Life-Cycle Fertility, Human Capital, and Family Polices: A Discrete-Continuous Choice Framework*

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ABSTRACT: We combine vast quasi-experimental variation in leave and tax-transfer policies in the US between 1968-2017 with a dynamic, discrete-continuous choice framework to study how these policies affect women's labor market decisions and outcomes, fertility decisions, and tax revenue. Crucially, we incorporate the trade-off between leisure, work, and child-rearing time, and integrate the multiple dimensions of leave policies (work requirements, length, job-protection, reimbursement) and tax-transfer policies (welfare transfers, family allowances, marginal tax rate, progressivity, marriage benefits). We show identification and develop a corresponding three-stage estimation strategy that combines the policy variation with a long panel of individual data. The variation in policy over time and across states is key to our identification, estimation, and counterfactual evaluation of the national implementation of policies. Our results reveal a policy trade-off between policies that best foster fertility (family allowances) and those that best foster labor market outcomes (leave policies). However, the opposing effects of these policies on fertility and labor market outcomes can be balanced while increasing tax revenue.

KEYWORDS: Fertility, Female Labor Supply, Protected Leave, Paid Leave, Taxation, Family Allowances, Transfers, Motherhood Penalty.
JEL: J13, J18, J22, J24, J28

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1 Introduction

Female labor supply and fertility behavior entail complex dynamics over the life cycle. For instance, childrearing demands, which disproportionately fall upon women, can constrain the amount of labor women are able to supply. At the same time, while labor supply builds women's human capital and yields monetary resources for their families, it can make raising children more difficult. These dynamic behaviors can have substantial socio-economic implications. For example, lower fertility can affect intergenerational wealth transfers and the demand for public infrastructure and privately produced goods, and higher female labor supply can increase tax revenue and economic growth. It is thus not surprising that policy makers across the world have tried to foster fertility and women's labor supply in multiple ways (Committee on Women's Rights, 1990; Olivetti and Petrongolo, 2017; Albanesi, Olivetti, and Petrongolo, 2022). However, the complexity of the policies and the interdependence between these choices has complicated the evaluation of these measure and their costs. We tackle these challenges here.

We combine vast quasi-experimental variation over time and across states in leave and tax-transfer policies in the United States with a structural discrete-continuous choice model to uncover the effects of a large set of policy arrangements on women's labor market decisions and outcomes, fertility decisions, partnership dynamics, and tax revenue. Our model provides a unified framework to evaluate leave and tax-transfer policies which integrates policy characteristics in detail and policy interactions. By explicitly incorporating the quasi-experimental variation we are able to evaluate the counterfactual national implementation of policies observed at the local level. Moreover, by endogenizing labor market and fertility choices we explicitly account for dynamic selection. Finally, our framework delivers a control group to assess the impact of family policies on long term outcomes such as completed fertility and life cycle labor market attachment. It is difficult, if not altogether unfeasible, to construct such control groups to study long term outcomes in reduced-form evaluations of leave policies.

We compile information on leave policies introduced at the state and national level in the US between 1968-2017 from a multitude of sources. This exercise yields 40 different leave arrangements that vary in their tier structure (number of tiers), eligibility criteria (prior work hours required at each tier), and generosity (protected and/or paid, length, and replacement rate).[1] In addition, we use data from the Panel Study of Income

[1]The tier structure refers to different levels of eligibility criteria which give women access to different

Dynamics (PSID), the NBER's TAXISM program (Feenberg and Coutts, 1993), and a flexible functional form with a long tradition in public finance (Feldstein, 1969; Heathcote, Storesletten, and Violante, 2011) to back out tax-transfer schedules across 21 regimes that include the six major federal reforms under presidents Reagan, G.H. Bush, Clinton, G.W. Bush, and Obama. The tax-transfer regimes differ in lump sums, child transfers, marginal tax rates, progressivity, and treatment of married households.

We then develop a structural dynamic discrete-continuous choice model of women's labor supply and fertility. Women choose whether to work, how many hours to supply, and whether to have a child during fertile years. Working yields human capital which determines future wages. Households earn labor income (hers and her spouse's) and non-labor income. Women have preferences over consumption, leisure, births and birth spacing. Children require nurturing time which constrains mothers' time available. Partnership dynamics include partnership status (single, married, or cohabiting), and partner's education and labor market participation. Partnership is not a choice in the model but its joint distribution depends on women's characteristics, their prior labor and fertility choices, and the policy environment. Women smooth household resources overtime splitting net income between consumption and savings. The optimality conditions of the dynamic problem are represented using conditional choice probabilities (CCPs) and conditional densities (for the continuous choices).

Women's incentives in the model are shaped by the policy environment. Leave policies have a static and a dynamic impact. On the one hand, paid leave increases current household income. On the other, protected leave affects future household income as it protects women against post-birth declines in wages by guaranteeing that women are paid their pre-birth wages, effectively covering for losses in human capital. In the aggregate, the presence of paid and protected leave policies affects the rate at which employers compensate all women, not only those taking up leave. Tax-transfer policies directly impact current and future household net income via lump sums, child transfers, marginal tax rates, and differential treatment of married households.

We prove the utility function is identified and use the introduction of leave and tax-transfer policies as a source of identifying variation. The estimation strategy, which proceeds in three stages, couples the policy variation with corresponding 50 years of individual data from the PSID between 1968-2017. First, we consistently estimate the wage and non-labor income equations, partnership distributions, and CCPs. Second,

levels of benefits. This structure is a result of different policies being introduced over time.

we use the first order condition of the dynamic problem with respect to work hours to estimate the marginal utility of work and leisure and the degree of risk aversion, using the simulated method of moments. Third, we use the conditional value functions to estimate the utility cost of labor market participation and the lifetime expected utility from births and spacing, using a maximum likelihood estimator.

A number of estimated mechanisms affect the work-leisure and fertility trade-offs. For instance, the wage equation reveals human capital depreciates rapidly and part-time labor market attachment hinders future wages (the part-time penalty on wages). The utility estimates indicate there is a fixed cost of participation that declines with age and education, and is higher for black and partnered women. The marginal utility of leisure increases with education and displays adjacent complementarity between current leisure and leisure the year prior, which generates persistency in labor market attachment. Further shaping the work-leisure trade-off, our estimates of the partnership dynamics indicate women who are more strongly attached to the labor market are less likely to stay single but more likely to become single if partnered, which can affect their household income and taxes. Regarding fertility, children 1 to 3 years old entail the highest nurturing time costs and there are strong preferences for birth spacing of 2-4 years between the first two children. The estimated lifetime expected utility from birth is higher for women with more completed education, black women, and partnered women, and is lower for working mothers. In addition, the partnership dynamics indicate women who have had births in the recent past are less likely to stay single and to separate.

Using our model we counterfactually evaluate the national implementation of a large set of leave and tax-transfers policies observed in the data. Concretely, we create a policy grid of seven leave policies by four tax-transfer policies resulting in 28 different policy regimes. The leave policies in the grid include variation in tier structure (one or two tiers) and type of leave (protected and/or paid). The tax-transfer policies in the grid include variation in lump sums, child transfers, progressivity and marginal tax rates. We simulate life cycle choices and outcomes under all 28 regimes.

