First Comes Love, Then Comes Marriage?
Marriage, Labor Supply, and Poverty

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Abstract

Parents who raise their children without a spouse make up a substantial and rising share of all families in the United States. Notably, a large fraction of single mothers live in poverty with their children. This suggests that the current welfare state does not provide sufficient insurance against the risk of becoming a single parent. Moreover, the US tax code provides incentives for marriage and the auxiliary social security benefit system favors married women over singles. We develop a life cycle model of couples and singles where individuals decide their marital state and females face the probability of getting children. Both of these events govern the likelihood of becoming a single mother and ending up in poverty. We seek to understand why such a large fraction of single mothers fall into poverty, and to evaluate policy reforms that reduce poverty, such as free child care, taking the behavioral effects on labor supply and marital transitions into account.

JEL Classification: D15, D63, H31, H53, J12, J13, J22

Keywords: Single Mothers, Marriage, Fertility, Poverty, Welfare, Life Cycle Model

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1 Introduction

A substantial fraction of mothers raise their children alone without a father. In the US, 30 percent of all mothers are single. Single mothers are faced with tremendous financial consequences. If they work, they bear large childcare costs which amount to on average $9,600 for center care and $28,400 for home care annually. Children are also associated with substantial time costs. According to data from the ATUS, even full-time working mothers spend up to 20 hours per week caring for their young children. The data show substantial poverty for single mothers. According to the CPS poverty line, 40 percent of all single mothers live in poverty. Conversely, only eight percent of married females with children are below the poverty line. High poverty rates are associated with low employment rates for single mothers, who receive a large fraction of their income from welfare benefits. Yet, being a single mother is at least partly the consequence of individual marital and fertility decisions, and therefore not solely the result of exogenous shocks.

In this paper, we aim to understand why so many single mothers live in poverty, which suggests that the current programs in place in the US provide insufficient support for these women and their children. We analyze policy reforms that can improve the income of the very poor, while quantifying the efficiency effects of these measures in terms of changes in female labor supply and marital decisions (i.e., the decision to get divorced or to marry). To this end, we develop a life cycle model of singles and couples. Agents face a set of decisions under various uncertainties. Individuals decide about marriage and divorce, subject to specific match quality and love shocks. They make decisions regarding consumption-savings and labor supply, subject to labor productivity risk. We model fertility as an exogenous process. In addition, we model the following costs and support associated with having children: (i) time costs (forgone leisure) of young children, (ii) childcare time inputs from parents and/or the ex-spouse, (iii) monetary costs of childcare if the parent(s) work, and (iv) monetary support from the ex-spouse if single. Finally, we model the US tax and transfer system in detail. We calibrate the model to a relatively young cohort, those born 1965-69, by matching the life cycle profile of employment and marital transitions over education.

We show that our model replicates important non-targeted moments, in particular, poverty rates over education and the number of children, as well as the life cycle profile of employment over the number of children in the household. Our model suggests that the monetary and time costs associated with children go along way in explaining the high poverty rates among single mother, even with the full-blown welfare state that we model.

We then use the model to contrast two alternative policy reforms, an increase in means-tested welfare payments and a full subsidy on childcare payments. By

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1 CPS data from 2015. Note, we focus on mothers throughout the paper. There are also single fathers. Their overall fraction is small though, about 6 percent of all fathers in the cohort born 1965-69 that we study.

2 Data from SIPP.
modeling the labor supply margin we capture the decline in the incentive to work resulting from an expansion of welfare benefits. Marriage provides substantial insurance against poverty. However, more comprehensive welfare policies reduce the need for such insurance. By endogenizing marital decisions, we allow for this mechanism. We find that increasing welfare payments results in a reduction in poverty, but reduces female employment especially for lower educated women. It also results in higher divorce rates, which in turn raises the fraction of single mothers. Conversely, a full subsidy on child care expenditures also results in a reduction in poverty – especially for single mothers – while resulting in a slight increase in female employment and almost no effect on marital transition.

Our paper is related to the literature studying female labor supply in the presence of children. Guner et al. (2017) use a structural model to quantify the labor supply and welfare effects of child-related transfers. However, they abstract from the risks and choices associated with becoming a single mother (marital status is a fixed state in their model). Moreover, they do not study poverty. Other papers studying childcare subsidies, labor supply, and welfare include Bick (2016), Domeij and Klein (2013), and Attanasio et al. (2008). Although Braun et al. (2017) study a somewhat different question, namely old-age poverty in the presence of health risks, our paper is similar to theirs in terms of approach. They study the impact of health risks and the associated out-of-pocket health expenditures in old-age for private savings and poverty. Their main finding is that an extension of means-tested welfare programs would imply large positive welfare gains due to the significant health risks at older ages. Our paper is also related to studies of endogenous marital transition, e.g., Grogger and Bronars (2001), Low et al. (2018), and Moffitt et al. (2018) who generally find significant, albeit small, effects of welfare reforms on divorce rates.

Contrary to the aforementioned studies, our paper focuses on single mothers and the associated high poverty rates. We strive to understand why single mothers end up in poverty, despite the fact that there are a number of welfare measures aimed at supporting low-income families. Moffitt (2015) and Guner et al. (2017) give an overview of welfare programs in the US. Moffitt (2015) notes that single-mother families are historically the primary recipient group for welfare programs in the US. There are three main programs: Unemployment Insurance (UI), Aid to Families with Dependent Children (AFDC/ADC) and Temporary Assistance for Needy Families (TANF). AFDC is a program specifically targeted to single parent households, while TANF is for poor families with children in general. In addition, there are other programs that effect poor families, such as Social Security Disability Insurance (SSDI), Supplemental Nutrition Assistance Program (SNAP, formerly food stamps), Earned Income Tax Credit (EITC), Medicaid and Medicare. Moffitt (2015) provides a historical overview of the aforementioned programs and finds that, while there was an expansion of most welfare programs in recent decades, the replacement of AFDC by the TANF program under the Clinton administration resulted in higher poverty rates for single mothers. This implies that single mothers receive less in 2004 compared to 1983. In contrast, the elderly and the disabled receive more compared to the 1980s.
2 Stylized Facts

Here we present descriptive statistics on single mothers using CPS data. We show data by female educational type\(^3\) We start by showing the prevalence of single motherhood. We then show statistics on the number of children, employment and poverty. We focus on the cohort born 1965-69 at ages 20-49, whenever possible. We start our model at age 23. We focus on the householder and the spouse of the householder. This way we exclude adult children who still reside with their parents (e.g., teenage pregnancies and young mothers). However, the vast majority of co-resident adult children are non-married and childless. Only about 9\% of all single mothers aged 23 and above still reside with their parents\(^4\).

2.1 Prevalence of Single Parenthood

Tables[1] shows the distribution of females over marital status, education and whether or not they have kids. Overall, 15.7\% of women in our sample are single mothers. Of single mothers, about two thirds are divorced, and one third are never married. In addition, observe that there is a strongly declining education gradient to single motherhood: 27\% of high school dropout females are single mothers, whereas only 7\% of college graduate females are single mothers. In general, more educated women are more likely to be childless.

Table 1: Distribution of Women over Education, Marital Status and Children (in \%)

<table>
<thead>
<tr>
<th></th>
<th>Not Married</th>
<th>Married</th>
<th>Total</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>Mother</td>
<td>No Child</td>
<td>Mother</td>
</tr>
<tr>
<td>Dropout</td>
<td>27.35</td>
<td>7.17</td>
<td>57.20</td>
</tr>
<tr>
<td>High school</td>
<td>17.91</td>
<td>11.33</td>
<td>56.19</td>
</tr>
<tr>
<td>College</td>
<td>7.20</td>
<td>15.99</td>
<td>58.75</td>
</tr>
<tr>
<td>Total</td>
<td>15.66</td>
<td>12.30</td>
<td>57.21</td>
</tr>
</tbody>
</table>

Note: Row frequencies of females aged 23-46, cohort born 1965-69. CPS data.

2.2 Poverty

Table[2] shows poverty rates over marital status and the number of children. Marriage effectively reduces the likelihood of poverty. Although, poverty rates are twice

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\(^3\)We classify education into three categories: high school dropout (Dropout), high-school graduate but less than a B.Sc. degree (High School) and a B.Sc. degree or above (College).

