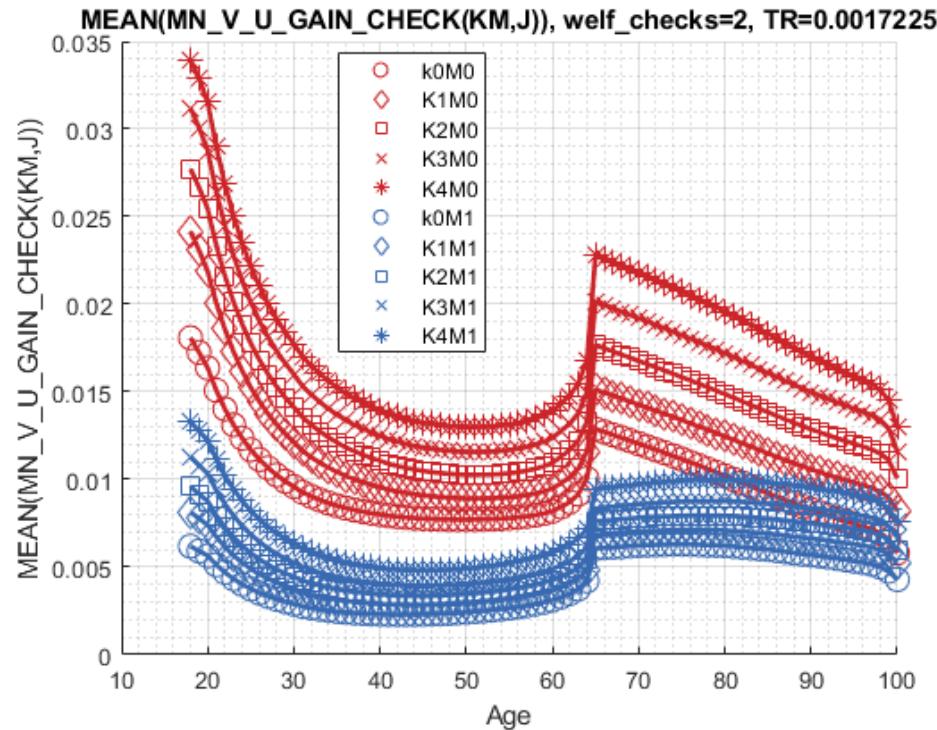
Graph Mean Values:

```
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};
```

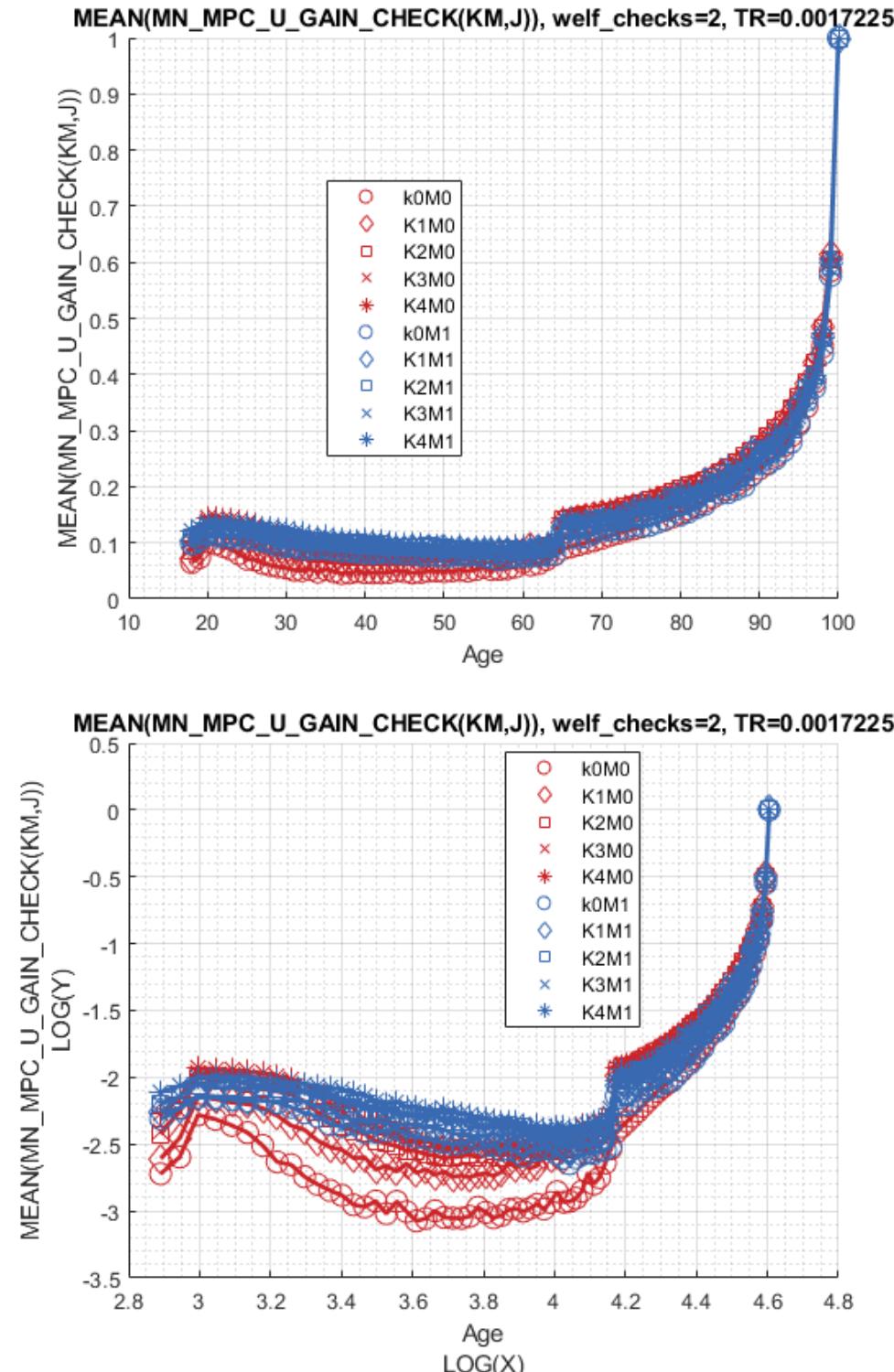
```
mp_support_graph('cl_st_ytitle') = {'MEAN(MN_V_U_GAIN_CHECK(KM,J))'};
```

```
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(TR)];
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);
```



### 7.1.9 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))

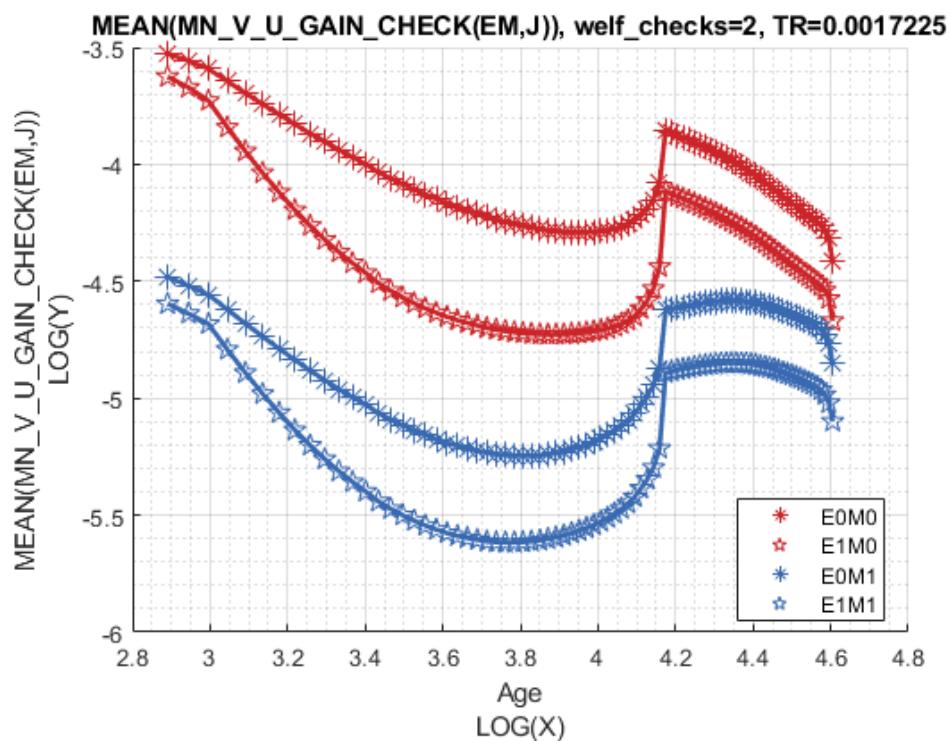
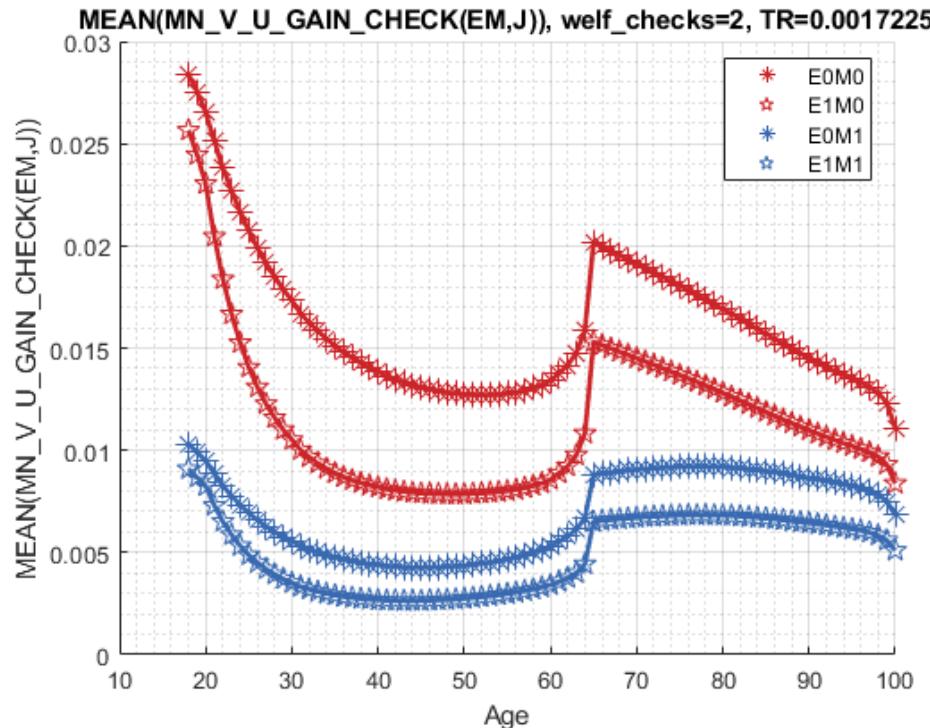
Tabulate value and policies:

```
% 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=0.0017225 xxxxxxxxxxxxxxxxxxxxxxxx
group   edu   marry   mean_age_18   mean_age_19   mean_age_20   mean_age_21   mean_age_22
-----  ---  -----  -----  -----  -----  -----  -----
1       0       0       0.0284      0.027529     0.026552     0.025115     0.023836
2       1       0       0.025651     0.024457     0.023039     0.020461     0.018371
3       0       1       0.01032      0.0099016    0.0094945    0.0088461    0.0082733
4       1       1       0.0090905    0.0086775    0.0082596    0.0072981    0.0065136

% 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 xxxxxxxxxxxxxxxxxxxxxxxx
group   edu   marry   mean_age_18   mean_age_19   mean_age_20   mean_age_21   mean_age_22
-----  ---  -----  -----  -----  -----  -----  -----
1       0       0       0.073692     0.083211     0.1068      0.10496     0.10269
2       1       0       0.092928     0.10951      0.14677     0.14526     0.14305
3       0       1       0.10086      0.1066      0.11448     0.11496     0.11372
4       1       1       0.11603      0.12207     0.13453     0.13306     0.13399
```

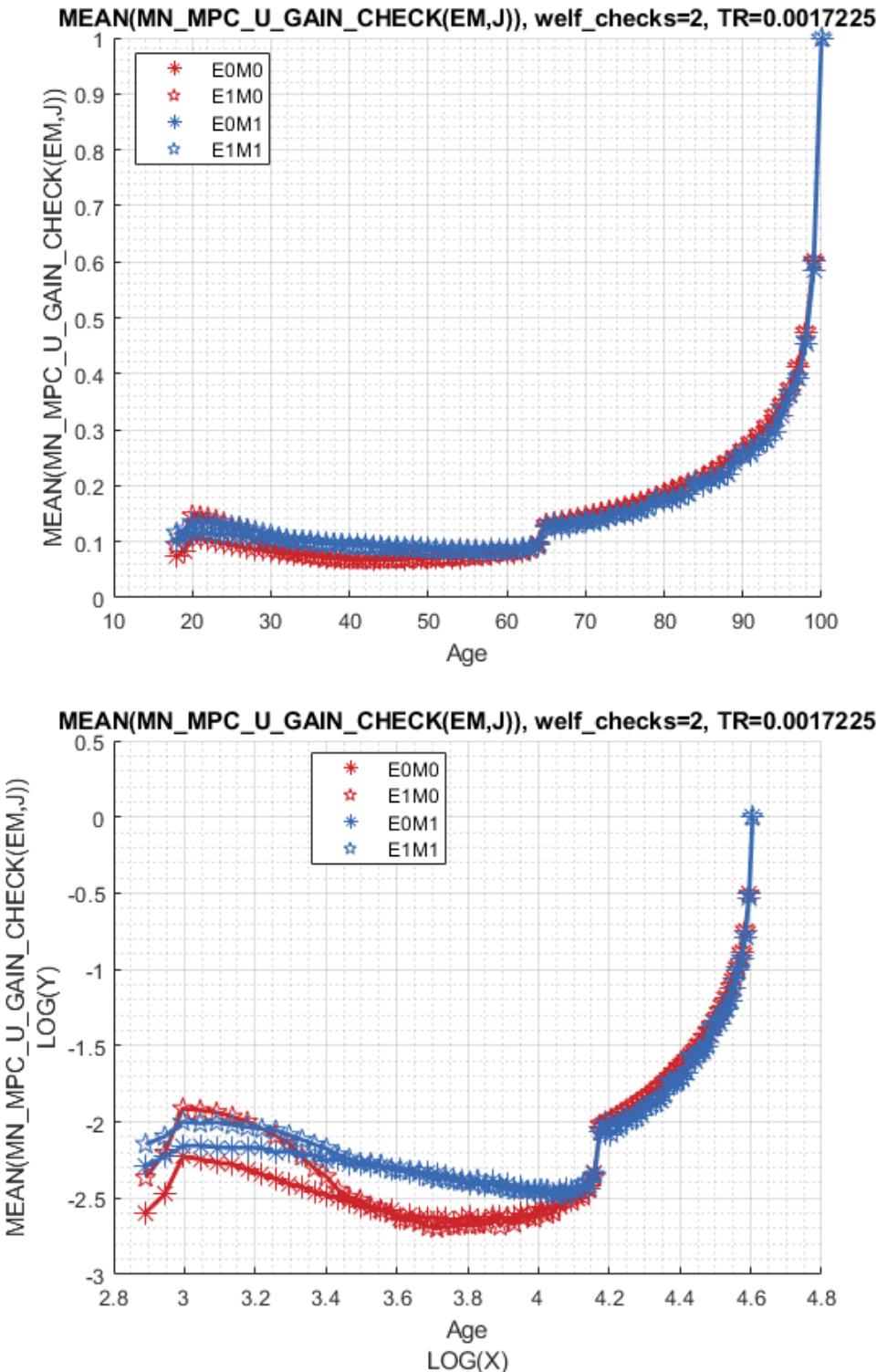
Graph Mean Values:

```
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(TR)];
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);
```



## 7.2 2019 Full States EV and EC of One Check

This is the example vignette for function: `snw_evuvw20_jaeemk` from the **PrjOptiSNW Package**. 2019 integrated over VU and VW, given optimal savings choices, unemployment shocks and various expectations.

