Online Appendix - Rethinking the Welfare State

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1 Age-Profiles: Data and Sample Restrictions

In this section of the Appendix, we presents details on data sources and sample restrictions for the constructions of age-profiles presented in Section 2 of the paper. We use the March Supplement of the CPS from 1980 to 2019 to document how average hourly wages, inequality of hourly wages and earnings, and labor market statistics (hours and participation) change over the life cycle. Our measure of inequality is the variance of logs. The analysis is restricted to household heads and their spouses who are between ages 25 to 60. If a head or a spouse reports positive earnings or hours, we require that they work at least 520 hours in a year. To account for top-coded observations, we fit a Pareto distribution to the right tail, as in Heathcote, Perri and Violante (2010). Finally, we drop observations where the hourly wage rate (calculated as yearly earnings divided by yearly hours) is less than half of the federal minimum wage. Given the sensitivity of variance of logs to observations at the lower tail, we also trim the observations associated with the bottom 0.5% of hourly-wages. These restrictions are standard in the literature – see Heathcote, Perri, and Violante (2010) and Huggett, Ventura and Yaron (2011). We calculate total earnings, hours, and hourly wage rates for each individual in the sample. For households, we sum the head and spouse's earnings and assign the age of the head to the households.

We then repeat an equivalent procedure using data from the CEX for consumption. We construct for each household a measure of expenditure of nondurables and services, which includes food, alcoholic beverages, tobacco products, apparel and services, personal care, gasoline for transportation, public transportation, household operations, medical care, entertainment, reading, and education. The definition of nondurable consumption follows Heathcote, Perri, and Violante (2010). The analysis is again based on repeated cross-sections from the CEX between 1984 and 2019.

Let $m_{j,t,c}$ be any statistic of interest for an age-j individual (or household) at time t, of cohort c. For example, $m_{j,t,c}$ could be the variance of log hourly wages among $j = 30$ year olds in 2000, who are born in $c = t - j = 1970$; i.e. the variance within a (j, t, c)-cell. Since age, time and cohort are linearly dependent, we construct age profiles using two approaches. We first consider a time-effects specification by regressing $m_{j,t,c}$ on a set of age and time (year) dummy variables, i.e.,

$$m_{j,t,c} = \beta_j' \mathbf{D}_j + \beta_t' \mathbf{D}_t + \varepsilon_{j,t,c}, \tag{1}$$

where $\mathbf{D}_j$ and $\mathbf{D}_t$ are a set of age and time dummies. The underlying assumption in the time-effects specification is that changes in $m_{j,t,c}$ over time are due to time-varying factors that affect every age (cohort), and once we control for time effects we recover the age profiles. Equation (1) is estimated separately for each gender (men and women), marital status (married and single), and skill group. For skills, we divide individuals in two groups; *skilled (s)*, those with at least four years of college education or more, and *unskilled (u)*, with strictly less than college education. The age profiles are given by the estimated β_j values. Then, we also estimate a cohort-effects specification, given by

$$m_{j,t,c} = \beta_j' \mathbf{D}_j + \beta_c' \mathbf{D}_c + v_{j,t,c}, \tag{2}$$

where $\mathbf{D}_c$ is a set cohort dummies. In contrast to equation (1), the underlying assumption in the cohort-effects specification is that changes in $m_{j,t,c}$ over time reflect differences between younger and older cohorts.

All life-cycle profiles we use in the benchmark calibration, targeted or non-targeted, are constructed by controlling for year effects (YE). Here, we show how the life-cycle profiles look like when we control for cohort effects (CE) and discuss the properties of the alternative benchmark economy that uses these profiles as targeted moments.

Figure A1 shows the variance of log wages by age, skill level, and marital status for year-effect (dash lines) and cohort-effect (solid lines) specifications. The main message that emerges is that these two specifications are broadly consistent. For males, inequality increases more or less linearly along the life cycle. For females, that is not the case; the increase in inequality slows down after an initial rise around age 35. Quantitatively, there is a higher increase in inequality over the life cycle under the cohort-effect specification, which is consistent with estimates provided by Heathcote, Storesletten, and Violante (2010) and Huggett, Ventura, and Yaron (2011). Figures A2 and A3 show the other life-cycle profiles we report in Section 2 of the paper: the gender wage gap, married female labor force participation, the variance of log hours worked for females and the correlation of earnings for husbands and wives. The impact of two alternative specifications on these outcomes is negligible.

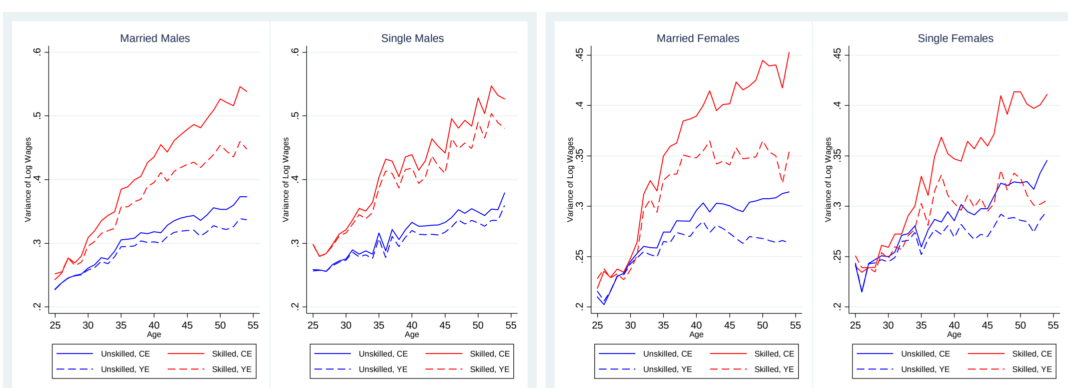

Figure A1 - Variance of Log Wages, Males (left) and Females (right), YE and CE

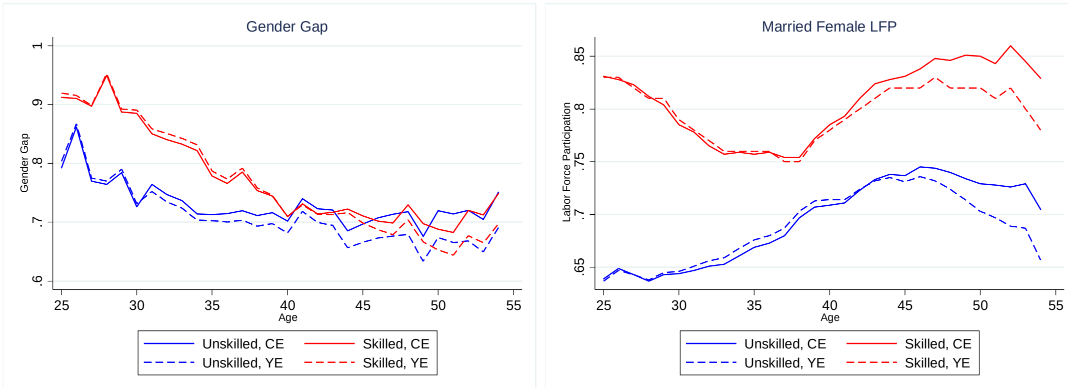

Figure A2 - The Gender Wage Gap (left), LFP of Married Females (right), YE and CE

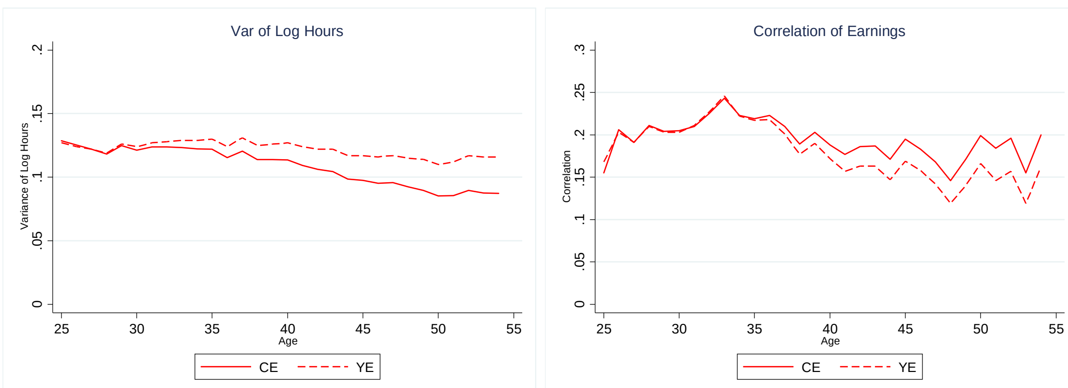

Figure A3 - Var. of Log Hours, Mar. Females (left), Cor. of Spousal Earnings (right), YE and CE

2 Model Inputs and Calibration

2.1 Demographics

The model period is a year. The population grows at the annual rate of 1.1%, the average values for the U.S. economy between 1960-2000. We determine the distribution of individuals by productivity types for each gender, using data from the 2008 American Community Survey (ACS). We consider all household heads or spouses between ages 30 and 39 and for each gender calculate the fraction of population in each education cell. For the same age group, the distribution of married working couples, as shown in Table A1. Given the fractions of individuals in each education group and the fractions of married households, we calculate the implied fractions of single households. The resulting values are reported in Table A2. About 74% of households consist of married households, while the rest (about 26%) are single. Since we assume that the distribution of individuals by marital status is independent of age, we use the 30-39 age group in the calibration. This age group captures the marital status of recent cohorts during their prime-working years, while being at the same time representative of older age groups.

