Online Appendix: Hours and Wages

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A Appendix Figures and Tables

A.1 Figures

Figure A.1: Main Facts by Gender

(a) Distribution of Usual Weekly Hours (b) Long Hours Distribution

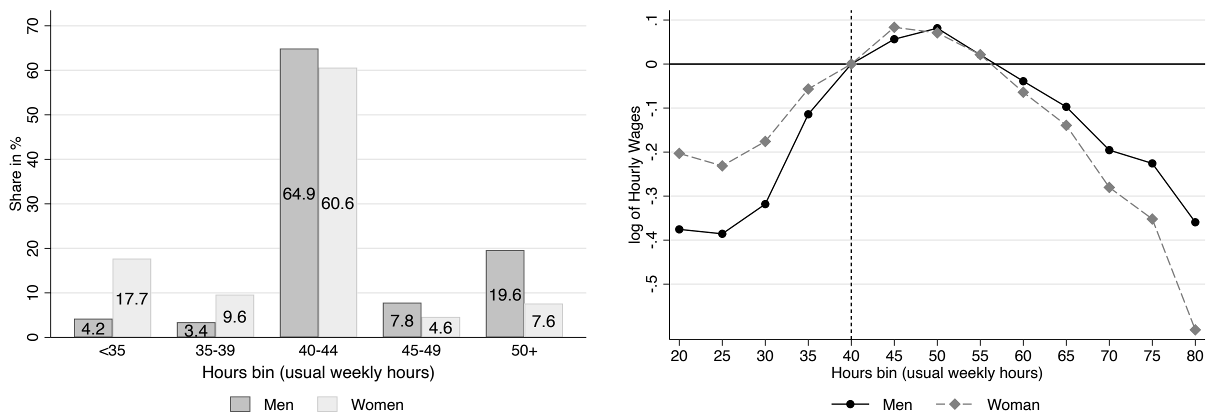


Figure A.2: Time-Series in CPS ORG

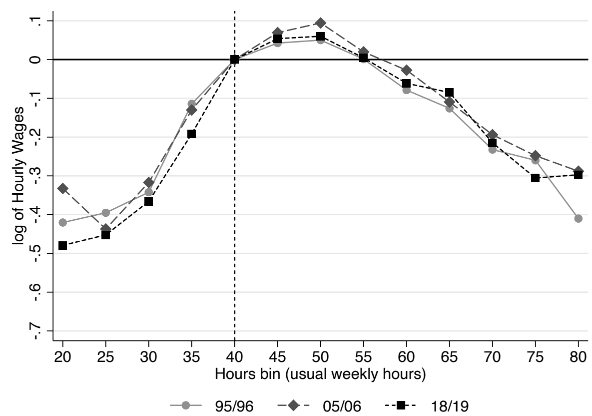
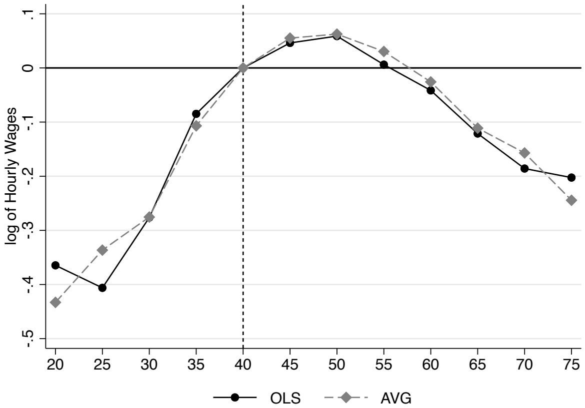


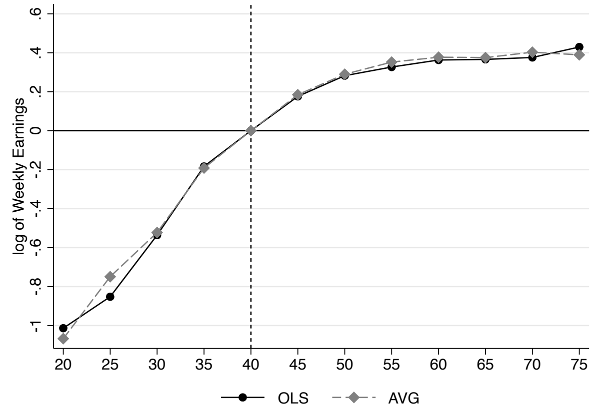
Figure A.3: Cross-Section vs. Cross-Section of Individual Averages

CPS ORG

(a) log Weekly Wage

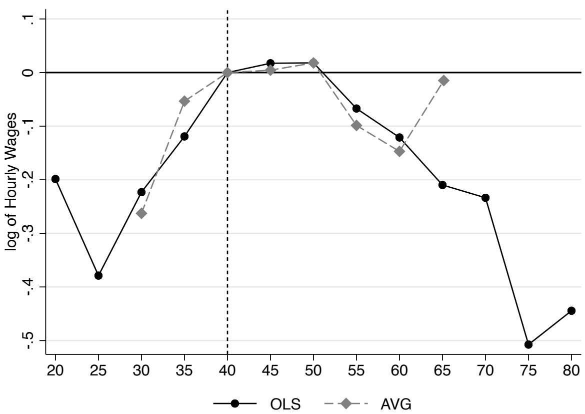


(b) log Weekly Earnings

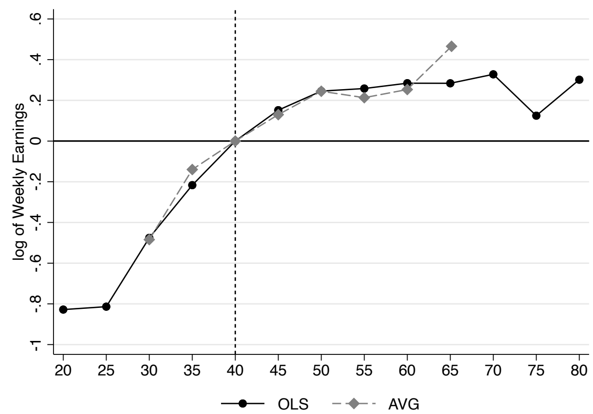


NLSY 79

(c) log Weekly Wage

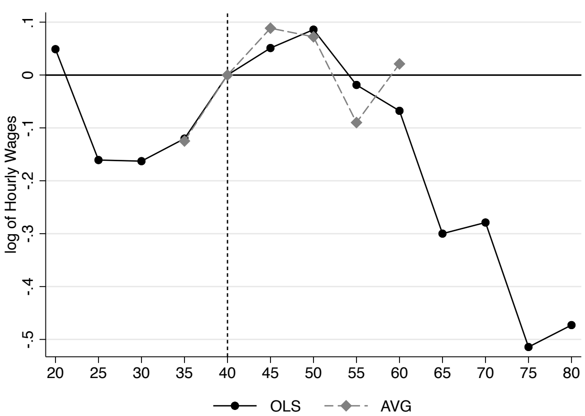


(d) log Weekly Earnings



PSID

(e) log Weekly Wage



(f) log Weekly Earnings

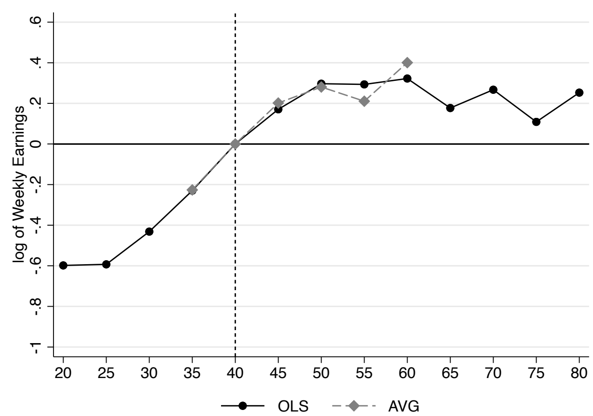
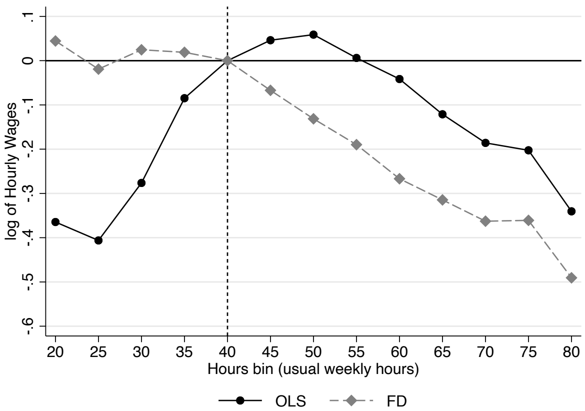


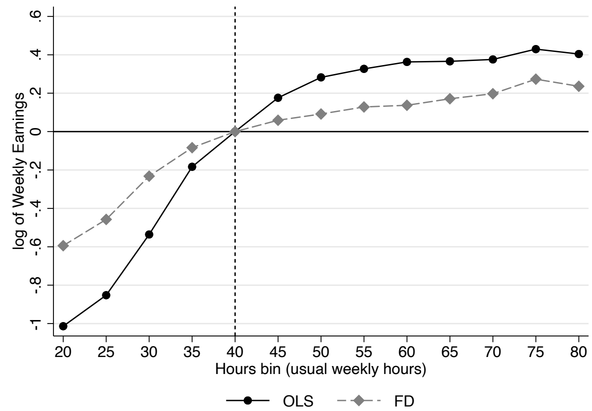
Figure A.4: Cross-Section vs. Within-Person Varation