\(^4\)The reason for excluding them from the data is that not all variables that we need in the CPS are available for sample members who are not the householder. In addition, in our model we abstract from the possibility to live with ones’ parents.
as high for married women with children than without, 8 versus 4%. Conversely, poverty rates are high for non-married females – even without children. 19% of divorced and 15% of never married childless women live in poverty. The share of women in poverty rises sharply with children, with 33% of divorced women with children and 53% of never married women with children living in poverty. Moreover, the poverty share is increasing in the number of children. Never married females with three or more children are most likely (77%) to live in poverty.

Table 2: Female Poverty by Marital Status and No. of Children

<table>
<thead>
<tr>
<th>Children</th>
<th>Married</th>
<th>Divorced</th>
<th>Never married</th>
</tr>
</thead>
<tbody>
<tr>
<td>No child</td>
<td>0.04</td>
<td>0.19</td>
<td>0.15</td>
</tr>
<tr>
<td>With child</td>
<td>0.08</td>
<td>0.33</td>
<td>0.53</td>
</tr>
<tr>
<td>One</td>
<td>0.05</td>
<td>0.25</td>
<td>0.41</td>
</tr>
<tr>
<td>Two</td>
<td>0.06</td>
<td>0.30</td>
<td>0.55</td>
</tr>
<tr>
<td>Three+</td>
<td>0.14</td>
<td>0.52</td>
<td>0.77</td>
</tr>
</tbody>
</table>

Note: Poverty according to the official poverty line. Cohort born 1965-69. CPS data.

Table 3 summarizes employment rates by marital status and the number of children. The table shows that the employment rate is decreasing in the number of children. However, employment does not differ much by marital status. In fact, employment rates for single mothers are actually higher than for married mothers. Overall, employment is 6 pp higher for non-married females than for married females. Moreover, single women are more likely to work full-time. It is important to note that employment rates are also quite high for single mothers who are living in poverty. Employment rates for single mothers below the poverty line are between 30 and 46%, depending on education. Hence, a large fraction of single mothers belong to the so-called working poor.

2.3 Child Costs and Support

Table 4 summarizes the main time and monetary costs associated with having children. While child care costs are huge, amounting to $14,100 for a single mother with two children, there is also child support from the former spouse. 60% of all single mothers with two children receive child support, which covers roughly half of the child care expenses. In addition, around one third of mothers receive support from their parents, who on average spend 14 hours per week with their grandchildren while the mother is working. Still, also employed mothers spend around 19 hours per week caring for their children.
Table 3: Female Employment over Marital Status and Children

<table>
<thead>
<tr>
<th></th>
<th>Married</th>
<th>Not Married</th>
</tr>
</thead>
<tbody>
<tr>
<td>No children</td>
<td>0.80</td>
<td>0.80</td>
</tr>
<tr>
<td>One child</td>
<td>0.70</td>
<td>0.74</td>
</tr>
<tr>
<td>Two children</td>
<td>0.68</td>
<td>0.70</td>
</tr>
<tr>
<td>Three+ children</td>
<td>0.58</td>
<td>0.57</td>
</tr>
<tr>
<td>Total Employment</td>
<td>0.69</td>
<td>0.75</td>
</tr>
<tr>
<td>Total Parttime</td>
<td>0.20</td>
<td>0.13</td>
</tr>
</tbody>
</table>


Table 4: Childcare costs and Child support

<table>
<thead>
<tr>
<th>No Children</th>
<th>One</th>
<th>Two</th>
<th>Three+</th>
</tr>
</thead>
<tbody>
<tr>
<td><strong>Childcare costs (in $ p.a.)</strong></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Amount</td>
<td>7,400</td>
<td>14,100</td>
<td>15,100</td>
</tr>
<tr>
<td><strong>Child support from former spouse</strong></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Incidence</td>
<td>44%</td>
<td>60%</td>
<td>50%</td>
</tr>
<tr>
<td>Hours</td>
<td>5,600</td>
<td>7,200</td>
<td>5,700</td>
</tr>
<tr>
<td><strong>Time caring for child (hrs./week) ft-working mothers</strong></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Hours</td>
<td>18</td>
<td>19</td>
<td>17</td>
</tr>
<tr>
<td><strong>Informal care from (grand)parents</strong></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Incidence</td>
<td>39%</td>
<td>32%</td>
<td>27%</td>
</tr>
<tr>
<td>Amount</td>
<td>18</td>
<td>14</td>
<td>18</td>
</tr>
</tbody>
</table>

*Note:* SIPP and ATUS. Costs (time, monetary) for all mothers with youngest child below age 3. Child support and care for single mothers with children below age 9.
3 The Model

We develop a life cycle model of singles and couples who make decisions regarding marriage and divorce, as well as consumption, savings and labor supply. Fertility is assumed to be exogenous\textsuperscript{5}. Our analysis aims at capturing single mothers, while taking the relevant decisions about marital transitions explicitly into account. Households face uncertainty with respect to the quality of the match with the (potential) partner, the birth of children and labor income.

All females face a probability of getting children. Mothers derive utility from children, but children also impose costs. We model a time cost and a monetary childcare cost, if the mother works when the child is young. Singles choose whether or not to get married, subject to a matching process, and married households decide whether to stay married or get divorced, subject to love shocks.

Agents enter the model at age 23; the terminal age is 83. A model period corresponds to three years in the data. The labor supply decision of females includes an extensive and an intensive margin; they can work full-time, part-time or not at all. However, a mother who works needs to pay childcare costs. Through work, the woman accumulates human capital, which positively affects future wages and social security claims. If a woman choose not to work, her human capital depreciates.

Single men choose their employment, while we assume that married men always work full-time until the assumed retirement age of 65, which is also when we assume that the household claims benefits. Social security payments are linked to marital status through auxiliary benefit payments, in particular spousal benefits.

3.1 Demographics

We treat decisions made before model age zero as initials (education, marital status, number of children, current income state). Agents fall into one of three categories based on marital status: never married, married, and divorced. Single agents can choose to (re-)marry, and married couples can choose to divorce. In the case of divorce, the children stay with the mother and the father has to pay child support.

Education, $e$, is classified as high school dropouts, high school degree and college degree (defined as Bachelor’s degree and above). We allow the disutility from work to depend on education.

Over the life cycle, households’ heterogeneity evolves with respect to female labor market experience, the income shock realization, asset holdings, marital transitions, and the number and age of children in the household.

Upon retirement, we shut down all risks and only leave the households with the consumption-saving decision. Households receive benefits according to a measure of their life-time income. Married females get the maximum of their own benefit and 50\% of the husbands benefit (spousal benefit). For simplicity, we assume that divorced agents are not eligible for spousal benefits.

\textsuperscript{5}In future versions, we plan to endogenize fertility.
3.2 Choices and Preferences

Households face a large set of decisions regarding (i) marriage and divorce, (ii) labor supply, $L_{g,t}$, and (iii) consumption, $c_t$ and savings, $a_{t+1}$. Fertility is modelled as an exogenous process for now. We assume the following timing. First, after love-shocks and labor productivity shocks have been realized, agents decide their marital status. Second, given the marital status decision, agents learn whether they have children and how many children to have. Finally, taking the marital status and the number of children as given, agents make consumption/savings and labor supply decisions.

Preferences and decisions depend on marital status. First, let’s turn to married households. We assume that married couples make decisions jointly within a unitary household model. They jointly decide on female labor supply, conditional on being married. Children affect household utility in three ways. First, children reduce household consumption through equivalence scaling. Second, children pose a fixed time cost, $\xi(n, k)$, which we take from the data and which depends on the number, $n$, and the age, $k$, of children. This cost is attributed to the female only. Third, households incur monetary childcare costs if the female works. The preferences of a married couple are given by:

$$U(c_t, L_t) = \chi \left[ \frac{c_t^{1-\theta}}{1-\theta} - \frac{\Phi_{1,s,e,v}(L_{1,t} + \xi(n, k))^{\gamma_1}}{\gamma_1} \right] + (1 - \chi) \left[ \frac{c_t^{1-\theta}}{1-\theta} - \frac{\Phi_{2,s,e,v}(L_{2,t})^{\gamma_1}}{\gamma_1} \right] + \Xi_t$$

where $\chi$ is the weight on the wife’s utility and $1 - \chi$ on the husband’s. $c_t = \hat{c}_{t, eq(n)}$ is total equivalence-scaled household consumption, where $eq(n) = 1.0 + 0.5 * \text{spouse} + 0.3 * n$, where $n$ is the number of children, and $\hat{c}$ consumption spending. Preferences are assumed to be separable. $\gamma_1$ governs the curvature of the disutility of labor, and $\theta$ is the parameter of relative risk aversion, determining the intertemporal elasticity of substitution.