Table A1: Distribution of Married Working Households by Type

	Females	
Males	Unskilled	Skilled
Unskilled	51.37	12.81
Skilled	8.93	26.90

Note: Entries show the fraction of marriages out of the total married pool, by wife and husband educational categories. The data used is from the 2008 ACS, ages 30-39. Entries add up to 100.

Table A2: Fraction of Agents by Type, Gender and Marital Status

	Males			Females		
	All	Married	Singles	All	Married	Singles
Unskilled	65.38	48.19	17.19	62.23	44.03	18.21
Skilled	34.62	26.51	8.11	37.77	29.10	8.66

Note: Entries show the fraction of individuals in each educational category, by marital status, constructed under the assumption of a stationary population structure.

2.2 Children

In the model each single female and each married couple belong to one of three groups: *without* children, *early* child bearer and *late* child bearer. We use information on the age of last birth of mothers by skill to determine who is in each category. The unskilled early child bearers have all children at age 1 (age 25). Skilled early-child bearers have children at age 1 (25) and at age 3 (27). Late child bearers have their children at ages 8 and 10, corresponding to ages 32 and 34. This structure captures the fact that births occur within a short time interval; between 25 and 29 for unskilled and between 30 and 34 for skilled households in the 2008 CPS June (Fertility) Supplement.[1] From the 2008 CPS June Supplement, we also calculate the fraction of 40 to 44 years old single (never married or divorced) females with zero live births. This provides us with a measure of lifetime childlessness. Then we calculate the fraction of all single women above age 25 with a total number of two live births who were below age 30 at their last birth. This fraction gives us those who are early child bearers, and the remaining fraction are assigned as late child bearers. The resulting distribution is shown in Table A3.

We follow a similar procedure for married couples, combining data from the CPS June Supplement and the U.S. Census. For childlessness, we use the larger sample from the U.S. Census.[2] The Census does not provide data on total number of live births but the total number of children in the household is available. Therefore, as a measure of childlessness

[1] The CPS June Supplement provides data on the total number of live births and the age at last birth for females, which are not available in the U.S. Census.

[2] The CPS June Supplement is not particularly useful for the calculation of childlessness in married couples. The sample size is too small for some married household types for the calculation of the fraction of married females, aged 40-44, with no live births.

we use the fraction of married couples between ages 35-39 who have no children at home.[3] Then, using the CPS June supplement we look at all couples above age 25 in which the female had a total of two live births and was below age 30 at her last birth. This gives us the fraction of couples who are early child bearers, with the remaining married couples labeled as the late ones. Table A4 shows the resulting distributions. Table A5 displays the number of children for single mothers by skill, and the corresponding ones for married couples.

Table A3: Childbearing Status, Single Females

	Childless	Early	Late
Unskilled	29.27	57.42	13.31
Skilled	54.63	28.17	17.20

Note: Entries show the distribution of childbearing among single females, using data from the CPS-June supplement.

Table A4: Childbearing Status, Married Couples

Childless			Early		
	Females			Females	
Male	Unskilled	Skilled	male	Unskilled	Skilled
Unskilled	9.22	13.17	Unskilled	63.46	40.58
Skilled	9.89	11.51	Skilled	45.88	26.95

Note: Entries show the distribution of childbearing among married couples. For childlessness, data used is from the U.S. Census. For early childbearing, the data used is from the CPS-June supplement. Values for late childbearing can be obtained residually for each cell.

Table A5: Fertility Differences

Singles		Married		
			Females	
		Male	Unskilled	Skilled
Unskilled	2.21	Unskilled	2.34	2.05
Skilled	1.82	Skilled	2.33	1.98

Note: Entries show, conditional on having children, the total number of children different types of households have by age 40-44. The authors' calculations from the 2008 CPS-June supplement.

[3] Since we use children at home as a proxy for childlessness, we use age 35-39 rather than 40-44. Using ages 40-44 generates more childlessness among less educated people. This is counterfactual, and simply results from the fact that less educated people are more likely to have kids younger, and hence these kids are less likely to be at home when their parents are between ages 40-44.

Childcare Costs We use the U.S. Bureau of Census data from the Survey of Income and Program Participation (SIPP) to calibrate childcare costs. We estimate a relation that represents the relation between the average age of children at home and per-child childcare costs, conditional on mother's skills and marital status. We estimate:

$$\widehat{d}(x, t; mar) = a_x^{mar} + b_x^{mar} \ln(t),$$

where $mar \in \{M, S\}$ stands for marital status, and t is the average age of children at home. The childcare spending per children in the data, $\widehat{d}(x, t; mar)$, reflects effective spending, so captures differences among household in access to informal care or quality of childcare chosen. Figure A4 (right panel) shows the estimated values. Our estimates imply that childcare costs are larger for skilled mothers and decline fast as children age. The annual rate of decline is about 11-12% (10-11%) when the child age is five for skilled (unskilled) mothers.

The childcare costs of a married couple where the wife is of skill x are given by $w^u d^M(x, t) = \widehat{d}(x, t; M)$ for each t, while for a single woman are given by $w^u d^S(x, t) = \widehat{d}(x, t; S)$. The resulting values for efficiency units are scaled so that the total childcare expenditure for children between ages 0 to 5 is in line with the data. As documented in Guner, Kaygusuz, and Ventura (2022), the total yearly cost for employed mothers, who have children between 0 and 5 and who make childcare payments, was about \$6,414.5 in 2005, which is about 10% of average household income. In the benchmark economy, this choice of parameter values results in 1.1% of the total labor input being used to produce childcare services. This is in line with the share of employment in the childcare sector in the U.S., which was about 1.1% in 2012.[4]

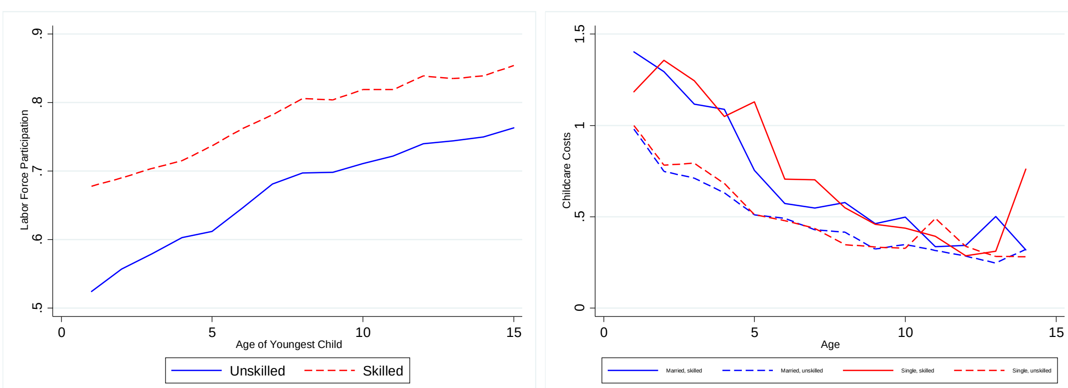

Figure A4 - LFP of Mar. Fem., by age of the youngest child (left); Childcare Costs per Child (right)

2.3 Taxes

2.3.1 Income Taxes

The tax function parameters are taken from Guner, Kaygusuz and Ventura (2022), who follow Guner, Kaygusuz and Ventura (2014) and estimate *effective tax rates* as a function

[4] Total employment in childcare services (NAICS 6244) was about 1.6 million in 2012. This number is the sum of total paid employment and the number of establishments without paid employees. See http://thedataweb.rm.census.gov/TheDataWeb_HotReport2/econsnapshot/2012/snapshot.hrml?NAICS=6244.

of reported income, marital status, and the number of children. The data is tax-return, micro-data from Internal Revenue Service for the year 2000 (Statistics of Income Public Use Tax File).