CPS ORG

(a) log Weekly Wage



(b) log Weekly Earnings



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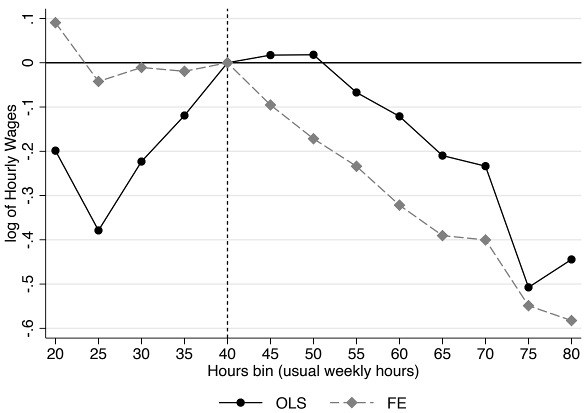
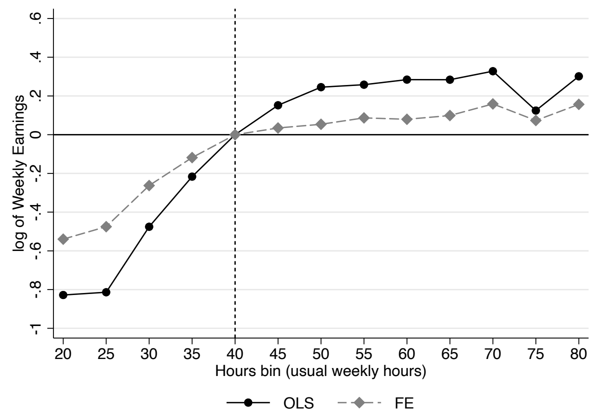
(c) log Weekly Wage

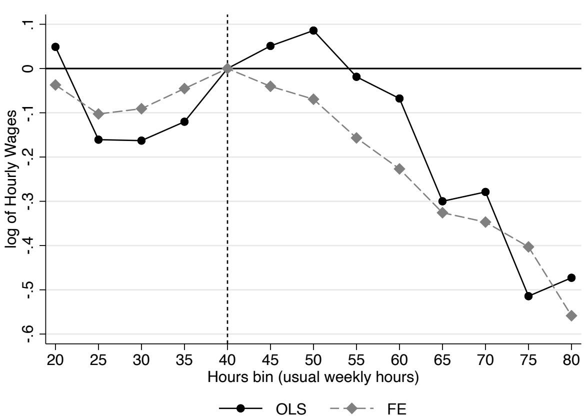


(d) log Weekly Earnings



PSID

(e) log Weekly Wage



(f) log Weekly Earnings

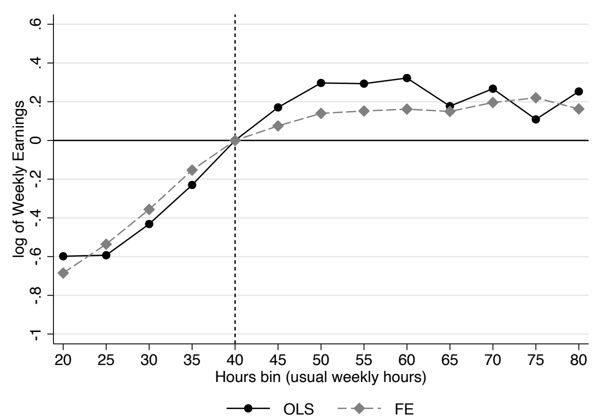
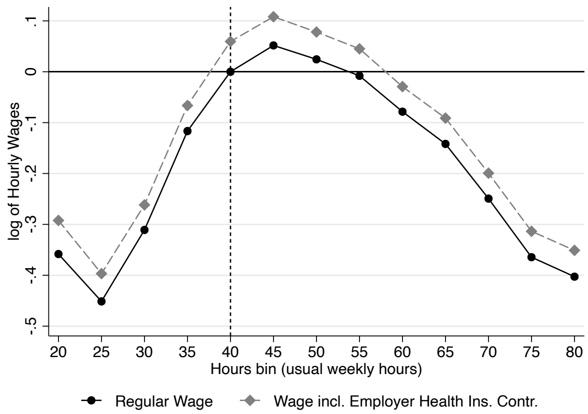
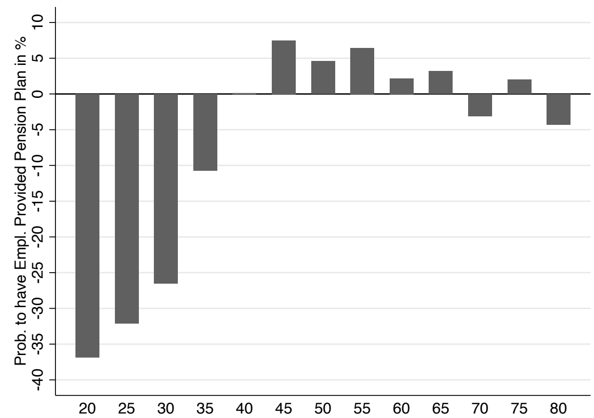


Figure A.5: The Role of Benefits (ASEC)

(a) Wages vs. Wages + Employer Contributions to Health Insurance



(b) Probability of Being Included in an Employer-Provided Pension or Retirement Plan



A.2 Tables

A.2.1 Determinants of Hours Worked in the CPS-ASEC

Table A.1: Coefficients of Different Determinants of Log Usual Weekly Hours Worked in the CPS ASEC

	No Control for Lagged Hours				Control for Lagged Hours			
	LHS	HS	Bach	Bach+	LHS	HS	Bach	Bach+
Unconditional Mean	3.703	3.740	3.771	3.803	3.705	3.742	3.774	3.804
Constant	3.679***	3.703***	3.720***	3.754***	2.028***	1.877***	1.762***	1.606***
Ages 35-44	0.004	0.011***	0.019***	0.019***	-0.008	0.004*	0.006*	-0.015**
Ages 45-54	-0.002	0.006***	0.015***	0.017***	-0.005	0.000	0.000	-0.009
Ages 55-64	-0.041***	-0.045***	-0.042***	-0.045***	-0.041***	-0.025***	-0.031***	-0.041***
Hispanic	-0.017***	-0.033***	-0.033***	-0.018***	-0.016***	-0.018***	-0.014**	-0.016
Black	-0.033***	-0.035***	-0.030***	-0.033***	0.005	-0.012***	-0.016***	-0.011
Married	0.046***	0.049***	0.045***	0.053***	0.037***	0.023***	0.020***	0.021***
1 Child Aged 0-4	-0.002	0.008***	0.006**	0.003	-0.008	0.004	0.002	0.000
2 Children Aged 0-4	-0.004	0.008***	0.021***	0.029***	0.000	0.004	0.009	0.006
3+ Children Aged 0-4	-0.027**	-0.007	0.011	0.039**	-0.024	-0.005	0.003	-0.019
1 Child Aged 5+	0.015***	0.014***	0.018***	0.005	0.010*	0.008***	0.007**	0.000
2 Children Aged 5+	0.014***	0.016***	0.019***	0.013***	0.003	0.011***	0.013***	0.006
3+ Children Aged 5+	0.015***	0.017***	0.027***	0.028***	0.004	0.011***	0.005	0.013*
1st Quintile Other Inc.	0.030***	0.027***	0.024***	0.023***	0.024***	0.013***	0.012***	-0.012*
2nd Quintile Other Inc.	-0.003	0.013***	0.020***	0.005	0.008	0.004*	0.017***	-0.006
4th Quintile Other Inc.	0.001	-0.005***	-0.005**	-0.020***	0.004	-0.006***	-0.001	-0.016***
5th Quintile Other Inc.	0.002	-0.014***	-0.010***	-0.013***	0.001	-0.011***	0.000	-0.012**
Lagged log Hours	–	–	–	–	0.445***	0.493***	0.528***	0.583***
R^2	0.022	0.028	0.030	0.025	0.237	0.264	0.306	0.367
Observations	52311	247952	85345	46478	7631	51763	19169	10419

Note: */**/*** indicate statistical significance at the 10%/5%/1% level, respectively.

Table A.2: Probability of Working Long Hours (Usual Weekly Hours $\geq$ 50) as Dependent Variable (CPS ASEC)

(a) Explantory Power of Different Determinants

	No Control for Lagged Hours				Control for Lagged Hours			
	LHS	HS	Bach	Bach+	LHS	HS	Bach	Bach+
All Regressors	0.012	0.015	0.019	0.015	0.163	0.194	0.241	0.280
Excluded Regressors								
Age	0.012	0.014	0.018	0.014	0.162	0.193	0.241	0.279
Race/Ethnicity	0.003	0.009	0.016	0.012	0.160	0.193	0.240	0.279
Marital Status	0.010	0.012	0.016	0.012	0.162	0.193	0.240	0.279
Age & # of Children	0.012	0.015	0.018	0.013	0.162	0.194	0.240	0.279
Other Income Quintile	0.012	0.014	0.017	0.013	0.162	0.194	0.240	0.279
Lagged Hours	–	–	–	–	0.015	0.014	0.023	0.014

Note: R^2 are based on a linear regression model. In the right panel, "Lagged Hours" corresponds to an indicator taking the value 1 if the individual worked at least 50 hours usually per week in the previous year.

(b) Coefficient Estimates

	No Control for Lagged Hours				Control for Lagged Hours			
	LHS	HS	Bach	Bach+	LHS	HS	Bach	Bach+
Unconditional Mean	0.138	0.204	0.301	0.394	0.135	0.196	0.298	0.393
Constant	0.158***	0.168***	0.234***	0.339***	0.060***	0.087***	0.123***	0.208***
Ages 35-44	0.008**	0.010***	0.026***	0.020***	0.010	0.009**	0.012	-0.017
Ages 45-54	-0.003	-0.002	0.021***	0.020***	0.003	0.001	-0.003	-0.010
Ages 55-64	-0.013**	-0.037***	-0.031***	-0.027***	-0.013	-0.024***	-0.021**	-0.031**
Hispanic	-0.066***	-0.080***	-0.081***	-0.072***	-0.047***	-0.047***	-0.039**	-0.047*
Black	-0.066***	-0.074***	-0.084***	-0.101***	-0.013	-0.041***	-0.048***	-0.063***
Married	0.035***	0.057***	0.071***	0.073***	0.033***	0.031***	0.048***	0.042***
1 Child Aged 0-4	-0.005	0.015***	0.015***	0.019**	0.003	0.011*	0.015	0.009
2 Children Aged 0-4	-0.012	0.020***	0.056***	0.071***	-0.017	0.009	0.031**	0.012
3+ Children Aged 0-4	0.025	-0.005	0.020	0.052	0.091	-0.029	0.018	-0.019
1 Child Aged 5+	0.010**	0.015***	0.028***	-0.011	0.011	0.011**	0.024***	-0.012
2 Children Aged 5+	-0.002	0.017***	0.037***	0.024***	-0.017	0.014***	0.035***	0.010
3+ Children Aged 5+	0.009*	0.024***	0.048***	0.053***	-0.005	0.020***	0.024*	0.010
1st Quintile Other Inc.	0.014***	0.022***	0.025***	0.017**	0.014	0.013***	0.000	-0.011
2nd Quintile Other Inc.	0.007	0.035***	0.040***	0.004	0.019*	0.013***	0.037***	-0.008
4th Quintile Other Inc.	0.003	-0.002	-0.023***	-0.045***	0.037***	-0.002	-0.013	-0.022*
5th Quintile Other Inc.	-0.001	0.004	-0.007	-0.006	-0.011	0.000	-0.004	-0.001
Lagged Prob. $h \geq 50$	–	–	–	–	0.367***	0.411***	0.467***	0.516***
R^2	0.012	0.015	0.019	0.015	0.163	0.194	0.241	0.280
Observations	52311	247952	85345	46478	7631	51763	19169	10419

Note: */**/*** indicate statistical significance at the 10%/5%/1% level, respectively.