The time cost of children, $\xi(n, k)$, enters symmetrically to hours worked. The female labor supply choice is given by $L_{1,t} = \{0, 0.2, 0.4\}$. We assume that full-time work corresponds to working 40 hours per week, while part-time work corresponds to working 20 hours per week. Agents retire at age 65. The husband is assumed to work full time until age 64, hence $L_{2,t} = 0.4$. $\Phi_{g,s,e,v}$ denotes disutility from work depending on gender $g$, education $e$, and marital status $s$. In addition, we assume two disutility types, $v$, to match female full-time and part-time employment.

The value of $\Xi_t$ represents match quality (or love) for the couple and is assumed to evolve according to an AR(1) process, see further below for details.

The instantaneous utility of an unmarried woman ($g = 1$) is given by:

$$U(c_t, L_t) = c_t^{1-\theta} - \frac{\Phi_{1,s,e,v}(L_{1,t} + \xi(n, k))^{\gamma_1}}{\gamma_1}$$

where $c_t = \hat{c}_{t, eq(n)}$ is total equivalence-scaled household consumption, where $eq(n) = 1.0 + 0.5 * \text{spouse} + 0.3 * n$, where $n$ is the number of children, and $\hat{c}$ consumption spending. Preferences are assumed to be separable. $\gamma_1$ governs the curvature of the disutility of labor, and $\theta$ is the parameter of relative risk aversion, determining the intertemporal elasticity of substitution.
For an unmarried man \((g = 2)\) it is given by:

\[
U(c_t, L_t) = \frac{c_t^{1-\theta}}{1-\theta} - \Phi_2(s,e) \frac{L_{2,t}^{\gamma_1}}{\gamma_1}.
\]

Hence, we assume that children always stay with the mother after divorce (note that also never married women can have children), while men have to pay child support to the mother, which enters their budget constraint.

### 3.3 Marital Decisions and Love Shocks

We model endogenous (re-)marriage and divorce decisions. Marital transition decisions are made subject to a matching process and love-shocks. We assume that individuals can make these decisions between ages 23 and 47 (=9 model periods). Marital transition decisions will be made at the beginning of the period, after all shocks have been realized, but before making other decisions, i.e., consumption, savings, and labor supply.

Non-married individuals meet a potential mate with certainty. Conditional on the quality of the match, they decide whether or not to marry. Due to our focus on single mothers, and the computational complexity of our approach, we simplify the marital matching process by assuming that a woman can only match with a man with identical characteristics - apart from higher earnings due to a gender wage gap. Matches differ in initial match quality, governed by the parameter \(\Xi_0\). Recall that single men do not have children in their household. However, given our assumption of potential spouses being alike, we assume that if a non-married woman has children, her potential spouse has the same number of children, implying that he has to pay child support.

The initial draw of the match quality, \(\Xi_0\), is assumed to be normally distributed with \(N(\mu_\Xi, \sigma_\Xi)\). If agents decide to get married, their love evolves according to a random walk, such that

\[
\Xi_t = \Xi_{t-1} + u_t
\]

where \(u_t\) are love-shocks which are again normally distributed, \(u_t \sim N(0, \sigma_u)\).

Married agents observe their current love, \(\Xi_t\), which is subject to the love shock, \(u_t\). Observing this, the couple jointly decides whether or not to divorce based on a comparison of the value of staying married relative to the value of being alone.

The initial marital status of individuals is married \(m\), unmarried/single, \(u\), or divorced \(d\). Marital status is thus given by \(s_t \in \{m, u, d\}\).

### 3.4 Children and Childcare

Between ages 23 and 38 (6 periods in our model), females face a probability of getting children. For simplicity, we assign each female a per-period probability of getting one, two or three children, with each of these as absorbing states. These probabilities, \(\alpha_{t,e}^s\), are conditional on education and marital status, where \(s\) can be
either married or non-married. In other words, fertility rates for divorced and never married are assumed to be identical. For a 23 year old agent entering the model, we take an initial distribution of children from the data. We then keep track of the age of the child in order to determine childcare costs, which vary greatly by age.

Childcare costs are taken from the data and depend on the employment status of the mother, and the number and age of children. For childcare costs we use the SIPP 2008 topical module No.8, which gives information about childcare expenditures for various categories. We denote childcare costs by \( w_{k,n} \), depending on the number and age of children as well as the labor force participation decision. Recall that we simplify our modeling of children by assuming that a woman gets one, two or three children at once, such that we only have to keep track of the age of one child. Childcare costs are only paid when the female decides to work. The costs are multiplied by 0.5 if the women only works part time.

In addition, children impose a fixed time costs \( \xi(n,k) \), which enters negatively into the utility function of females. This is taken from ATUS data. Finally, children affect the level of household consumption, which is equivalence scaled. We do not assume any positive utility effect from children, since children are not modeled as an endogenous choice.

3.5 Income Process

The wage process is uncertain, containing an idiosyncratic permanent component, \( z_t \). Since men are assumed to work full-time until retirement, their income is a function of age. Income for women depends on human capital, \( h_t \). We allow for human capital depreciation by assuming that income is lower if the agent did not work in the previous period. Income risk differs by gender and education. Further, total earnings depend on labor force participation decisions. To ease notation, we define \( y_{g,t} \) as shorthand for total earnings:

\[
y_{g,t} = \begin{cases} 
1.0 \cdot y(g, t, e, h_t, z_t) & \text{if } L_{1,t} = 0.4 \text{ and } y_{g,t} \geq \bar{y}^w \\
0.5 \cdot y(g, t, e, h_t, z_t) & \text{if } L_{1,t} = 0.2 \text{ and } y_{g,t} \geq \bar{y}^w \\
y^w & \text{if } L_{1,t} = 0.0 \text{ or } y_{g,t} < \bar{y}^w 
\end{cases}
\]

If household income is below a certain threshold \( \bar{y}^w \), agents receive welfare payments. Welfare payments, \( y^w \) include the following means-tested programs: Supplemental Social Security Income (SSSI), Temporary Assistance for Needy Families (TANF formerly AFDC), Supplemental Nutrition Assistance Program (SNAP formerly food stamps), Supplemental Nutrition Program for Women, Infants, and Children (WIC), and Housing Assistance.

Income for women depends on human capital, \( h_t \), which we model as a learning-
by-doing technology with depreciation:

$$h_{t+1} = \begin{cases} 
    h_t - \delta \cdot h_t & \text{if not working} \\
    h_t + \iota \cdot \Delta t & \text{if working part-time} \\
    h_t + \Delta t & \text{if working full-time}
\end{cases}$$ (6)

Human capital is measured in years of experience, where $\Delta t$ constitutes one model period, or three years. Human capital is subject to depreciation (at rate $\delta$) if the woman does not work. We follow Blundell et al. (2016) and assume a part-time penalty, $\iota < 0.5$, implying that part-time work accumulates less than 50% of the human capital of full-time work.

3.6 The Government

3.6.1 Child Support
In modeling the tax and transfer system, we closely follow Guner et al. (2017). Households receive various support for children in the US. In particular, they receive: (1) childcare subsidies provided by the Children Childcare and Development Fund (CCDF), (2) Child and Dependent Care Tax Credit (CDCTC), (3) Child Tax Credits (CTC), and (4) The Earned Income Tax Credit (EITC) favoring families with children.

A household below a certain threshold income level, $\bar{y}$, receives a subsidy of $\nu_y$ percent of all childcare payments if the household qualifies for these.

The CCDF is the most important program for low-income families providing vouchers for child care. But only a small fraction of people who qualify actually get the benefit: 5.5% of all children. Following Guner et al. (2017) we use the average rate of childcare costs that is covered (76%) but we set the threshold income level such that only 5.5% of children receive it.