### 7.2.1 Test SNW\_EVUVW19\_JAEEMK Defaults Dense

VFI and Distribution

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_docdense');
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_precache') = false;
mp_controls('bl_print_precache_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_dense;SNW_MP_CONTROL=default_test;time=16.9824

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;
% 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_dense;SNW_MP_CONTROL=default
[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_dense;SNW_MP_CONTROL=default_test;time=61.7368

% Get Matrixes
cl_st_precache_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_precache_verbose') = false;
[mp_precache_res] = snw_hh_precache(mp_params, mp_controls, cl_st_precache_list, ap_ss, Phi_tr

Wage quintile cutoffs=0.49295      0.79302      1.3138      2.1063
Completed SNW_HH_PRECOMPUTE;SNW_MP_PARAM=default_dense;SNW_MP_CONTROL=default_test;time cost=35.3213

```

## 7.2.2 Solve for 2019 Evuvw With 0 and 2 Checks

% 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_ss, cons_ss, V_unemp, cons_unemp, mp_precompute_res);
```

Completed SNW\_A4CHK\_UNEMP\_BISEC\_VEC;welf\_checks=0;TR=0.0017225;xi=0.5;b=0;SNW\_MP\_PARAM=default\_dense  
Completed SNW\_A4CHK\_WRK\_BISEC\_VEC;welf\_checks=0;TR=0.0017225;SNW\_MP\_PARAM=default\_dense;SNW\_MP\_CONTROL=default\_test;timeEUEC=0.67039  
Completed SNW\_EVUVW20\_JAEEMK;SNW\_MP\_PARAM=default\_dense;SNW\_MP\_CONTROL=default\_test;time=8.1727

---

xxxxxxxxxxxxxxxxxxxxxxxxxxxxxxxxxxxxxx

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

xxxxxxxxxxxxxxxxxxxxxxxxxxxxxxxxxxxxxx

	i	idx	ndim	numel	rowN	colN	sum	mean	std
	-	---	----	-----	----	----	-----	-----	-----
ec19_jaeemk	1	1	6	1.8942e+06	82	23100	8.2855e+06	4.3742	5.23
ec20_jaeemk	2	2	6	1.9173e+06	83	23100	9.7703e+06	5.0959	8.37
ev19_jaeemk	3	3	6	1.8942e+06	82	23100	-3.7288e+06	-1.9685	22.2
ev20_jaeemk	4	4	6	1.9173e+06	83	23100	-4.1377e+06	-2.1581	22.8

xxx TABLE:ec19\_jaeemk xxxxxxxxxxxxxxxxx

	c1	c2	c3	c4	c5	c23096	c23097	c23098
	-----	-----	-----	-----	-----	-----	-----	-----
r1	0.08064	0.080744	0.082559	0.086958	0.092876	10.7	10.935	11.171
r2	0.081432	0.081432	0.084644	0.089174	0.095493	10.86	11.091	11.32
r3	0.083622	0.083622	0.085501	0.091223	0.097903	11.024	11.249	11.471
r4	0.086619	0.086619	0.088508	0.094197	0.10085	11.168	11.388	11.601
r5	0.089528	0.089528	0.091431	0.097077	0.1037	11.309	11.521	11.724
r78	0.21707	0.21707	0.21707	0.21707	0.22416	26.837	28.052	29.222
r79	0.21707	0.21707	0.21707	0.21707	0.22416	28.992	31.165	32.888
r80	0.21707	0.21707	0.21707	0.21707	0.22416	32.266	33.961	36.121
r81	0.21707	0.21707	0.21707	0.21707	0.22416	38.348	39.931	42.54
r82	0.21707	0.21707	0.21707	0.21707	0.22361	51.027	52.913	57.047

xxx TABLE:ec20\_jaeemk xxxxxxxxxxxxxxxxx

	c1	c2	c3	c4	c5	c23096	c23097	c23098
	-----	-----	-----	-----	-----	-----	-----	-----
r1	0.078786	0.079375	0.080372	0.084318	0.090081	10.601	10.841	11.082
r2	0.078786	0.079674	0.081595	0.086622	0.09285	10.755	10.992	11.228
r3	0.079575	0.080463	0.084561	0.089582	0.096059	10.912	11.145	11.375
r4	0.082616	0.083505	0.087581	0.092591	0.099121	11.281	11.504	11.718
r5	0.085578	0.086467	0.090513	0.095505	0.10201	11.412	11.627	11.83
r79	0.21707	0.21796	0.22416	0.241	0.26692	34.627	36.056	37.896
r80	0.21707	0.21796	0.22416	0.241	0.26692	39.694	41.355	43.554
r81	0.21707	0.21796	0.22416	0.241	0.26692	47.978	51.293	53.451
r82	0.21707	0.21796	0.22416	0.241	0.26745	63.659	68.583	71.594
r83	0.21707	0.21796	0.22416	0.241	0.27378	112.67	119.43	126.45

xxx TABLE:ev19\_jaeemk xxxxxxxxxxxxxxxxx

	c1	c2	c3	c4	c5	c23096	c23097	c23098	c2
	-----	-----	-----	-----	-----	-----	-----	-----	-----
r1	-231.16	-231.1	-230.08	-227.9	-224.17	20.989	21.13	21.27	2
r2	-222.14	-222.14	-221.33	-219.39	-215.84	20.973	21.11	21.246	2
r3	-213.6	-213.6	-213.21	-211.33	-207.93	20.953	21.086	21.219	2

r4	-205.67	-205.67	-205.31	-203.55	-200.36	20.925	21.055	21.185	2
r5	-198.45	-198.45	-198.11	-196.45	-193.44	20.891	21.018	21.145	2
r78	-9.9698	-9.9698	-9.9698	-9.9698	-9.824	2.4708	2.4858	2.5001	2
r79	-8.9313	-8.9313	-8.9313	-8.9313	-8.7855	2.2408	2.2553	2.2677	1
r80	-7.6669	-7.6669	-7.6669	-7.6669	-7.5211	1.9523	1.9632	1.9722	1
r81	-5.9967	-5.9967	-5.9967	-5.9967	-5.8508	1.5534	1.5588	1.5654	1
r82	-3.6113	-3.6113	-3.6113	-3.6113	-3.4767	0.9548	0.95648	0.95963	0.

xxx TABLE:ev20\_jaeemk xxxxxxxxxxxxxxxxxxxxxxxxx

	c1	c2	c3	c4	c5	c23096	c23097	c23098	c
	-----	-----	-----	-----	-----	-----	-----	-----	-----
r1	-235.08	-234.92	-233.84	-231.32	-227.14	21.095	21.236	21.376	
r2	-226.34	-226.18	-225.14	-222.7	-218.72	21.082	21.219	21.356	
r3	-217.94	-217.78	-216.77	-214.45	-210.67	21.065	21.198	21.331	
r4	-209.81	-209.67	-208.73	-206.55	-203.01	21.045	21.174	21.304	
r5	-202.41	-202.27	-201.4	-199.35	-196.01	21.014	21.14	21.267	
r79	-9.9634	-9.9447	-9.8178	-9.5061	-8.9993	2.5241	2.5372	2.5494	
r80	-8.9252	-8.9064	-8.7795	-8.4679	-7.9637	2.2926	2.3026	2.3118	
r81	-7.661	-7.6423	-7.5154	-7.2037	-6.7021	1.9992	2.0061	2.0125	
r82	-5.9911	-5.9724	-5.8455	-5.5339	-5.0346	1.5919	1.5958	1.5994	
r83	-3.6067	-3.588	-3.4611	-3.1494	-2.6526	0.97826	0.97949	0.98063	0.

% 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_ss, cons_ss, V_unemp, cons_unemp, mp_precompute_res);
```

```
Completed SNW_A4CHK_UNEMP_BISEC_VEC;welf_checks=2;TR=0.0017225;xi=0.5;b=0;SNW_MP_PARAM=default_dense
Completed SNW_A4CHK_WRK_BISEC_VEC;welf_checks=2;TR=0.0017225;SNW_MP_PARAM=default_dense;SNW_MP_CONTROL=
Completed SNW_EVUVW20_JAEEMK;SNW_MP_PARAM=default_dense;SNW_MP_CONTROL=default_test;timeEUEC=0.4338
Completed SNW_EVUVW19_JAEEMK;SNW_MP_PARAM=default_dense;SNW_MP_CONTROL=default_test;time=9.4255
-----
```

xxxxxxxxxxxxxxxxxxxxxxxxxxxxxxxxxxxxxx

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

	i	idx	ndim	numel	rowN	colN	sum	mean	std
	-	---	----	-----	---	----	-----	-----	-----
ec19_jaeemk	1	1	6	1.8942e+06	82	23100	8.2866e+06	4.3747	5.23
ec20_jaeemk	2	2	6	1.9173e+06	83	23100	9.7714e+06	5.0964	8.37
ev19_jaeemk	3	3	6	1.8942e+06	82	23100	-3.7109e+06	-1.9591	22.
ev20_jaeemk	4	4	6	1.9173e+06	83	23100	-4.1188e+06	-2.1482	22.8

xxx TABLE:ec19\_jaeemk xxxxxxxxxxxxxxxxxxxxxxxxx

	c1	c2	c3	c4	c5	c23096	c23097	c23098	
	-----	-----	-----	-----	-----	-----	-----	-----	-----
r1	0.081703	0.081806	0.0836	0.087675	0.09332	10.7	10.935	11.171	
r2	0.083719	0.083719	0.085961	0.089966	0.095955	10.86	11.091	11.32	
r3	0.086201	0.086201	0.087481	0.092085	0.098395	11.024	11.25	11.471	
r4	0.089189	0.089189	0.090472	0.095056	0.10134	11.168	11.388	11.601	
r5	0.092085	0.092085	0.093374	0.097931	0.10419	11.309	11.521	11.724	
r78	0.22052	0.22052	0.22052	0.22052	0.22761	26.838	28.053	29.223	
r79	0.22052	0.22052	0.22052	0.22052	0.22761	28.993	31.166	32.889	
r80	0.22052	0.22052	0.22052	0.22052	0.22761	32.267	33.963	36.122	
r81	0.22052	0.22052	0.22052	0.22052	0.22761	38.349	39.933	42.542	

r82	0.22052	0.22052	0.22052	0.22052	0.22706	51.03	52.916	57.05
xxx TABLE:ec20_jaeemk xxxxxxxxxxxxxxxxxxxx								
	c1	c2	c3	c4	c5	c23096	c23097	c23098
-----	-----	-----	-----	-----	-----	-----	-----	-----
r1	0.079785	0.079927	0.081177	0.084922	0.09046	10.601	10.841	11.082
r2	0.080464	0.080738	0.082621	0.087274	0.093237	10.755	10.992	11.228
r3	0.082148	0.082733	0.085586	0.090261	0.096428	10.913	11.145	11.375
r4	0.085181	0.085763	0.088604	0.093275	0.099485	11.281	11.504	11.718
r5	0.088131	0.088709	0.091532	0.096187	0.10238	11.412	11.627	11.83
r79	0.22052	0.2214	0.22761	0.24372	0.26885	34.627	36.057	37.898
r80	0.22052	0.2214	0.22761	0.24372	0.26914	39.694	41.356	43.555
r81	0.22052	0.2214	0.22761	0.24372	0.26933	47.98	51.294	53.452
r82	0.22052	0.2214	0.22761	0.24378	0.26982	63.662	68.584	71.596
r83	0.22052	0.2214	0.22761	0.24444	0.27722	112.67	119.43	126.45
xxx TABLE:ev19_jaeemk xxxxxxxxxxxxxxxxxxxx								
	c1	c2	c3	c4	c5	c23096	c23097	c23098
-----	-----	-----	-----	-----	-----	-----	-----	-----
r1	-230.56	-230.51	-229.56	-227.46	-223.78	20.989	21.13	21.27
r2	-221.56	-221.56	-220.82	-218.96	-215.47	20.973	21.11	21.246
r3	-213.05	-213.05	-212.7	-210.91	-207.58	20.953	21.086	21.219
r4	-205.16	-205.16	-204.83	-203.16	-200.03	20.926	21.055	21.185
r5	-197.97	-197.97	-197.66	-196.08	-193.13	20.891	21.018	21.145
r78	-9.8986	-9.8986	-9.8986	-9.8986	-9.7602	2.4708	2.4859	2.5001
r79	-8.8601	-8.8601	-8.8601	-8.8601	-8.7216	2.2408	2.2553	2.2677
r80	-7.5957	-7.5957	-7.5957	-7.5957	-7.4572	1.9523	1.9632	1.9722
r81	-5.9255	-5.9255	-5.9255	-5.9255	-5.787	1.5534	1.5588	1.5654
r82	-3.5401	-3.5401	-3.5401	-3.5401	-3.4123	0.9548	0.95648	0.95963
xxx TABLE:ev20_jaeemk xxxxxxxxxxxxxxxxxxxx								
	c1	c2	c3	c4	c5	c23096	c23097	c23098
-----	-----	-----	-----	-----	-----	-----	-----	-----
r1	-234.48	-234.32	-233.33	-230.88	-226.76	21.095	21.236	21.377
r2	-225.75	-225.6	-224.64	-222.29	-218.36	21.082	21.219	21.356
r3	-217.37	-217.22	-216.3	-214.05	-210.33	21.065	21.198	21.331
r4	-209.28	-209.15	-208.29	-206.18	-202.69	21.045	21.174	21.304
r5	-201.91	-201.79	-200.98	-199	-195.71	21.014	21.14	21.267
r79	-9.8923	-9.8742	-9.754	-9.4529	-8.9555	2.5241	2.5372	2.5494
r80	-8.8541	-8.8359	-8.7157	-8.4149	-7.9203	2.2926	2.3026	2.3118
r81	-7.5899	-7.5718	-7.4516	-7.151	-6.6591	1.9992	2.0061	2.0125
r82	-5.9201	-5.9019	-5.7817	-5.4814	-4.9918	1.5919	1.5958	1.5994
r83	-3.5356	-3.5175	-3.3973	-3.0972	-2.6142	0.97826	0.97949	0.98063

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'))
```