Table A.3: Explantory Power of Different Determinants of Hours Worked in the CPS ASEC incl. Dummies for 3-digit Occupation

(a) Dependent Variable — Log Usual Weekly Hours

	No Control for Lagged Hours				Control for Lagged Hours			
	LHS	HS	Bach	Bach+	LHS	HS	Bach	Bach+
All Regressors	0.089	0.106	0.124	0.143	0.299	0.298	0.353	0.408
Excluded Regressors								
Age	0.085	0.101	0.118	0.137	0.294	0.296	0.350	0.405
Race/Ethnicity	0.088	0.105	0.123	0.143	0.299	0.298	0.353	0.408
Marital Status	0.084	0.102	0.121	0.141	0.296	0.298	0.353	0.407
Age & # of Children	0.088	0.105	0.123	0.143	0.299	0.298	0.353	0.408
Other Income Quintile	0.085	0.102	0.121	0.141	0.297	0.297	0.352	0.407
Occupation	0.022	0.028	0.030	0.025	0.237	0.264	0.306	0.367
Lagged Hours	–	–	–	–	0.148	0.115	0.142	0.146

(b) Dependent Variable — Probability of Working Long Hours (Usual Weekly Hours $\geq$ 50)

	No Control for Lagged Hours				Control for Lagged Hours			
	LHS	HS	Bach	Bach+	LHS	HS	Bach	Bach+
All Regressors	0.080	0.086	0.091	0.120	0.227	0.230	0.279	0.325
Excluded Regressors								
Age	0.080	0.085	0.090	0.119	0.226	0.229	0.278	0.324
Race/Ethnicity	0.076	0.083	0.090	0.118	0.225	0.229	0.279	0.324
Marital Status	0.079	0.085	0.090	0.119	0.226	0.229	0.278	0.324
Age & # of Children	0.080	0.086	0.090	0.119	0.226	0.229	0.278	0.325
Other Income Quintile	0.080	0.085	0.089	0.119	0.226	0.229	0.278	0.325
Occupation	0.012	0.015	0.019	0.015	0.163	0.194	0.241	0.280
Lagged Hours	–	–	–	–	0.120	0.092	0.108	0.128

A.2.2 Determinants of Hours Worked in the CPS-ASEC When Using the Same Sample in the Regressions With and Without Lagged Hours

Table A.4: Explantory Power of Different Determinants of Log Usual Weekly Hours Worked in the CPS ASEC Using the Same Sample in Both Table Panels

	LHS	HS	Bach	Bach+	LHS	HS	Bach	Bach+
All Regressors	0.030	0.027	0.031	0.027	0.237	0.264	0.306	0.367
Excluded Regressors								
Age	0.021	0.021	0.023	0.018	0.232	0.262	0.303	0.364
Race/Ethnicity	0.028	0.024	0.029	0.026	0.236	0.263	0.306	0.367
Marital Status	0.018	0.020	0.024	0.023	0.232	0.262	0.305	0.367
Age & # of Children	0.029	0.025	0.029	0.026	0.237	0.263	0.306	0.367
Other Income Quintile	0.026	0.022	0.027	0.024	0.235	0.262	0.305	0.367
Lagged Hours	–	–	–	–	0.030	0.027	0.031	0.027

Notes: The right table panel is identical to the right table panel of Table 1. The left panel table reports results for using the same sample as used in the right panel, which is a subsample of the one used in the left panel of Table 1.

Table A.5: Explantory Power of Different Determinants of Probability of Working Long Hours (Usual Weekly Hours ≥ 50) as Dependent Variable in the CPS ASEC Using the Same Sample in Both Table Panels

	LHS	HS	Bach	Bach+	LHS	HS	Bach	Bach+
All Regressors	0.015	0.014	0.023	0.014	0.163	0.194	0.241	0.280
Excluded Regressors								
Age	0.014	0.012	0.021	0.013	0.162	0.193	0.241	0.279
Race/Ethnicity	0.008	0.009	0.021	0.012	0.160	0.193	0.240	0.279
Marital Status	0.013	0.011	0.018	0.012	0.162	0.193	0.240	0.279
Age & # of Children	0.014	0.013	0.021	0.013	0.162	0.194	0.240	0.279
Other Income Quintile	0.013	0.012	0.019	0.012	0.162	0.194	0.240	0.279
Lagged Hours	–	–	–	–	0.015	0.014	0.023	0.014

Notes: The right table panel is identical to the right table panel of Table A.2a. The left panel table reports results for using the same sample as used in the right panel, which is a subsample of the one used in the left panel of Table A.2a.

Table A.6: Explantory Power of Different Determinants of Log Usual Weekly Hours Worked in the CPS ASEC Incl. Dummies for 3-digit Occupation Using the Same Sample in Both Table Panels

	LHS	HS	Bach	Bach+	LHS	HS	Bach	Bach+
All Regressors	0.148	0.115	0.142	0.146	0.299	0.298	0.353	0.408
Excluded Regressors								
Age	0.140	0.110	0.135	0.138	0.294	0.296	0.350	0.405
Race/Ethnicity	0.148	0.113	0.141	0.145	0.299	0.298	0.353	0.408
Marital Status	0.140	0.111	0.139	0.144	0.296	0.298	0.353	0.407
Age & # of Children	0.147	0.113	0.141	0.145	0.299	0.298	0.353	0.408
Other Income Quintile	0.145	0.111	0.138	0.144	0.297	0.297	0.352	0.407
Occupation	0.030	0.027	0.031	0.027	0.237	0.264	0.306	0.367
Lagged Hours	–	–	–	–	0.148	0.115	0.142	0.146

Notes: The right table panel is identical to the right table panel of Table A.3a. The left panel table reports results for using the same sample as used in the right panel, which is a subsample of the one used in the left panel of Table A.3a.

Table A.7: Explantory Power of Different Determinants of Probability of Working Long Hours (Usual Weekly Hours ≥ 50) as Dependent Variable in the CPS ASEC Incl. Dummies for 3-digit Occupation Using the Same Sample in Both Table Panels

	LHS	HS	Bach	Bach+	LHS	HS	Bach	Bach+
All Regressors	0.120	0.092	0.108	0.128	0.227	0.230	0.279	0.325
Excluded Regressors								
Age	0.119	0.091	0.107	0.127	0.226	0.229	0.278	0.324
Race/Ethnicity	0.117	0.090	0.107	0.127	0.225	0.229	0.279	0.324
Marital Status	0.119	0.091	0.105	0.127	0.226	0.229	0.278	0.324
Age & # of Children	0.119	0.092	0.107	0.128	0.226	0.229	0.278	0.325
Other Income Quintile	0.118	0.091	0.105	0.128	0.226	0.229	0.278	0.325
Occupation	0.015	0.014	0.023	0.014	0.163	0.194	0.241	0.280
Lagged Hours	–	–	–	–	0.120	0.092	0.108	0.128

Notes: The right table panel is identical to the right table panel of Table A.3b. The left panel table reports results for using the same sample as used in the right panel, which is a subsample of the one used in the left panel of Table A.3b.

Table A.8: Coefficients of Different Determinants of Log Usual Weekly Hours Worked in the SCF

	LHS	HS	Bach	Bach+
Unconditional Mean	3.755	3.779	3.771	3.814
Constant	3.719***	3.748***	3.712***	3.709***
Ages 35-44	0.038***	-0.001	0.009	-0.017***
Ages 45-54	0.013	-0.005	0.004	-0.027***
Ages 55-64	-0.031**	-0.028***	-0.025***	-0.043***
Hispanic	-0.026***	-0.045***	-0.047***	-0.052***
Black	-0.059***	-0.035***	-0.055***	0.023**
Married	-0.014	0.030***	0.041***	0.058***
1 Child Aged 0-4	-0.020*	0.006	0.005	-0.010
2 Children Aged 0-4	-0.068***	-0.004	0.042***	0.000
3+ Children Aged 0-4	0.004	-0.041	0.108**	0.005
1 Child Aged 5+	0.000	0.012**	0.019***	-0.011**
2 Children Aged 5+	0.044***	0.016***	0.029***	0.028***
3+ Children Aged 5+	0.026*	0.023***	0.040***	0.031***
1st Quintile Other Inc.	0.029***	0.033***	0.056***	0.040***
2nd Quintile Other Inc.	-0.004	-0.007	0.028***	0.017**
4th Quintile Other Inc.	-0.008	-0.021***	0.011	-0.010
5th Quintile Other Inc.	0.022	-0.013*	0.024***	0.008
log Wealth-Income Ratio	0.005**	-0.003**	-0.002	0.010***
R^2	0.058	0.026	0.035	0.032
Observations	3133	9459	7561	12283

Note: */**/*** indicate statistical significance at the 10%/5%/1% level, respectively.