Each household can receive three different tax credits: Earned Income Tax Credits (EITC), Child Tax Credits (CTC), and Child and Dependent Care Tax Credit (CDCTC).

The CDCTC is a non-refundable tax credit to all parents that allows parents to deduct a fraction of their childcare expenses (children below age 12) from their tax liabilities. The maximum qualified childcare expenditure is $3,000 per child, with an overall maximum of $6,000. Parents receive 35% qualifying expenses as a tax credit which eventually declines with household income. Due to its non-refundable nature it is not targeted to the poor.

The Child Tax Credit (CTC) is a non-refundable tax credit for each child, independently of their childcare expenditures and the labor market status of parents. The CTC starts at $1,000 per child under age 17, and stays at this level up to a household income level of $75,000 for single and $110,000 for married couples. Beyond this income limit, the credit declines at a 5% rate until it is completely phased out. CTC is also non-refundable. To also target the poor, an Additional Child Tax Credit (ACTC) is in place that gives part or full of the unused portion of the CTC back to families. The ATCT requires some minimum earnings.
We subsume these credits in the overall transfer $T$ depending on household income $y_1 + y_2$, asset holdings, employment status, gender, and the number and age of the children. [TBC: Add details that we already modeled]

If the income is below the threshold, $y_t < \bar{y}$, total childcare costs are $(1 - \nu_{\bar{y}}) \cdot w_{n,k}$. The tax credits follow certain formulas that depend on income, see Guner et al. for details. Note that $w_{n,k} = 0$ if $n = 0$.

### 3.6.2 Social Security

Social security benefits, $b_g$, are paid out as an annuity and depend on past income, and hence on gender, education (own and spousal), human capital (for women), and marital status (due to auxiliary benefit payments).

**AIME and PIA** To determine benefits based on one’s own work history one must first compute the so called Average Indexed Monthly Earning (AIME), which is computed by averaging over life-time earnings from the highest 35 years (including possible zeros). In our model, we approximate AIME $\tilde{y}$ with human capital and adjust the 35 years to $12 \times 3 = 36$ years, because a period is three years in our model. For men we take the last income realization and compute, for each permanent income state in the last working period, the expected value of income from the last 35 years recursively, making use of the Markov transition probability.

A concave benefit formula is then applied to AIME to get the Primary Insurance Amount (PIA):

$$B(\tilde{y}_t) = \begin{cases} \lambda_1 \tilde{y}_t & \text{if } \tilde{y}_t < \kappa_1 \\ \lambda_1 \kappa_1 + \lambda_2 (\tilde{y}_t - \kappa_1) & \text{if } \kappa_2 \geq \tilde{y}_t \geq \kappa_1 \\ \lambda_1 \kappa_1 + \lambda_2 (\kappa_2 - \kappa_1) + \lambda_3 (\tilde{y}_t - \kappa_2) & \text{if } \tilde{y}_t > \kappa_2 \end{cases}$$

(7)

$\lambda_i$ are replacement rates that differ by average income such that $\lambda_1 > \lambda_2 > \lambda_3$; $\kappa_1$ and $\kappa_2$ are bend points at which the replacement rate changes. This ensures a redistributional element in favor of low earners.

The PIA is not allowed to exceed a maximum, which corresponds to the earnings cap, see below. Finally, benefits are adjusted according to age at benefit claiming.

**Contributions and earnings cap** Social security benefits are funded by a payroll tax, $\tau_{ss}$. Only earnings up to a cap of $y_{\text{max}}$ are subject to the payroll tax. This introduces a regressive element to the U.S. social security system. Formally, income that is considered for social security taxes is given by:

$$\hat{y}_{g,t} = \min\{L_{g,t} y_{g,t}, y_{\text{max}}\}.$$

(8)

---

7This is an approximation of the AIME calculation which abstracts from indexing past earnings, see https://www.socialsecurity.gov/policy/docs/statcomps/supplement/2004/apnd.html for details.
**Spousal benefits** Spousal benefits are claimed based on the spouse’s earnings record. As such, they are dependent on marital status. Spousal benefits are granted to married persons (if married for at least one year) and consist of the higher of one’s own benefit and 50% of the spouse’s entitlement. For computational reasons, we abstract from eligibility for divorced individuals (divorcees are also eligible, if their marriage lasted for at least 10 years). In our model, only women \((g = 1)\) decide on labor supply (prior to the retirement decision), so this yields:

\[
b_{1}^{\text{spouse}} = \max \left\{ b_{1}, \frac{1}{2} b_{2} \right\}
\]

if \(s_{t} = m_{t}\), or if \(s_{t} = d_{t}\).

Since we do not model survival risk, we do not have survivor benefits. We view this abstraction as not so severe, as we simply assume that married individuals stay married in retirement (which gives them a similar insurance as survivor benefits).

### 3.7 Budget Sets of Households

A household during working life faces the budget constraint given by:

\[
(1 + \tau_{c})\hat{c}_{t} + a_{s,t+1}^{s} = a_{t}^{s} + (1 - \tau^{s}(y_{t})) \cdot (r \cdot a_{t}^{s} + y_{t}) - \tau_{ss} \hat{y}_{t} - (1 - \nu_{\bar{y}})w(n, k, L_{1,t}) + T^{\text{eitc}}(n, s, y, a_{i}^{s}) + T^{\text{wel}}(n, s, y, a_{i}^{s}) + T.
\]

where \(y_{t} = y_{1,t} + y_{2,t}\) is household labor income, \(T^{\text{eitc}}(\cdot)\) are transfers from the EITC, \(T^{\text{wel}}(\cdot)\) are welfare benefits, and \(T\) is a household transfer calibrated to balance the budget. Asset holdings at age \(t\) are denoted by \(a_{t}^{s}\) and dependent on marital status \(s\). As mentioned above, \((1 - \nu_{\bar{y}})w(n, k, L_{1,t})\) are childcare costs depending on the number and age \((n, k)\) of children, the employment decisions of the female, \(L_{1,t}\), and the threshold income, \(\bar{y}\), which determines whether the household receives a subsidy, \(\nu\).

Note that, when retired, agents receive social security benefits instead of labor income and they do not have to pay child costs or social security contributions anymore. Further, single men do not have to bear child care costs \((1 - \nu_{\bar{y}})w(n, k, L_{1,t})\).

Due to marital status risk, \(a_{t+1}^{s}\) is uncertain to the household in period \(t\). In particular, we assume

\[
a_{t+1}^{d} = \frac{1}{2} a_{t+1}^{m} \\
a_{t+1}^{m} = 2 a_{t+1}^{u,d}
\]

Hence, we assume that assets are split evenly between spouses in the event of a divorce and doubled in the event of a marriage.

[TBC: add child support in the model]

Since we are interested in labor supply incentives, it is important to model the details of the tax schedule. Our model includes a proportional consumption tax, \(\tau_{c}\), a proportional social security payroll tax, \(\tau_{ss}\), and a progressive income tax, \(\tau^{s}_{y}\).
The progressive income tax, \( \tau^s_y \), which depends on marital status, is levied on total income, i.e., the sum of labor income of both spouses and the returns from assets. We follow \cite{Guner et al. (2014)} and assume a simple linear tax function:

\[
\tau^s_y = \alpha_{s,n} + \beta_{s,n} \cdot \frac{(y_t + Ra^s_t)}{\bar{y}} \tag{10}
\]

where \( \bar{y} \) is average income in the economy. The parameters \( \alpha_{s,n} \) and \( \beta_{s,n} \) are estimated from tax-return, micro-data from the Internal Revenue Service for the year 2000, and depend on marital status, \( s \), and the number of children, \( n \).

### 3.8 Recursive Problem

In what follows, we lay out the recursive maximization problem. In our model, we focus on working age, age 23 to a fixed retirement age of 65. During retirement all uncertainties are resolved, and the remaining decisions are regarding consumption and savings only, until the fixed time of death.

We assume a Markov-process for the stochastic processes for wages and love, such that we can state the household problem recursively. In terms of notation, we define the value function for each age \( t \), marital status \( s = \{m, u, d\} \), and gender \( g = 1, 2 \) as \( V_{g,s}^t(\Gamma_t) \), where

\[ \Gamma_t = \{n, k, h, a, e, z, \Xi, v\} \]

are the remaining state variables: the number of children \( n \), the age of children \( k \), human capital \( h \), assets \( a \), education type \( e \), persistent income component \( z \), the match quality of a marriage \( \Xi \), and the disutility type of labor \( v \).