Given any of the tax-transfer regimes in the grid, all leave policies in the grid decrease completed fertility relative to no-leave. In particular, leave policies with two tiers of eligibility and both types of leave decrease completed fertility the most (by up to 40 children per 100 women). Leave policies also delay the age of first birth by up to 8 months. Comparing across tax-transfer regimes, relative to regimes with low child transfers, those with high child transfers generate the largest gains in completed fertility (by up to 32 children per 100 women). Regarding birth spacing the policy effects are marginal, indicating that mothers' preferences are the dominant force.

In the labor market, we find that relative to no-leave all leave policies in the grid increase the motherhood penalty in labor income (by up to $7,803), in hours (by up to 177) and in wages (by up to $0.74), and decrease the motherhood penalty in participation (by up to 7.8 percentage points).[2] Despite their impact on the motherhood penalty, we find all leave policies in the grid increase life cycle labor market outcomes. In particular, two-tier leave policies generate the largest labor market gains, increasing participation by at least 5.8 percentage points (pp), average hours by at least 264, and average wages by at least $1.6. By attracting women at two different levels of prior attachment, two-tier policies increase leave take-up, allowing more women to reduce work hours while protecting their human capital, which increases future wages and induces them to participate and work more, a process that is further fueled by the adjacent complementarity in the marginal utility of leisure. Ultimately, it is their effectiveness in the labor market what explains the negative effect of leave policies on completed fertility, since having children is less preferred while working.

Among tax-transfer policies, those with high child transfers generate the highest motherhood penalty in participation, and the lowest motherhood penalty in labor income and hours. This is because mothers who receive higher child transfers are more willing to drop from the labor market, but conditional on participating, they try to avoid the part-time penalty on wages. Relative to the tax-transfer regime with the lowest child transfers, the regime with the highest child transfers reduces labor market outcomes the most, revealing a weakening of labor market incentives. Given the complementarity in the marginal utility of adjacent leisure, the negative labor market effects of child transfers can last long after children transition into adulthood.

Finally, given any tax-transfer regime in the grid, our in-sample counterfactuals reveal that all leave policies in the grid increase tax revenue net of policy costs, relative to no-leave, by a minimum of $7,052 per household in present value. This happens primarily because the financial costs of leave policy are fairly temporary while the labor market gains are long-term. Consistent with their stronger labor market effects, two-tier policies

[2] The motherhood penalty is defined as the persistent drop in women's labor market outcomes following child birth. Our measure of the motherhood penalty is standard and follows the specifications in Kleven, Landais, and Søgaard (2019) and Flores, Gayle, and Hincapié (2024). Notably, while we do not target in estimation the reduced-form causal policy effects or even the motherhood penalty itself, our results are largely consistent with the DID results in Flores, Gayle, and Hincapié (2024). All monetary values throughout the paper are expressed in real dollars indexed to 2015.

generate the highest gains in tax revenue net of leave policy costs. While our results reveal a policy trade-off between fertility and labor market outcomes, they also indicate it is possible to balance out the opposing effects of leave and child transfer policies, all the while increasing the government's budget. A combination of two-tier leave structures with high child transfers is a promising candidate.

Many tools have been used in the social science literature to study the impact of public policies on women's labor supply and fertility decisions, including survey responses to hypotheticals (Goldstein, Lutz, and Testa, 2003), time series analysis (Butz and Ward, 1979, 1980; Buttner and Lutz, 1990), cross-sectional comparisons across countries (Billari and Kohler, 2004; Kögel, 2004), event studies (Milligan, 2005; Laroque and Salanié, 2008; Cohen, Dehejia, and Romanov, 2013), and causal designs studying the effects of policies not only on women but also on their children in the US (Baum, 2003; Flores, Gayle, and Hincapié, 2024; Bailey et al., 2024) and abroad (Lalive and Zweimüller, 2009; Dustmann and Schönberg, 2012; Carneiro, Løken, and Salvanes, 2015; Ginja, Jans, and Karimi, 2020). Our work joins a handful of studies that explicitly model and estimate the dynamic interdependence between female labor supply and fertility using panel data (Hotz and Miller, 1988; Francesconi, 2002; Keane and Wolpin, 2010; Adda, Dustmann, and Stevens, 2017) and that also conduct counterfactual policy simulations (Keane and Wolpin, 2010; Adda, Dustmann, and Stevens, 2017; Wang, 2022). In this literature, our paper is closest to Wang (2022) who uses a dynamic model of endogenous fertility and discrete labor supply and variation from two parental leave reforms in Germany.

We expand the literature in several ways. First, we evaluate the long-term effects of a wide array of leave and tax-transfer policies taking into account dynamic selection in labor supply and fertility. Second, to the best of our knowledge, we are the first ones to analyze the impact of the tier structure of leave policies, which proves to be a critical policy lever. Third, we integrate the time cost of children in the dynamic labor-fertility trade-off. Fourth, we allow the hours decision to be continuous, a non-trivial modeling change, key to capture leave take-up and the role of marginal taxes influencing labor supply and working hours induced by leave policies. Fifth, we integrate employers' responses to leave policies through the wage returns to human capital. Lastly, we prove identification of the utility function.

The next two sections describe the policy variation in the US between 1968-2017 and the individual-level data. Section 4 introduces the structural model. Sections 5 and 6 prove identification and describe the estimation strategy. Section 7 discusses the structural estimates and Section 8 presents the counterfactual national implementation of policies. Section 9 concludes.

2 Leave and Tax Policies in the United States, 1968-2017

We incorporate two main sources of quasi-experimental policy variation across the US from 1968 to 2017: leave and tax-transfer policies. These arrangements affect women's labor market and fertility decisions over the life cycle. Leave policies target working women of fertile age who have children, providing job-protected time and/or paid time around the time of birth. Tax-transfer policies affect all individuals, providing different incentives for married individuals and parents with dependent children. Below we describe these policies in more detail.

2.1 Leave Policies

We gather information on leave policies using a multitude of sources including Skolnik (1952), Women's Legal Defense Fund (1991), Women's Bureau (1993), Kallman Kane (1998) and Waldfogel (1999). We complement these sources with information from government and think thank websites. The collection of state and federal leave policies, and a complete list of our sources, are presented in detail in Table S1 in Appendix A. Table 1 presents and summarizes the collection of unique policies in the US during our sample period derived from the information in Table S1. These policies have three main components: *eligibility*, *generosity* and *number of tiers*. Eligibility indicates the number of hours a woman must have worked in the prior year to access leave benefits upon having a child. Generosity indicates the level and type of benefits. The number of tiers indicates whether the policy has one or two levels of eligibility and generosity. There are 21 one-tier policies and 19 policies with a second tier with stricter eligibility but greater generosity. On average, one-tier policies require 628 hours of prior work, and two-tier policies require 457 (first tier) and 1,197 (second tier) hours of prior work. Of all first tiers, 40 percent do not require any prior hours.