Since the EITC, CTC and CDCTC are explicitly modeled in the benchmark economy, tax liabilities in the absence of these credits are considered. To this end, let I stand for multiples of mean household income in the data and denote by $\widetilde{t}(I)$ the corresponding tax liabilities after any tax credits. Tax credits reduce the tax liability first to zero and if there is any refundable credit left, the household receives a transfer. Let $credit(I)$ be the total credits without any refunds, which we can identify in the IRS micro tax data. Taxes in the absence of credits is then given by $t(I) = \widetilde{t}(I) + credit(I)$. The incomes tax functions, i.e. $T^S(I, k)$ and $T^M(I, k)$,take the following form

$$\tau(I) = 1 - \lambda I^{-\tau},$$

where I is measured in multiples of mean household income, $\tau(I)$ is the average tax rate, parameter τ determines the progressivity of taxes and λ determines the taxes at the mean household income ($I = 1$). Parameters τ and λ depend on marital status and the number of children. The total tax liabilities amount to $\tau(I) \times I \times \textit{mean household income}$.

Estimates for λ and τ are contained in Table A6. Further details are provided in Guner, Kaygusuz and Ventura (2022). Guner, Kayusuz and Ventura (2014) show that this functional form does a great job matching average and marginal tax rates in the data. We estimate tax functions for households with zero and two children (and assign the number of children from Table A5 by rounding the numbers to the nearest integer). Figure A5 (left panel) displays estimated average and marginal tax rates for different multiples of household income.

Table A6: Tax Functions

Estimates	Married		Single	
	(no child)	(2 child.)	(no child)	(2 child.)
λ	0.9024	0.9078	0.8815	0.9227
τ	0.0569	0.0596	0.0356	0.0351

Note: Parameter estimates from Guner, Kaygusuz, and Ventura (2022).

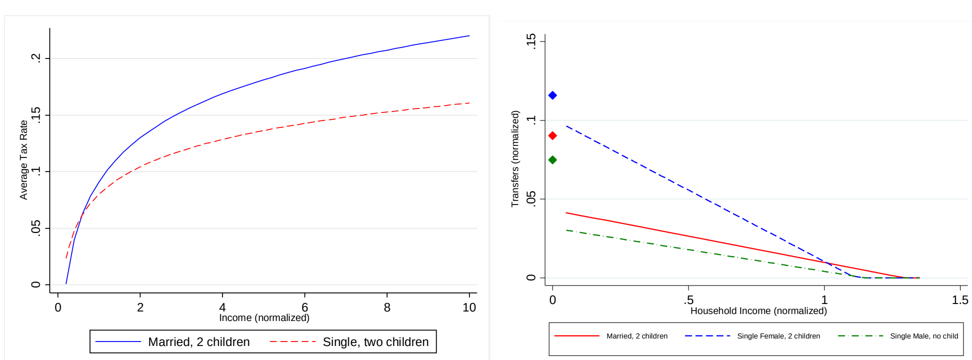

Figure A5 - Average Taxes (left); Welfare Payments (right)

2.3.2 Social Security and Capital Taxation

We calculate $\tau_p = 0.086$, as the average value of the social security contributions as a fraction of aggregate labor income for 1990-2000 period.[5] Using the 2008 ACS, we calculate total Social Security benefits for all single and married households.[6] Tables A7 shows Social Security benefits, normalized by the level corresponding to single males of the lowest type, $p_m^S(z_1)$. We treat $p_m^S(z_1)$ as a free parameter, and determine all other benefit levels according to Table A7. Then, given τ_p, choose $p_m^S(z_1)$ to balance the budget for the social security system. Hence, while the relative values social security benefits come from the data, the absolute level of one, $p_m^S(z_1)$, is adjusted to balance the budget of the system. The implied value of $p_m^S(x_1)$ for the benchmark economy is about 18.1% of the average household income in the economy.We use τ_k to proxy the U.S. corporate income tax. We estimate this tax rate as the one that reproduces the observed level of tax collections out of corporate income taxes after the major reforms of 1986. Such tax collections averaged about 1.92% of GDP for 1987-2000 period. Using the technology parameters we calibrate in conjunction with our notion of output (business GDP), we obtain $\tau_k = 0.097$.

Table A7: Social Security Benefits

	Single		Married		
				Females	
	Unskilled	Skilled	Males	Unskilled	Skilled
Males	1	1.166	Unskilled	1.764	1.911
Females	0.888	0.995	Skilled	1.981	2.093

Note: Entries show Social Security benefits, normalized by the mean Social Security income of the lowest type male, using data from the 2008 ACS.

2.4 Welfare State

Transfers, $TR_f^S(I, k, D), TR_m^S(I)$, and $TR^M(I, k, D)$, consist of three components. The first component is the Earned Income Tax Credit (EITC). The second part is child-related transfers, which consists of Child Tax Credit (CTC), the Child and Dependent Care Tax Credit (CDCTC), and childcare subsidies. The final component is the means-tested transfers.

2.4.1 Earned Income Tax Credits (EITC)

We model all tax credits as they appear in 2004 tax code. Since we represent all variables as a fraction of the mean household income, in the absence of any changes in the tax code, the reference year is not critical. The Earned Income Tax Credit is a fully refundable tax credit that subsidizes low income working families. The EITC amounts to a fixed fraction

[5] The contributions considered are those from the Old Age, Survivors and DI programs. The Data comes from the Social Security Bulletin, Annual Statistical Supplement, 2005, Tables 4.A.3.

[6] Social Security income is all pre-tax income from Social Security pensions, survivors benefits, or permanent disability insurance. Since Social Security payments are reduced for those with earnings, we restrict our sample to those above age 70. For married couples we sum the social security payments of husbands and wives.

of a family's earnings until earnings reach a certain threshold. Then, it stays at a maximum level, and when the earnings reach a second threshold, the credit starts to decline, so that beyond a certain earnings level the household does not receive any credit. The amount of maximum credits, income thresholds, as well as the rate at which the credits declines depend on the tax filing status of the household (married vs. single) as well as on the number of children. In 2004, for a married couple with 0 (2 or 3) children, the EITC started at $2 ($10) and increased by 7.6 (39.9) cents for each extra $ in earnings up to a maximum credit of $3,900 ($4,300). Then the credit stays at this level until the household earnings are $7,375 ($15,025). After this level of earnings, the credit starts declining at a rate of 7.6 (21) cents for each extra $ in earnings until it becomes zero for earrings above $12,490 ($35,458). The formulas for a single household with 0 (2 or 3) children are very similar. We calculate the level of $EITC$ as a function of earnings with the following formula,

$$\begin{aligned} EITC &= \max\{CAP\text{-}\max\{slope_1 \times (bend_1 - earnings), 0\} \\ &\quad - \max\{slope_2 \times (earnings - bend_2), 0\}, 0\}, \end{aligned}$$

where CAP, the maximum credit level, $bend_1$ and $bend_2$, the threshold levels, and $slope_1$ and $slope_2$, the rate at which credit increase and decline are given by (as a fraction of mean household income in 2014):

	CAP	$slope_1$	$bend_1$	$slope_2$	$bend_2$
Married					
No ch.	0.006	0.076	0.085	0.076	0.122
2 or 3 ch.	0.071	0.399	0.178	0.21	0.248
Single					
No ch.	0.006	0.076	0.085	0.076	0.105
2 or 3 ch.	0.071	0.399	0.178	0.21	0.232

Figure A6 (left panel) shows the EITC as a function of household income and the tax filing status.