#### 3.8.1 Problem of a married couple

**Married Households Without Children** We assume that a married household maximizes joint utility of consumption and assets, applying Pareto-weights of \( \chi \) for the wife and \( 1 - \chi \) for the husband, by taking their decisions on marital transition and fertility in this period as given. The decision to marry takes place at the start of the period, after all shocks are realized, but before any consumption, or labor supply decisions are implemented. At the beginning of the next period, agents first decide on marital transitions and (potentially) learn about the number of children they get. We assume that children arrive in period \( t + 1 \), after which the agent decides about the future marital state.

\cite{Guner et al. (2017)} report estimates for families with zero, two or three children. We interpolate the tax coefficients for families with one child by fitting a polynomial.
\begin{align}
V_{t}^{m,n=0} (\Gamma_t) &= \max_{c_t, L_{t,1,\alpha_{t+1}}} \chi \left[ \frac{c_t^{1-\theta}}{1-\theta} - \Phi_{1,s,e,v} (L_{1,t} + \xi(n,k)) \right] \\
&\quad + \left[ \frac{c_t^{1-\theta}}{1-\theta} - \Phi_{2,s,e,v} (L_{2,t}) \right] + \Xi_t \\
&\quad + (1 - \mu_t) \alpha_{t,e} m \beta E \left[ V_{t+1}^{m,n=0} (\Gamma_{t+1} | \Gamma_t) \right] \\
&\quad + (1 - \mu_t) (1 - \alpha_{t,e} m) \beta E \left[ V_{t+1}^{m,n=0} (\Gamma_{t+1} | \Gamma_t) \right] \\
&\quad + \mu_t (1 - \alpha_{t,e} m) \beta \left( \chi E \left[ V_{t+1}^{d,n=0} (\Gamma_{t+1} | \Gamma_t) \right] + (1 - \chi) E \left[ V_{t+1}^{d,n=0} (\Gamma_{t+1} | \Gamma_t) \right] \right) \\
&\quad \text{subject to the budget constraint given by equation (10).} 
\end{align}

\begin{align}
V_{t}^{m,n>0} (\Gamma_t) &= \max_{c_t, L_{t,1,\alpha_{t+1}}} \chi \left[ \frac{c_t^{1-\theta}}{1-\theta} - \Phi_{1,s,e,v} (L_{1,t} + \xi(n,k)) \right] \\
&\quad + (1 - \mu_t) \beta E \left[ V_{t+1}^{m,n>0} (\Gamma_{t+1} | \Gamma_t) \right] \\
&\quad + \mu_t \beta \left( \chi E \left[ V_{t+1}^{d,n>0} (\Gamma_{t+1} | \Gamma_t) \right] + (1 - \chi) E \left[ V_{t+1}^{d,n>0} (\Gamma_{t+1} | \Gamma_t) \right] \right) \\
&\quad \text{subject to the budget constraint given by equation (10).} 
\end{align}

\begin{align}
V_{g,t}^{d,n=0} (\Gamma_t) &= \max_{c_t, a_t, \alpha_{t+1}} \ln(c_t) - \Phi_{e,v} \frac{L_{g,t}^{\gamma}}{\gamma} \\
&\quad + (1 - \Pi_t) \alpha_{t,e} \beta E \left[ V_{g,t+1}^{d,n=0} (\Gamma_{t+1} | \Gamma_t) \right] \\
&\quad + (1 - \Pi_t) (1 - \alpha_{t,e} \beta) E \left[ V_{g,t+1}^{d,n=0} (\Gamma_{t+1} | \Gamma_t) \right] \\
&\quad + \Pi_t \alpha_{t,e} \beta E \left[ V_{g,t+1}^{m,n=0} (\Gamma_{t+1} | \Gamma_t) \right] \\
&\quad + \Pi_t (1 - \alpha_{t,e} \beta) E \left[ V_{g,t+1}^{m,n=0} (\Gamma_{t+1} | \Gamma_t) \right] \\
&\quad \text{again subject to the budget constraint given by equation (10).} 
\end{align}
$V^{m,n}$ is the value function if the agent (re)marries. The maximization is subject to the budget constraint (10).

Note that our definition of divorced individuals includes both eligible and non-eligible agents for auxiliary benefits.

**Single and Divorced Households With Children** The value function for non-married households is given by:

$$
V_{g,t}^{j,n>0} (\Gamma_t) = \max_{c_t, a_{t+1}} u_g (c_t, L_{g,t}) \\
+ (1 - \Pi_t) \beta E \left[ V_{g,t+1}^{j,n>0} (\Gamma_{t+1} | \Gamma_t) \right] \\
+ \Pi_t \beta E \left[ V_{g,t+1}^{m,n>0} (\Gamma_{t+1} | \Gamma_t) \right]
$$

where

$$
\begin{align*}
\ln (c_t) - \Phi_e v \left( L_{1,t} + \xi(n,k) \right) \\
\ln (c_t) - \Phi_e v \left( L_{2,t} \right)
\end{align*}
$$

Again, the maximization is subject to the budget constraint (10).

### 3.8.2 Retirement

From age 65 onward all agents are retired and the household is left with a consumption-saving decision. Moreover, there is no divorce risk any more.

For a married couple the maximization problem is given by:

$$
V_{g,t}^{m,n} (\Gamma_t) = \max_{c_t, a_{t+1}} \chi \ln (c_t) + (1 - \chi) \ln (c_t) + \beta V_{g,t+1}^{m,n} (\Gamma_{t+1} | \Gamma_t)
$$

and for a single household it is given by

$$
V_{g,t}^{j,n} (\Gamma_t) = \max_{c_t, a_{t+1}} \ln (c_t) + \beta V_{g,t+1}^{j,n} (\Gamma_{t+1} | \Gamma_t)
$$

subject to the budget constraint (10).

### 3.9 Aggregation

TBC

### 3.10 Government Budget Constraint

TBC
4 Parameterization

In what follows, we describe the parametrization of the model. We focus on the cohort born 1965-69 and characterize their birth rates, child related costs, income processes, and employment patterns over age.

The parameterization of our model is a two-stage process. In the first stage we assign values to parameters that can be estimated outside our model. These are the birth rates, child related costs, and the income process.

In the second stage we use our model to calibrate some parameters, in particular the preference parameters that govern the disutility of work as well as the parameters governing the initial match quality and the love shocks. There are also a number of parameters which we take directly from the literature.

4.1 Children

We approximate age-specific fertility by assuming that the birth of children is a one-time event. Hence, every period females face a probability of getting zero, one, two, or three or more children in our model. This simplification is done for computational reasons. However, when assigning the appropriate childcare costs, we assume a sequential arrival of children, see below for details.

The fertility probabilities, \( \alpha_{s,e}^{t} \), depend on marital status, \( s \), education, \( e \), and age, \( t \). To compute the probabilities, we use the June Supplement of the CPS on fertility. This survey contains information on the number and timing of births. As a first statistic, we compute the probability of the first birth depending on age.\(^9\) We then compute the fraction of women aged 40-45 who have one, two, or three plus children, conditional on having children, by using the total number of births for all women of that age. Multiplying the two gives us the age-specific probability of getting a certain number of children. The probabilities are depicted in the following figures.

Note that, in our model, we assume two fertility rates, one for married and one for not married, i.e., fertility between divorced and never married is assumed to be equal. Given that many divorced women had their children when they were married, this still gives rise to fertility differences between divorced and never married women.

4.2 Childcare Costs

Children incur both time and monetary costs.