### 7.2.3 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;
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 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 xxxxxxxxxxxxxxxxxxxxxxxxxxxxxxxx
group      savings      mean_eta_1      mean_eta_2      mean_eta_3      mean_eta_4      mean_eta_5      mean_eta_6
-----      -----      -----      -----      -----      -----      -----      -----
1           0           0.16422       0.072711      0.044261      0.035185      0.031921      0.029301
2           0.00085734    0.16411       0.072685      0.044254      0.035183      0.031921      0.029301
3           0.0068587     0.16089       0.072203      0.044174      0.03516       0.031906      0.029301
4           0.023148      0.14347       0.068722      0.043233      0.034539      0.031319      0.029301
5           0.05487       0.12489       0.062983      0.040587      0.032437      0.029572      0.026538
6           0.10717       0.10956       0.056872      0.037152      0.029572      0.026538      0.023930
7           0.18519       0.093145      0.050122      0.032855      0.025873      0.022971      0.020563
8           0.29407       0.076208      0.042336      0.027832      0.021566      0.018844      0.016389
9           0.43896       0.063079      0.035973      0.023726      0.018152      0.015638      0.013319
10          0.625         0.052632      0.030859      0.020414      0.01541       0.013081      0.010971
11          0.85734       0.044007      0.026566      0.017638      0.013131      0.010971      0.008606
12          1.1411        0.036806      0.022912      0.015283      0.011232      0.0092306     0.0071926
13          1.4815        0.030786      0.019772      0.013268      0.0096429     0.0077925     0.006606
14          1.8836        0.025765      0.017067      0.011541      0.0083128     0.006606      0.005241
15          2.3525        0.021575      0.014731      0.010054      0.0071926     0.0056241     0.0048017
16          2.8935        0.018077      0.012701      0.0087613     0.006238      0.0048017     0.00411
17          3.5117        0.015151      0.010936      0.0076339     0.0054202     0.00411       0.0035306
18          4.2121        0.012711      0.0094052     0.0066501     0.0047191     0.0035306     0.0030444
19          5             0.010676      0.008083      0.0057903     0.0041163     0.0030444     0.0025638

```

20	5.8805	0.008979	0.0069435	0.0050432	0.003597	0.0026352	0.
21	6.8587	0.0075642	0.0059636	0.0043935	0.0031477	0.002289	0.
22	7.9398	0.0063835	0.0051226	0.003827	0.0027577	0.001995	0.
23	9.1289	0.0053974	0.0044023	0.0033352	0.0024197	0.0017445	0.
24	10.431	0.0045736	0.0037863	0.0029093	0.0021264	0.0015304	0.
25	11.852	0.0038839	0.0032595	0.0025394	0.0018711	0.0013461	0.0
26	13.396	0.0033057	0.0028093	0.0022181	0.0016485	0.001187	0.0
27	15.069	0.0028204	0.0024245	0.0019392	0.0014539	0.0010493	0.0
28	16.875	0.0024123	0.0020957	0.0016969	0.0012837	0.00092975	0.0
29	18.82	0.0020683	0.0018143	0.0014864	0.0011352	0.00082552	0.0
30	20.91	0.0017776	0.0015732	0.0013032	0.0010051	0.00073426	0.0
31	23.148	0.0015314	0.0013663	0.0011438	0.00089056	0.00065417	0.0
32	25.541	0.0013225	0.0011887	0.001005	0.00079002	0.00058386	0.0
33	28.093	0.0011448	0.0010361	0.00088415	0.00070181	0.00052199	0.0
34	30.81	0.00099337	0.00090469	0.00077879	0.00062417	0.0004674	0.0
35	33.697	0.00086393	0.00079137	0.00068687	0.00055572	0.00041911	0.0
36	36.758	0.00075305	0.0006935	0.0006066	0.00049531	0.0003762	0.0
37	40	0.00065787	0.00060885	0.00053645	0.00044195	0.00033809	0.0
38	43.427	0.00057598	0.0005355	0.00047505	0.00039475	0.00030432	0.0
39	47.044	0.00050536	0.00047182	0.00042126	0.00035297	0.00027428	0.0
40	50.856	0.00044434	0.00041648	0.00037408	0.00031594	0.00024745	0.0
41	54.87	0.00039149	0.00036829	0.00033267	0.00028312	0.00022344	0.0
42	59.089	0.00034563	0.00032626	0.00029627	0.00025398	0.00020201	0.
43	63.519	0.00030574	0.00028952	0.00026422	0.00022808	0.00018284	0.0
44	68.164	0.00027097	0.00025735	0.00023597	0.00020506	0.00016566	0.0
45	73.032	0.00024062	0.00022915	0.00021104	0.00018456	0.00015024	0.0
46	78.125	0.00021406	0.00020439	0.00018901	0.00016629	0.00013638	0.0
47	83.45	0.00019078	0.00018259	0.00016951	0.00015	0.00012392	9.4
48	89.011	0.00017032	0.00016338	0.00015223	0.00013545	0.00011269	8.6
49	94.815	0.00015233	0.00014643	0.00013691	0.00012244	0.00010258	7.9
50	100.87	0.00013647	0.00013144	0.00012329	0.00011081	9.3454e-05	7.2
51	107.17	0.00012246	0.00011817	0.00011118	0.0001004	8.5225e-05	6.6
52	113.73	0.00011007	0.0001064	0.0001004	9.1075e-05	7.78e-05	6.1
53	120.55	9.9117e-05	9.5971e-05	9.0813e-05	8.2743e-05	7.113e-05	5.6
54	127.64	8.9565e-05	8.6875e-05	8.2434e-05	7.5433e-05	6.5251e-05	5.2
55	135	8.5718e-05	8.3153e-05	7.8927e-05	7.2281e-05	6.2631e-05	5.0

% Consumption

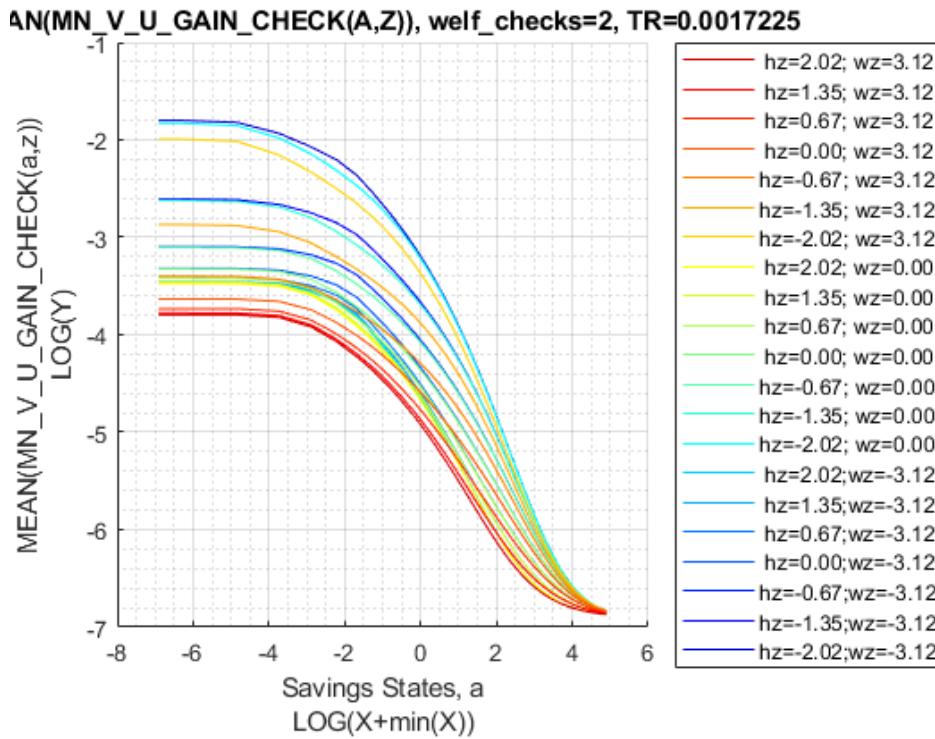
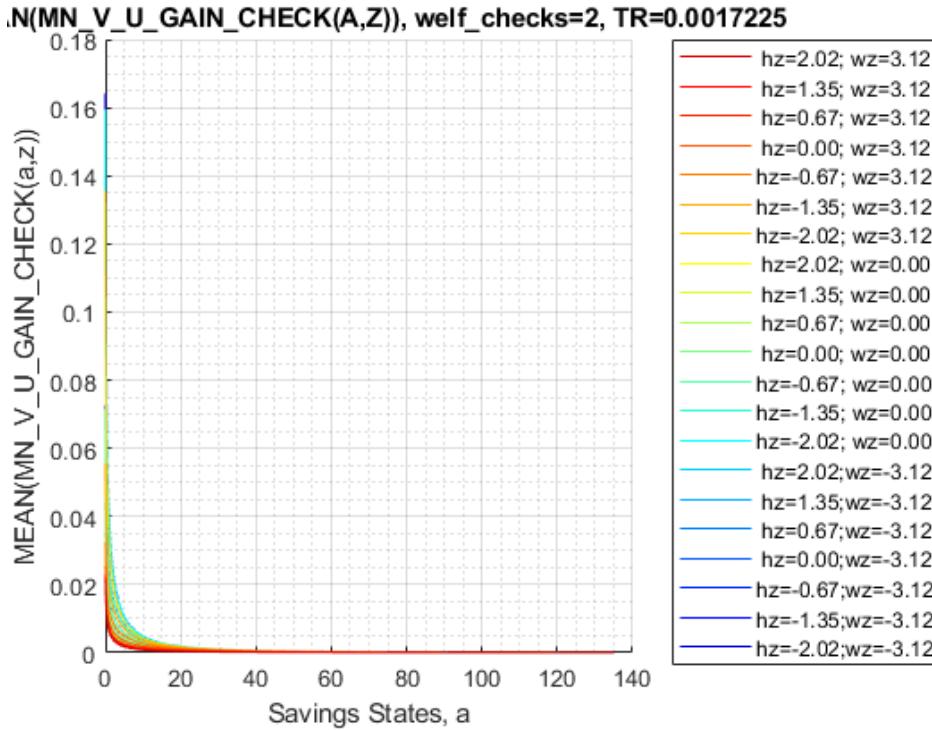
```
st_title = ['MEAN(MN_MPC_U_GAIN_CHECK(A,Z)), welf_checks=' num2str(welf_checks) ', TR=' num2str(mp_p
tb_az_c = ff_summ_nd_array(st_title, mn_MPC_U_gain_share_check, true, ["mean"], 4, 1, cl_mp_datasetd
```

group	savings	mean_eta_1	mean_eta_2	mean_eta_3	mean_eta_4	mean_eta_5	mean
1	0	0.74098	0.72618	0.66567	0.62344	0.58432	0.
2	0.00085734	0.7405	0.72615	0.66568	0.62348	0.58437	0.
3	0.0068587	0.72669	0.71733	0.66211	0.62125	0.58261	0.
4	0.023148	0.61478	0.61585	0.59388	0.58469	0.55844	0.
5	0.05487	0.52118	0.52002	0.51447	0.51652	0.50302	0.
6	0.10717	0.4677	0.46139	0.46307	0.46985	0.45963	0.
7	0.18519	0.3973	0.37778	0.38896	0.39697	0.38775	0.
8	0.29407	0.32167	0.31637	0.29863	0.31313	0.31844	0.
9	0.43896	0.25268	0.24569	0.2474	0.24208	0.24978	0.
10	0.625	0.20528	0.20521	0.20529	0.20426	0.20225	0.
11	0.85734	0.1787	0.17548	0.175	0.17606	0.17597	0.
12	1.1411	0.16031	0.1574	0.15581	0.15574	0.15674	0.
13	1.4815	0.14645	0.14407	0.14238	0.14223	0.14334	0.

14	1.8836	0.13586	0.1339	0.13226	0.13233	0.13318	0.
15	2.3525	0.12905	0.12748	0.12583	0.12631	0.12672	0.
16	2.8935	0.1248	0.12332	0.12186	0.12224	0.12237	0.
17	3.5117	0.12316	0.12217	0.12089	0.121	0.12082	0.
18	4.2121	0.1215	0.12046	0.11937	0.11949	0.11943	0.
19	5	0.11643	0.11587	0.1151	0.1147	0.11496	0.
20	5.8805	0.11287	0.11225	0.11191	0.11124	0.11141	0.
21	6.8587	0.112	0.11157	0.11084	0.11056	0.11096	0.
22	7.9398	0.11185	0.11153	0.11102	0.11039	0.11115	0.
23	9.1289	0.11312	0.1128	0.11262	0.11186	0.11264	0.
24	10.431	0.1119	0.11162	0.11143	0.11076	0.11149	0.
25	11.852	0.10944	0.10926	0.10903	0.10841	0.10905	0.
26	13.396	0.10862	0.10843	0.10826	0.10771	0.10818	0.
27	15.069	0.10932	0.10916	0.109	0.1085	0.10883	0.
28	16.875	0.1099	0.10978	0.10963	0.10944	0.10935	0.
29	18.82	0.10798	0.10788	0.10777	0.10777	0.10737	0.
30	20.91	0.10705	0.10696	0.10687	0.10661	0.10637	0.
31	23.148	0.10761	0.10755	0.10746	0.10724	0.10705	0.
32	25.541	0.1096	0.10954	0.10947	0.1095	0.10909	0.
33	28.093	0.11004	0.10999	0.10994	0.11	0.10956	0.
34	30.81	0.10764	0.1076	0.10756	0.10759	0.10721	0.
35	33.697	0.10612	0.10609	0.10605	0.10605	0.10566	0.
36	36.758	0.10599	0.10597	0.10593	0.10592	0.10557	0.
37	40	0.10721	0.1072	0.10716	0.10717	0.10715	0.
38	43.427	0.10865	0.10862	0.10859	0.10859	0.10875	0.
39	47.044	0.10816	0.10813	0.1081	0.10808	0.1081	0.
40	50.856	0.10782	0.10782	0.10778	0.10777	0.10749	0.
41	54.87	0.10726	0.10727	0.10724	0.10722	0.10708	0.
42	59.089	0.10707	0.10706	0.10706	0.10703	0.10722	0.
43	63.519	0.10759	0.10756	0.10757	0.10755	0.10766	0.
44	68.164	0.1073	0.10729	0.10727	0.10728	0.10734	0.
45	73.032	0.10665	0.10665	0.10662	0.10663	0.10666	0.
46	78.125	0.10663	0.10662	0.10661	0.1066	0.10665	0.
47	83.45	0.10789	0.10788	0.10787	0.10785	0.10789	0.
48	89.011	0.10873	0.10873	0.10872	0.10871	0.10873	0.
49	94.815	0.10779	0.10779	0.10779	0.10778	0.10777	0.
50	100.87	0.10679	0.10679	0.10678	0.10677	0.10675	0.
51	107.17	0.10631	0.1063	0.10629	0.10627	0.10623	0.
52	113.73	0.10697	0.10696	0.10694	0.10689	0.10681	0.
53	120.55	0.1072	0.10716	0.10708	0.10697	0.10673	0.
54	127.64	0.10698	0.10688	0.10673	0.10652	0.10612	0.
55	135	0.10607	0.10591	0.10572	0.10546	0.10504	0.

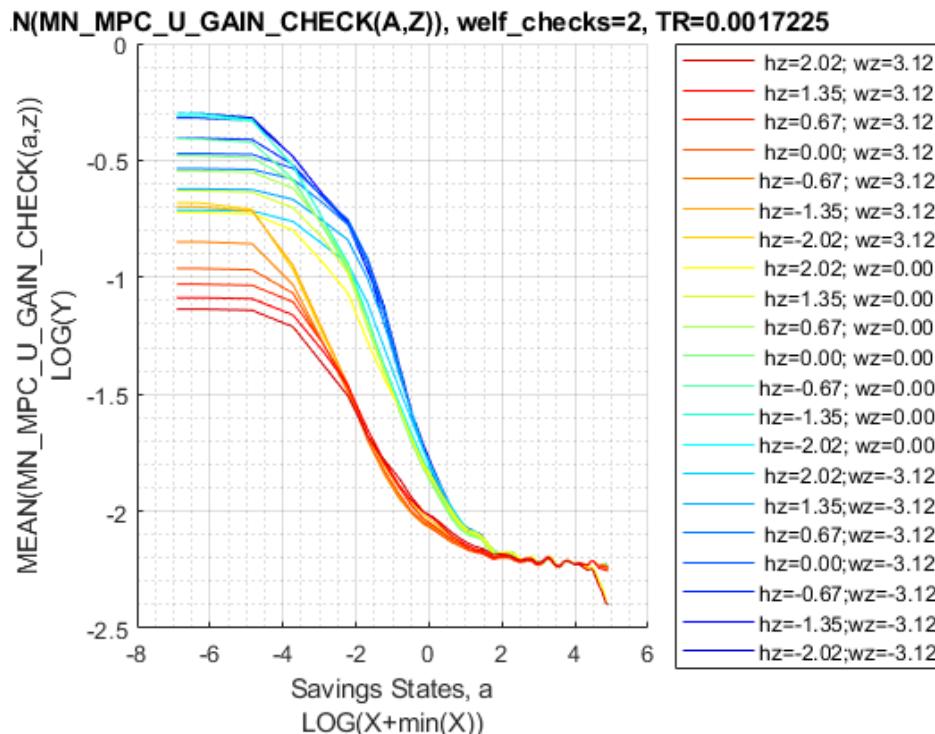
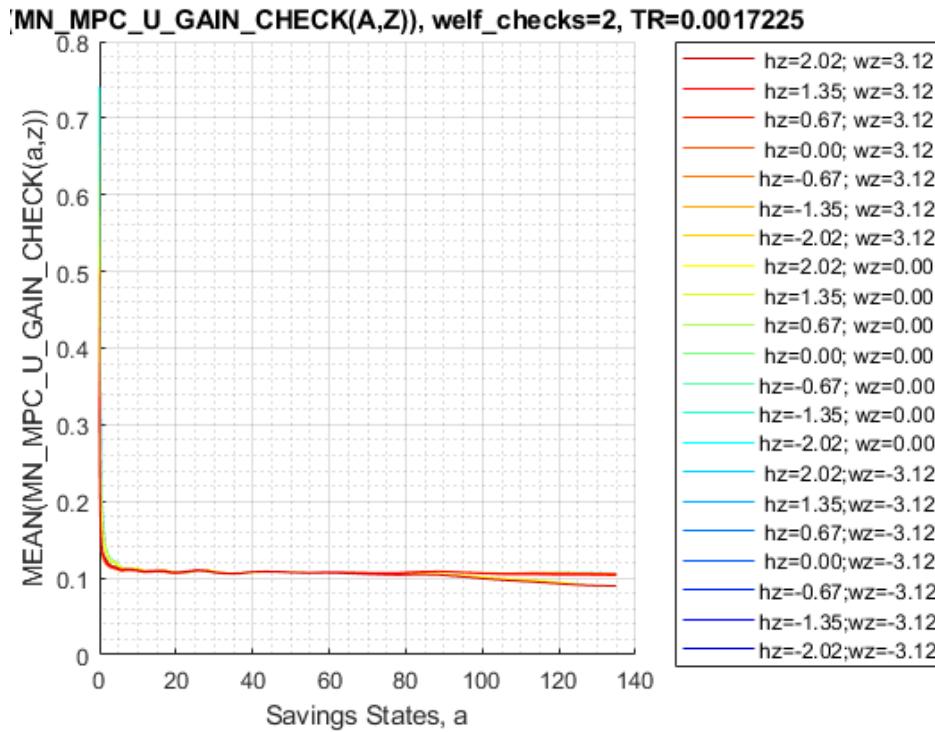
Graph Mean Values:

```
st_title = ['MEAN(MN\_V\_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\_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);
```



### 7.2.5 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

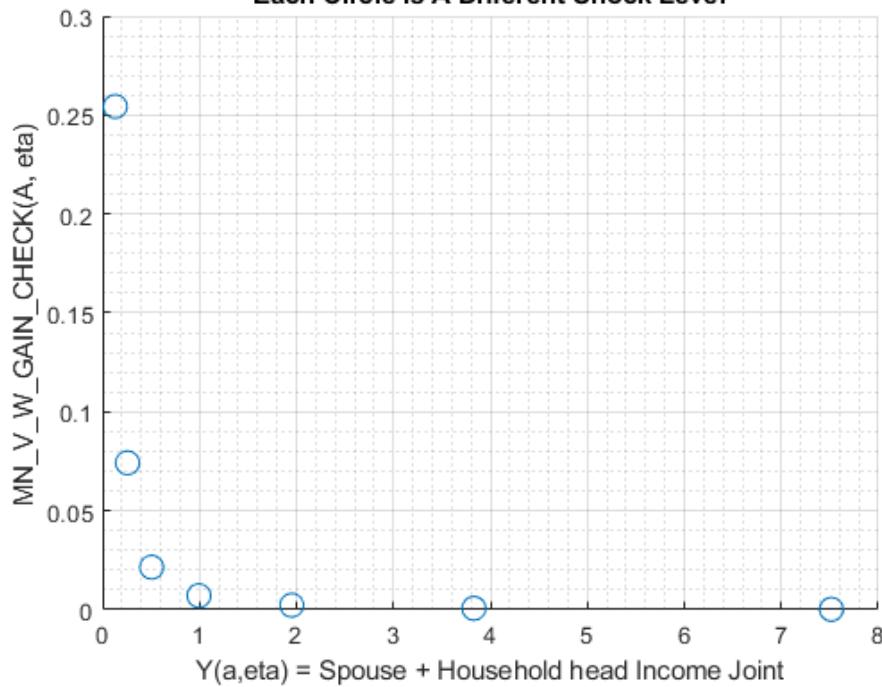
```
% Selections
it_age = 21; % +18
it_marital = 1; % 1 = unmarried
it_kids = 1; % 1 = kids is zero
it_educ = 1; % 1 = lower education
% Select: NaN(n_jgrid,n_agrid,n_etagrid,n_educgrid,n_marriedgrid,n_kidsgrid);
mn_C_W_gain_check_jemk = mn_C_W_gain_check_use(it_age, :, 1:mp_params('n_eta_H_grid'), it_educ, 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);
```

## 7.2.6 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:

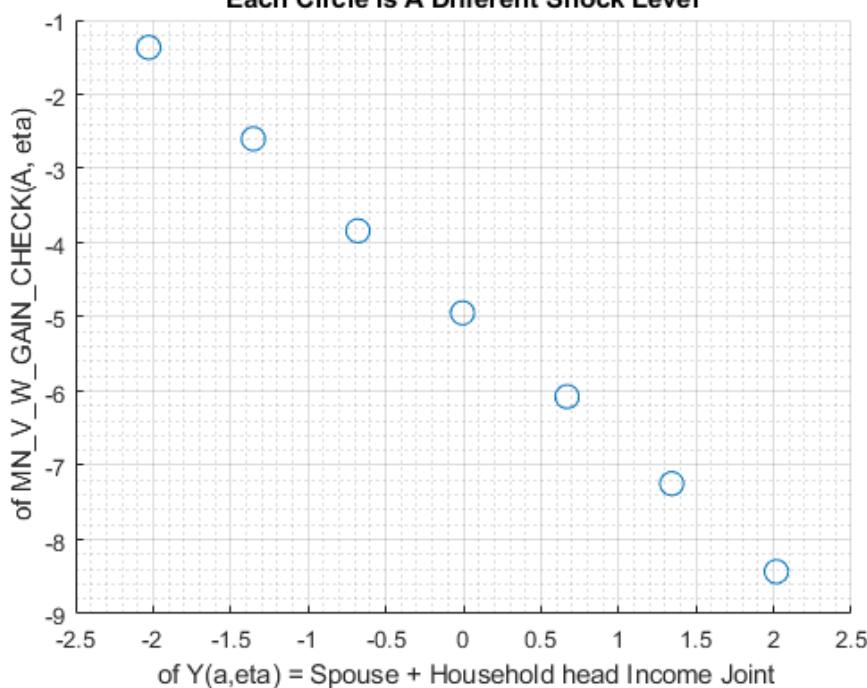
```
figure();
it_a = 1;
scatter((mt_total_inc_jemk(:,it_a)), (mt_V_W_gain_check_jemk(:,it_a)), 100);
title({'MN\_V\_W\_GAIN\_CHECK(Y(A, eta)), Lowest A, J38M0EOK0', ...
'Each Circle is A Different Shock Level'});
xlabel('Y(a,eta) = Spouse + Household head Income Joint');
ylabel('MN\_V\_W\_GAIN\_CHECK(A, eta)');
grid on;
grid minor;
```

**MN\_V\_W\_GAIN\_CHECK(Y(A, eta)), Lowest A, J38M0E0K0**  
**Each Circle is A Different Shock Level**



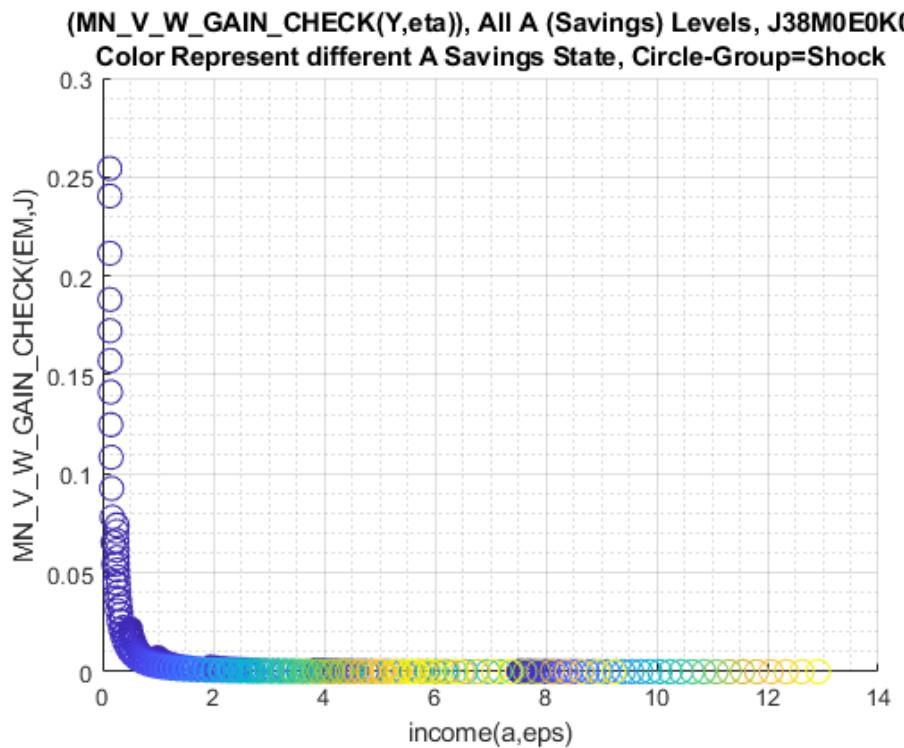
```
figure();
it_shock = 1;
scatter(log(mt_total_inc_jemk(:,it_a)), log(mt_V_W_gain_check_jemk(:,it_a)), 100);
title({'MN_V_W_GAIN_CHECK(Y(A, eta)), Lowest A, J38M0E0K0', ...
    'Each Circle is A Different Shock Level'});
xlabel(' of Y(a,eta) = Spouse + Household head Income Joint');
ylabel(' of MN_V_W_GAIN_CHECK(A, eta)');
grid on;
grid minor;
```

**MN\_V\_W\_GAIN\_CHECK(Y(A, eta)), Lowest A, J38M0E0K0**  
**Each Circle is A Different Shock Level**

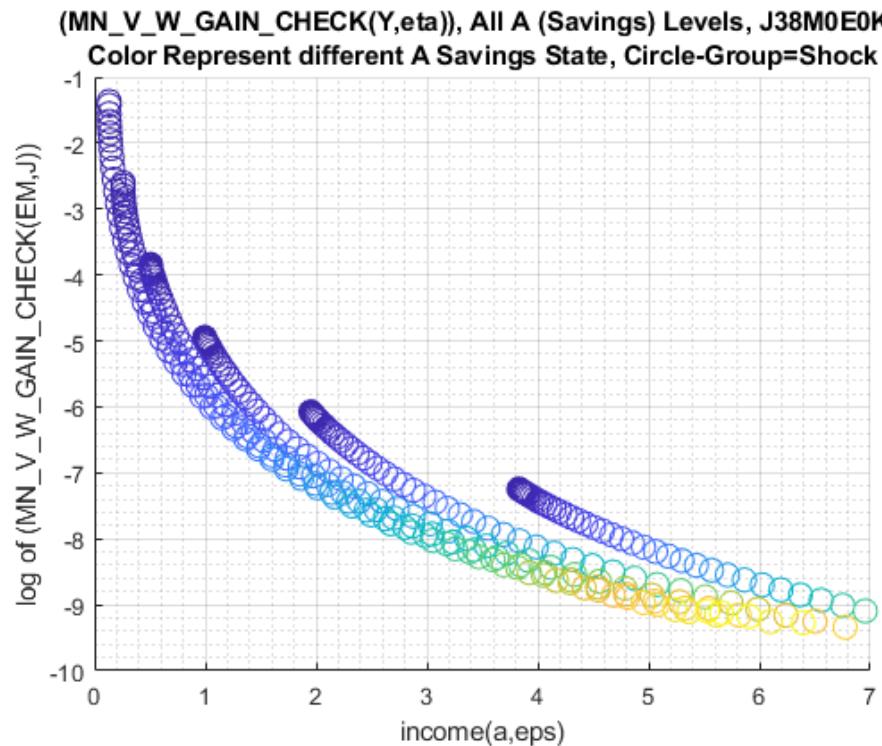


Plot all asset levels:

```
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;
```



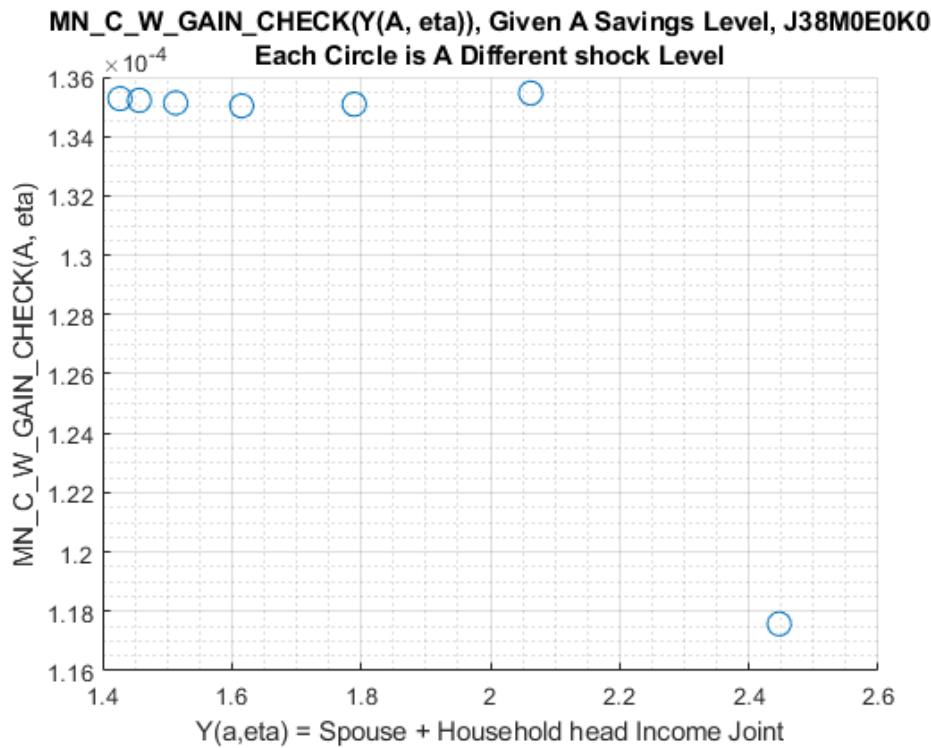
```
figure();
scatter((mt_total_inc_jemk(:)), log(mt_V_W_gain_check_jemk(:)), 100, mt_a(:));
title({'(MN\_V\_W\_GAIN\_CHECK(Y,eta)), All A (Savings) Levels, J38M0E0K0', ...
    'Color Represent different A Savings State, Circle-Group=Shock'});
xlabel('income(a,eps)');
ylabel('log of (MN\_V\_W\_GAIN\_CHECK(EM,J))');
xlim([0,7]);
grid on;
grid minor;
```



### 7.2.7 Marginal Consumption Gains, Color as Shock, Conditional on Age, Marital, Kids, and Education

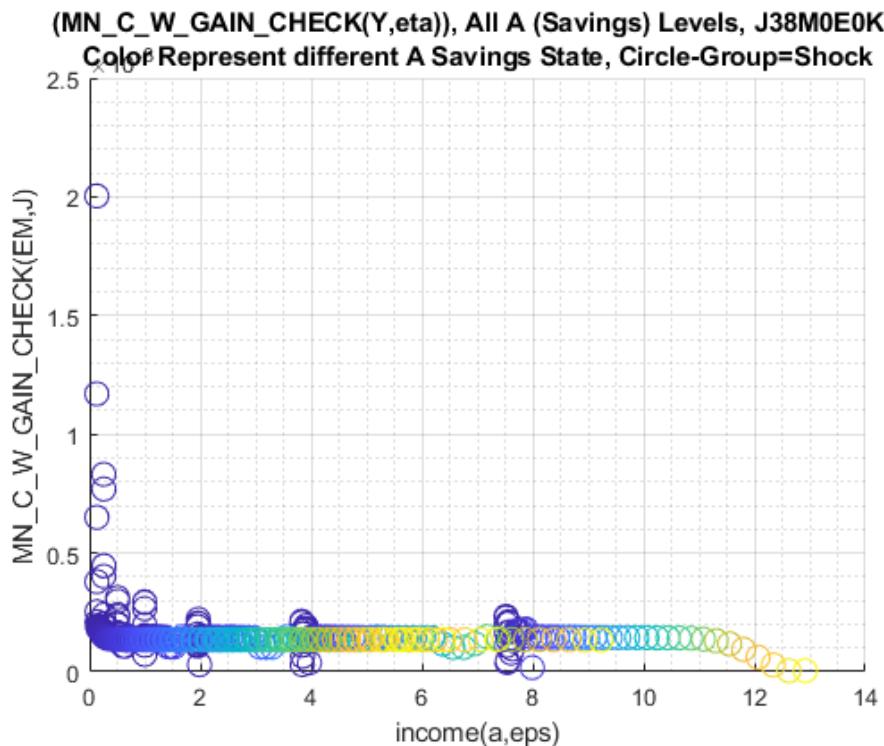
How do shocks and a impact marginal value. First plot one asset level, variation comes only from increasingly higher shocks:

```
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, 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;
```

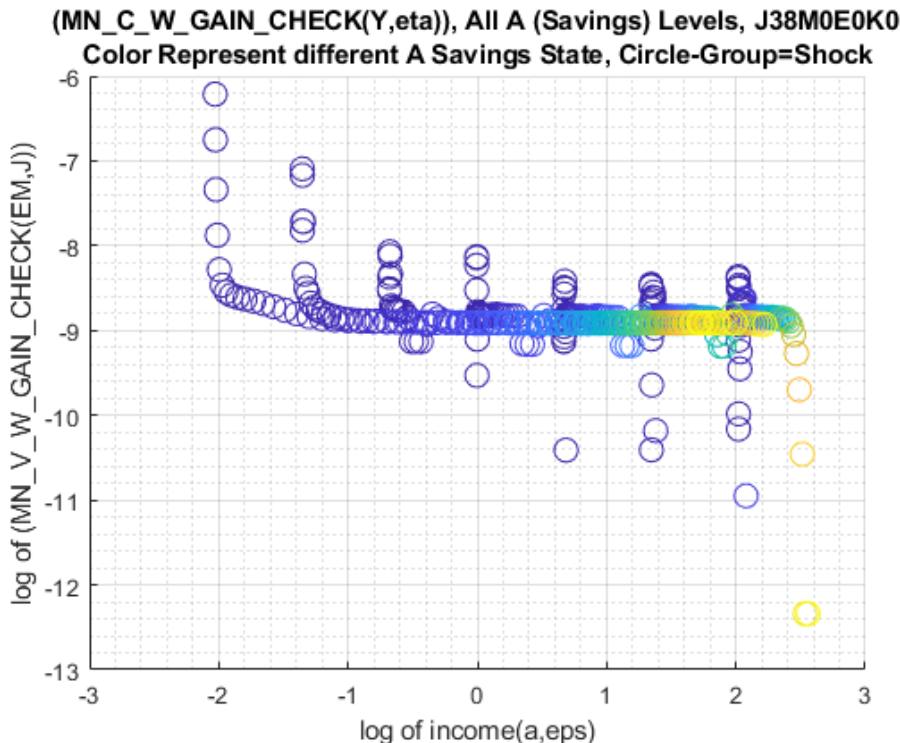


Plot all asset levels:

```
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;
```



### 7.2.8 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=0.0017225 xxxxxxxxxxxxxxxxxxxxxxxxx							
group	kids	marry	mean_age_18	mean_age_19	mean_age_20	mean_age_21	mean_age_22
1	1	0	0.018081	0.017399	0.016444	0.015175	0.014111
2	2	0	0.024198	0.023312	0.022022	0.020238	0.018732
3	3	0	0.027972	0.027119	0.025477	0.023434	0.021711
4	4	0	0.031555	0.030668	0.028763	0.026469	0.024532
5	5	0	0.034448	0.033614	0.031423	0.028959	0.026879
6	1	1	0.0041769	0.0038579	0.0035234	0.0032138	0.00294777
7	2	1	0.0057601	0.0053292	0.004867	0.0044266	0.0040531
8	3	1	0.0068486	0.0063558	0.0058113	0.0052918	0.0048508
9	4	1	0.0083574	0.007782	0.0071369	0.006497	0.0059602
10	5	1	0.010213	0.0095931	0.0088366	0.0080803	0.0074291

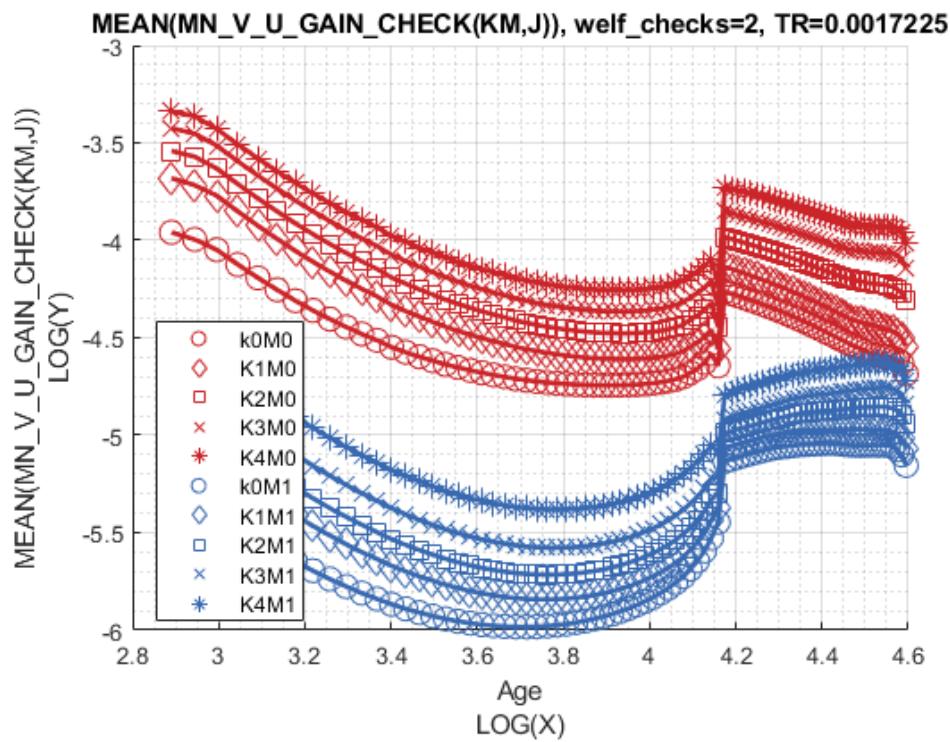
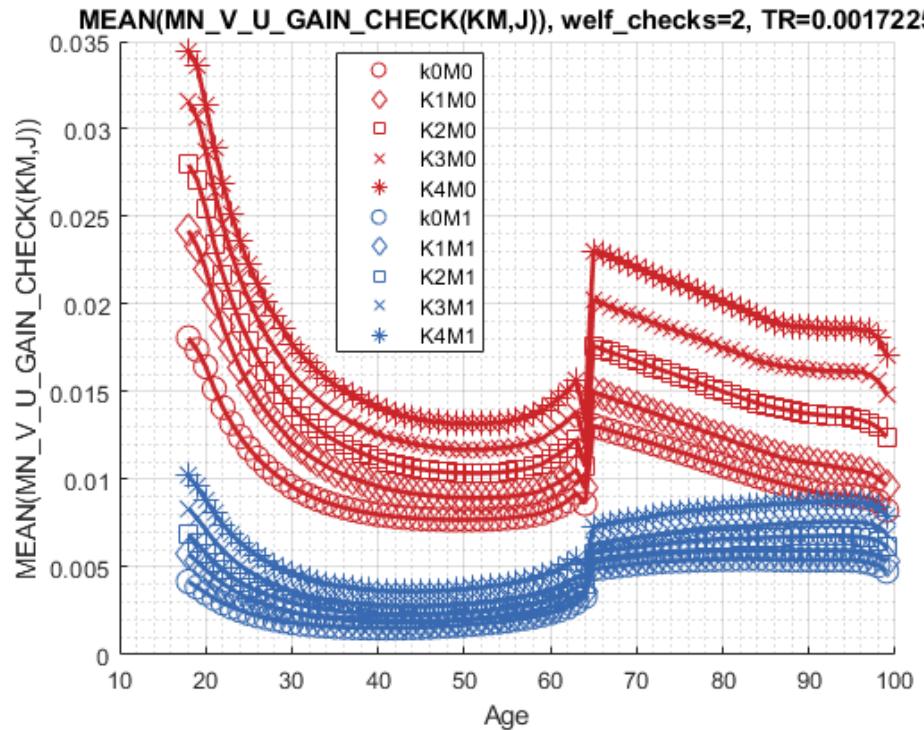
```
% Consumption Function
```