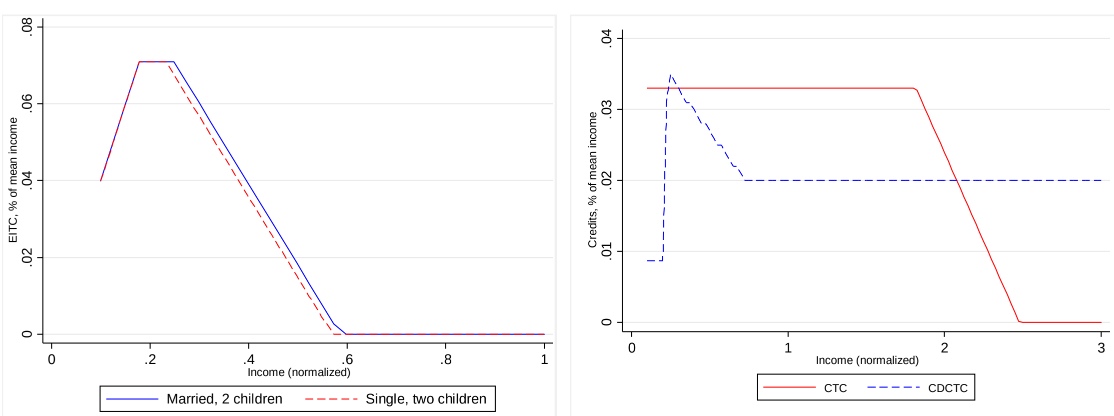

Figure A6 - The Earned Income Tax Credit (left); Potential CTC and CDCTC (right)

2.4.2 Child Tax Credits

Child credits operate as a means-tested transfer to households with children. If a household's income is below a certain limit, $\widehat{I}_{CTC}$, then the potential credit is $d_{CTC} = \$1,000$ per child in 2004. If the household income is above the income limit, then the credit amount declines by 5% for each additional dollar of income. In the current tax code, $\widehat{I}_{CTC}$ is \$110,000 for a married couple and \$75,000 for singles. As a result, a married couple with two children whose total household income is below \$110,000 has a potential child credit of \$2,000, a household with two children whose total household income is \$120,000 can only get \$1,500. The child credit becomes zero for married couples (singles) whose total household income is above \$150,000 (\$115,000). As the CTC is not fully refundable, the actual CTC that a household gets depends on the total tax liabilities of the household and other child-related credits that the household might qualify.

For a household with income level I (again indicated as a multiple of mean household income in the economy) and k children, the *potential CTC* is given by

$$CTC_{potential}(I) = \max\{[k \times 0.0165 - \max(I - \widehat{I}_{CTC}, 0) \times 0.05], 0\}, \tag{3}$$

with

$$\widehat{I}_{CTC} = \begin{cases} 1.819, & \text{if married filing jointly} \\ 1.240, & \text{if single} \end{cases},$$

where again the maximum amount of credit per child, 0.0165, and income limits, 1.819 and 1.240, are in multiples of mean household income in the U.S. in 2004. Both the CTC and the CDCTC are *non-refundable*, as a result, how much of the potential credit a household actually gets depends on its total tax liabilities and total tax credits (CTC plus CDCTC). Let $Credit_{potential}(I) = CTC_{potential}(I) + CDCTC_{potential}(I)$ and $Taxes(I)$ be the total potential tax credits and the tax liabilities of the household. Then,

$$CDCTC_{actual}(I) = \begin{cases} CDCTC_{potential}(I), \text{ if } Taxes(I) > Credit_{potential}(I) \\ \max\{Taxes(I) - CDCTC_{potential}(I), 0\}, \text{ if } Taxes(I) < Credit_{potential}(I) \\ \qquad \text{and } CDCTC_{potential}(I) > Taxes(I) \\ CDCTC_{potential}(I), \text{ if } Taxes(I) < Credits_{potential}(I) \\ \qquad \text{but } CDCTC_{potential}(I) < Taxes(I) \end{cases},$$

and

$$CTC_{actual}(I) = \begin{cases} CTC_{potential}(I), \text{ if } Taxes(I) > Credits_{potential}(I) \\ 0, \text{ if } Taxes(I) < Credits_{potential}(I) \\ \qquad \text{and } CDCTC_{potential}(I) > Taxes(I) \\ Taxes(I) - CDCTC_{potential}(I), \text{ if } Taxes(I) < Credits_{potential}(I) \\ \qquad \text{but } CDCTC_{potential}(I) < Taxes(I) \end{cases}$$

Hence, if the tax liabilities of a household are larger than the total potential credit implied by the CTC and the CDCTC, the household receives the full credit and its tax liabilities are reduced by $CTC_{potential} + CDCTC_{potential}$. If the total potential credits are larger than tax liabilities, then the household only receives a credit up to its tax liabilities. As a result, the households with low tax liabilities do not benefit from the CTC or CDCTC.

This is partially compensated by the Additional Child Tax Credit (ACTC), which gives a household additional tax credits if its potential child tax credit is higher than the actual child tax credits it receives. In order to qualify for the ACTC, however, a household must have earnings above \$10,750. Thus, a household with very low earnings does not qualify for the ACTC. Given CTC_{actual} and CTC_{credit}, the ACTC is calculated as

$$ACTC(I) = \begin{cases} \min\{\max[(earnings - 0.178), 0] * 0.15, CTC_{potential}(I) - CTC_{actual}(I)\} \\ \qquad\qquad \text{if } CTC_{actual}(I) \leq CTC_{credit}\ (I) \\ 0, \text{ otherwise} \end{cases}.$$

2.4.3 Childcare Credits

All households with positive income can qualify for the Child and Dependent Care Tax Credit (CDCTC), or, as we refer in the paper, for *childcare credits*. Potential childcare credits are calculated in two steps, using the total childcare expenditures of the household, a cap, and rates that depend on household income. First, for each household, a childcare expenditure that can be claimed against credits is calculated. This expenditure is simply the minimum of the earnings of each parent in the household, a cap and actual childcare expenditures. The cap is set \$3,000 and \$6,000 for households with one child and with more than one child in 2004. Second, each household can claim a certain fraction of this qualified expenditure as a tax credit. This fraction starts at 35%, and declines by household income by 1% for each \$2,000 above \$15,000 until it reaches 20%, and then remains constant at this level. For a married couple with k children, the qualified expenditure is calculated as follows

$$\text{Expense } = min\{d_{CDCTC} \times \min\{k, 2\}, earnings_1, earnings_2, d\},$$

where $earnings_1$ and $earnings_2$ are the earnings of the household head and his/her spouse and d is the child care expenditure (net of any childcare subsidy that a household might qualify). Note that a married couple household can have qualified expenses only if both the husband and the wife have non-zero earnings. The child care expenditures for the calculation of the childcare credits are capped at d_{CDCTC} per child per year, with a maximum of $2 \times d_{DCCTC}$.

For a single female household, the equivalent formula is given by

$$\text{Expense } = min\{d_{CDCTC} \times \min\{k, 2\}, earnings, d\}.$$

In 2004, d_{CDCTC} was \$3,000, i.e. maximum qualified expenditure for households with more than 1 child was capped at \$6,000. In multiples of mean household income in the U.S. (\$60,464 in that year), d_{CDCTC} was equal to 0.0496, i.e. about 5% of mean household income in the US. A household, however, only receives a fraction $\theta_{CDCTC}(I)$ of qualified expenses. The rate, θ_{CDCTC}, is a declining function of household income. It is set at 35% for households whose income is below \$15,000 ($\widehat{I}_{CDCTC}$), and after this point the rate declines by 1% for each extra \$2,000 that the household earns down to a minimum of 20%. Hence, the potential $CDCTC$ that a household can receive is then given by

$$CDCTC_{potential}(I) = \text{Expense} \times \theta_{CDCTC}(I), \tag{4}$$

with

$$\theta_{CDCTC}(I) = \begin{cases} 0.35, \text{ if } I \leq \widehat{I}_{CDCTC} \\ 0.35 - \min\{[\text{integer}(\frac{I-\widehat{I}_{CDCTC}}{0.033}) + 1] \times 0.01, 0.15\}, \text{ otherwise} \end{cases},$$

where $\widehat{I}_{CDCTC}$ is equal to 0.248 is in multiples of mean household income in the U.S. in 2004. Figure A6 (right panel) illustrates the sum of $CDCTC_{potential}(I)$ and $CTC_{potential}(I)$.[7]

2.4.4 Childcare Subsidies

We assume that the childcare subsidies in the model economy reflect the childcare subsidies provided by the Children Child Care and Development Fund (CCDF) in the US. Following Guner, Kaygusuz and Ventura (2022), we set $\theta = 0.75$ and choose $\widehat{I}$ such that the poorest 5.5% of families with children receive a subsidy from the government. This procedure sets $\widehat{I}$ at about 24.2% of mean household income in the benchmark economy. In the main policy experiments that we consider, we make the childcare subsides universal by setting $\widehat{I}$ to an arbitrarily large number.

2.4.5 Means-Tested Transfers

The means tested transfers are taken from Guner, Kaygusuz and Kaygusuz (2022), who use the 2004 wave of the Survey of Income and Program Participation (SIPP) to approximate a welfare schedule as a function of labor earnings for different household types. The "effective transfer function" (conditional on marital status and the number of children) takes the following form

$$W(I) = \begin{cases} \omega_0 \text{ if } I = 0 \\ \max\{0, \omega_1 - \omega_2 I\} \text{ if } I > 0 \end{cases},$$

where ω_0 is the transfers for a household with zero income and ω_2 is the benefits reduction rate and I is reported in multiples of mean household income. To determine ω_0, the average amount of welfare payments for households with zero non-transfer income is used. Then an OLS regression of welfare payments on household non-transfer income is estimated to determine α_0 and α_1. In Table A8 shows the estimated values of ω_0, α_1 and α_2 and Figure A5 (left panel) shows the welfare payments as a function of household income. Further details are provided in Guner, Kaygusuz and Ventura (2022).