Time costs associated with children, \( \xi(n,k) \), which depend on the number \( n \) and age \( k \) of children, are computed using the 2003 American Time Use Survey (ATUS). We compute the weekly total hours spent on childcare. This includes time spent

---

\(^9\)For this probability we employ the variables \( frever \) and \( frage1 \), i.e., the total number of births and the age of the mother at the birth of the first child. The latter variable is only available for waves 1980, 1985 and 1990 and hence we cannot focus on our cohort born 1965-69 due to small sample size.
caring for, teaching and playing with children. We restrict the sample to full-time working females, and compute values for women conditional on the number and age of children. [TBC: describe in more detail]

To compute monetary childcare costs, $w_{n,k}$, we use data from the SIPP 2008 topical module Nr.8 on childcare. The data gives detailed information on childcare arrangements (extensive and intensive margin) and their associated costs, including (family) childcare, nursery, (non-)relative care, sports, after-school activities, etc. for all children between ages 0 and 14. Data availability does not allow us to focus on our specific cohort, implying that the data is for a somewhat younger cohort.

Childcare costs are computed as follows. We first define institutionalized childcare costs as the sum of daycare, family daycare, nursery schools, and care from non-relatives and compute the total costs for these arrangements. We assume that households with children below age nine incur cost for childcare. Hence, we compute childcare costs for three age bins: 0-2, 3-5, and 6-8. For the statistics we focus on mothers who reported working the entire proceeding month of the interview.

We assume children are born in consecutive periods. For families with one child, we simply use the costs of one child for three age bins, and no costs thereafter. For families with two children, the childcare cost in the first period after birth simply corresponds to the cost of having one child (0-2). In the second period, the costs correspond to two children, one aged 0-2 and one aged 2-4, and similarly in the third period to two children, one aged 3-5 and one aged 6-8, and so forth. We proceed analogously for a three-child family. The corresponding numbers are depicted in Table 5. Note that for computational reasons we add childcare costs with three children in age bins 4 and 5 to age 4. [TBC]

**Table 5: Annual Childcare Costs (in $)**

<table>
<thead>
<tr>
<th>Age bin</th>
<th>One child</th>
<th>Two children</th>
<th>Three children</th>
</tr>
</thead>
<tbody>
<tr>
<td>1</td>
<td>7,424</td>
<td>7,424</td>
<td>7,424</td>
</tr>
<tr>
<td>2</td>
<td>6,034</td>
<td>14,867</td>
<td>14,130</td>
</tr>
<tr>
<td>3</td>
<td>3,283</td>
<td>11,492</td>
<td>15,076</td>
</tr>
<tr>
<td>4</td>
<td>0,0</td>
<td>4,131</td>
<td>8,775</td>
</tr>
<tr>
<td>5</td>
<td>0,0</td>
<td>0,0</td>
<td>4,386</td>
</tr>
</tbody>
</table>

*Note: SIPP June Supplement on Childcare Costs. Values conditional on paying anything for institutionalized childcare for children aged 0-5. Weekly data multiplied by 50 to approximate annual values. Institutionalized care defined as (a) family daycare, (b) daycare, (c) nursery school, and (d) paid care by non-relatives. Age bin refers to age of the mother after first birth.*

### 4.3 Income Process

We assume that labor income is determined by age (men) or human capital accumulation (women), and differs by education. In addition to the deterministic
component, we model an idiosyncratic component, $w_{t,e}$, which is assumed to be the same for both genders, and correlated between spouses.

For men ($g = 2$), we assume that wages for each age bin are given by

$$y_{2,t,e} = \gamma_{e} + \alpha_{e} \cdot \text{age}_{t,e} + \bar{\alpha}_{e} \cdot \text{age}^{2}_{t,e} + w_{t,e}$$ (18)

The deterministic wage-equation thus consists of a constant term, $\gamma_{e}$, and an age polynomial captured by the coefficients $\alpha_{e}$ and $\bar{\alpha}_{e}$. The regression is performed separately for the different education groups.

To estimate this wage process, we use data on male household heads in the PSID for the years 1969-2013. Our variable is household head’s wages and salaries, CPI-adjusted to 2010 prices where we take the aggregate of three years for each of the age bins in our model. We focus on the SRC (Survey Research Center) sample. To eliminate outliers, we drop the top and bottom 1% of the income distribution in each year, as well as individuals with less than 1,000 annual hours worked. We also drop all individuals with imputed wages.

The estimated coefficients are depicted in Table 6.

<table>
<thead>
<tr>
<th>Table 6: Estimated Deterministic Wage Component</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
</tr>
<tr>
<td>Constant, $\gamma_{e}$</td>
</tr>
<tr>
<td>Coefficient for age, $\alpha_{e}$</td>
</tr>
<tr>
<td>Coefficient for age$^{2}$, $\bar{\alpha}_{e}$</td>
</tr>
<tr>
<td>Depreciation rate (annual), $d$</td>
</tr>
</tbody>
</table>

*Source: Parameter estimates for earnings (in $1,000) from regression (18).*

Women’s wages are modeled according to the following specification:

$$y_{1,t,e} = (1 - \zeta_{e}) \cdot \left\{ \gamma_{e} + \alpha_{e} \cdot h_{t,e} + \bar{\alpha}_{e} \cdot h^{2}_{t,e} \right\} + w_{t,e}$$ (19)

The most notable difference to men is that women’s income depends on human capital, $h_{t}$, not age. We use the coefficients $\gamma_{t,e}$, $\alpha_{e}$, and $\bar{\alpha}_{e}$ that we estimated for men (the spells of non-employment make estimating this equation separately for women challenging). In addition, since even women working full-time face lower wages than their male counterparts, we scale down women’s income in order to match the data on the gender wage gap. We follow an approach taken by [Jones et al., 2015] who assume an age-specific wedge as a proxy for either direct wage discrimination or, e.g., a glass ceiling. We choose a $\zeta_{e}$ for each education type based on the CPS data. The gender-wage gap for our cohort is quite substantial; female hourly wages are on average 76% (dropouts), 82% (high school), and 91% (college) of male wages. Recall that our human capital specification, equation (6), implies a penalty for time.

---

10In case there are less than three wage observations per id and age bin we multiply the average existing values by three.
away from work. We assume depreciation at rate $\delta = 0.025$ if the woman worked part-time or stayed at home.\footnote{The value of $\delta = 0.025$ is in line with the literature estimating the human capital depreciation from one year away from the labor market, which is in the range of 2-5%. See, e.g., Attanasio et al. (2008).}

The residuals from regressions \((18)\) and \((19)\) represent the stochastic part of wages, $w_{i,t,e}$, for each individual $i$. As is standard in the macroeconomic literature, we follow Storesletten et al. (2004) and assume this process can be represented by a time-invariant process (where we assume only a persistent and no transitory component). The parameters are estimated with a GMM estimator. Results are given in Table 7. We assume the same shock process for high school dropouts and high school graduates.

### Table 7: Estimated Parameters for the Idiosyncratic Wage Component

<table>
<thead>
<tr>
<th></th>
<th>College</th>
<th>High School</th>
</tr>
</thead>
<tbody>
<tr>
<td>Autocorrelation coefficient, $\rho$</td>
<td>0.935</td>
<td>0.921</td>
</tr>
<tr>
<td>SD of Persistent shock, $\sigma_\epsilon$</td>
<td>0.251</td>
<td>0.272</td>
</tr>
</tbody>
</table>

\textit{Source:} Parameters for 3-year adjusted data estimated using the GMM specified in (??). SD is standard deviation.

We discretize the persistent stochastic component with a 4-state Markov-process using Tauchen’s method. This yields the transition probability matrix $\pi_z(z_{t+1}|z_t)$.

### 4.4 Exogenous Parameters

The policy parameters are set to match the U.S. social security and tax systems. In modeling the tax and transfer system, we closely follow Guner et al. (2017).\footnote{[TBC: describe in more detail]}

The bend-point values in the social security formula, as well as the adjustments for early and delayed claiming are given in the following tables.

### Table 8: Parameters for the PIA formula

| $\kappa_1$ | First Bend Point of AIME | $\$761$ |
| $\kappa_2$ | Second Bend Point of AIME | $\$4,586$ |
| $\lambda_1$ | PIA formula slope parameter 1 | $0.9$ |
| $\lambda_2$ | PIA formula slope parameter 2 | $0.32$ |
| $\lambda_3$ | PIA formula slope parameter 3 | $15$ |

\textit{Notes:} Values taken from www.ssa.gov for the year 2010. Bend point values are adjusted to 3-year aggregates in our model.
Table 9: Tax Parameters

<table>
<thead>
<tr>
<th>Parameter</th>
<th>Description</th>
<th>Value</th>
</tr>
</thead>
<tbody>
<tr>
<td>$\tau_c$</td>
<td>Consumption tax</td>
<td>7.5%</td>
</tr>
<tr>
<td>$\tau_{ss}$</td>
<td>Payroll tax</td>
<td>15.3%</td>
</tr>
<tr>
<td>$y_{max}$</td>
<td>Earnings cap for payroll tax in 2010</td>
<td>$106,800</td>
</tr>
<tr>
<td>$y^m$</td>
<td>Average earnings in 2010</td>
<td>$53,063</td>
</tr>
</tbody>
</table>

The consumption tax rate is from McDaniel (2007). The payroll tax is the statutory rate (including the 2.9% for Medicare).