```
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 xxxxxxxxxxxxxxxxxxxxxxxxx							
group	kids	marry	mean_age_18	mean_age_19	mean_age_20	mean_age_21	mean_age_22
1	1	0	0.074031	0.10225	0.11599	0.11147	0.10577
2	2	0	0.089094	0.11803	0.13543	0.132	0.12978
3	3	0	0.10426	0.14094	0.15528	0.1534	0.15067
4	4	0	0.1102	0.15019	0.16182	0.16053	0.1588
5	5	0	0.12088	0.15838	0.16724	0.16598	0.16431
6	1	1	0.088885	0.10829	0.11259	0.10847	0.10521
7	2	1	0.093837	0.11495	0.1194	0.11493	0.11003
8	3	1	0.10258	0.126	0.1301	0.12812	0.12491
9	4	1	0.10896	0.1303	0.1351	0.13564	0.13402
10	5	1	0.12962	0.14112	0.14504	0.14418	0.14327

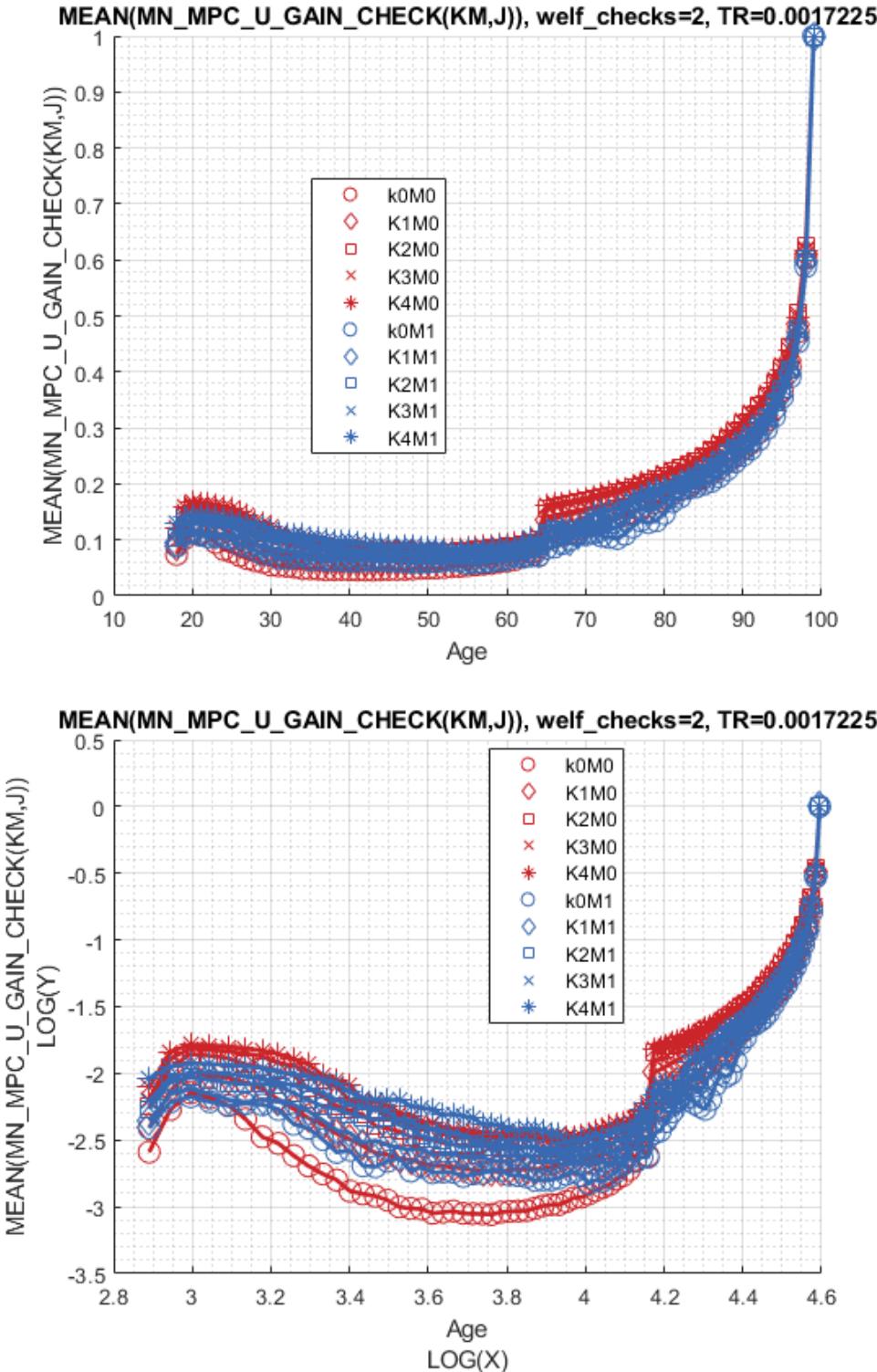
Graph Mean Values:

```
st_title = ['MEAN(MN_V_U_GAIN_CHECK(KM,J)), welf_checks=' num2str(welf_checks) ', TR=' num2str(mp_
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(TR)];
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);
```



### 7.2.9 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...

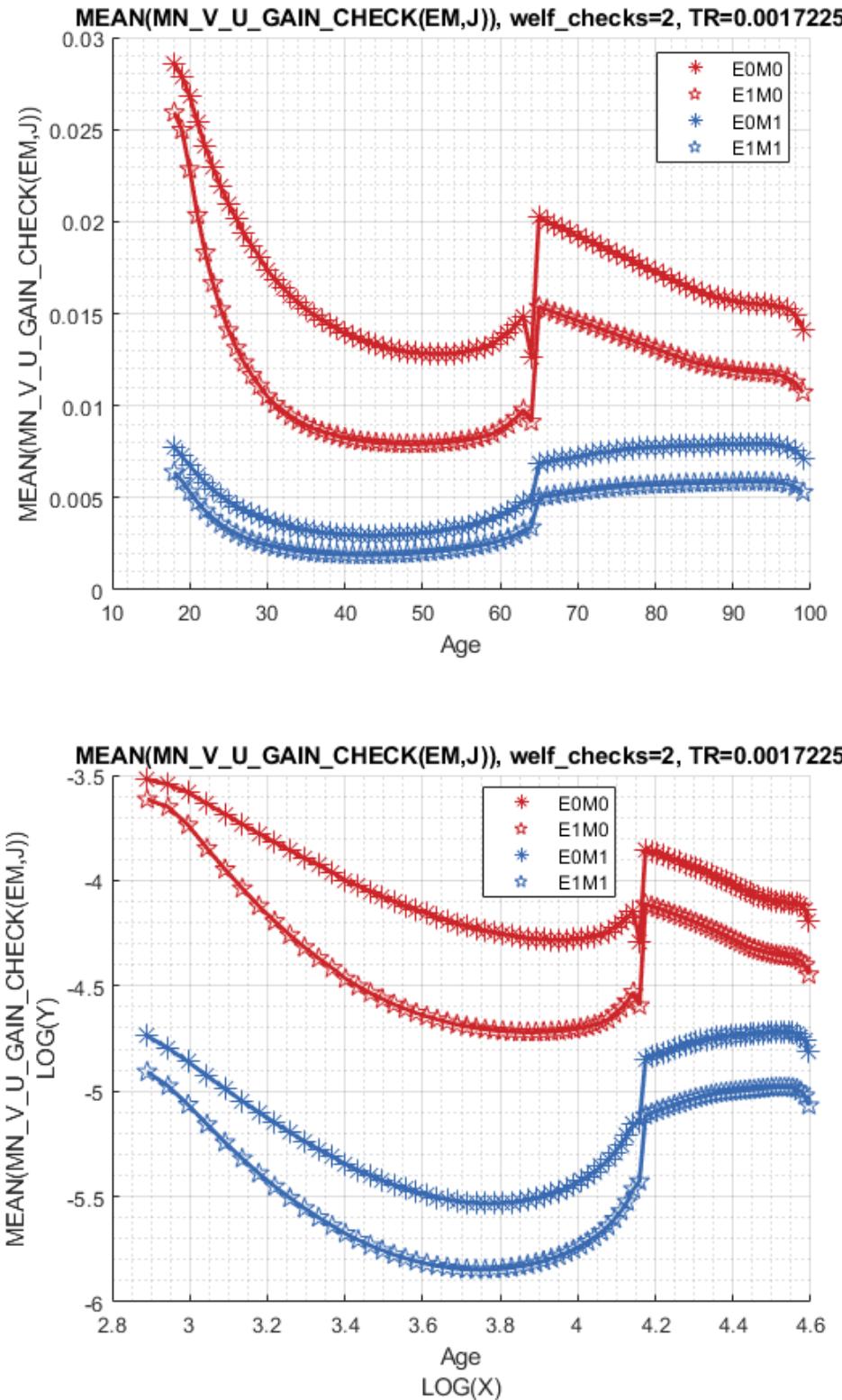
xxx MEAN(MN_V_U_GAIN_CHECK(EM,J)), welf_checks=2, TR=0.0017225 xxxxxxxxxxxxxxxxxxxxxxxxx
group   edu   marry   mean_age_18   mean_age_19   mean_age_20   mean_age_21   mean_age_22
-----  ---  -----  -----  -----  -----  -----  -----
1       0       0       0.028598   0.027879   0.026816   0.02537    0.024081
2       1       0       0.025917   0.024966   0.022835   0.02034    0.018305
3       0       1       0.0077546  0.0072639  0.0067503  0.0062497  0.0058142
4       1       1       0.0063878  0.0059033  0.0053197  0.0047542  0.0042822

% 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 xxxxxxxxxxxxxxxxxxxxxxxxx
group   edu   marry   mean_age_18   mean_age_19   mean_age_20   mean_age_21   mean_age_22
-----  ---  -----  -----  -----  -----  -----  -----
1       0       0       0.083839   0.10872    0.12214    0.11934    0.11723
2       1       0       0.11555    0.1592     0.17216    0.17002    0.1665
3       0       1       0.096421   0.11218    0.11688    0.11343    0.11043
4       1       1       0.11313    0.13609    0.14001    0.13911    0.13655
```

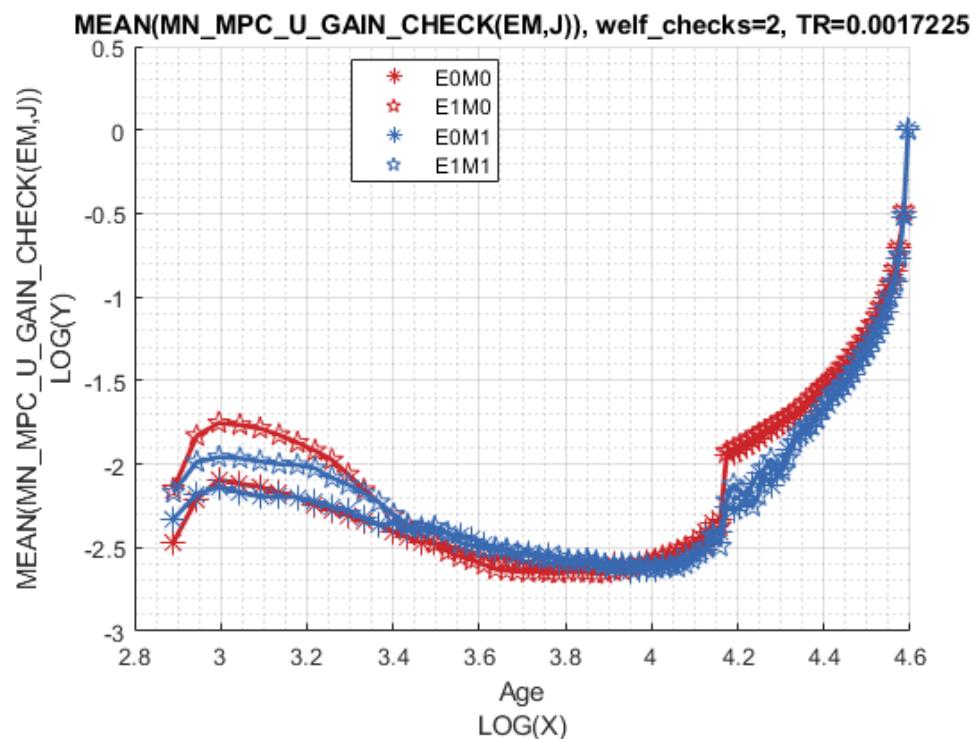
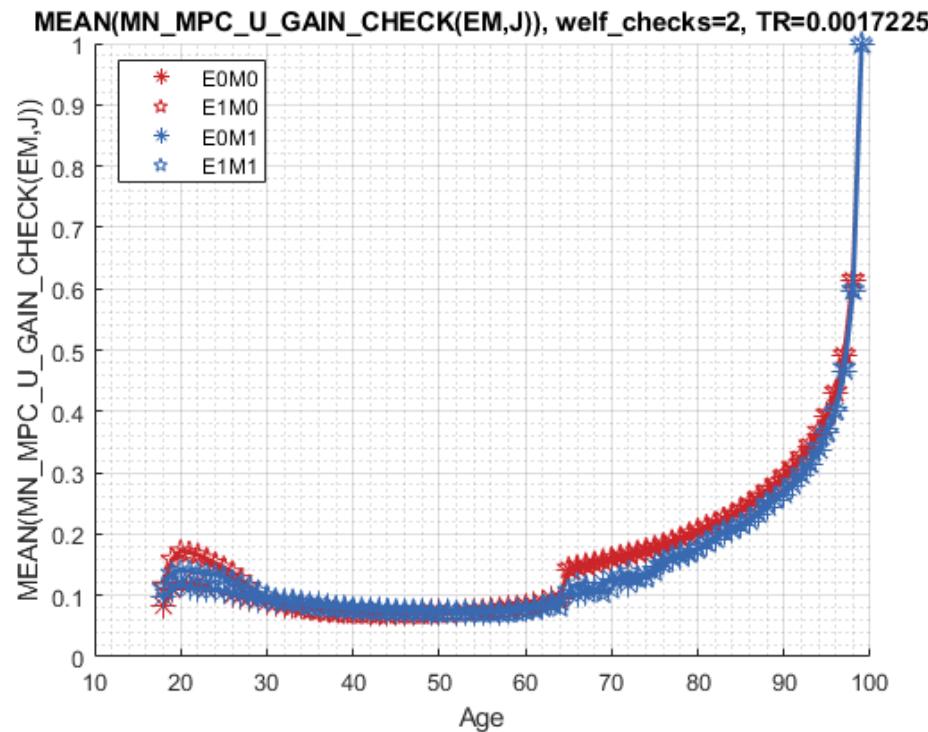
Graph Mean Values:

```
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(TR)];
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 8

## 2019 Expectations Given Income, Age, Kids and Marital Status

### 8.1 2019 Age, Income, Kids, Marry EV and EC of One Check

This is the example vignette for function: [snw\\_evuvw20\\_jaeemk](#) from the [PrjOptiSNW Package](#). 2019 integrated over VU and VW

#### 8.1.1 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_moredense_a100z266_e0m0');
% mp_params = snw_mp_param('default_tiny');
% mp_params = snw_mp_param('default_dense');
mp_params = snw_mp_param('default_docdense');
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_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;
```

### 8.1.2 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_moredense;SNW_MP_CONTROL=default_test;time=116

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;
% 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;SNW_MP_CONTROL=
[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_moredense;SNW_MP_CONTROL=default_test;time=192.6858

% 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;
```

### 8.1.3 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_true);

Wage quintile cutoffs=0.48006      0.84085      1.2804      2.2175
Completed SNW_HH_PRECOMPUTE;SNW_MP_PARAM=default_moredense;SNW_MP_CONTROL=default_test;time cost=123

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_moredense;SNW_MP_CONTROL=default_test;time=2.66
-----
xxxxxxxxxxxxxxxxxxxxxxxxxxxxxxxxxxxxxx
CONTAINER NAME: mp_outcomes ND Array (Matrix etc)
xxxxxxxxxxxxxxxxxxxxxxxxxxxxxxxxxxxxxx
```

	i	idx	ndim	numel	rowN	colN	sum	mean
	-	---	----	-----	---	-----	-----	-----
Phi_true	1	1	6	1.128e+07	83	1.359e+05	45.793	4.0598e-06
Phi_true_jmky	2	2	4	1.6482e+05	82	2010	45.787	0.0002778

### 8.1.4 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, cons_ss, V_unemp, cons_unemp, mp_precompute_res);

Completed SNW_A4CHK_UNEMP_BISEC_VEC;welf_checks=0;TR=0.0017225;xi=0.5;b=0;SNW_MP_PARAM=default_moredense;
Completed SNW_A4CHK_WRK_BISEC_VEC;welf_checks=0;TR=0.0017225;SNW_MP_PARAM=default_moredense;SNW_MP_CONTROL=default_test;timeEUEC=2.000000;
Completed SNW_EVUVW20_JAEEMK;SNW_MP_PARAM=default_moredense;SNW_MP_CONTROL=default_test;timeEUEC=2.000000;
Completed SNW_EVUVW19_JAEEMK;SNW_MP_PARAM=default_moredense;SNW_MP_CONTROL=default_test;time=77.360300;
```

% 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\_moredense;SNW\_MP\_CONTROL=default\_test;time=5.0081

---

xxxxxxxxxxxxxxxxxxxxxxxxxxxxxx

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

xxxxxxxxxxxxxxxxxxxxxxxxxxxxxx

	i	idx	ndim	numel	rowN	colN	sum	mean
	-	---	----	-----	---	-----	-----	-----
Phi_true	1	1	6	1.128e+07	83	1.359e+05	45.793	4.0598e-06
Phi_true_jmky	2	2	4	1.6482e+05	82	2010	45.787	0.0002778
ec19_jaeemk	3	3	6	1.1144e+07	82	1.359e+05	4.7069e+07	4.223
ec19_jmky	4	4	4	1.6482e+05	82	2010	3.2335e+05	1.961
ev19_jaeemk	5	5	6	1.1144e+07	82	1.359e+05	-2.1277e+07	-1.909
ev19_jmky	6	6	4	1.6482e+05	82	2010	-16603	-0.1007

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, cons_ss, V_unemp, cons_unemp, mp_precompute_res);
```

```
Completed SNW_A4CHK_UNEMP_BISEC_VEC;welf_checks=1;TR=0.0017225;xi=0.5;b=0;SNW_MP_PARAM=default_moredense;
Completed SNW_A4CHK_WRK_BISEC_VEC;welf_checks=1;TR=0.0017225;SNW_MP_PARAM=default_moredense;SNW_MP_CONTROL=default_test;timeEUEC=1.900000;
Completed SNW_EVUVW20_JAEEMK;SNW_MP_PARAM=default_moredense;SNW_MP_CONTROL=default_test;timeEUEC=1.900000;
Completed SNW_EVUVW19_JAEEMK;SNW_MP_PARAM=default_moredense;SNW_MP_CONTROL=default_test;time=85.813500;
```

% 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\_moredense;SNW\_MP\_CONTROL=default\_test;time=4.5581

```

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

```

	i	idx	ndim	numel	rowN	colN	sum	mean
	-	---	----	-----	---	-----	-----	-----
Phi_true	1	1	6	1.128e+07	83	1.359e+05	45.793	4.0598e-0
Phi_true_jmky	2	2	4	1.6482e+05	82	2010	45.787	0.000277
ec19_jaeemk	3	3	6	1.1144e+07	82	1.359e+05	4.7072e+07	4.224
ec19_jmky	4	4	4	1.6482e+05	82	2010	3.2336e+05	1.961
ev19_jaeemk	5	5	6	1.1144e+07	82	1.359e+05	-2.1225e+07	-1.904
ev19_jmky	6	6	4	1.6482e+05	82	2010	-16281	-0.09877

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'));

```

### 8.1.5 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});

```

### 8.1.6 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_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_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(:);

```

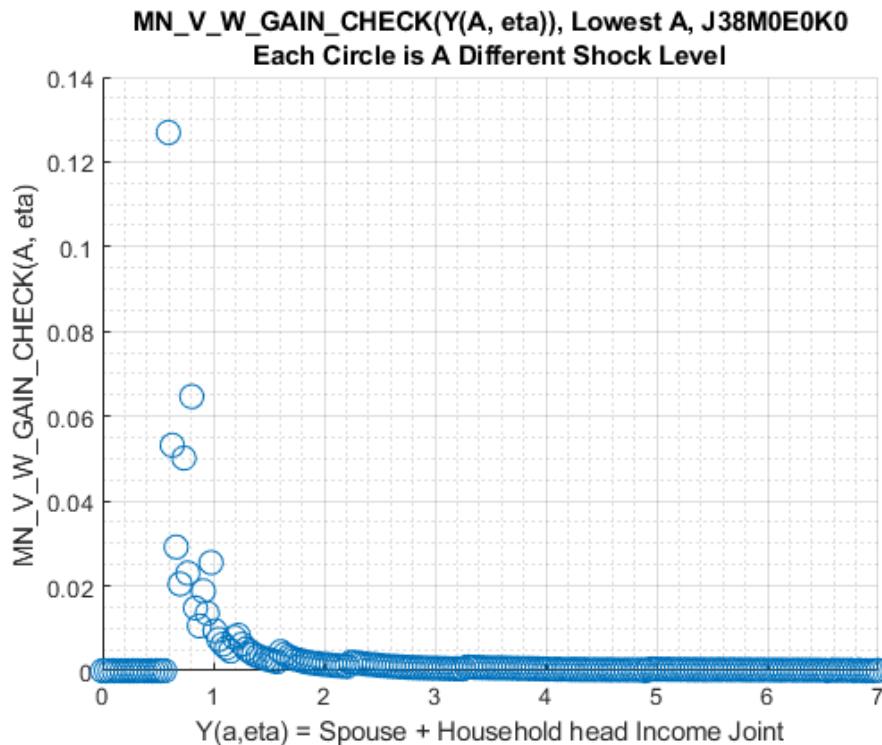
Marginal Value Gains, Color as Shock, Conditional on Age, Marital, Kids, and Education

How do shocks and age 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, J38M0EOK0', ...
    '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;

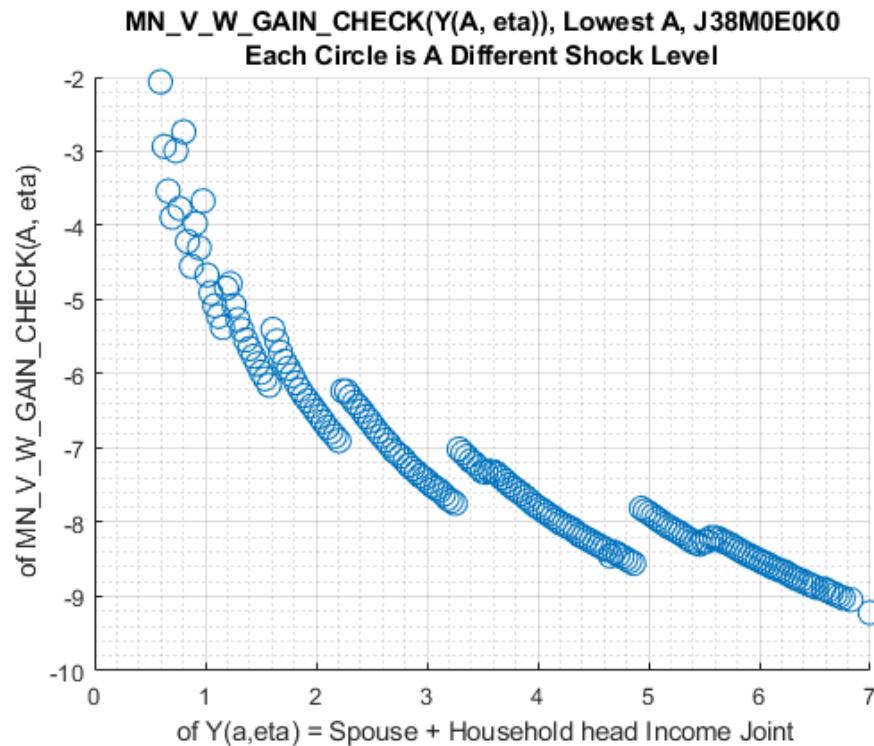
```



```

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, J38M0EOK0', ...
    '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;

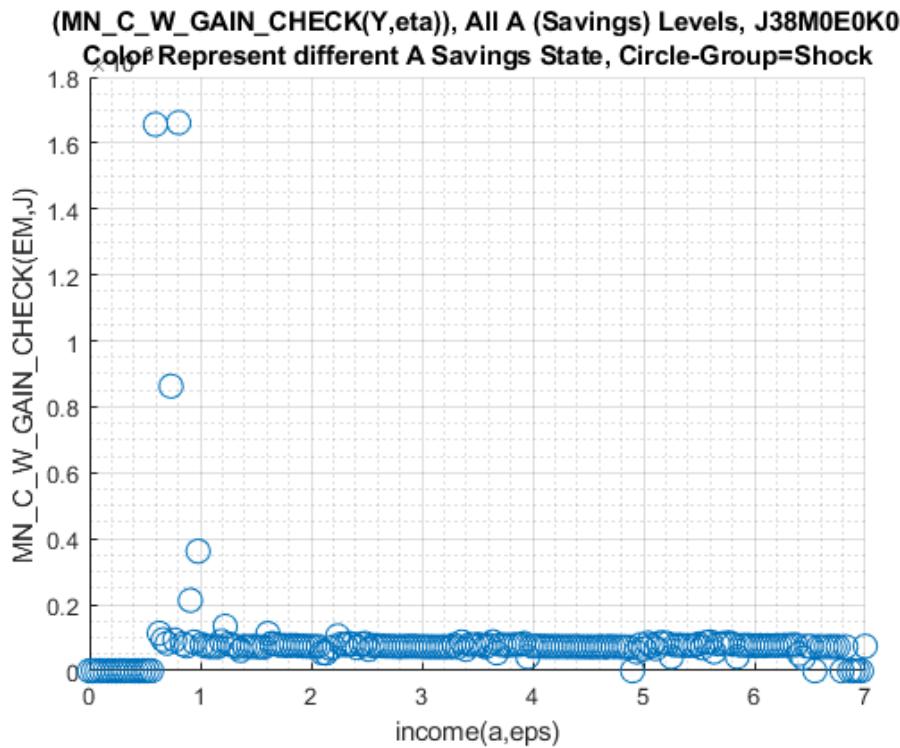
```



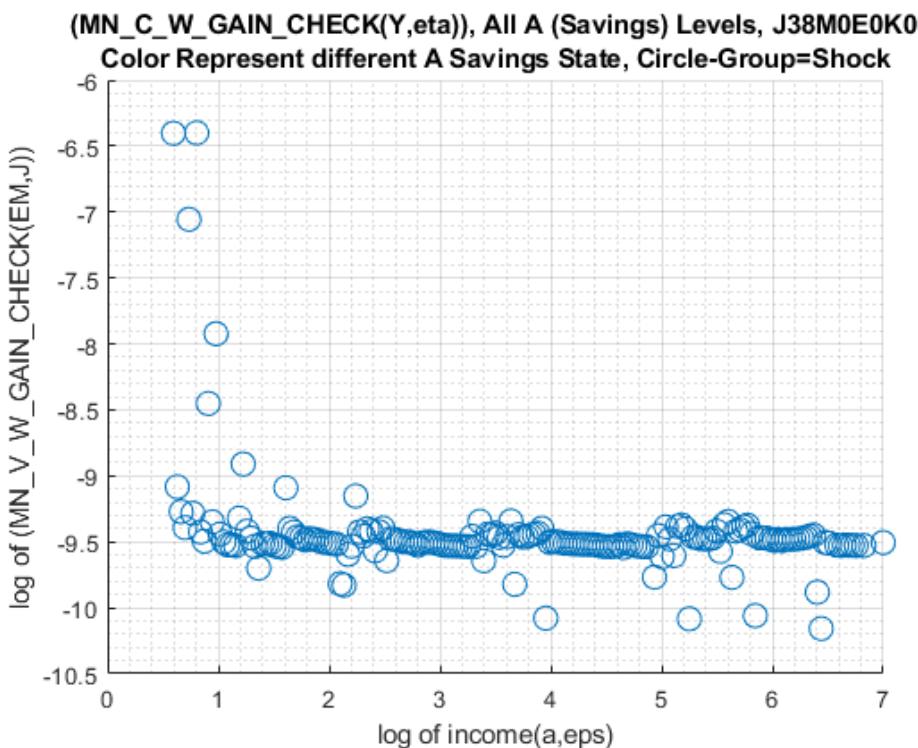
Marginal Consumption Gains, Color as Shock, Conditional on Age, Marital, Kids, and Education

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_V_W_GAIN_CHECK(EM,J))');
grid on;
grid minor;
```