Generosity has three components: *protected leave*, *paid leave* and *replacement rate*. Protected leave is not necessarily paid and vice versa. Protected leave refers to time off a woman can take while having her job protected. In other words, upon returning to the firm after a spell of protected leave a woman is entitled to her before-leave job or to an equivalent job if her exact job is no longer available. One-tier policies grant 9.2 weeks of protected leave on average, and two-tier policies grant 6.3 (first tier) and 17.1 (second tier) weeks. Paid leave refers to time off that is paid at a fraction (replacement rate) of the woman's wage. As opposed to most developed countries, paid leave is much less common in the US. One-tier policies grant 2.6 weeks of paid leave on average, and two-tier policies grant 4.4 (first tier) and 4.7 (second tier) weeks. Replacement rates vary from half to two thirds of the woman's wage.

The heterogeneous implementation of these unique polices over time and across states provides a rich source of policy variation shown in Figure 1. The top-left panel displays the proportion of states with leave policies by region. It shows significant variation in availability from the early 1970s up to 1993, when the Family and Medical Leave Act (FMLA) was introduced at the federal level. During the 1980s and before 1993 there was a substantial difference between regions with high (North East and West) and low (North Central and South) availability of leave. The top-right panel displays the average number of prior hours required for eligibility. Before FMLA there was also a substantial difference in eligibility between the North East and the West, the latter requiring almost no prior hours on average. After FMLA a difference emerges between regions that require around 900 hours on average (North East and West) and those who require around 1,200 (North Central and South). This difference in average required hours is caused by the higher prevalence of two-tier policies (with lower required hours in their first tiers) in the North East and West regions.

The bottom panels of Figure 1 describe generosity. The left panel shows that the largest change in average protected weeks is the introduction of FMLA. However, there is substantial pre-FMLA variation in protected leave driven mainly by the North East and West regions.[3] Post-FMLA the North-East has lower protected weeks on average; this is an artifact of the prevalence of two-tier policies in the region (the first tier granting less protected weeks). The right panel of Figure 1 shows that neither the North Central region nor the South region had paid leave policies during the sample period. By contrast, paid leave provision emerged in the North East and West regions starting in 1979 as a consequence of the introduction of the Pregnancy Discrimination Act of October 30, 1978 which allowed women to use Temporary Disability Insurance (TDI) policies, enacted well before 1979, as paid maternity leave (Stearns, 2015).

[3]This rich pre-FMLA variation in protected leave is exploited in Flores, Gayle, and Hincapié (2024) for causal identification of the effects of protected leave on parents' labor market outcomes, child investments, and fertility decisions, as well as on children's long term outcomes and intergenerational mobility.

2.2 Tax Policies

We use data from the Panel Study of Income Dynamics (PSID) on state of residence, marital status, dependents, annual earnings, and government transfers, in combination with the NBER's TAXISM program (Feenberg and Coutts, 1993) to recover tax-transfer schedules for our sample period. We use a well-known functional form (Feldstein, 1969) which flexibly captures the tax-transfer schedules. Variations of this function have been used to study optimal taxation (Heathcote, Storesletten, and Violante, 2011, 2017; Heathcote and Tsujiyama, 2021) and to describe income taxation in the U.S. (Guner, Kaygusuz, and Ventura, 2014). The tax-transfer function $T(y)$ we use is:

$$T(y) = \left(\pi_0^{tax} + \pi_1^{tax} y^{\pi_2^{tax}}\right) \tag{1}$$

where y is gross pre-government income, π_0^{tax} are lump sum taxes or transfers, π_1^{tax} is the slope shaping the tax rate, and π_2^{tax} captures the degree of progressivity.[4] Financial incentives to parents are captured in the lump sum and slope of the schedule (π_0^{tax}, π_1^{tax}), which vary with the number of dependent children. Financial incentives to individuals in different family structures are captured in all features of the schedule, which all vary by marital status.

We further modify the standard specification with fixed tax-transfer schedule in the literature to account for the major tax and welfare policy changes during our sample period. This quasi-experimental variation contains six major federal reforms under presidents Reagan, G.H. Bush, Clinton, G.W. Bush and Obama: the Economic Recovery Tax Act of 1981 (ERTA), the Tax Reform Act of 1986 (TRA), the Omnibus Budget Reconciliation Act of 1990 (OBRA-90), the Personal Responsibility and Work Opportunity Reconciliation Act of 1996 (PRWORA), the Economic Growth and Tax Relief Reconciliation Act of 2001, and the Tax Relief Act of 2010. While these reforms are federal, they induce significant variation at the state level because they add to state tax-transfer policies. Hence, to capture differences in tax policies at the state level, we also group all states and the District of Columbia into three time-invariant types based on income tax: low (e.g. Florida or Texas), medium (e.g. Illinois or Virginia), and high (e.g. California or Wisconsin). The quasi-experimental policy variation generated by the six major reforms across all three state types generates 21 tax-transfer policy regimes presented in Table 2. (Further details are in Appendix A.)

[4]The schedule is progressive if $\pi_2^{tax} > 1$, flat if $\pi_2^{tax} = 1$, and regressive if $\pi_2^{tax} \in (0, 1)$.

On average, the lump sum of the regimes (π_0^{tax}) is negative, capturing welfare transfers which are higher for the married ($5,997) than for the unmarried ($1,845). Parents receive financial incentives through lump sum transfers per dependent child which are also higher on average for the married ($836) than for the unmarried ($572). The average base slope (π_1^{tax}) is virtually the same in married and unmarried schedules (3.8%), though it decreases slightly for unmarried mothers (.12 pp per child). Average progressivity (π_2^{tax}) is higher for the unmarried (1.26) than for the married (1.22). Using the features of the tax-transfer regimes, and fixing husband income at $65,000, Figure S1 in Appendix A shows that the means of the implied average and marginal tax rates across regimes are comparable to those in Heathcote, Storesletten, and Violante (2017).[5] Importantly, our tax-transfer schedules capture differences by marital status and number of children. We find evidence of a marriage penalty in taxes as marginal tax rates tend to be higher for married women. For example, among women with two children, marginal tax rates are higher among the married for women with incomes below $160,000. Moreover, average tax rates tend to decline with the number of children. For example, for married women with income of $50,000 (and implied household income of $115,000) the mean average tax rate across regimes goes from 20.0% with no children to 19.1% with two children.

3 Individual Data and Leave Take-up

We combine the extensive variation in leave policy with 50 years of individual information from the PSID between 1968 and 2017, which includes labor and fertility choices of women across the country. Specifically, we use PSID information from the Family-Individual File, the Childbirth and Adoption History File, and the Marriage History File. The variables we use for our empirical application include: annual hours worked, real average hourly earnings, history of births, household non-labor income, age, state, years of completed education, race (black or white), and partnership status (single, married, or cohabiting). For women in partnerships we also use partner variables including age, years of education, labor participation and labor income.