Table 10: Exogenous Parameters

<table>
<thead>
<tr>
<th>Parameter</th>
<th>Description</th>
<th>Value</th>
</tr>
</thead>
<tbody>
<tr>
<td>$\rho$</td>
<td>the discount rate</td>
<td>0.03</td>
</tr>
<tr>
<td>$\gamma$</td>
<td>Curvature on disutility from work</td>
<td>2.43</td>
</tr>
<tr>
<td>$\chi$</td>
<td>Pareto weight</td>
<td>0.5</td>
</tr>
<tr>
<td>$\iota$</td>
<td>Return of experience from part-time</td>
<td>0.1</td>
</tr>
</tbody>
</table>

The curvature parameter on the disutility from work is related to the labor supply elasticity and consistent with estimates from models incorporating human capital accumulation (see, e.g., Imai and Keane (2004) and Wallenius (2011)). We assume a pareto-weight of 0.5, implying equal bargaining power for both spouses. This is a common practice in the literature. For equivalence scaling we follow the modified OECD scaling by assuming a weight of 0.5 for the spouse. The value for the accumulation of experience from part-time work is taken from Blundell et al. (2016).

4.5 Second Stage Parameters

The parameters that we calibrate using our model are the utility-cost of working, the mean and standard deviation of the distribution of the initial match quality when a single household meets a mate, as well as the standard deviation of the distribution of the love shocks.

**Disutility of Labor** We calibrate the utility-cost of working, $\Phi_{v,e}$, by matching the life cycle employment profile of females and the respective profile for part-time work. Note that we need heterogeneity in preferences (i.e. two preference for leisure types) in order to simultaneously match overall employment and part-time figures. In the current version, we match employment over education assuming that employment is similar across marital status (see Table 13 showing the similarities for married and unmarried females in employment). Table 11 lists the resulting parameters.

The parameters governing the disutility of work are critical for matching female employment, as well as the prevalence of part-time work, over the life cycle. We allow the disutility parameters to differ across utility-types, and education. In addition,\(^{12}\) Note that this estimate is for the UK. However, a related study for the U.S., Blank (2012), also finds very low accumulation of experience from working part-time.
Table 11: Disutility of Work for Females

<table>
<thead>
<tr>
<th></th>
<th>Dropouts</th>
<th>High school</th>
<th>College</th>
</tr>
</thead>
<tbody>
<tr>
<td>high disutility</td>
<td>28</td>
<td>28</td>
<td>30</td>
</tr>
<tr>
<td>low disutility</td>
<td>6</td>
<td>5</td>
<td>4</td>
</tr>
<tr>
<td>Fraction high-disutility types</td>
<td>0.4</td>
<td>0.4</td>
<td>0.4</td>
</tr>
</tbody>
</table>

we calibrate the fraction of females with high disutility, $\alpha$. The parameters are chosen to match employment over age and education.

We assign all married men low disutility from work.

Initial Match and Love Shocks  We calibrate the moments of the distribution of the initial match draw, $\mu_{\Xi}$, and $\sigma_{\Xi}$. The Fraction of never married and married agents over age and education helps us to identify these parameters. In addition, the standard deviation of the distribution of love-shock, $\sigma_u$, is identified by the fraction of divorced agents over age and education.

Table 12: Parameters of Love

<p>| | |</p>
<table>
<thead>
<tr>
<th></th>
<th></th>
</tr>
</thead>
<tbody>
<tr>
<td>$\mu_{\Xi}$</td>
<td>Mean of distribution of initial match</td>
</tr>
<tr>
<td>$\sigma_{\Xi}$</td>
<td>SD of distribution of initial match</td>
</tr>
<tr>
<td>$\sigma_u$</td>
<td>SD of love shock distribution</td>
</tr>
</tbody>
</table>

In order to discretize the non-stationary unit-root process of love, we follow a procedure described in Fella et al. (2017) which basically gives us age-specific transition probabilities for the discretized love process.
5 Calibrated Economy

5.1 Targeted Moments

In the following, we present preliminary results from a rough calibration. We choose the disutility from work so as to match female employment – full time and part time – over the life cycle.

We start by showing the fit of the model to the data for the average employment rate over the working life, i.e., an aggregate statistic as a first calibration target, see Table 13. [Note: We are currently working on the calibration and aim to match the whole age-profile for female employment that is available for our specific cohort].

Table 13: Targeted Moments I: Female Employment

<table>
<thead>
<tr>
<th></th>
<th>Total Employment</th>
<th>Part Time</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>Model</td>
<td>Data</td>
</tr>
<tr>
<td>Dropout</td>
<td>0.59</td>
<td>0.47</td>
</tr>
<tr>
<td>High school</td>
<td>0.75</td>
<td>0.73</td>
</tr>
<tr>
<td>College</td>
<td>0.79</td>
<td>0.79</td>
</tr>
<tr>
<td>Total</td>
<td>0.75</td>
<td>0.72</td>
</tr>
</tbody>
</table>

Note: CPS data, cohort 1965-69. Target: Average female employment, age 23-47.

We closely match overall employment, although employment of females with low education (dropouts) is still too high. Table 14 compares the age-specific fraction of married, never married and divorced females in our model with the data. We can broadly match the age-profile of marital transitions and the education gradient with our model. Note, that this is (so far) not even assuming education specific parameters for the initial match quality and for the love-process.

5.2 Non-Targeted Moments

Next, we evaluate the model fit with respect to moments that we did not directly target. In particular, we show the life cycle employment profile of females depending on the number of children compared to the data. Further, we show that our model is able to generate the large share of single mothers living in poverty.

Figure 1 compares the life cycle employment of females depending on the number of kids generated by our model (upper three panels) and compares these with the data in the lower three panels. Our (first rough) calibration is already able to (partially) generate the gradient of employment over the number of kids. The difference is generated in our model by the monetary costs, and the time spend with children, both taken from the data, as well as from equivalence scaling consumption. Note, that the difference in employment between having no children and
Table 14: Targeted Moments II: Marital Transitions

<table>
<thead>
<tr>
<th></th>
<th>Never Married</th>
<th></th>
<th>Married</th>
<th></th>
<th>Divorced</th>
<th></th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>Model</td>
<td>Data</td>
<td>Model</td>
<td>Data</td>
<td>Model</td>
<td>Data</td>
</tr>
<tr>
<td>Dropout</td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>age 23-34</td>
<td>0.21</td>
<td>0.24</td>
<td>0.71</td>
<td>0.63</td>
<td>0.08</td>
<td>0.13</td>
</tr>
<tr>
<td>age 35-47</td>
<td>0.13</td>
<td>0.14</td>
<td>0.61</td>
<td>0.68</td>
<td>0.26</td>
<td>0.18</td>
</tr>
<tr>
<td>High school</td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>age 23-34</td>
<td>0.23</td>
<td>0.20</td>
<td>0.73</td>
<td>0.69</td>
<td>0.04</td>
<td>0.10</td>
</tr>
<tr>
<td>age 35-47</td>
<td>0.15</td>
<td>0.11</td>
<td>0.64</td>
<td>0.71</td>
<td>0.21</td>
<td>0.18</td>
</tr>
<tr>
<td>College</td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>age 23-34</td>
<td>0.25</td>
<td>0.23</td>
<td>0.74</td>
<td>0.72</td>
<td>0.01</td>
<td>0.05</td>
</tr>
<tr>
<td>age 35-47</td>
<td>0.16</td>
<td>0.10</td>
<td>0.65</td>
<td>0.79</td>
<td>0.18</td>
<td>0.11</td>
</tr>
</tbody>
</table>

Note: CPS data, cohort 1965-69.