Table A.9: Probability of Working Long Hours (Usual Weekly Hours ≥ 50) as Dependent Variable (SCF)

(a) Explantory Power of Different Determinants

	LHS	HS	Bach	Bach+
All Regressors	0.049	0.020	0.038	0.019
Excluded Regressors				
Age	0.045	0.019	0.035	0.018
Race/Ethnicity	0.044	0.014	0.030	0.018
Marital Status	0.047	0.020	0.035	0.017
Age & # of Children	0.041	0.018	0.029	0.015
Other Income Quintile	0.047	0.015	0.028	0.018
log Wealth-Income Ratio	0.048	0.020	0.038	0.015

Note: R^2 are based on a linear regression model. In the right panel, "Lagged Hours" corresponds to an indicator taking the value 1 if the individual worked at least 50 hours usually per week in the previous year.

(b) Coefficient Estimates

	LHS	HS	Bach	Bach+
Unconditional Mean	0.199	0.266	0.265	0.397
Constant	0.112***	0.218***	0.176***	0.270***
Ages 35-44	0.052***	-0.019	-0.039***	-0.042***
Ages 45-54	-0.007	-0.024*	-0.026*	-0.024*
Ages 55-64	-0.037	-0.060***	-0.092***	-0.020
Hispanic	-0.062***	-0.069***	-0.094***	-0.097***
Black	-0.057**	-0.100***	-0.106***	0.001
Married	0.067***	0.021	0.069***	0.066***
1 Child Aged 0-4	-0.027	0.011	0.003	0.014
2 Children Aged 0-4	-0.020	-0.016	0.071***	0.084***
3+ Children Aged 0-4	-0.215***	-0.060	0.414***	0.021
1 Child Aged 5+	-0.032	0.016	0.040***	-0.029**
2 Children Aged 5+	0.057***	0.055***	0.088***	0.060***
3+ Children Aged 5+	-0.033	0.059***	0.109***	0.044**
1st Quintile Other Inc.	-0.006	0.054***	0.130***	0.011
2nd Quintile Other Inc.	-0.008	-0.019	0.041***	-0.010
4th Quintile Other Inc.	-0.059**	-0.037***	0.010	-0.023
5th Quintile Other Inc.	0.030	-0.023	0.059***	0.007
log Wealth-Income Ratio	0.010**	-0.001	0.002	0.029***
R^2	0.049	0.020	0.038	0.019
Observations	3133	9459	7561	12283

Note: */**/*** indicate statistical significance at the 10%/5%/1% level, respectively.

A.2.3 Determinants of Hours Worked in the SCF by Age

Dependent Variable Log Usual Weekly Hours Worked

Table A.10: Ages 25-34

	LHS	HS	Bach	Bach+
All Regressors	0.127	0.039	0.086	0.051
Excluded Regressors				
Race/Ethnicity	0.120	0.031	0.076	0.049
Marital Status	0.120	0.034	0.078	0.047
Age & # of Children	0.112	0.038	0.071	0.043
Other Income Quintile	0.077	0.032	0.058	0.034
log Wealth-Income Ratio	0.127	0.036	0.083	0.050

Table A.11: Ages 35-44

	LHS	HS	Bach	Bach+
All Regressors	0.131	0.039	0.049	0.068
Excluded Regressors				
Race/Ethnicity	0.125	0.034	0.045	0.064
Marital Status	0.131	0.036	0.045	0.065
Age & # of Children	0.093	0.029	0.032	0.038
Other Income Quintile	0.114	0.025	0.040	0.062
log Wealth-Income Ratio	0.113	0.038	0.048	0.061

Table A.12: Ages 45-54

	LHS	HS	Bach	Bach+
All Regressors	0.067	0.032	0.049	0.069
Excluded Regressors				
Race/Ethnicity	0.056	0.019	0.034	0.068
Marital Status	0.065	0.030	0.044	0.064
Age & # of Children	0.060	0.026	0.039	0.055
Other Income Quintile	0.051	0.019	0.040	0.057
log Wealth-Income Ratio	0.066	0.032	0.049	0.064

Table A.13: Ages 55-64

	LHS	HS	Bach	Bach+
All Regressors	0.170	0.077	0.166	0.125
Excluded Regressors				
Race/Ethnicity	0.141	0.070	0.134	0.111
Marital Status	0.170	0.077	0.165	0.094
Age & # of Children	0.160	0.047	0.131	0.123
Other Income Quintile	0.135	0.036	0.154	0.063
log Wealth-Income Ratio	0.170	0.077	0.107	0.120

Dependent Variable: Probability of Working Long Hours

Table A.14: Ages 25-34

	LHS	HS	Bach	Bach+
All Regressors	0.123	0.036	0.093	0.043
Excluded Regressors				
Race/Ethnicity	0.113	0.022	0.086	0.043
Marital Status	0.120	0.035	0.092	0.043
Age & # of Children	0.110	0.031	0.071	0.033
Other Income Quintile	0.077	0.034	0.058	0.036
log Wealth-Income Ratio	0.121	0.036	0.090	0.039

Table A.15: Ages 35-44

	LHS	HS	Bach	Bach+
All Regressors	0.129	0.040	0.051	0.059
Excluded Regressors				
Race/Ethnicity	0.125	0.036	0.048	0.057
Marital Status	0.118	0.039	0.050	0.058
Age & # of Children	0.107	0.031	0.037	0.034
Other Income Quintile	0.120	0.027	0.037	0.053
log Wealth-Income Ratio	0.109	0.040	0.051	0.053

Table A.16: Ages 45-54

	LHS	HS	Bach	Bach+
All Regressors	0.056	0.020	0.053	0.033
Excluded Regressors				
Race/Ethnicity	0.053	0.016	0.040	0.027
Marital Status	0.056	0.020	0.046	0.028
Age & # of Children	0.040	0.016	0.042	0.031
Other Income Quintile	0.035	0.012	0.039	0.025
log Wealth-Income Ratio	0.056	0.020	0.053	0.031

Table A.17: Ages 55-64

	LHS	HS	Bach	Bach+
All Regressors	0.246	0.061	0.160	0.065
Excluded Regressors				
Race/Ethnicity	0.220	0.042	0.107	0.063
Marital Status	0.245	0.060	0.156	0.047
Age & # of Children	0.193	0.046	0.127	0.054
Other Income Quintile	0.132	0.044	0.107	0.034
log Wealth-Income Ratio	0.246	0.058	0.116	0.064

A.2.4 Determinants of Hours Worked in the SCF by Age and Using log Wealth instead of the log Wealth to Income Ratio

Dependent Variable Log Usual Weekly Hours Worked

Table A.18: Ages 25-34

	LHS	HS	Bach	Bach+
All Regressors	0.131	0.041	0.108	0.061
Excluded Regressors				
Race/Ethnicity	0.124	0.036	0.101	0.059
Marital Status	0.124	0.036	0.100	0.058
Age & # of Children	0.118	0.039	0.093	0.053
Other Income Quintile	0.086	0.034	0.077	0.043
log Wealth	0.127	0.037	0.083	0.050

Table A.19: Ages 35-44

	LHS	HS	Bach	Bach+
All Regressors	0.136	0.044	0.066	0.099
Excluded Regressors				
Race/Ethnicity	0.128	0.042	0.065	0.095
Marital Status	0.136	0.042	0.064	0.097
Age & # of Children	0.094	0.035	0.051	0.075
Other Income Quintile	0.103	0.027	0.055	0.089
log Wealth	0.126	0.038	0.046	0.061

Table A.20: Ages 45-54

	LHS	HS	Bach	Bach+
All Regressors	0.072	0.038	0.055	0.103
Excluded Regressors				
Race/Ethnicity	0.064	0.029	0.041	0.103
Marital Status	0.070	0.035	0.051	0.101
Age & # of Children	0.066	0.032	0.044	0.090
Other Income Quintile	0.054	0.021	0.044	0.093
log Wealth	0.066	0.032	0.049	0.064

Table A.21: Ages 55-64

	LHS	HS	Bach	Bach+
All Regressors	0.181	0.083	0.125	0.124
Excluded Regressors				
Race/Ethnicity	0.159	0.078	0.097	0.107
Marital Status	0.180	0.083	0.124	0.093
Age & # of Children	0.167	0.053	0.081	0.123
Other Income Quintile	0.139	0.036	0.115	0.057
log Wealth	0.170	0.077	0.107	0.120

Dependent Variable: Probability of Working Long Hours

Table A.22: Ages 25-34

	LHS	HS	Bach	Bach+
All Regressors	0.122	0.044	0.109	0.057
Excluded Regressors				
Race/Ethnicity	0.113	0.033	0.104	0.057
Marital Status	0.119	0.044	0.109	0.057
Age & # of Children	0.110	0.039	0.088	0.048
Other Income Quintile	0.077	0.040	0.073	0.050
log Wealth	0.121	0.036	0.092	0.040

Table A.23: Ages 35-44

	LHS	HS	Bach	Bach+
All Regressors	0.141	0.043	0.060	0.083
Excluded Regressors				
Race/Ethnicity	0.137	0.041	0.058	0.081
Marital Status	0.129	0.043	0.059	0.083
Age & # of Children	0.120	0.035	0.046	0.064
Other Income Quintile	0.126	0.030	0.044	0.078
log Wealth	0.110	0.040	0.050	0.053

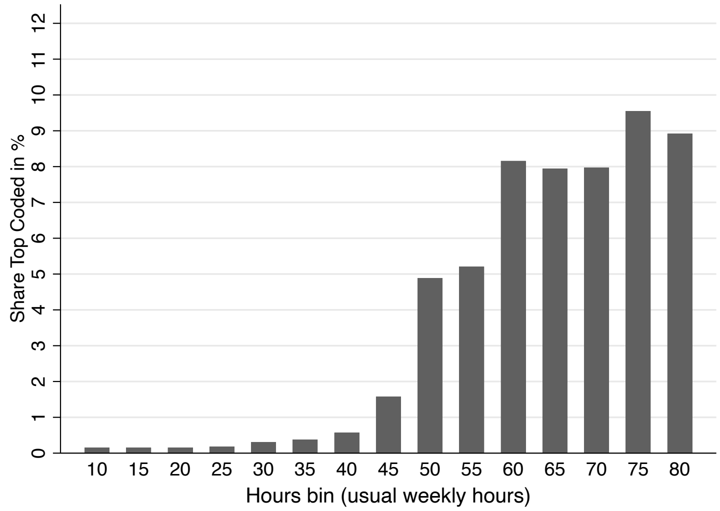
Table A.24: Ages 45-54

	LHS	HS	Bach	Bach+
All Regressors	0.066	0.022	0.055	0.066
Excluded Regressors				
Race/Ethnicity	0.063	0.020	0.043	0.062
Marital Status	0.066	0.022	0.048	0.064
Age & # of Children	0.049	0.019	0.043	0.064
Other Income Quintile	0.044	0.012	0.040	0.060
log Wealth	0.056	0.020	0.053	0.031