Table 3 presents the characteristics of fertile-age (15-45) women in our sample. The

[5] Given the shape of our tax-transfer function $T(y)$, the average tax rate is $\frac{T(y)}{y} = \frac{\pi_0^{tax}}{y} + \pi_1^{tax} y^{\pi_2^{tax}-1}$, and the marginal tax rate is $T'(y) = \pi_1^{tax}\pi_2^{tax} y^{\pi_2^{tax}-1}$.

observations are split into three descriptive groups of women: before FMLA in states with and without leave policy, and after FMLA. Compared to women in states without leave policy before FMLA, those in states with leave policies before FMLA are slightly older, much less likely to be black (22% versus 44%), more likely to be partnered (married or cohabiting), more likely to participate in the labor market (72% vs 62%), likely to work more hours per year (1,084 vs 883), had higher hourly wages (18.6$ vs 14.7$), and were less likely to have a birth during the year (7.7% vs 8.8%). Comparing women in states with leave policy before FMLA against all women after federal policy was introduced reveals that the latter are older, more likely to participate in the labor market (82% vs 72%) and work more hours per year (1,421 vs 1,084).

Measuring leave take-up. The PSID data files do not contain information on leave take-up. To circumvent this data limitation we combine our extensive data on leave policies available in the US with women's work and birth histories to create a measure of leave take-up. For women who give birth in year t or $t-1$ (to account for rollover of benefits), we measure leave take-up in year t as a woman's decrease in worked hours in year t relative to her recent worked hours when she did not have a birth (during the four years prior). For every woman, take-up is bounded above by the amount of leave available, itself determined by the policy effective during year t in her state and her eligibility to it. Our measure of take-up accounts for institutional differences between protected and paid leave. On the one hand, women must return to work before their protected leave has ended to avoid losing protection. Hence, protected take-up is zero (effectively, lost protection) if the woman reduces her working hours beyond the protected amount available. On the other, no such constraint exists for paid leave, whose benefits are obtained immediately and are not lost if the woman reduces her working hours beyond the available paid leave.[6]

Importantly, our measure of leave take-up does not assume that women always use the leave available to them. As Rossin-Slater, Ruhm, and Waldfogel (2013) and Baum and Ruhm (2014) show, this is not the case. Instead, our measure requires a much weaker assumption: if a woman reduces her worked hours upon birth in a state with leave policy, she utilizes any protected or paid leave she is eligible for during those reduced hours. This is equivalent to assuming that preferences are monotonically increasing in income: if a woman reduces her worked hours without using available protected leave,

[6]The formal definition of leave take-up is given in Section 4 as it is part of our model.

then she would be allowing her expected future income to decrease by not protecting her current job; if a woman reduces her worked hours without using available paid leave, then she would be giving up current earnings.

Table 3 presents summary statistics of leave available and take-up among women who gave birth. Only 28% and 7% of all births in the sample were from women who had protected and paid leave available, respectively. This is not surprising given eligibility requirements, the late introduction of federal protected leave (1993), the scarcity of paid leave at the state level and its absence at the federal level. After federal protected leave was introduced, 59% of births were from women who satisfied eligibility requirements. Conditional on having protected and paid leave granted, the average number of granted hours went, respectively, from 215 and 222 before FMLA, to 464 and 333 after. This increase in hours granted is consistent with both policy generosity and labor market participation increasing over time.

Although leave availability has increased since the introduction of FMLA, leave take-up has moved in the opposite direction falling from 78.4% and 79.8% for protected and paid leave, respectively, before FMLA, to only 58.9% and 67.7% after. Leave take-up also varies substantially across states. Figure 2 shows that women in liberal-leaning states such as Massachusetts, Connecticut, and Washington tend to have a higher protected leave take-up than their counterparts in conservative-leaning states such as Alabama, Iowa and Mississippi. Among the few states that offer paid-leave in the sample (New York, New Jersey and California), the level of take-up is fairly similar.[7] Overall, paid-leave take-up is higher, which is consistent it not being lost even if the reduction in working hours goes beyond the amount available.

Who takes up leave? We explore the association between leave take-up and women's characteristics by regressing leave take-up on demographics, birth and work history (Table 4). Relative to white women, protected take-up is lower for black women: 4.0 pp lower among partnered women and 7.3 pp lower among singles. Women with college or more use 8.2 pp less protected leave. These associations are consistent with Rossin-Slater, Ruhm, and Waldfogel (2013) who find that women with high school or less, black women, and unmarried women in California have lower leave take-up before the introduction of paid family leave in the state in 2004.

Consistent with Figure 2, women in conservative-leaning regions use less protected

[7] Hawaii and Rhode Island are excluded from the paid-leave figure due to insufficient data.

leave, 11.0 pp less in the South and 13.9 pp less in the North Central region. In general, there are no statistically significant correlations between birth history and protected take-up, although women who also had a birth two years ago use 6.6 pp less protected leave in the current period. Work history both at the extensive and intensive margins is much more strongly correlated with protected take-up. Women heavily attached to the labor market use less protected leave. For instance, women who have worked full-time during the last four years use 22.5 pp less protected leave.

Table 4 shows that the gap in leave take-up between partnered white women and all other women more than doubles for paid leave. Paid take-up is 8.7 pp lower for partnered black women, 22.2 pp lower for single black women, and 17.8 pp lower for single white women. There are no statistically significant correlations between paid take-up and education, region or birth history. Again, work history at the extensive and intensive margins is much more strongly correlated with paid take-up. Women who have worked full-time during the last four years use 20.13 pp less paid leave.

4 A Model of Fertility and Female Labor Supply

We develop a dynamic model of life-cycle women's labor supply and fertility that integrates the impact of leave and tax-transfer policies. Women choose whether to work, how many hours to supply, and whether to have a child (during fertile years). Working yields human capital that determines futures wages, and that depreciates over time. Other sources of household income include spouse (men) labor income and household non-labor income. Women's decisions are affected by both maternity leave and tax-transfer policies that vary over time and across states. Leave policies have a static and dynamic impact: if paid leave is available, women obtain replacement income that increases current household income; if protected leave is available, women who return to the labor market after birth are guaranteed their pre-birth wages, effectively being compensated for human capital losses. In the aggregate, the presence of paid and protected leave policies affect the rate at which employers compensate all women's human capital. Tax-transfer policies impact current household net income depending on the household's marital status and number of dependents. Women have preferences over consumption, leisure and births (including spacing). Having children requires nurturing time which constrains mothers' time available for work and leisure. Partnership status (single, married, or cohabiting) as well as partner's education and labor participation are stochastic variables whose distributions depend on women's characteristics and their choices. Women smooth their households' net-income overtime using savings.

Choice set. Let $t \in \{0, 1, \ldots, T\}$ denote a woman's age in years beyond adolescence, let τ_t denote the calendar year when she is of age t, let $0 < T^F < T$ denote the last fertile age, and let $\pi_t \in \{\pi_0, \pi_1, \ldots, \pi_{\rho_r}\}$ denote the policy environment she is exposed to. Each period she chooses two continuous variables: consumption, $c_t \in \mathbf{R}_+$, and (scaled) working hours, $h_t \in [0, 1]$.[8] Define the indicator of labor force participation $d_t \in \{0, 1\}$ as:

$$d_t \equiv \mathbf{1}\{h_t > 0\} \tag{2}$$

A woman of fertile age ($t \leq T^F$) also decides whether to have a child ($b_t = 1$) or not ($b_t = 0$). Hence, at every period during her fertile years she chooses one of four discrete alternatives $k \in \{1, \ldots, 4\}$: neither to work nor to have a child ($k = 1$), to work and not to have a child ($k = 2$), to have a child and not to work ($k = 3$), and both to work and to have a child ($k = 4$). After her fertility age ($t > T^F$) she only decides whether to work or not. Let $d_{kt} \in \{0, 1\}$ indicate whether she chooses alternative k at t.