Table A8: Welfare System

Estimates	Married		Single Female		Single Male
	(no child)	(2 child.)	(no child)	(2 child.)	(no child)
ω_0	0.063	0.090	0.090	0.116	0.075
ω_1	0.023	0.043	0.044	0.101	0.032
ω_2	-0.017	-0.033	-0.042	-0.091	-0.028

Note: Parameter estimates from Guner, Kaygusuz, and Ventura (2022).

[7] The simulations for $CDCTC_{potential}(I)$ in Figure A4 are done under the assumption th at at each income level, the husband and the wife earns 60% and 40% of the household income, respectively, and the households spend 10% of their income on childcare.

2.5 Heterogeneity

There are 2 education types of males, corresponding to educational attainment levels *less than college* (u), and *college or more* (s). We use the March Supplement of the CPS from 1980 to 2019 to calculate age-efficiency profiles for each male type. For the benchmark economy, we construct age profiles for different outcomes from cross-sectional data by removing year effects, as detailed in Section 2 of the paper. Within a skill group, efficiency levels correspond to mean weekly wage rates, which we construct using annual wage and salary income and weeks worked, normalized by the mean weekly wages for all males and females between ages 25 and 64. Figure A7 (left panel) shows the third-degree polynomials that we fit to the wage data. In the quantitative exercises, the male efficiency units, $\varpi_m(z, j)$, correspond to these fitted values.

There are also 2 education types for females. Table A9 reports the initial (age 25) efficiency levels for females together with the initial male efficiency levels and the corresponding gender wage gap. We use the initial efficiency levels for females to calibrate their initial human capital levels, $h_1 = \varpi_f(x, 1)$. After age 25, the human capital level of females evolves endogenously according to

$$h' = \mathcal{H}(x, h, l, e) = \exp\left[\ln h + \alpha_x^e \chi(l) - \delta_x(1 - \chi(l))\right], \quad x \in X = \{u, s\},$$

where e stands for labor market experience and $\chi(.)$ is an indicator function that is 1 if hours worked are positive and zero otherwise. Parameter α_x^e is experience-skill growth rate and δ_x stands for the depreciation rate.

We calibrate the values for δ_x and α_x^e as follows. First, we select α_x^e so that if a female of a particular education type works in every period, her wage profile has exactly the same shape as a male of the same type. This procedure takes the initial gender differences as given, and assumes that the wage growth rate for a female who works full time will be the same as for a male worker with the same level of experience; hence, it sets α_x^e values equal to the growth rates of male wages at each age. Figure A7 (right panel) shows the calibrated values for α_x^e. We then select two values of δ_x so that we match the level of gender gap for skilled and unskilled women by age 25-35 as closely as possible.[8]

Table A9: Initial Productivity Levels, by Type and Gender

	$\varpi_m(1, z)$	$\varpi_f(1, x)$	$\varpi_f(1, x)/\varpi_m(1, z)$
Skilled	0.88	0.81	0.92
Unskilled	0.69	0.56	0.80

Note: Entries are the productivity levels of males and females, ages 25, using 1980-2019 data from the CPS March Supplement. These levels are constructed as weekly wages for each type.

[8] We target the gender gap in hourly wages *all* married females in the model. We impute wages for females who do not participate using a standard Heckman (1979) selection correction. For the population equation for wages, we assume a standard Mincer equation, i.e. log wages of women depend on years of education, age, and age squared. For the selection equation, we assume that the probability of participation in the labour market for a female depends on her marital status, number of children younger than age 5, and the variables in the population equation.

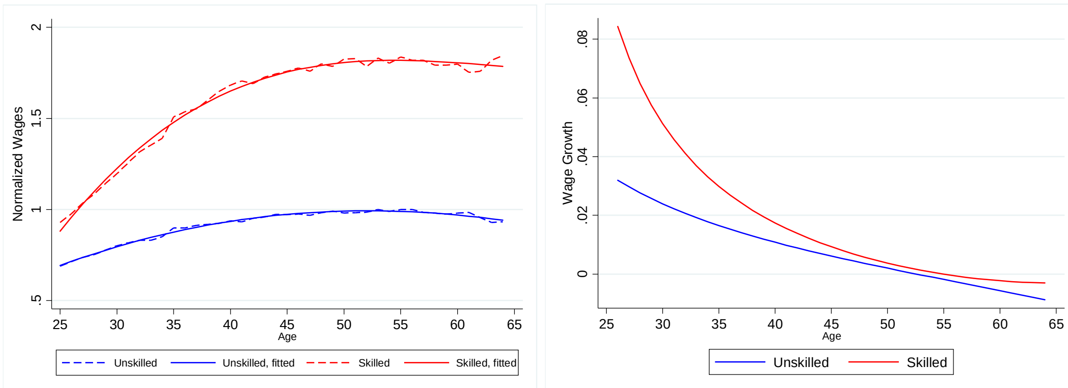

Figure A7 - Age-Labor Productivity Profiles, Males (left); Female Human Capital Growth (right)

2.6 Preferences and Technology

In this section of the Appendix, we provide further details on how we assign parameter values to the endowment, preference, and technology parameters of the benchmark economy. There are three utility-function parameters to be determined: the intertemporal elasticity of labor supply (γ), the parameter governing the disutility of market work for males and females, B_m and B_f, and the disutility shock of market work for married females, θ. We set the Frisch elasticity parameter γ to 0.2. This is on the low side of recent available estimates, but via other choices in our economy, the macro elasticity is broadly consistent with estimates. Given γ, we select the parameter B_f and B_m to reproduce average market hours per worker observed in the data, about 42.7% and 37.0% of available time for males and females in 2008.[9] Finally, the disutility shocks are specified as $\theta_L = \exp(-\Delta)$ and $\theta_H = \exp(+\Delta)$. The parameter Δ is set so as to reproduce the observed variance of log-hours of married females at age 40 (0.127 in the data). As it is the standard in the literature, we select the discount factor β, so that the steady-state capital to output ratio matches the value in the data (2.93).

Utility costs associated to joint work allow us to capture the residual heterogeneity among couples, beyond heterogeneity in endowments and childbearing status, that is needed to account for the observed heterogeneity in participation choices. We assume that the utility cost parameter of joint participation is distributed according to a gamma distribution, approximated on a discrete grid, with parameters k_z and θ_z. Thus, conditional on the husband's type z,

$$q \sim \zeta(q|z) \equiv q^{k_z-1} \frac{\exp(-q/\theta_z)}{\Gamma(k_z)\theta_z^{k_z}},$$

where $\Gamma(.)$ is the Gamma function. This procedure allows us to exploit the information contained in the differences in the labor force participation of married females as their own wage rate changes with skill. In this way, we indirectly control the 'slope' of the distribution

[9] The numbers are for people between ages 25 and 54 and are based on data from the CPS. We find mean yearly hours worked by all males and females by multiplying usual hours worked in a week and number of weeks worked. We assume that each person has an available time of 5,000 hours per year.

of utility costs, which is potentially key in assessing the effects of changing incentives for labor force participation.

Table A10: Labor Force Participation of Married Females, 25-54

	Females	
Males	Unskilled	Skilled
Unskilled	69.1	85.2
Skilled	64.8	73.3

Note: Each entry shows the labor force participation of married females ages 25 to 54, calculated from the 2008 ACS. The outer row shows the weighted average for a fixed male or female type.

Using the Census data, we calculate that the employment-population ratio of married females between ages 25 and 54, for each of the educational categories defined earlier.[10] Table A11 shows the resulting distribution of the labor force participation of married females by the productivities of husbands and wives for married households. The aggregate labor force participation for this group is 71.8%, and it increases from 68.2% for the unskilled group to 77.4% for the skilled. Our strategy is then to select the two parameters governing the gamma distribution, for every husband type, so as to reproduce each of the rows in Table A10 as closely as possible. This process requires estimating four parameters (i.e. a pair (θ, k) for each husband educational category). Given the estimated values for k_z and θ_z, we determine the loading factors $\vartheta_x(t_{min})$ so that the model is consistent with the participation rate of mothers by the age of their youngest child present at home, shown in Figure A4 (left panel). To compute the participation rate of married females by skill by the age of their youngest child at home, we use data from the 2008 ACS.