Table A.25: Ages 55-64

	LHS	HS	Bach	Bach+
All Regressors	0.250	0.058	0.125	0.087
Excluded Regressors				
Race/Ethnicity	0.232	0.040	0.078	0.081
Marital Status	0.247	0.057	0.122	0.070
Age & # of Children	0.193	0.042	0.091	0.076
Other Income Quintile	0.133	0.039	0.072	0.041
log Wealth	0.246	0.058	0.116	0.064

Figure B.1: Probability of being Top-Coded by Usual Weekly Hours bin for Men



Sample Period: Sep 1995-August 2007

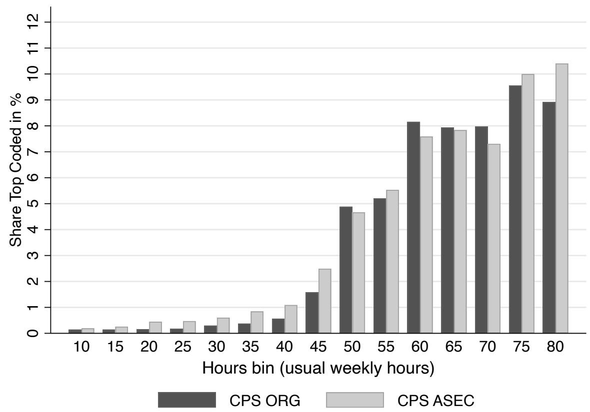
B The Role of Top-Coding

Figure 3b of the main text showed that, for our sample of men in the ORG, mean earnings were relatively flat in usual weekly hours beyond 50 hours per week. In this section we attempt to analyze the quantitative role of top-coding for this pattern. To see why top-coding could potentially be relevant, consider an extreme case where no one working less than 50 hours is top coded, everyone from 50 hours on is top-coded, and all top-coded earnings are replaced with a single value. In this case, even if true earnings were increasing in hours, observed earnings would be completely flat beyond 50. The following paragraphs provide suggestive evidence against this possiblity, i.e. we conclude that top-coding is not the major driver of the relatively flat earnings-hours relationship beyond 50 hours. One partial exception is that those with graduate degrees have a higher incidence of top-coding, and for these workers top-coding may modestly dampen the rate at which earnings increase in the long hours region. But this is only the case in the CPS ORG because of the specific top-coding procedure, and not in the other datasets.

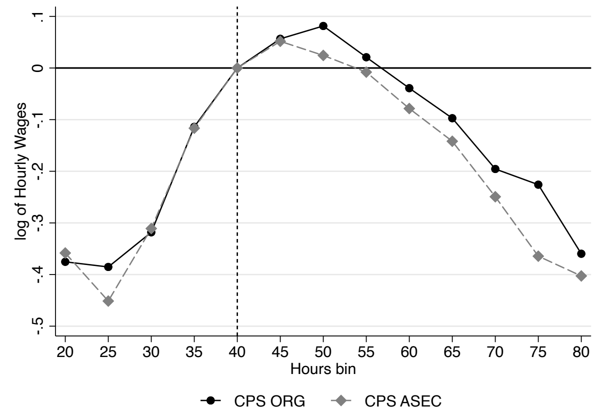
The sample for our analysis starts in September 1995, the first months from which onwards IPUMS provide information whether earnings have been imputed or not in the ORG. Between September 1995 and December 1996 earnings were top-coded at \$1,923 per week (corresponding to \$100,000 per year assuming 52 weeks of work) in nominal terms. Since January 1998, earnings have been toop-coded at \$2,885.61 per week (corresponding to \$150,000 per year assuming 52 weeks of work) in nominal terms. Figure B.1 shows results for our sample of men age 25-64. Below 45 hours, top-coding is negligible and even in the 45-49

Figure B.2: Different Top Codes in CPS ORG and ASEC for Men (1995-2007)

(a) Top-Coding Probability



(b) Wages-Hours Relationship



hours bin the earnings of only 2% of men are subject to top-coding. From 50 hours onwards, the probability of earnings being top-coded becomes more prevalent and increases in usual hours worked, although not monotonically.

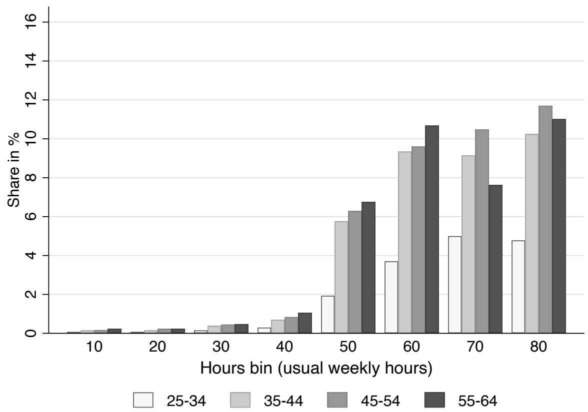
Our first step is to compare results in the CPS ORG and ASEC, using the same years and sample criteria for the ASEC as in our ORG sample.[1] In contrast to the ORG, the nominal top-codes in the ASEC are regularly adjusted and are generally higher. As one might expect, this leads to a lower probability of being top-coded in ASEC than in ORG, as seen in Figure B.2a. In addition to different top-code thresholds, ORG and ASEC also differ in how earnings are assigned to top-coded individuals. In the ORG, top-coded individuals are assigned the top-code. In contrast, until 2011 in the ASEC top-coded individuals were assigned the mean earnings of the top-coded. Specifically, the means earnings were calculated and assigned by cells defined by gender, race (black vs. hispanic vs. rest) and labor supply (full-year-full-time workers, i.e. weeks worked $\geq$ 50 and weekly hours $\geq$ 35, vs. rest). Figure B.2b shows that despite the different top-coding procedures, the aggregate wage-hours relationship is virtually identical. This is consistent with the notion that top-coding is not a major issue in the aggregate.

Next, we analyze the role of top-coding among specific groups of workers. Figure B.3 shows the probability of being top-coded in ORG by age and education. The probability of top-coding is increasing in age up to the 60 hours bin, although the differences are relatively small beyond age 34. The probability of top-coding is strongly increasing in education, and peaks around 23% of workers with a graduate degree working 70-79 hours.

[1] To be precise, the sample period for the ASEC is 1996 through 2008 since hours and earnings are reported for the previous year.

Figure B.3: Top-Coding Probabilities in ORG for Men (1995-2007)

(a) By Age



(b) By Education

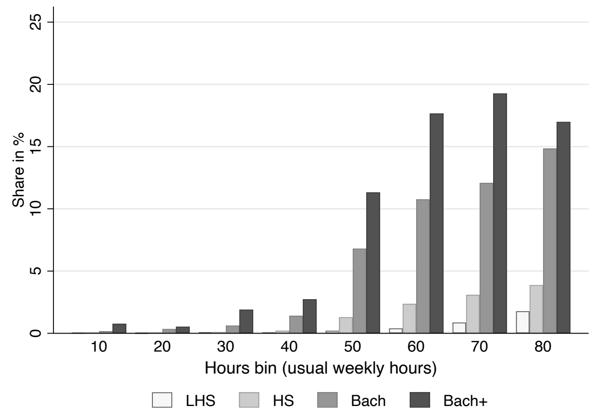
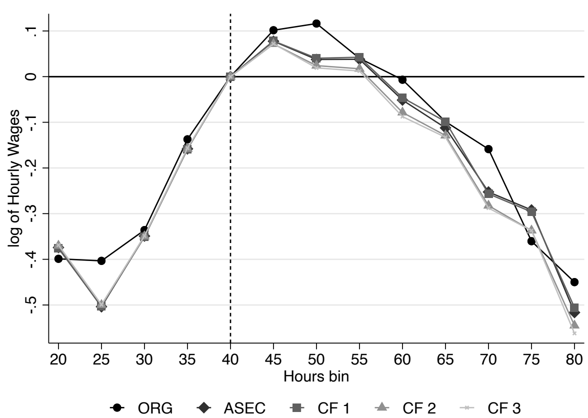


Figure B.4: Comparing Top-Coding Procedures: ORG vs. ASEC (1995-2007)

(a) Age Group 55-64



(b) Bach+

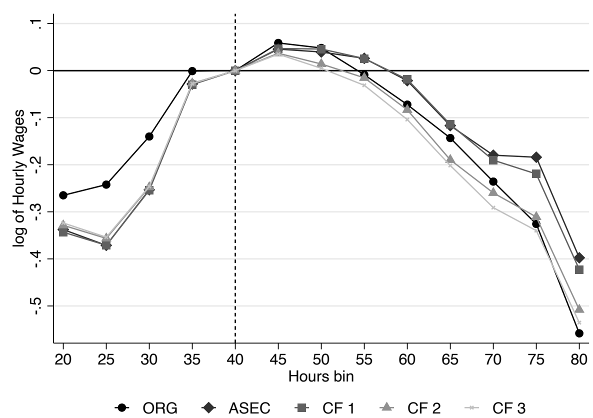


Figure B.4 plots the cross-sectional wage-hours relationship for the ORG and ASEC for the age and education group with the overall highest probability of being top-coded: men aged 55-64, and men with a graduate degree. In addition, we also analyze the following counterfactual top-coding procedures using the ASEC:

CF 1. Impose ORG top-code threshold, replace top-coded with average earnings of top-coded by race and labor supply.