Individual characteristics, human capital and children. Women's individual characteristics, denoted z_t, include their age, race (black, white), education, and partnership status (single, married, cohabiting). Her partner's characteristics, if she is partnered (married or cohabiting), are denoted z'_t, the superscript $'$ referring to her partner. Let x_t denote her state variables. Her human capital $\underline{h}_{t-1}$ is defined as her vector of recent work hours:

$$\underline{h}_{t-1} \equiv [h_{t-1}, \ldots, h_{t-\rho_w}] \tag{3}$$

Human capital accumulated more than ρ_w periods ago depreciates entirely. Let her number of dependent children be $n_t \in \mathbf{Z}_+$, and let their age vector be $\underline{a}_t \in \{0, 1, \cdots, 17\}^{n_t}$. The laws of motion for n_t and $\underline{a}_t$ are endogenous to the woman's fertility choices.[9]

The total available time is normalized to one. The amount of time a woman can spend working or in leisure is constrained by her children's nurturing demands. Let ϕ_s be nurturing time required by a child of age s. Nurturing time becomes constant at $\phi > 0$

[8] Work hours are scaled as a proportion of total annual hours by dividing them by (24 × 365).

[9] Each additional birth increases n_t by one unit and each child reaching age 18 decreases n_t by one unit. The ages of each child, as well as the age of the mother, increase one year every period.

after age $\rho_c < 18$, and it falls to zero once a child reaches age 18. Hence, the total amount of time a mother of age t spends nurturing her children, denoted ς_t, is given by:[10]

$$\varsigma_t \equiv \sum_{s=0}^{\rho_c} \phi_s b_{t-s} + \phi \sum_{s=\rho_c+1}^{17} b_{t-s} \tag{4}$$

Time available for work and leisure is thus endogenously constrained by previous fertility choices. Leisure l_t is the residual time not spent at work or nurturing children:

$$l_t = 1 - h_t - \varsigma_t \tag{5}$$

Partnership and separation. Let m_t denote the woman's partnership status (single, married, or cohabiting). At the beginning of period t, before labor market and fertility decisions are made, a partnership shock is realized in the following sequence. If she is single, she first draws a partnership status; conditional on forming a partnership, she draws partner characteristics z'_t. If she is in a partnership, she first draws a separation shock; if her partnership ends, she remains single for that period; if her partnership does not end, she continues married if she was married, or she draws a marriage shock if she was cohabiting. Spouse (men) type does not change within a partnership. Hence, with minor abuse of notation, partnership dynamics follow the distribution $G(m_t, z'_t | m_{t-1}, z_{t-1}, z'_{t-1}, x_{t-1})$ which is conditional on her prior partnership status, hers and her partner's characteristics, and state variables such as tax and leave policies, human capital and birth history.

Leave policies. There are two types of leave, protected and paid, which are not mutually exclusive. Protected leave targets future income; it guarantees working women the same job they had before taking time off, effectively covering for losses in human capital. Paid leave targets current income; it pays working women a fraction $\iota(\pi_t) \in [0,1]$ of their wages (*replacement rate*) during their time off. Let $h^\ell_t = \{h^\ell_{1t}, h^\ell_{2t}\} \in \mathbf{R}^2_+$ be the vector of protected and paid leave take-up, respectively. In our framework, protected leave attains its objective by crediting working women with additional, wage-relevant human capital to cover for human capital losses due to time taken off work upon birth. This

[10]This specification of maternal time inputs is broadly consistent with those considered in the literature. For example, using data from time diaries, Hill and Stafford (1980) found that maternal time devoted to child care declines as the children age. Equation (4) implies that the child care process exhibits constant returns to scale in the number of existing children. Evidence on the importance of scale economies is mixed; Lazear and Michael (1980) find evidence of large scale economies while Espenshade (1984) finds them to be small.

operationalization of protected leave gives rise to two measures of human capital. *Actual* human capital accumulated at t are the actual working hours (h_t). *Protected* human capital accumulated at t, denoted h_t^*, is the sum of actual hours and protected take-up:

$$h_t^* = h_t + h_{1t}^{\ell} \tag{6}$$

Leave take-up is constrained by the policy environment π_t. Conditional on having a child, a woman is granted $\bar{h}_t \in \mathbf{R}_+^2$ hours of protected and paid leave given by:

$$\bar{h}_t = b_t \cdot \kappa(\pi_t, h_{t-1}) \cdot h_t^B(\underline{h}_{t-1}) \tag{7}$$

The function $\kappa \in [0,1)^2$ captures the policy's eligibility and generosity criteria (i.e., how much prior work is required and how much leave is granted in each policy tier); it is simply a compact way of writing the policy details described in Table 1 and whether prior hours satisfy eligibility.[11] The function $h_t^B(\underline{h}_{t-1})$, which depends on prior work history, determines the base hours used to scale leave time.[12] For instance, if a policy eligibility criterion is half of full-time work hours in $t-1$ and it grants 16 weeks of protected leave, then a woman who worked full time last year and has a current birth would be granted the scaled equivalent of 640 protected hours (16 weeks × 40 hours/week). Following most policy guidelines, leave hours granted at t can be used in t or $t+1$. Hence, total leave available at t is the sum of leave granted at t plus leave rolled over from $t-1$, $h_t^R \in \mathbf{R}_+^2$.

Consistent with our take-up measure in Section 3, leave take-up is determined by her work intensity during birth years. Available leave benefits are used (fully or partially) by reducing working hours. Hence, women who do not reduce their working hours upon birth do not take up leave. Formally, protected and paid leave take-up are given by:

$$h_{1t}^{\ell} = (h_t^B - h_t)\mathbf{1}\{0 \leq h_t^B - h_t \leq \bar{h}_{1t} + h_{1t}^R\} \tag{8}$$

$$h_{2t}^{\ell} = (h_t^B - h_t)\mathbf{1}\{0 \leq h_t^B - h_t \leq \bar{h}_{2t} + h_{2t}^R\} + (\bar{h}_{2t} + h_{2t}^R)\mathbf{1}\{h_t^B - h_t > \bar{h}_{2t} + h_{2t}^R\} \tag{9}$$

The factor $(h_t^B - h_t)$ in (8) and (9) is the reduction (or increase) in hours relative to her base hours h_t^B. The indicator function in (8) captures two conditions: if a woman increases

[11] For example, for a one-tier policy that requires $a \in \{0,1\}$ prior hours and grants $b \in \{0,1\}$ weeks of protected leave, $\kappa(\pi_t, h_{t-1}) = \mathbf{1}\{h_{t-1} \geq a\} \times b$, where b is written as a share of weeks per year.