Finally, we set the capital share to $\alpha = 0.343$ and the depreciation rate of capital to $\delta^k = 0.055$.[11] To select the parameter governing the elasticity of substitution, ρ, we use standard estimates of this elasticity that suggest a value of 1.5 – see Katz and Murphy (1992) and Heckman, Lochner and Taber (1998). This dictates $\rho = 1/3$. To calibrate the share parameter ξ, we force the model to reproduce the aggregate *skill premium* in the data, defined as per-worker earnings of workers in the skilled category to per-worker earnings of workers in the unskilled category. For this statistic, we target a value of 1.8.[12] Tables A11

[10] We consider all individuals who are *not* in armed forces.

[11] We calibrate the capital share and the depreciation rate using a notion of capital that includes fixed private capital, land, inventories and consumer durables. For the period 1960-2000, the resulting capital to output ratio averages 2.93 at the annual level. We estimate the capital share and the capital to output ratio following the standard methodology; see Cooley and Prescott (1995). The data for capital and land are from Bureau of Economic Analysis (Fixed Asset Account Tables) and Bureau of Labor Statistics (Multifactor Productivity Program Data).

[12] The empirical target for the skill premium is from our calculations using data from the 2005 American Community Survey (ACS). We restrict the sample to the civilian adult population of both sexes, between ages 25 and 54 who work full time, and exclude those who are unpaid workers or make less than half of the minimum wage. Full time workers are defined as those who work at least 35 hours per week and 40 weeks per year. We estimate a value tightly centered around 1.8, when we include self-employed individuals or not.

and A12 shows full set of parameters.

Table A11: Parameter Values - Idiosyncratic Shocks
Benchmark Calibration

Statistic	Permanent Shocks	Persistent Shocks
Variance Single Skilled Males	0.2980	0.0063
Variance Single Unskilled Males	0.2570	0.0036
Variance Single Skilled Females	0.2510	0.0019
Variance Single Unskilled Females	0.2440	0.0018
Variance Married Skilled Males	0.2520	0.0068
Variance Married Unskilled Males	0.2270	0.0038
Variance Married Skilled Females	0.2240	0.0040
Variance Married Unskilled Females	0.2500	0.0008
Covariance (male, female)	0.0580	0.0010

3 Benchmark Economy - Additional Outcomes

In this section of the Appendix we present two additional outcomes that are mentioned in the paper. Figure A8 shows the variance of log household consumption in the data and the model. The model does an excellent job matching the level of inequality in household consumption at the start of the life cycle and the size of increase along the life cycle.

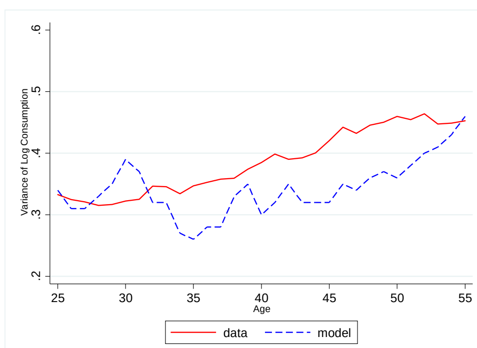

Figure A8 - Variance of Log Household Consumption

Figure A9 shows what happens to the variance of log wages and the labor force participation of married females in the benchmark economy when we set all childcare costs to zero, while keeping all other parameters constant. The children matter critically in determining the levels of participation rates, and how inequality in wages and earnings evolve over the life-cycle for married females. When childcare costs are set to zero, the participation rate of unskilled married females is much higher/ Furthermore, without children, the variance of log wages grows linearly along the life cycle for women, exactly as it does for men.

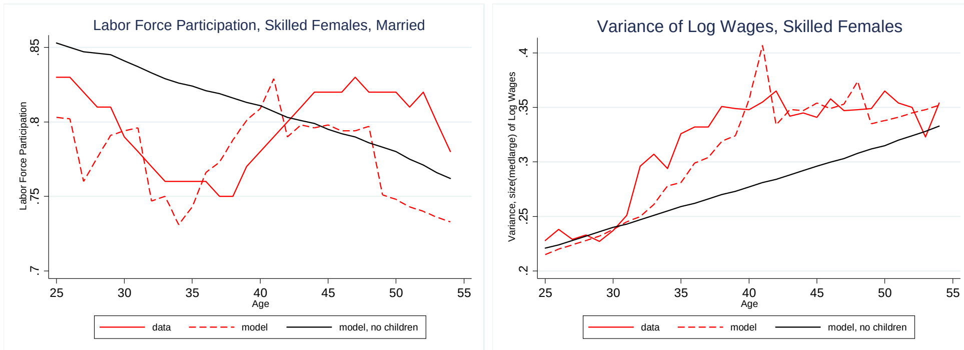

Figure A9 - LFP (left); Var. of Log Wages (right), Married Skilled Females

Table A12: Parameter Values
Benchmark Calibration

Parameter	Value	Comments
Population Growth (n)	0.011	U.S. Data
Discount Factor (β)	0.9829	Calibrated - matches K/Y
Labor Supply Elasticity (γ)	0.2	Literature estimates.
Disutility from work, $(B_f,\ B_m)$	82.15, 28.67	Calibrated
Preference Shock $\triangle$	1.9	See text – Matches variance log hours at age 40
Skill depreciation, females (δ_x)	0.025, 0.059	Calibrated
Growth of skills (α_x^e)	-	See text - CPS data
Distribution of utility costs $\zeta(.\|z)$ (Gamma Distribution)	-	See text - matches LFP by education conditional on husband's type
Loading Factor $\vartheta_x(t_{\min})$	-	See text – matches LFP by age of youngest child
Capital Share (α)	0.343	Calibrated
Skilled Labor Share (ν)	0.5085	Calibrated
Substitution Elasticity (ρ)	1/3	Literature estimates
Depreciation Rate (δ_k)	0.055	Calibrated
Childcare costs for single females, $d^S(x,t)$	-	See text - matches expenditure by age, and skills.
Childcare costs for married females $d^M(x,t)$	-	See text - matches expenditure by age, and skills.
Tax functions $T^M(I,k)$ and $T^S(I,k)$	-	See Appendix - IRS Data
Transfer functions $TR^M(I,k)$,	-	See text and Appendix
$TR_f^S(I,k)$ and $TR_m^S(I,k)$	-	
Payroll Tax Rate (τ_p)	0.086	See Appendix
Social Security Incomes,	-	See Appendix - U.S. Census
$p_m^S(z)$, $p_f^S(x)$ and $p^M(x,z)$	-	
Capital Income Tax Rate (τ_k)	0.097	See Appendix - matches corporate tax collections

4 Optimal NIT

Figure A10 displays how aggregate output, ex-ante welfare for all, and majority support changes with the NIT transfers. When the transfer equals zero, the tax system is simply a proportional tax with no transfers whatsoever, and output is about 3.2% higher than in the benchmark case. As transfers increase, tax rates, welfare and popular support increase as well, but changes in output relative to the benchmark case become gradually lower and eventually become negative. Figure 10 shows that as the lump-sum transfer increases, both welfare and support for the reform first sharply increase and then decline. For a transfer level of about 6% of mean income, ex-ante welfare gains are negative and majority support disappears. At this level, the tax rate required is not trivially higher than at the welfare-maximizing level (about 23.8%). Output is about 1.8% lower than in the benchmark case.

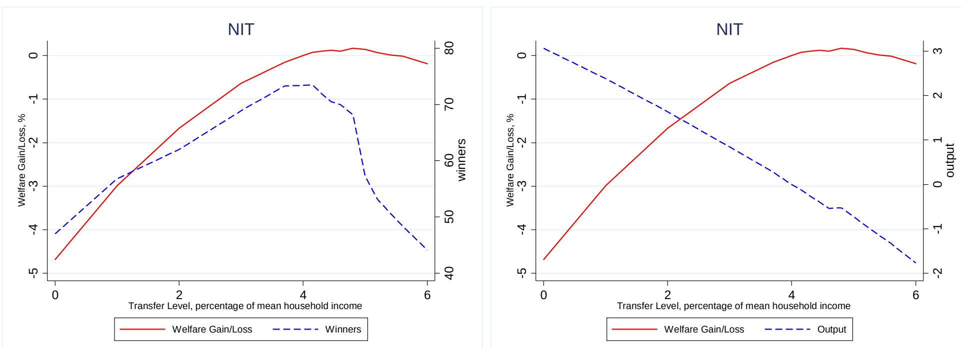

Figure A10 - Welfare Gains and Winners, NIT(left); Welfare Gains and Output, NIT (right)

5 Benchmark Economy with CE Profiles

Figure A11 shows that a recalibrated version of the benchmark economy has no trouble matching the age-inequality profiles produced using a cohorts-effects specification. Table A13 shows the other model outcomes. The parameter values we use for this alternative benchmark are presented in Tables A17-19.