CF 2. Keep ASEC top-code threshold, replace top-coded with ASEC top-code

CF 3. Impose ORG top-code threshold, replace top-coded with ORG top-code

Counterfactual 1 is informative about how important a more binding top-code is, holding fixed the top-coding replacement strategy in ASEC. Counterfactual 2 is informative about how important the replacement strategy of top-coded values is, holding fixed the top-code in ASEC. Countefactual 3 is informative about the combination of Counterfactuals 1-2 together.

Figure B.4a shows that for the age group 55-64 all wage-hours profiles look very similar. This suggests, similar to the aggregate pattern, that the more restricted top-coding in the ORG does not have important effects when distinguishing between age groups.

By contrast, in Figure B.4b, we observe noticeably different wage-hours profiles for men with a graduate degree in the ORG vs. the ASEC. Specifically, in the 50 hour bin the average hourly wage in the ORG is 5 log points below the ASEC; in the 60 hour bin this difference has increased to 9 log points. When we replace both the ASEC top-code threshold with the ORG threshold, and the ASEC top-coding replacement procedure with the ORG replacement procedure (this can be seen by comparing CF 3 and the ORG profile), we find nearly identical results to the actual ORG results. The main reason for the difference between the ASEC profile and the ORG profile is thus not the lower top-coding threshold (this can be seen by comparing CF 1 with the ASEC profile). Instead, the major source of the difference is the difference in the replacement strategies (this can be seen by comparing CF 2 and the ASEC profile).

Figure B.5a shows again the patterns by education in the ORG from the main text, from which one can see that the profile is more depressed for those with a Bachelor and a graduate degree (Bach+). Figure B.4b suggests that some of this pattern might be related to top-coding. Figure B.5b shows the patterns by education for the ASEC, where the profiles lie mostly on top of each other. Hence, while the gaps by education in the ORG may partly reflect top-coding, the ASEC results are in line with our main interpretation on the role of top-coding, namely that top-coding is not the main driver of our finding.

We conclude this section by addressing a final potential issue, which is that if true earnings above the top-code are increasing in hours worked, then replacing the top-coded earnings of all long hours workers with the same value could flatten the earnings profile among these workers. (Recall that the replacement values for the top-coded in the ASEC did account for whether workers worked at least 35 hours per week, but did not distinguish between, for example, workers who worked 50 hours per week and those who worked 60 hours per week). To address this, we turn to the PSID. Since the mid-nineties, the PSID's top-code for wage earnings of the household head is $10 million. In fact, this threshold is so high that no one in the PSID satisfying our sample selection criteria is top-coded. Given the small sample size in the PSID, the following exercise will be for the years 1996-2018. Similar to the previous counterfactuals, we know impose the

Figure B.5: Cross-Sectional Relationship between Wages and Hours: ORG vs. ASEC

(a) ORG (b) ASEC

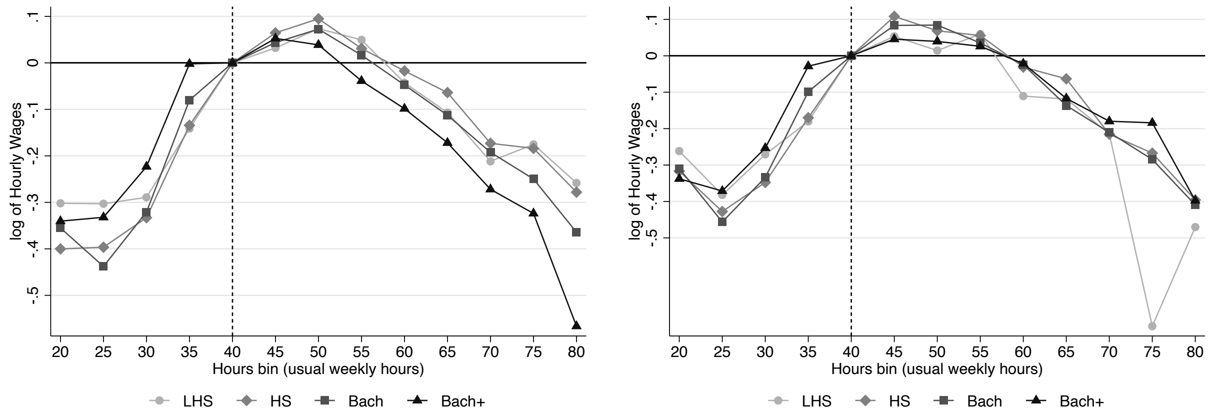
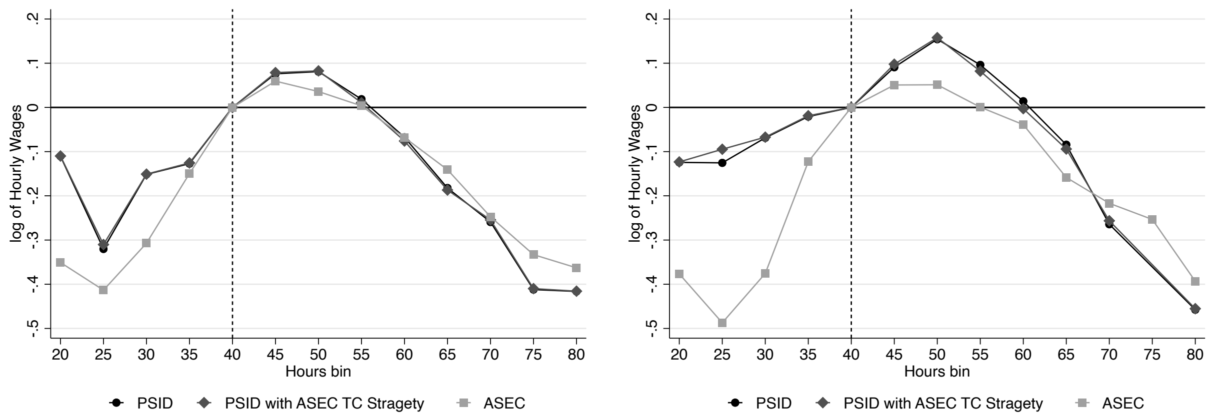


Figure B.6: Comparing Top-Coding Procedures: PSID vs. ASEC (1995-2018)

(a) Aggregate (b) College Degree



ASEC top-coding strategy on the PSID and compare this to the actual PSID withou no top-coding.[2] Figure B.6 shows results for the aggregate as well as for those with a college degree (for sample size reasons we do not distinguish between a bachelor and graduate degree). While the PSID shows slightly different patterns than ASEC, the main take-away is that imposing the ASEC top coding strategy yields very similar results to the actual PSID which effectively had no top-coding. This is consistent with the notion that earnings among top-coded workers do not vary strongly with hours worked above 50.

[2]When implementing this strategy, we focus on the top-codes for inclongj in ASEC which is the dominant income measure for wage and salary earners. For sample size reasons, we also group top-coded individuals only by whether someone is a full-year-full-time worker but not on race.

C The Role of Measurement Error in Hours

In Figure 3b of the main text, mean earnings were relatively flat in usual weekly hours beyond 50 hours per week. If people with high hours tend to be people who have over-reported their hours, then this will artificially lead to a flatter pattern even if true earnings are increasing in hours. In this section we attempt to analyze the quantitative role of measurement error in hours for this pattern.

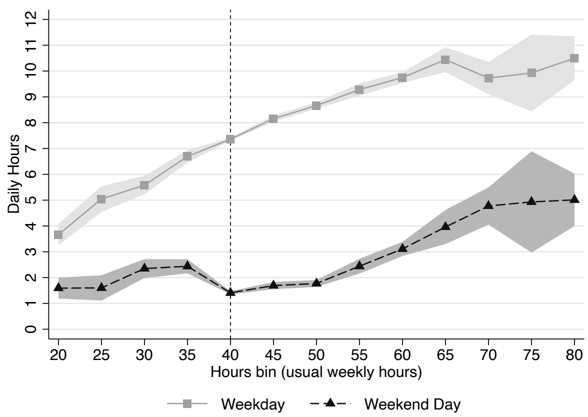
To assess the impact of measurement error we link observations between the CPS ORG and the American Time Use Survey (ATUS). Since 2003 the ATUS collects a time diary for a sample of individuals (not households) 2 to 5 months after their 8th CPS interview. The diary records all activities between 4am of the day preceding the ATUS interview and 4am of the interview day. It records the type of activity, starting and end point as well the location it took place. IPUMS provides a variable that aggregates these activities into "hours spent working on the main job". Importantly, this variable does not include commuting or social activities around work like a lunch break or dinner. From the last CPS interview, we also know usual hours worked, which maybe updated by the respondent at the time of the ATUS interview.

For our analysis we use the same sample restrictions as laid out in Section 2.1, but impose two further restrictions. First, the ATUS provides a variable about the interviewer's perception of data quality indicating whether or not interviewers believe the data from a particular interview should be used. Reasons for why an interview should not be used are if the interviewer thinks that the respondent intentionally provided a wrong answer, could not correctly remember activities, deliberately reported very long durations, or some other reason. We only use interviews which the interviewers suggest to use. Second, because we are interested in usual hours worked, we drop all individuals who did not work at all in the last 7 days. For example, consider someone who was an entire week on vacation and therefore reports zero hours in the time use diary. This zero is simply not informative about the person's usual hours worked, or more precisely for the usual hours worked of people with similar characteristics. Finally, to ensure a sufficiently large sample size we use all years for which the ATUS is available, i.e. 2003 through 2018.