[12] A simple rule could be $h_t^B(\underline{h}_{t-1}) = h_{t-1}$. We use a more complete measure specified in Section 6.

her working hours ($h_t^B < h_t$) she does not use leave; if she reduces her working hours ($h_t^B \geq h_t$) but goes beyond the amount available ($h_t^B - h_t > \bar{h}_{1t} + h_{1t}^R$), employers are not required to protect her human capital. Equation (9) indicates that paid leave is not lost if she reduces her working hours beyond what is available. In such case, captured by the second term of (9), she takes up all paid leave available $\bar{h}_{2t} + h_{2t}^R$.[13] Given the definition of leave take-up, protected and paid leave rolled over are given by:

$$\begin{aligned} h_{jt}^R = & \ \bar{h}_{jt-1}\mathbf{1}\{h_{t-1}^B - h_{t-1} \leq h_{jt-1}^R\} \\ & + (\bar{h}_{jt-1} + h_{jt-1}^R - (h_{t-1}^B - h_{t-1}))\mathbf{1}\{h_{jt-1}^R \leq h_{t-1}^B - h_{t-1} \leq \bar{h}_{jt-1} + h_{jt-1}^R\}, \quad \text{for } j = 1,2 \end{aligned} \tag{10}$$

The first term in (10) indicates that all leave granted at $t-1$ can be rolled over if she did not reduce her hours beyond what she had rolled over into $t-1$, h_{jt-1}^R. The second term indicates that she is able to roll over the residual between leave available and her reduction in hours if her take-up was greater that h_{jt-1}^R but smaller than available leave.

Tax-transfer policies. In addition to leave policies, the policy environment π_t contains tax-transfer policies that shape households' disposable income. Consistent with equation (1), for a given amount of gross household income W, the tax-transfers amount is:

$$T_k(W, \pi_t, x_t) = \pi_{0kt}^{tax}(x_t) + \pi_{1kt}^{tax}(x_t)W^{\pi_{2t}^{tax}(x_t)} \tag{11}$$

Both the lump sum tax-transfers π_{0kt}^{tax} and the slope shaping the tax rate π_{1kt}^{tax} are linear functions of the number of dependent children. Both components are indexed by the current discrete choice k because women's current choices can increase the number of dependent children during fertile years. The degree of progressivity $\pi_{2t}^{tax}(x_t)$, which captures redistributive features of the tax code, does not vary with the number of children. Importantly, all components of the function T, including the interactions with the number of children, vary by marital status (married versus unmarried).

The resulting ten-parameter tax-transfer function in (11) captures a wide array of policies aiming to shape fertility choices. First, the tax-transfer function integrates fixed family allowances (child transfers) for underage children by allowing the lump sum π_{0kt}^{tax} to vary with the number of dependent children.[14] Second, the function T integrates

[13]Importantly, the specifications in (8) and (9) eliminate the need for additional continuous choices to determine leave take-up.

[14]Various policies implemented in countries such as France have included one-time payments to parents

tax breaks given to parents by allowing the slope parameter π_{1kt}^{tax} to also vary with the number of dependent children. Finally, by allowing all parameters to vary by marital status the tax-transfer function captures differences in incentives provided to married and unmarried individuals, including differences in family allowances and child-related tax-breaks.

Tax-transfer policies also provide incentives for both the extensive and intensive margins of labor supply. The tax-transfer amount affects the decision to participate in the labor market by changing the amount of disposable income. For example, child transfer policies affect the participation choice through their effect on current utility. The marginal tax-rate shapes the decision on the intensive margin by changing the marginal value of an hour of work. Thus, since child transfers are not work-tested, only child-related tax breaks affect the choice of hours through current marginal utility. Dynamically, child transfers and child-related tax breaks affect labor choices through their impact on future resources. Lastly, given the non-linear, non-additive nature of both leave and tax-transfer policies, the interaction between these two types of policies also shapes women's fertility and labor supply decisions.

Women's wages. Women's real wages are the product of $\omega(\tau_t)$, the current wage for one efficiency unit of labor, and the number of efficiency units she embodies. The latter is determined by her individual-specific productivity μ, her protected human capital h_t^*, and her demographic characteristics z_t. Concretely, her wage rate in calendar year τ_t is:

$$w_t = \omega\left(\tau_t\right)\mu \exp\left\{\sum_{r=1}^{\rho_r} \mathbf{1}\{\pi_t = \pi_r\}\left[z_t B_{r,3} + \sum_{s=1}^{\rho_w}\left(\delta_{r,1s} h_{t-s}^* + \delta_{r,2s} d_{t-s}\right)\right]\right\} \tag{12}$$

The sum over policy regimes in (12) captures firms' responses to leave policies via compensation schedules. In other words, employers are able to reward hours differently in regimes with mandated protected and paid leave, relative to a regime without mandated leave benefits. Aggregate trends in women's labor efficiency are captured by ω.

Men's wages and labor participation. Married or cohabiting households are modeled as unitary decision-makers. Following Blundell et al. (2016) we assume that men either work full time (h' hours) with $Prob[d_t' = 1|z_t, z_t', d_{t-1}', x_t]$, or not at all, where the prob-

of newborn babies (baby bonus), child allowances that vary by the order of the child such as a higher amounts for the third child, and shorter time spans such as allowances until age three (Thévenon, 2016).

ability depends on the household's state variables. Importantly, in our framework such state variables include the policy environment. Men's hourly wage w'_t is parsimoniously modeled as an education-specific function of potential experience:

$$\ln w'_t = \ln \omega'(\tau_t) + \ln \mu' + B(ed') \ln(t - 18) \tag{13}$$

where μ' is a deterministic, fixed individual-specific productivity which depends on the man's education (ed') and race, and ω' captures the aggregate trend in labor efficiency for men. Hence, men's labor income e'_t is given by:

$$e'_t \equiv w'_t d'_t h' \tag{14}$$

Non-labor income. Non-labor household income e^{NL}_t follows an AR(1) process in logs:

$$\ln e^{NL}_t = B^e \ln e^{NL}_{t-1} + B^{NL} X_t + \omega^{NL}(\tau_t) + u^e_t \tag{15}$$

where B^e measures non-labor income persistence, X_t includes age, race, education, partnership status, and partner's education, ω^{NL} is the aggregate trend of non-labor income, and u^e_t is a non-labor income shock distributed $N(0, \sigma^2_e)$.