## 8.2 2019 Age, Income, Kids, Marry EV and EC All Checks

This is the example vignette for function: `snw_evuvw20_jaeemk` from the [PrjOptiSNW Package](#). 2019 integrated over VU and VW

### 8.2.1 Test SNW\_EVUVW19\_JMKY\_ALLCHECKS Parameters

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 retrievel costs

```
clear all;
% Start mp contorls
mp_controls = snw_mp_control('default_test');
% 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;
mp_controls('bl_print_evuvw19_jmky_verbose') = false;
```

Dense default, and unemployment parameters:

```
% default dense load
mp_params = snw_mp_param('default_docdense');
% Unemployment
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 wezlfare check (can receive multiple checks). TO DO: Update with alternat
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;
```

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 betwen 238000,
fl_max_phaseout = 238000;
fl_multiple = 58056;
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;
```

### 8.2.2 SNW\_EVUVW19\_JMKY\_ALLCHECKS Low Storage Invoke

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_solu_type = 'biseq_vec';  
bl_parfor = false;  
it_workers = 1;  
bl_export = false;  
snm_suffix = ['_ybin' num2str(it_bin_dollar_before_phaseout)];  
[ev19_jmky_allchecks, ec19_jmky_allchecks, output] = ...  
    snw_evuvw19_jmky_allchecks(mp_params, mp_controls, ...  
        st_solu_type, bl_parfor, it_workers, bl_export, snm_suffix);
```



# Chapter 9

# Calibration

## 9.1 Calibrate Beta and Normalize GDP

Taking advantage of `snw.ds.main` from the [PrjOptiSNW Package](#), this function calibrates the discount factor and also solves for the normalizing constant.

### 9.1.1 Calibrate Parameter Controls for SNW Functions

Set up controls for shock process and tiny/small/dense/densemore

```

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') = timer;
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;
```

### 9.1.2 Calibrate Routine

Test this for 3 iterations

```
%% Calibration  
err=1;  
tol=0.005;
```

## Start calibration

```
it_counter = 1;  
while err>tol && it_counter <= 3  
    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);
A_prime_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
```

```
a2_old:1.5286, a2_new:1.5286, tm_end_a2:4134.1075
Median household income (target=1.0)=0.99853
Aggregate wealth to aggregate income (target=3.0)=3.0026
counter=2;beta=0.97116;theta=0.56523
```



# Appendix A

## Index and Code Links

### A.1 Parameters links

1. Model Parameters: [mlx](#) | [m](#) | [pdf](#) | [html](#)
  - Model parameters, transition matrices, permanent heterogeneities.
  - **PrjOptiSNW:** [\*snw\\_mp\\_param\(\)\*](#)
2. Model Controls Parameters: [mlx](#) | [m](#) | [pdf](#) | [html](#)
  - Parameters to control display options etc.
  - **PrjOptiSNW:** [\*snw\\_mp\\_control\(\)\*](#)

### A.2 Solving the Dynamic Life Cycle Problem links

1. Policy and Value Functions Dynamic Life Cycle Vectorized Bisection: [mlx](#) | [m](#) | [pdf](#) | [html](#)
  - Solving for policy and value functions from 18 to 100 years of age, at 1 year interval.
  - Households face persistent productivity shocks for household heads, stochastic shocks for spousal income, exogenous children under age 17 transition probability, and age-specific household-head survival probabilities.
  - The household can have up to four children under age 17, and has permanent heterogeneity in marital status and education types.
  - Problem solved for exact savings choices using [vectorized bisection](#) from from MEconTools.
  - **PrjOptiSNW:** [\*snwx\\_vfi\\_bisec\\_vec\(\)\*](#)

### A.3 Alternative Value Function Solution Testing links

1. Small Test Looped Minimizer Routine to Solve for Exact Savings Choices: [mlx](#) | [m](#) | [pdf](#) | [html](#)
  - Solve for the exact savings choices using matlab minimizer in an iterative loop.
  - The code demonstrates the solution structure. We use [\*snwx\\_vfi\\_bisec\\_vec\(\)\*](#) with [vectorized bisection](#) for working implementations.
  - Due to speed, only show testing results at small grid without spousal shocks.
  - **PrjOptiSNW:** [\*snw\\_vfi\\_main\(\)\*](#)
2. Small Test Looped over States Grid Search Solution: [mlx](#) | [m](#) | [pdf](#) | [html](#)
  - The savings choice grid is the same as the savings states grid. Solve for optimal savings choices using grid-search. Loop over the state space, at each state-space point, vectorized optimization.
  - Our problem requires very high precision to solve for the marginal gains to households from each increment of welfare checks. We rely on the exact solution method from [\*snwx\\_vfi\\_bisec\\_vec\(\)\*](#) for the working code.
  - Due to speed, only show testing results at small grid without spousal shocks.
  - **PrjOptiSNW:** [\*snw\\_vfi\\_main\\_grid\\_search\(\)\*](#)
3. Small Test Vectorized Bisection Solve for Exact Savings Choices: [mlx](#) | [m](#) | [pdf](#) | [html](#)

- Vectorized bisection exact solution code tested with small grid to compare to alternative solution methods.
  - Small grid without spousal shocks.
  - PrjOptiSNW: [\*snwx\\_vfi\\_bisec\\_vec\(\)\*](#)
4. Small Test Spousal Shocks Test Vectorized Bisection Solve for Exact Savings Choices: [mlx](#) | [m](#) | [pdf](#) | [html](#)
- Vectorized bisection exact solution code tested with small grid to compare to alternative solution methods.
  - Small grid with spousal shocks. There are three shocks: persistent household head income shock, i.i.d. spousal income shock, and persistent kids count transition shocks.
  - PrjOptiSNW: [\*snwx\\_vfi\\_bisec\\_vec\(\)\*](#)

## A.4 Solution with Unemployment links

1. Policy and Value Functions Dynamic Life Cycle if Unemployed: [mlx](#) | [m](#) | [pdf](#) | [html](#)
  - Solving the dynamic programming problem conditional on having an one period unemployment shock.
  - There is an unemployment shock in 2020. We first solve for the policy and value functions without the unemployment shock.
  - Using the value function from the world without the 2020 covid unemployment shock as future values, we solve for optimal choices in 2020 given a COVID unemployment shock.
  - The COVID shock lowers the realization of household's stochastic income process proportionally, but the lost income might be replenished by unemployment benefits up to 100 percent. Unemployment benefits have to be paid for by taxes.
  - PrjOptiSNW: [\*snwx\\_vfi\\_bisec\\_vec\(\)\*](#)

## A.5 Household Life Cycle Distribution links

1. Assets and Demographic Distributions with Continuous Exact Savings Choices: [mlx](#) | [m](#) | [pdf](#) | [html](#)
  - Simulate the life cycle distribution of assets, consumptions, and demographic patterns up to age 100, given exogenous initial distributions at age 18.
  - Solves for budget clearing tax rates given distributional results.
  - Uses vectorized bisection to solve for exact savings choices, looped distribution code.
  - PrjOptiSNW: [\*snw\\_ds\\_main\(\)\*](#)
2. Assets and Demographic Distributions with Grid Search: [mlx](#) | [m](#) | [pdf](#) | [html](#)
  - Grid search solution using grid search for savings choices, the savings state-space grid is the same as the savings choice-grid.
  - Exact choice solution from [\*snw\\_ds\\_main\(\)\*](#) generates significantly smoother distributions.
  - PrjOptiSNW: [\*snw\\_ds\\_main\\_grid\\_search\(\)\*](#)

## A.6 Value of Each Check links

1. Marginal Gain Per Check 2020 Employed: [mlx](#) | [m](#) | [pdf](#) | [html](#)
  - Evaluate the marginal gain per check in 2020 if household head is employed.
  - Solve for the increase in savings that is equivalent to the impact of an additional check on a household's resource available in 2020, given tax and interest rates considerations.
  - PrjOptiSNW: [\*snw\\_a4chk\\_wrk\\_bisec\\_vec\(\)\*](#)
2. Marginal Gain Per Check 2020 Unemployed: [mlx](#) | [m](#) | [pdf](#) | [html](#)
  - Evaluate the marginal gain per check in 2020 if household head is unemployed.
  - Solve for the increase in savings that is equivalent to the impact of an additional check on a household's resource available in 2020, given tax and interest rates considerations.
  - PrjOptiSNW: [\*snw\\_a4chk\\_unemp\\_bisec\\_vec\(\)\*](#)

## A.7 Value of Each Check links

1. Marginal Gain Per Check 2020 Employed: [mlx](#) | [m](#) | [pdf](#) | [html](#)
  - Evaluate the marginal gain per check in 2020 if household head is employed.
  - Solve for the increase in savings that is equivalent to the impact of an additional check on a household's resource available in 2020, given tax and interest rates considerations.
  - PrjOptiSNW: [snw\\_a4chk\\_wrk\\_bisec\\_vec\(\)](#)
2. Marginal Gain Per Check 2020 Unemployed: [mlx](#) | [m](#) | [pdf](#) | [html](#)
  - Evaluate the marginal gain per check in 2020 if household head is unemployed.
  - Solve for the increase in savings that is equivalent to the impact of an additional check on a household's resource available in 2020, given tax and interest rates considerations.
  - PrjOptiSNW: [snw\\_a4chk\\_unemp\\_bisec\\_vec\(\)](#)

## A.8 Outcomes Full State Space with Savings, Shocks and Education links

1. Value in 2020 Given Age, Savings, Shocks, Kids, Education and Marriage: [mlx](#) | [m](#) | [pdf](#) | [html](#)
  - Expected value and expected consumption from 2020 for a household given at a particular age (18-100), with a particular savings level, at a particular combination of household head and spouse income shocks, with 0 to 4 children, high or low Education status, and married or not married.
  - This uses the unemployment probability and generates the average value given the probability of the unemployment state that is dependent on the state-space.
  - PrjOptiSNW: [snw\\_evuvw20\\_jaeemk\(\)](#)
2. Expected Value in 2019 Given Age, Savings, Shocks, Kids, Education and Marriage: [mlx](#) | [m](#) | [pdf](#) | [html](#)
  - Expected value and expected consumption from 2019 for a household at a particular age (18-99), savings level, shocks combinations, kids/education/marriage status, given 2019 optimal savings choices, income shock transition probability as well as household children count transition probabilities.
  - PrjOptiSNW: [snw\\_evuvw19\\_jaeemk\(\)](#)

## A.9 Expectations Given Income, Age, Kids and Marital Status links

1. Expected Value from 2019 Given Age, Kids, Income and Marriage: [mlx](#) | [m](#) | [pdf](#) | [html](#)
  - Expected Value from 2019 Given Age, Kids, Income and Marriage.
  - Each 2019 income group consists of individuals with varying productivity shocks, savings, and from lower and higher education groups.
  - PrjOptiSNW: [snw\\_evuvw19\\_jmky\(\)](#)
2. Expected Value from 2019 Given Age, Kids, Income and Marriage for All Checks: [mlx](#) | [m](#) | [pdf](#) | [html](#)
  - Expected Value from 2019 Given Age, Kids, Income and Marriage for All Checks.
  - This is the gateway function that solves policy functions, derive distributions, computes value in 2020 with and without unemployment shocks with varying check levels, derives 2019 planner expected values given household optimization and shocks, and finds the mass of individuals in different income/age/marital-status bins, and saves the simulated value of check results for the planner.
  - PrjOptiSNW: [snw\\_evuvw19\\_jmky\\_allchecks\(\)](#)

## A.10 Calibration links

1. Calibrate Discount Factor and Normalize GDP: [mlx](#) | [m](#) | [pdf](#) | [html](#)
  - We calibrate the model so that the Asset/Savings/Capital to GDP/Income ratio is 3.
  - We normalize the model so that median household income is equal to 1 in the model.
  - PrjOptiSNW: [snw\\_calibrate\\_beta\\_norm\\_gdp\(\)](#)



# Bibliography

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Vegard M. Nygaard, Bent E. Sorensen, F. W. (2020). Optimal allocation of the covid-19 stimulus checks.

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