Given our sample, our analysis proceeds as follows. We group individuals by their usual hours bin as reported in the CPS ORG. Next, we calculate the average ATUS hours worked on a weekday and on a weekend day, respectively, for each ORG hours bin. We report these reults in Figure C.1a. Average daily time use hours on a week day increase monotonically up to the up the 65-69 usual hours bin and flatten out subsequently. Individuals reporting usual hours in the 40-44 hours bin report slightly more than 7 hours of work on a week day based on the time use data. Individuals reporting usual hours in the 65-69 hours bin report more than 10 hours of work on a week day based on the time use data. Average daily time use

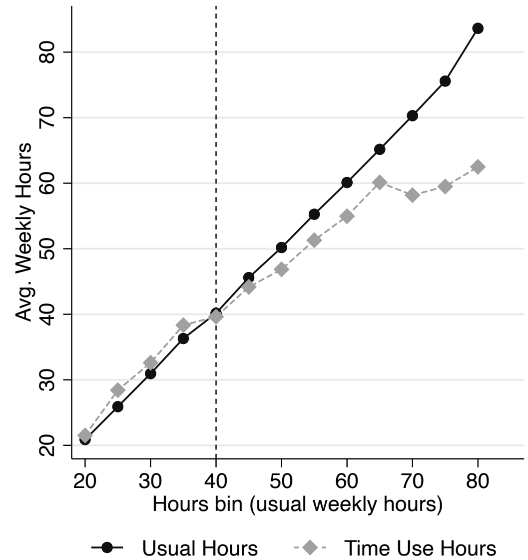
Figure C.1: Average Time Use Hours

(a) Avg. Daily Time Use Hours



Note: Shaded areas are 95% Confidence Intervals.

(b) Avg. Weekly Time Use Hours



hours on a weekend day are slightly above 1 hour for workers whose usual weekly hours are less than 50, and increase to close to 4 hours in the 65-69 usual hours bin. Taking the time use hours at face value, this provides clear evidence that actual hours worked are increasing in reported usual hours worked.

We next compute a synthetic measure of weekly hours worked using the ATUS data, and compare it to the reported usual weekly hours in the ORG. To do so, for each usual weekly hours bin we multiply the average daily time use hours on a weekday by 5 and on a weekend day by 2, then sum the two numbers. Figure C.1b displays the results. In what follows we will focus our attention on individuals with reported usual hours below 70. As we noted earlier, there are very few individuals with reported usual hours of 70 or more, and our estimation exercise does not use any information for these individuals. Moreover, Figure C.1b indicates that the discrepancy between the two measures becomes very large for these workers, thereby casting some doubt on the reliability of these responses. On average, workers who report usual hours in the CPS in in the 30-40 hours region tend to report slightly higher actual hours in the ATUS, while workers who report usual hours in the CPS in the 45-69 hours region tend to report slightly lower actual hours in the ATUS. Table C.1 reports the magnitude of the level and percentage differences across the hours distribution. For usual hours in the 50-69 hours region the gap varies in a relatively tight range of roughly 3-5 hours, corresponding to a percentage gap between roughly 6.6% and 8.6%.

Taking the ATUS measure at face value, this evidence suggests that workers in the long hours region tend to overreport their hours. We are particularly interested in assessing the possibility that overreporting of

Table C.1: Differences between Avg. Weekly Time Use and Usual Hours by Usual Hours Bin

Usual Hours Bin	Hours Difference Levels	Percent
20-24	0.6	3.0
25-29	2.5	9.7
30-34	1.7	5.4
35-39	2.0	5.6
40-44	-0.5	-1.3
45-49	-1.4	-3.1
50-54	-3.3	-6.6
55-59	-4.0	-7.2
60-64	-5.1	-8.6
65-69	-5.0	-7.7

hours in the long hours region has a large effect on our estimate of the cross-sectional wage-hours profile. To pursue this we implement the following exercise. Because the gap in the two measures is relatively constant in the 3-5 hours range over the 50-69 hours range, and most people report usual hours ending in either a 0 or a 5, we assume that all individuals with usual hours in this region have true hours in the immediate lower bin, i.e., an individual with reported usual hours in the 50-54 hours bin is now placed in the 45-49 hours bin etc... We then repeat our benchmark regression exercise to uncover the earnings-hours and wage-hours profile.

Figure C.2: Cross-Sectional Relationship between Earnings/Wages and Reported and Adjusted Hours

(a) log Weekly Earnings

(b) log Hourly Wages

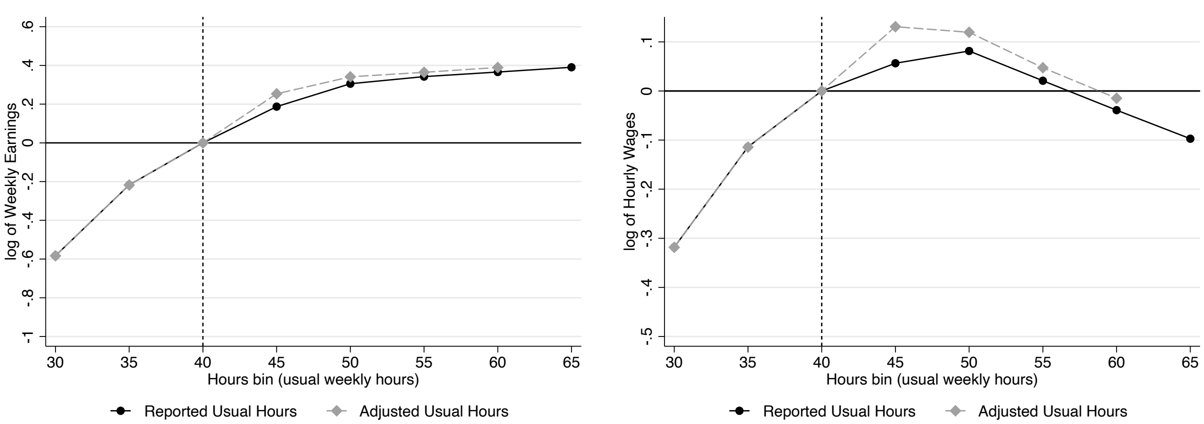
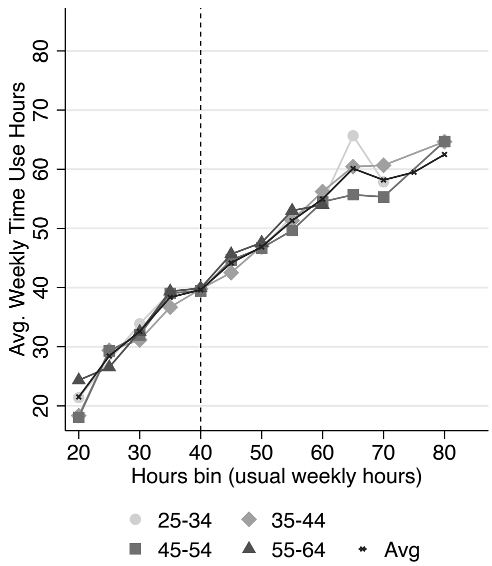


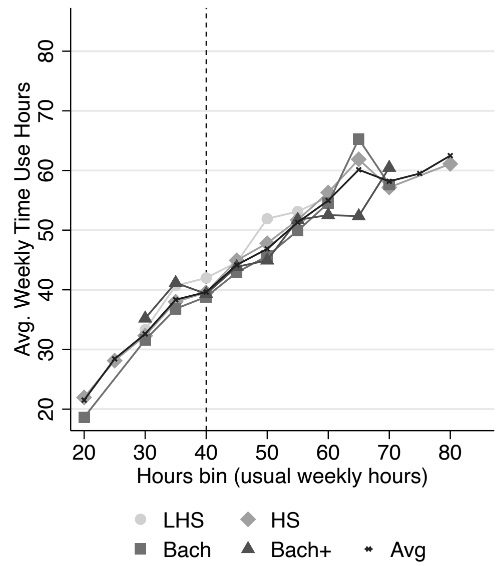
Figure C.2a shows how this affects the estimated earnings-hours profile. For comparison we have included our baseline estimate from Figure 3 in the main text. The key message is that this has virtually no impact on the finding that earnings are effectively flat in the 50-69 hours region. This should not be sur-

Figure C.3: Average Weekly Time Use Hours

(a) By Age



(b) By Education



prising—given that earnings are effectively flat in the CPS and our estimate of overreporting is relatively constant, the slope will be relatively unaffected.

To estimate the wage-hours profile it is not sufficient to just identify which 5 hour bin an individual belongs to; one must also assign a value for hours. Consistent with the tendency for individuals to report usual hours ending in either a 5 or a 0, we assign the lower endpoint of the newly assigned hours bin for each individual. The results of this exercise are shown in Figure C.2b. Again we include the results from our baseline estimation shown in Figure 3 for comparison. Not surprisingly given that the earnings-hours profile remains flat, our key finding continues to hold: wages decrease significantly as hours worked increase beyond 50. In fact, the decrease is somewhat larger on account of moving individuals from the 50-54 hours bin into the 45-49 hours bin.

The above results did not stratify by age or education. Figure C.3 shows that there is little variation in average weekly time use hours by age and education, and there is even less in average usual hours (not shown here).

We conclude that systematic overreporting of usual weekly hours is not the dominant explanation for the empirical pattern in Figure 3 of the main text.

D Additional Model Results

D.1 Additional Moments for Wages and Hours

This section displays additional comparisons between outcomes in the estimated M3 model and the data. Figures D.1 and D.2 display outcomes for High School, Bachelor, and Bachelor+ men ages 50-54. See the main text for additional details on the estimation exercise.