Net household income. Conditional on discrete alternative k being chosen and h_t hours worked, gross household income $W_k(h, x)$ is given by:

$$W_k(h_t, x_t) \equiv w(x_t)h_t + \iota(\pi_t)w(x_t)h^{\ell}_{2t} + e'(x_t) + e^{NL}(x_t) \tag{16}$$

where the first term is her labor income, the second term is her paid-leave income, the third term is her partner's labor income, and the last term is her household's non-labor income. Following equations (12) to (15), wage, partner income, and non-labor income depend on her state x_t. Net household income $Y_k(h_t, x_t)$ results from subtracting the total tax-transfer amount in (11) from the household's gross income:

$$Y_k(h_t, x_t) = W_k(h_t, x_t) - T_k(W_k(h_t, x_t), \pi_t, x_t) \tag{17}$$

Net household income incorporates leave and tax-transfer trade-offs. For example, it entails the trade-off from using protected or paid leave, when only one is offered: taking up protected leave generates sharper losses in current income but protects future wages, while taking up paid leave mitigates losses in current income but impairs future wages by not protecting human capital. In addition, the marginal returns from labor are directly affected by the marginal tax rate, and the current and future generosity of tax-transfer benefits (for example, lump sum transfers) are affected by current fertility decisions.

State and preferences. The vector x_t of state variables is

$$x_t \equiv \left(z_t, z'_t, d'_t, h_{t-\rho_w}, \ldots, h_{t-1}, h^{\ell}_{1t-\rho_w}, \ldots, h^{\ell}_{1t-1}, h^R_t, \underline{a}_t, \ln e^{NL}_t, \pi_t, \underline{\omega}_t \right)', \tag{18}$$

it contains her demographic characteristics z_t (including her labor productivity μ), her partner's characteristics z'_t and participation d'_t, her prior labor supply and protected take-up, rolled over leave, the ages of her underage children $\underline{a}_t$, her non-labor income, and all relevant aggregate variables including the policy environment π_t and other aggregate processes denoted $\underline{\omega}_t$, where $\underline{\omega}_t \supset \{\omega, \omega', \omega^{NL}\}$.

Her expected lifetime utility depends on consumption, labor supply, fertility choices, and demographic characteristics as follows:

$$-E\left\{ \left[\sum_{t=0}^{T^R} \sum_{k \in C_t} \beta^t d_{kt} \exp\left(-\alpha c_t - u_k\left(h_t, x_t\right) - h_t \xi_t - \varepsilon_{kt}\right) \right] + \left[\sum_{t=T^R+1}^{T} \beta^t \exp\left(-\alpha c_t\right) \right] \right\} \tag{19}$$

Her discrete choice set C_t has only two alternatives (work or not) after her fertile age T^F, and she only makes consumption smoothing choices after her retirement age T^R. The flow utility is CARA with absolute risk aversion α. It contains a non-pecuniary term u_k, idiosyncratic changes in the marginal utility of work ξ_t, and alternative-specific preference shocks ε_{kt}. The non-pecuniary utility u_k is the sum of her utility from having a child $u^{(b)}_t$ and her utility from leisure $u^{(\ell)}_t$. Her utility from having a child in t is:

$$u^{(b)}_t \equiv b_t \left(z_t \gamma_0 (1 - d_t) + z_t \tilde{\gamma}_0 d_t + \sum_{s=1}^{\rho_b} \gamma_s b_{t-s} + \gamma_b \sum_{s=\rho_b+1}^{t_a-1} b_{t-s} \right) \tag{20}$$

where demographics z_t include age, education, race, and partnership status and $t_a = 18$ is the adulthood age. The function $u^{(b)}_t$ captures preferences over birth spacing. Concretely, the additional lifetime expected utility is γ_0 ($\tilde{\gamma}_0$ if she works) from her first child, $\gamma_0 + \gamma_s$ from a second birth when the first child is s years old, $\gamma_0 + \gamma_s + \gamma_j$ from a third birth when the first children are s and j years old, and so on.

Her utility from leisure in t captures fix and variable components according to:

$$u_t^{(\ell)} \equiv z_t B_0 d_t + z_t B_1 l_t + \sum_{s=0}^{\rho_l} \delta_s l_t l_{t-s} \tag{21}$$

where B_0 captures fixed participation costs and B_1 captures the marginal utility of leisure. Decreasing utility returns from leisure (if any) are captured by δ_0 and intertemporal non-separabilities in leisure preferences are captured by $\delta_1, \ldots, \delta_{\rho_l}$.[15]

Finally, the disturbance ξ_t is received after discrete choices are made and is identically and independently distributed (iid) F_ξ, a mixture of normals with parameters θ_ξ. The distribution F_ξ is conditional on b_t which captures changes in the marginal utility of work upon birth. The preference shocks ε_{kt} are iid Type 1 Extreme Value.

Budget constraint. The setup for consumption and saving choices follows Margiotta and Miller (2000). Women have access to a contingent claims market for consumption goods that they use to smooth consumption. In this environment, aside from current policy π_t and aggregate trends $\underline{\omega}_t$, aggregate effects are transmitted through interest rates. Let $\lambda(\tau_t)$ be the price of consuming in year τ_t denominated in τ_0 consumption units. Equation (23) provides the law of motion for savings, denoted s_t:

$$E_t[\lambda(\tau_{t+1}) s_{t+1} | h_t, b_t, x_t] + \lambda(\tau_t) c_t \leq \lambda(\tau_t) \left(s_t + Y_k(h_t, x_t)\right) \tag{23}$$

Financial resources available at t, savings and net income, valued by the price of consuming at t, can be spent in current consumption valued by the price of consuming at t and future savings valued by the expected price of consuming at $t+1$.

Optimal choices. Let $\{c_t^o, h_t^o, b_t^o\}_{t=0}^T$ denote the woman's optimal choices, $\underline{d}_t^o = \left(d_{1t}^o, \ldots, d_{4t}^o\right)$ denote her discrete optimal choices, and $h_{kt} \equiv h_k(x_t, \xi_t)$ denote her optimal choice of hours given discrete choice k. By definition, $h_{kt} = h_t^o$ if $d_{kt}^o = 1$, and $h_{1t} = h_{3t} = 0$. She makes sequential choices to maximize (19) subject to (23). Our representation of the op-

[15]Equation (20) implies that siblings k years apart are complementary in lifetime utility if $\gamma_k > 0$. Equation (21) implies that utility is increasing in leisure if:

$$z_t' B_1 + 2\delta_0 l_t + \sum_{s=1}^{\rho_l} \delta_s l_{t-s} > 0 \tag{22}$$

and concave if $\delta_0 < 0$. Current and past leisure time are complements if $\delta_s > 0$ and substitutes otherwise.

timality conditions extends to our discrete-continuous framework previous related work that included only discrete choices (Altuğ and Miller, 1998; Gayle, Golan, and Miller, 2015; Hincapié, 2020; Khorunzhina and Miller, 2022). Let $p_{kt}(x_t) \equiv E\left[d^o_{kt} | x_t\right]$ denote the conditional choice probability (CCP) of making discrete choice k at age t conditional on state vector x_t, and let ε^*_{kt} denote the truncated variable that takes on the value of ε_{kt} only when $d_{kt} = 1$. Similarly, let $q_k(h|x_t)$ denote the conditional continuous choice density (CCD) function of choosing hours h given state x_t and choice k and let ξ^*_{kt} denote the marginal value of ξ_t that makes optimal her choice of hours h^o_{kt}. For notational ease define her expected (over ξ) per-period utility $\overline{u}_k(x_t)$ as

$$\overline{u}_k(x_t) \equiv E[u_k(h_k(x_t, \xi^*_{kt}), x_t)|x_t] + E[h_k(x_t, \xi^*_{kt})\xi^*_{kt}|x_t] + \alpha E[Y_k(h_k(x_t, \xi^*_{kt}), x_t)|x_t] \quad (24)$$