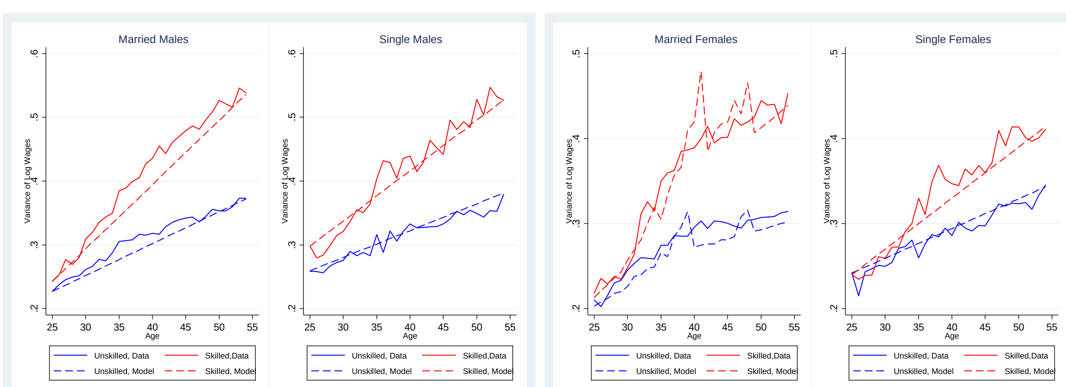

Figure A11 - Variance of Log Wages, Model vs. Data, Males (left), Females (right), data with CE

Table A13: Model and Data (YE and CE Calibration)

Aggregates	Data	BM (YE)	Data	CE
Capital Output Ratio	2.9	2.9	-	2.9
Total Transfers (% of GDP)	2.3	2.3	-	2.4
Skill Premium	1.8	1.8	-	1.8
LFP of Married Females (%), 25-54				
Unskilled	68.2	68.7	-	68.5
Skilled	77.4	77.7	-	78.8
Total	71.8	72.3	-	72.6
Life-Cycle Inequality				
Variance log-wages (Married Males, age 54, S)	0.45	0.45	0.54	0.54
Variance log-wages (Married Males, age 54, U)	0.34	0.34	0.37	0.37
Variance log-wages (Married Females, age 54, S)	0.35	0.35	0.44	0.45
Variance log-wages (Married Females, age 54, U)	0.26	0.26	0.31	0.30
Variance log-hours (Married Females, age 40)	0.13	0.13	0.11	0.11
Correlation Between Wages of Spouses (age 25)	0.31	0.31	0.30	0.31
Correlation Between Wages of Spouses (age 40)	0.34	0.33	0.34	0.33
Variance log-consumption (Age 55 vs 25)	0.12	0.12	0.15	0.16
Earnings Inequality (25-64)				
90-10 ratio	7.8	7.1	-	7.4
90-50 ratio	2.6	2.5	-	2.6
Share, bottom 10%	1.8	2.1	-	1.95
Share, bottom 20%	4.5	5.5	-	5.2
Share, bottom 40%	13.2	15.8	-	15.2

Note: Entries show model outcomes for benchmark economy and the case where moments created using cohorts effects, as discussed in Section 7 in the paper

6 Rethinking the Welfare State When Inequality is Lower

In this section of the Appendix, we present calibration details for "the 1980" economy in the paper. Recall that for the benchmark economy, we use life-cycle profiles generated using the CPS for the 1980-2019 period, complemented by cross-sectional facts from the 2008 American Community Survey. For the 1980 economy, we estimate the life-cycle profiles using CPS data for the 1980-1994 period and use cross-sectional facts from the 1980 and 1990 US Census.

The 1980 economy differs from the benchmark along three dimensions. First, only about 19% of females had a college degree in 1980, and this number more than doubled to nearly 39% in 2008. For males, the fraction with a college degree increased from 29% to 35%. Substantial changes in marital sorting accompanied these changes; about 14% of married households were of the skilled-skilled category in 1980, while the corresponding figure in our parameterization is nearly 27%. These facts for the 1980 economy are reported in Tables A16 and A17 below.

Second, there has been a significant increase in inequality. The skill premium was about 1.5 in 1980 and increased to 1.8 in our benchmark parameterization. The left panel in Figure A12 shows the age-productivity profiles for males for the 1980 and the benchmark economy. In both figures, hourly wages are normalized by mean hourly wages in the data for each year, and relative wages of skilled are much higher in the benchmark. In Figure A13, we report the variance of log wages by age, skill level, and marital status for the benchmark (dash lines) and the 1980 (solid lines) specifications. The 1980 profiles have a lower intercept (lower inequality at age 25) and, particularly for women, imply a lower increase in inequality along the life cycle.

Finally, the labor force participation of married females was lower in 1980. Table A16 shows the labor force participation of married females by their and their husbands' productivity. Compared to the numbers in Table A11, the labor force participation of married females is about 4 (9) percentage points lower for couples composed of two skilled (unskilled) partners. Figure A14 show the labor force participation of married females by their (left panel) and their children's (right panel) age, calculated using data for the 1980-1994 and the 1980-2019 periods.

We capture the effect of these changes on our results in two steps. First, we focus on the role of inequality. To this end, we calibrate an alternative benchmark economy, where as model inputs we use the 1980 demographics (Tables A14 and A15) and age-productivity profiles for males (Figure A13, left panel) and the associated wage growth rates, α_j^x (Figure A13, right panel) for females. We also target the life-cycle inequality profiles estimated using the 1980-1994 CPS data (Figure A15) and a skill premium of 1.5. We call this alternative the 1980 (I) case in the paper. Then, we also target the married female labor force participation (Table A16 and Figure A15-left panel) and call it the 1980 (II) case.

In both exercises, all other model inputs and targets remain the same as in our benchmark economy. Hence, these exercises should be interpreted as our benchmark economy with lower levels of inequality and married female labor force participation rather than representations of the 1980 US economy. The parameter values are reported in Tables A18-20.

Table A14: Distribution of Married Working Households by Type
1980

	Females	
Males	Unskilled	Skilled
Unskilled	67.07	4.52
Skilled	14.43	13.98

Note: Entries show the fraction of marriages out of the total married pool, by wife and husband educational categories. The data used is from the 1980 Census, ages 30-39. Entries add up to 100.

Table A15: Fraction of Agents by Type, Gender and Marital Status
1980

	Males			Females		
	All	Married	Singles	All	Married	Singles
Unskilled	70.65	61.75	8.91	80.85	68.40	12.45
Skilled	29.35	24.50	4.85	19.15	15.44	3.71

Note: Entries show the fraction of individuals in each educational category, by marital status, constructed under the assumption of a stationary population structure from the 1980 Census.

Table A16: Labor Force Participation of Married Females, 25-54
1980

	Females	
Males	Unskilled	Skilled
Unskilled	60.10	79.10
Skilled	58.15	69.80

Note: Each entry shows the labor force participation of married females ages 25 to 54, calculated from the 1980 and 1990 Census (the average values are reported).

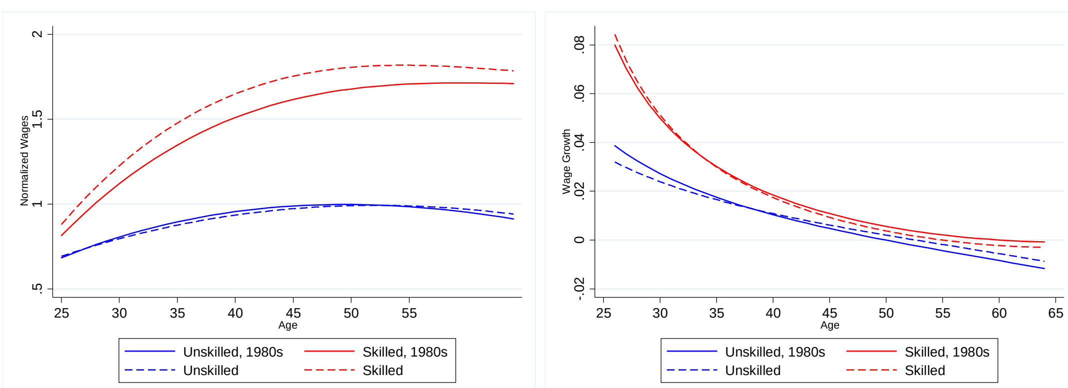

Figure A12 - Age-Labor Productivity Profiles, Males (left), Female Wage Growth, α_j^x (right), benchmark data vs. the 1980s