Figure D.1: Additional Comparisons Between Model M3 and Data: High School

(a) S.D. log Wages By Hours Bin (b) Mean Hours By Wage Decile (c) S.D. Hours By Wage Decile

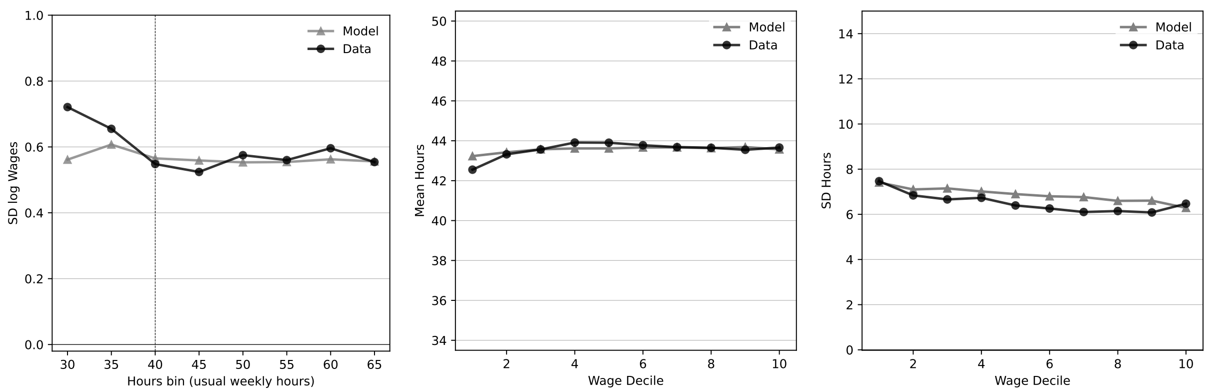
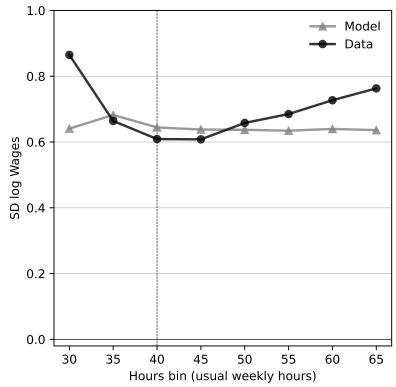


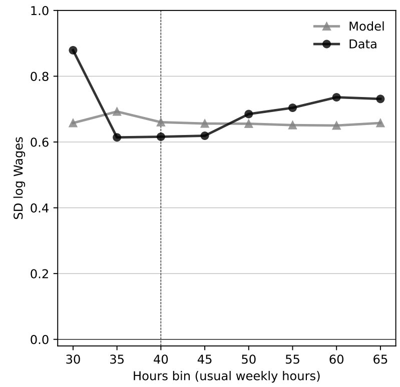
Figure D.2: Additional Comparisons Between Model M3 and Data: Bachelor and Bachelor+

Panel I: S.D. log Wages By Hours Bin

(a) Bachelor

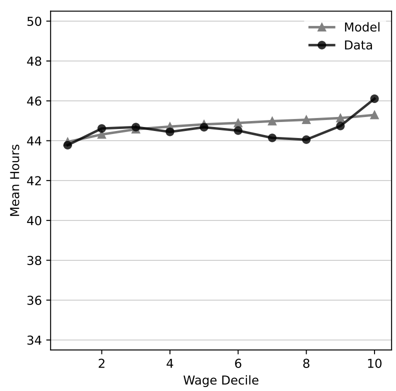


(b) Bachelor+

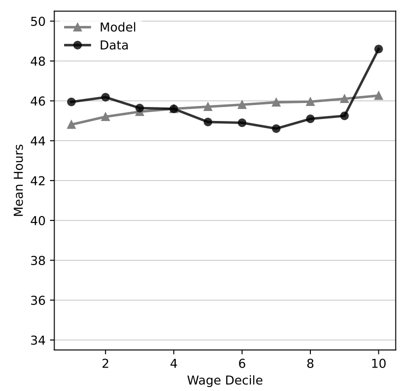


Panel II: Mean Hours By Wage Decile

(c) Bachelor

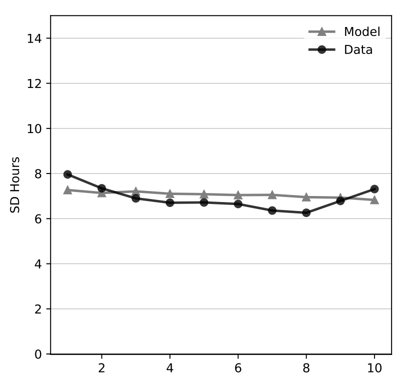


(d) Bachelor+

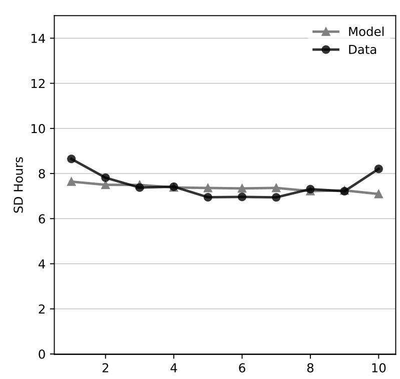


Panel III: S.D. Hours By Wage Decile

(e) Bachelor



(f) Bachelor+



D.2 Estimation of Model with Non-Labor Income

This section contains the results of our estimation exercise for High School men age 50-54 with non-labor income included. As discussed in Section 6.1, we assume that non-labor income y_i is distributed lognormally with mean μ_y and standard deviation σ_y, which we set using the SCF. We assume that y_i is uncorrelated with both α_i and z_i. We then run our standard estimation exercise.

The estimates with and without non-labor income for the 3-Region Model (M3) are displayed in Table D.1. With non-labor income, μ_α is lower to compensate for the income effect of non-labor income, and σ_α is slightly lower because there is an additional source of heterogeneity in motivations to work. With non-labor income $\rho_{\alpha,z}$ is less negative, implying a weaker positive selection of productivity across the hours distribution. This is intuitive, as non-labor income itself introduces some positive selection across the hours distribution: all else equal, a given transfer of non-labor income will reduce hours more for a low productivity worker relative to a high productivity individual.

Despite these differences, the key takeaway from Table D.1 is that the estimated earnings technology is quite similar with and without non-labor income. Specifically, $\theta_m = 0.061$ with non-labor income versus 0.058 without, and $\theta_l = 0.034$ with non-labor income versus 0.038 without. Figure D.3 shows that the overall fit of the model to the data is also barely affected by the introduction of non-labor income.

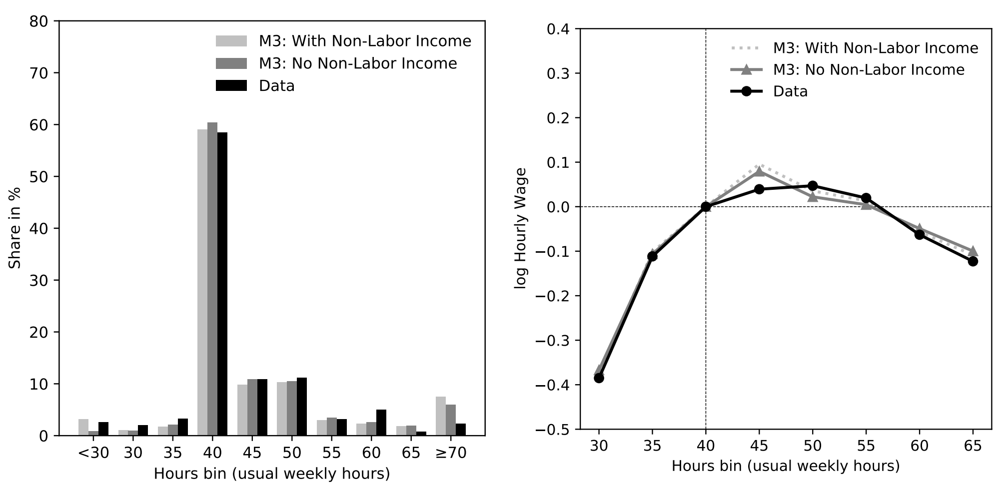
Table D.1: Estimated Parameters 3-Region Model (M3) with Non-Labor Income: High School Males 50-54

Specification	μ_α	σ_α	σ_z	$\rho_{\alpha,z}$	σ_m	θ_s	θ_m	θ_l
Benchmark	-13.64	1.61	0.589	-0.33	0.04	1.40	0.058	0.034
With Non-Labor Income	-14.22	1.50	0.583	-0.24	0.04	1.40	0.061	0.038

Figure D.3: Model Fit of 3-Region Model (M3) with Non-Labor Income: High School Males 50-54

(a) Hours Distribution

(b) Wage-Hours Profile



E Alternative Shock Process for Incomplete Markets Exercise

In Section 9.1 in the main text, we demonstrate that, within a standard incomplete markets economy, our estimated earnings technology has first order effects on the role of hours as a form of insurance. That analysis assumed that productivity followed an AR(1) process, in order to maintain comparability with benchmark results in Pijoan-Mas (2006). However, it is also standard practice to assume a shock process featuring both transitory and persistent components. In this Appendix section, we verify that such an alternative shock process does not meaningfully change our results.

We assume that assets must be non-negative, $a_t \geq 0$. We model $\log z_t$ as the sum of two orthogonal components: a persistent AR(1) process and a transitory shock:

$$\log z_t = \eta_t + \zeta_t \ ,$$

$$\log \eta_t = \rho_\eta \eta_{t-1} + \varepsilon_t \ ,$$

where $\varepsilon_t \sim N(0, \sigma_\varepsilon)$ and $\zeta_t \sim N(0, \sigma_\zeta)$.

To set parameters, we normalize w to unity and adopt the following parameterization. Following Pijoan-Mas (2006), we assume: $\sigma = 0.69$, $\gamma = 0.50$, $\beta = .94$, and $r = .05$. For the shock process we use parameter values from Heathcote, Storesletten, and Violante (2010): $\rho_\eta = 0.973$, $\sigma_\varepsilon = 0.021$, $\sigma_\zeta = 0.063$. We approximate the process for $\log z$ using the Rouwenhorst method, using 7 and 2 points for the persistent and transitory grids, respectively. We choose the value of α so as to target average hours in the ergodic distribution. As noted above, we consider three different targets for average hours: 30, 40, and 50. The rationale for these three values is that they correspond to different regions in the non-linear earnings specification: a region with convex earnings (30 hours), a region with concave earnings (50 hours) and a point at which earnings have a kink (40 hours). Note that the values of α will differ across the linear and non-linear specifications.

We then conduct the same analysis as in the main text. The resulting changes the standard deviation of hours and in welfare are displayed in Table E.1. Comparing these results to those in the corresponding table in Section 9.1, one can see that the results change little due to the different shock process.

Table E.1: Effects of Endogenizing Hours

	mean h	std h	CEV
linear earnings	40	0.22	3.8%
non-linear earnings	40	0.02	0.0%
non-linear earnings	30	0.24	6.2%
non-linear earnings	50	0.17	0.1%
non-linear earnings	60	0.16	0.3%