Figure 1: Female Employment over Kids
Table 15: Poverty Rates of Females

<table>
<thead>
<tr>
<th></th>
<th>Single</th>
<th>Married</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>Model</td>
<td>Data</td>
</tr>
<tr>
<td>Dropout</td>
<td></td>
<td></td>
</tr>
<tr>
<td>0 Kids</td>
<td>0.23</td>
<td>0.54</td>
</tr>
<tr>
<td>1 Kid</td>
<td>0.70</td>
<td>0.71</td>
</tr>
<tr>
<td>2 Kids</td>
<td>0.88</td>
<td>0.80</td>
</tr>
<tr>
<td>3 Kids</td>
<td>0.93</td>
<td>0.90</td>
</tr>
<tr>
<td>High-school</td>
<td></td>
<td></td>
</tr>
<tr>
<td>0 Kids</td>
<td>0.19</td>
<td>0.17</td>
</tr>
<tr>
<td>1 Kid</td>
<td>0.28</td>
<td>0.36</td>
</tr>
<tr>
<td>2 Kids</td>
<td>0.50</td>
<td>0.50</td>
</tr>
<tr>
<td>3 Kids</td>
<td>0.63</td>
<td>0.73</td>
</tr>
<tr>
<td>College</td>
<td></td>
<td></td>
</tr>
<tr>
<td>0 Kids</td>
<td>0.04</td>
<td>0.06</td>
</tr>
<tr>
<td>1 Kid</td>
<td>0.18</td>
<td>0.11</td>
</tr>
<tr>
<td>2 Kids</td>
<td>0.08</td>
<td>0.20</td>
</tr>
<tr>
<td>3 Kids</td>
<td>0.08</td>
<td>0.30</td>
</tr>
</tbody>
</table>

having one or more children is more pronounced in our model than it is in the data. A potential reason for this is that we assume monetary costs for child care for every working mother. However, the various other (informal) care possibilities, e.g., by grandparents are not taken into account up to now. [TBC add into model]

In Table 15 we present poverty rates according to our model compared to the CPS data. To this end, we calculate the fraction of females in the lowest income quintile for certain sub-populations. Note that we use per-capita household income, i.e., we include the income of a potential spouse. In addition, we control for age in our aggregate statistic by computing age-specific income quintiles. Our model captures the relative magnitude of poverty already quite well with our rough calibration exercise. In particular, poverty is heavily rising over the number of children, irrespective of marital status. In addition, poverty is especially high for single (=never married and divorced) females. Married females are insured by their spouse and, hence, their poverty rates are very low. The poverty-gradient over marital status is even more pronounced in our model than in the data.

6 Policy Analysis

In the policy analysis, we compare two policy reforms: (1) a 100% subsidy on childcare expenditures\textsuperscript{13} and (2) an increase in means-tested welfare payments\textsuperscript{14}.

\textsuperscript{13}Note that in this simple preliminary exercise we assume that the additional resources are used for government consumption.

\textsuperscript{14}In particular, we top up income of the household to 20% of average income in the economy, if household income is below this threshold.
We study the effect of these policies on female employment, marital transitions, and poverty rates.

Table 16: Change in Female Employment (in pp) Relative to Baseline

<table>
<thead>
<tr>
<th></th>
<th>∆ Childcare Subsidy</th>
<th>∆ Welfare Benefits</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>Employment</td>
<td>Part-time</td>
</tr>
<tr>
<td>Dropout</td>
<td>5.0</td>
<td>1.0</td>
</tr>
<tr>
<td></td>
<td>High school</td>
<td>-3.0</td>
</tr>
<tr>
<td></td>
<td>College</td>
<td>0.0</td>
</tr>
<tr>
<td>Total</td>
<td>1.0</td>
<td>-2.0</td>
</tr>
</tbody>
</table>


We find that a 100% subsidy on childcare expenditures is successful in reducing poverty among single mothers. Yet, the policy has only a small positive effect on female employment, with average female employment increasing by 1 pp. Thus, it helps the so-called working poor. The increase is, however, most pronounced for the least educated women, with the average employment of female high school dropouts increasing by 5 pp. Additionally, there is a small shift from part-time to full-time work. The employment effects are summarized in Table 16. The childcare subsidy has a negligible effect on marital transitions, see Table 17.

Replacing the current welfare benefits with a higher, means-tested benefit equal to 20% of average income in the economy also reduces poverty. However, employment decreases, especially among high school dropouts. This stems from the fact that the welfare expansion has a negative incentive effect on labor supply. This effect is not present with the childcare subsidy expansion, as it is only paid when the woman works. Note that the negative employment effects are particularly strong for low-educated single mothers, implying that a large share of them choose to stay out of the labor force to take care of their children. Moreover, the welfare expansion leads to a decline in marriage, both due to more divorces and fewer women choosing to marry. This effect is most pronounced for the least educated women. The intuition for this result stems from the fact that marriage provides insurance against poverty, but the expansion of welfare benefits reduces the need for this insurance.

7 Conclusion

Single mothers make up a large and rising share of all mothers. In the US, about 30% of mothers are raising their children alone. A large share of these, about 40%, live in poverty. This despite the fact that many welfare policies are targeted at single mothers.

In this paper, we seek to understand why so many single mothers live in poverty, and to contrast alternative policy measures targeted at alleviating said poverty. We
Table 17: Changes in Marital Transitions (in pp) relative to Baseline

<table>
<thead>
<tr>
<th></th>
<th>∆ Childcare Subsidy</th>
<th></th>
<th></th>
<th>∆ Welfare Benefits</th>
<th></th>
<th></th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>Never Married</td>
<td>Married</td>
<td>Divorced</td>
<td>Never Married</td>
<td>Married</td>
<td>Divorced</td>
</tr>
<tr>
<td>Dropout</td>
<td>23-34</td>
<td>0.0</td>
<td>0.1</td>
<td>-0.1</td>
<td>5.4</td>
<td>-11.1</td>
</tr>
<tr>
<td></td>
<td>35-47</td>
<td>0.4</td>
<td>1.1</td>
<td>-1.4</td>
<td>4.1</td>
<td>-13.3</td>
</tr>
<tr>
<td>High School</td>
<td>23-34</td>
<td>0.0</td>
<td>-0.1</td>
<td>0.0</td>
<td>5.4</td>
<td>1.8</td>
</tr>
<tr>
<td></td>
<td>35-47</td>
<td>0.4</td>
<td>-0.2</td>
<td>-0.3</td>
<td>4.1</td>
<td>-1.3</td>
</tr>
<tr>
<td>College</td>
<td>23-34</td>
<td>0.0</td>
<td>0.0</td>
<td>0.0</td>
<td>0.0</td>
<td>0.0</td>
</tr>
<tr>
<td></td>
<td>35-47</td>
<td>0.4</td>
<td>-0.2</td>
<td>-0.2</td>
<td>-0.6</td>
<td>0.4</td>
</tr>
</tbody>
</table>

*Note:* Changes in fraction being never married, married, and divorced in our counterfactuals (i) 100% child care subsidy (Child) and (ii) increase in welfare payments (Welf) relative to the baseline scenario. CPS data, cohort 1965-69. Target.

are also interested in the behavioral effects of potential policy reforms, notably the effect of reforms on labor supply and marital transitions. To this end, we develop a life cycle model of singles and couples where individuals make decisions regarding consumption and savings, labor supply, and marriage and divorce. For now, fertility is treated exogenously, as a shock. Agents face risks with respect to labor market productivity and the quality of the match.

We compare two alternative policy measures, namely higher welfare payments and free childcare. We find that a 100% subsidy on childcare expenditures is successful in reducing poverty among single mothers. Yet, the policy has only a small positive effect on female employment. Thus, it mainly helps the so-called working poor. The childcare subsidy has a negligible effect on marital transitions. According to our results, replacing the current welfare benefits with a higher, means-tested benefit equal to 20% of average income in the economy also reduces poverty among single mothers. However, it also leads to a substantial decline in female employment, particularly among high school dropouts. Moreover, the welfare expansion results in a decline in marriage. Again, this effect is most pronounced among the least educated.

Fertility is potentially an important margin when considering policies targeted at single mothers. We are currently working on an extension with endogenous fertility.
References