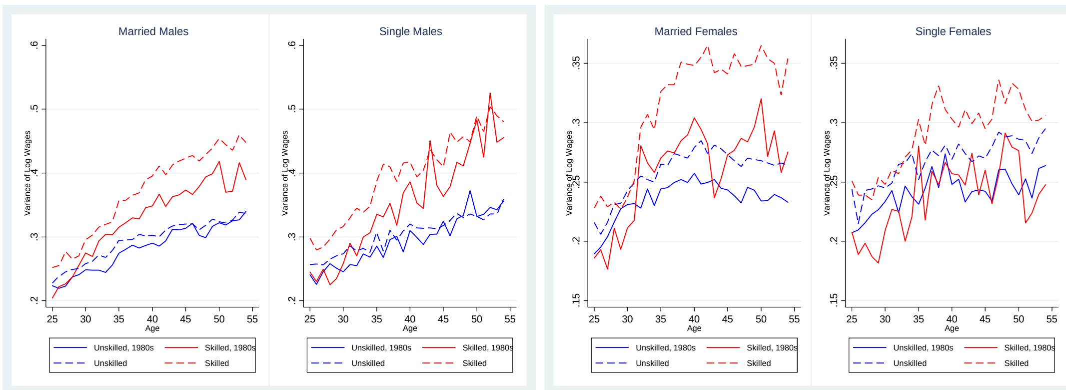

Figure A13 - Variance of Log Wages, Males (left) and Females (right), benchmark data vs. the 1980s

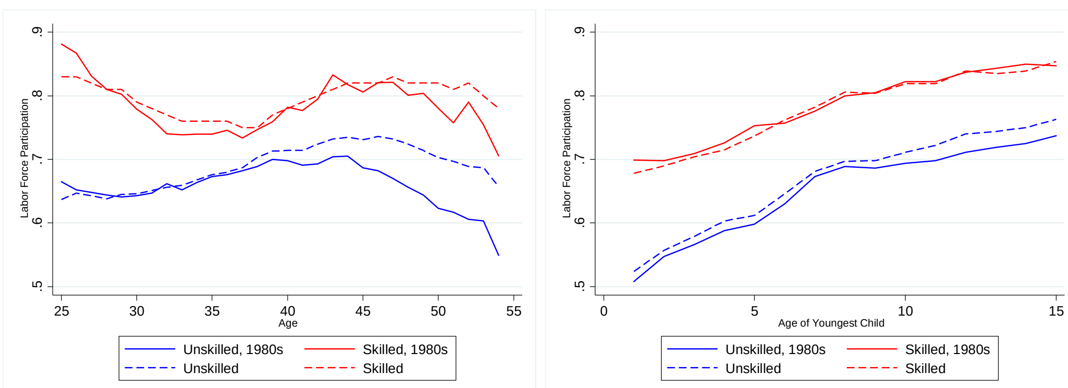

Figure A14 - LFP of Married Females (left panel), LFP by the age of youngest child (right panel), benchmark data vs. the 1980s

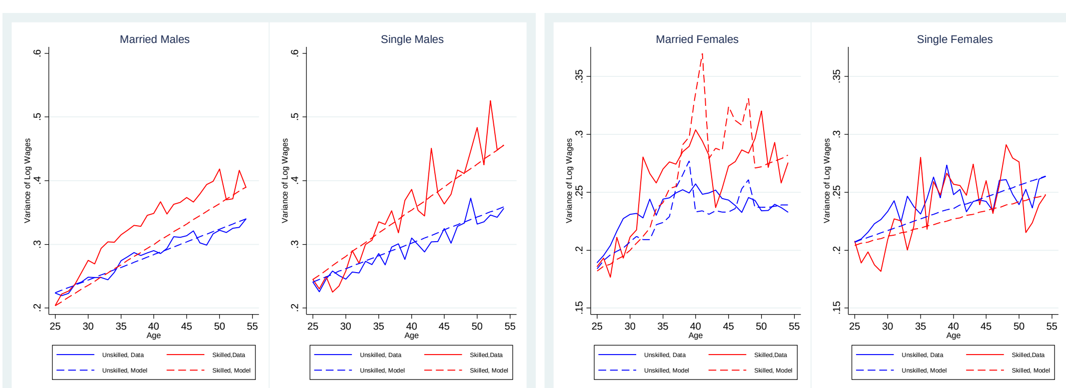

Figure A15 - Variance of Log Wages, Model vs. Data, Males (left), Females (right), the 1980 (I)

7 Other Parameterizations

In this section of the Appendix, we present the parameter values that are used for different economies discussed in Section 7 of the paper (Tables A17-A19). Table A20 shows the model outcomes.

Table A17: Parameter Values - Permanent Shocks
Different Cases

Statistic	BM	Cohort Effect	1980 I	1980 II	$\sigma = 1.5$ (scale econ.)
Variances					
Single Skilled Males	0.298	0.298	0.245	0.245	0.298
Single Unskilled Males	0.257	0.259	0.241	0.241	0.257
Single Skilled Females	0.251	0.24	0.204	0.204	0.251
Single Unskilled Females	0.244	0.242	0.207	0.207	0.244
Married Skilled Males	0.252	0.243	0.204	0.204	0.252
Married Unskilled Males	0.227	0.227	0.224	0.224	0.227
Married Skilled Females	0.224	0.224	0.192	0.192	0.224
Married Unskilled Females	0.250	0.228	0.220	0.220	0.250
Covariance (male, female)	0.058	0.059	0.043	0.039	0.053

Table A18: Parameter Values - Persistence Shocks
Different Models

Statistic	BM	Cohort E.	1980 I	1980 II	$\sigma = 1.5$	$\sigma = 1.5$ (scale econ.)
Variances						
Single Skilled Males	0.0063	0.0079	0.00727	0.00727	0.00627	0.00627
Single Unskilled Males	0.0036	0.0042	0.00406	0.00406	0.00356	0.00356
Single Skilled Females	0.0019	0.0060	0.00150	0.00150	0.00190	0.00190
Single Unskilled Females	0.0018	0.0035	0.00195	0.00195	0.00175	0.00175
Married Skilled Males	0.0068	0.0101	0.00642	0.00642	0.00675	0.00675
Married Unskilled Males	0.0038	0.0050	0.00400	0.00400	0.00380	0.00380
Married Skilled Females	0.0040	0.0072	0.00270	0.00270	0.00400	0.00400
Married Unskilled Females	0.0008	0.0028	0.00130	0.00130	0.00080	0.00080
Covariance (male, female)	0.0010	0.0017	0.00172	0.00172	0.001	0.0010

Table A19: Parameter Values
Different Cases

Parameter	Value	Cohort E.	1980 I	1980 II	$\sigma = 1.5$ (scale econ.)
Discount Factor (β)	0.9829	0.9825	0.9830	0.9829	0.9976
Preference Shock $\triangle$	1.88	1.70	1.957	2.055	1.9
Skill depreciation, females					
δ_s	0.025	0.025	0.025	0.025	0.025
δ_u	0.056	0.056	0.056	0.056	0.056
Skilled Labor Share (ν)	0.505	0.505	0.3745	0.3715	0.509

Table A20: Model and Data
Different Cases

Aggregates	Data	BM	$\sigma = 1.5$ (scale econ.)
Capital Output Ratio	2.9	2.9	2.9
Total Transfers (% of GDP)	2.3	2.3	2.3
Skill Premium	1.8	1.8	1.8
LFP of Married Females (%), 25-54			
Unskilled	68.2	68.7	68.1
Skilled	77.4	77.7	78
Total	71.8	72.3	72
Life-Cycle Inequality			
Variance log-wages (Married Males, age 54, S)	0.45	0.45	0.45
Variance log-wages (Married Males, age 54, U)	0.34	0.34	0.34
Variance log-wages (Married Females, age 54, S)	0.35	0.35	0.35
Variance log-wages (Married Females, age 54, U)	0.26	0.26	0.27
Variance log-hours (Married Females, age 40)	0.13	0.13	0.13
Correlation Between Wages of Spouses (age 25)	0.31	0.31	0.29
Correlation Between Wages of Spouses (age 40)	0.34	0.33	0.31
Variance log-consumption (Age 55 vs 25)	0.12	0.12	0.10
Earnings Inequality (25-64)			
90-10 ratio	7.8	7.1	6.5
90-50 ratio	2.6	2.5	2.4
Share, bottom 10%	1.8	2.1	2.3
Share, bottom 20%	4.5	5.5	5.9
Share, bottom 40%	13.2	15.8	16.8

References

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