Let $A_{T^R+1}(x_{T^R+1}) \equiv 1$. Adapting results in Gayle, Golan, and Miller (2015) and Hincapié (2020) to our framework we recursively define an index of household capital at t as:

$$A_t(x_t) \equiv \sum_{k \in C_t} p_{kt}(x_t) \exp\left(\frac{-\overline{u}_k(x_t)}{B_t}\right) E\left[\exp\left(\frac{-\varepsilon^*_{kt}}{B_t}\right)\middle| x_t\right] \left[\int\left(\int A_{t+1}(x_{t+1}) g_{kh}(x_{t+1}|x_t) dx_{t+1}\right) q_k(h|x_t) dh\right]^{1-\frac{1}{B_t}} \quad (25)$$

where g_{kh} is the probability density function of the future state conditional on the current state, choice k and hours h_{kt}, and B_t is the bond price at calendar year $\tau(t)$, where $B_t \in \underline{\omega}_t$. The strictly positive index A_t captures the value of household capital given the remaining years before retirement. Lower values of the index, which imply higher continuation values, are generated by higher income, lower work when it is disliked (for instance if ξ is large and negative), and higher utility from leisure and children in u_k. Women are surprised by changes in leave and tax-transfer policies but have perfect foresight over the aggregate objects in $\underline{\omega}_t$. Following Khorunzhina and Miller (2022), at each age $t \leq T^R$ the optimal discrete choices $\underline{d}^o_t$ maximize:

$$\sum_{k \in C_t} d_{kt}\left[\overline{u}_k(x_t) - (B_t - 1)\ln\left[\int\left(\int A_{t+1}(x_{t+1}) g_{kh}(x_{t+1}|x_t) dx_{t+1}\right) q_k(h|x_t) dh\right] + \epsilon_{kt}\right] \quad (26)$$

Intuitively, women maximize a weighted sum of current utility and future value. They obtain current utility from net income, leisure, birth choices, and idiosyncratic preference shocks. Their expected future value is affected by the current price of consumption streams, captured by B_t, the accumulation of human capital, and changes to family composition through births or partnership dynamics. Given $A_{t+1}(x_{t+1})$, equation (26) describes a standard discrete choice problem. At the intensive margin, optimal hours h^o_t

satisfy the first order condition:

$$\xi_{kt} = -\alpha w(x_t)\left(1+\iota(\pi)\frac{\partial h^{\ell}_{2t}}{\partial h}\right)\left(1-\pi_2^{tax}(x_t)\pi_{1k}^{tax}(x_t)W_k(h_{kt},x_t)^{\pi_2^{tax}(x_t)-1}\right)+\left(z_tB_1+2\delta_0 l_{kt}+\sum_{s=1}^{\rho_l}\delta_s l_{t-s}\right)$$
$$+\left(\frac{(B_t-1)}{\int A_{t+1}(x_{t+1};\theta_1)g_{kh}(x_{t+1}|x_t)dx_{t+1}}\times\right.$$
$$\left.\int\left[\frac{\partial A_{t+1}(x_{t+1};\theta_1)}{\partial h}+\frac{A_{t+1}(x_{t+1};\theta_1)}{g_{kh}(x_{t+1}|x_t)}\frac{\partial g_{kh}(x_{t+1}|x_t)}{\partial h}\right]g_{kh}(x_{t+1}|x_t)dx_{t+1}\right),\quad \text{for } k=2,4 \tag{27}$$

for $k \in \{2,4\}$, where the expectation over current hours is dropped as the disturbance ξ_t is observed before choosing hours, and where $\frac{\partial h^{\ell}_{2t}}{\partial h} \equiv 0$ for ages beyond her fertile age since no paid leave can be obtained then. Equation (27) captures several mechanisms. First, it captures the marginal effect of current work hours on current net income, including the marginal rate of compensation (wage), the marginal rate of replacement compensation, the marginal change in paid take-up, and the marginal effect on taxes and transfers. Second, it captures the marginal non-pecuniary benefits from current leisure. Finally, it captures the marginal effect of current work hours on the continuation value of the household, including their effect on future wages (via changes in protected and unprotected human capital) and their effect on the satisfaction of future eligibility criteria.

5 Identification

Following the terminology of Arcidiacono and Miller (2019) we first note that our data is a long panel, that is, in each policy regime π a synthetic panel can be constructed to string together histories of fertility and labor supply for each demographic group. Taking as given the exponential shape of the flow utility function and its constant absolute risk aversion with respect to consumption, we develop our identification argument for a general $u_k(h, x_t)$ and for the case with perfect foresight over the state space (except over π_t) to reduce notation. Let $x^{(kh,1)}_{t+1+s}$ for $s = 0, ..., T-t$ be the (perfectly anticipated) value of the state vector at $t+1+s$ given current state x_t, following choice k and hours h_{kt} in t and discrete alternative 1 (no work and no birth) from period $t+1$ to $t+1+s$. Decompose the observed state variables into pure demand shifters ν_t (such as policy variables π_t) and the rest by letting $x_t = (\widetilde{x}_t, \nu_t)$, and let $u_k(h, x_t) = u_k(h, \widetilde{x}_t)$.

Proposition 1. *Let* $x^{(kh)}_{t+1}$ *(or simply* $x^{(k)}_{t+1}$ *if* $k \in \{1,3\}$*) denote the evolution of the state into* $t+1$

given discrete choice k and hours choice h_{kt}. The index of household capital A_t can be written as:

$$A_t\left(x_t\right) = \prod_{s=0}^{T-t}\left[p_{1t+s}(x^{(1)}_{t+s})\Gamma\left(\frac{B_{t+s}+1}{B_{t+s}}\right)^{B_{t+s}}\exp\left\{-\overline{u}_1(x^{(1)}_{t+s})\right\}\right]^{\chi_t(s)} \tag{28}$$

where the cumulative discount factor $\chi_t(s)$ is defined as:

$$\chi_t(s) \equiv \frac{1}{B_{t+s}}\Big[\prod_{r=0}^{s-1}\Big(1-\frac{1}{B_{t+r}}\Big)\Big]^{\mathbf{1}\{s>0\}} \tag{29}$$

and the ex-ante conditional value function of the perfect-foresight version of the problem in (26) for choice k is given by:

$$\begin{aligned} V_k\left(x_t\right) =& \overline{u}_k(x_t) - (B_t-1)\sum_{s=0}^{T-t-1}\chi_{t+1}(s)\ln\Gamma\left(\frac{B_{t+1+s}+1}{B_{t+1+s}}\right)^{B_{t+1+s}} \\ &- (B_t-1)\ln\int\left(\prod_{s=0}^{T-t-1}\left[p_{1t+1+s}(x^{(kh,1)}_{t+1+s})\exp\left\{-\overline{u}_1(x^{(kh,1)}_{t+1+s})\right\}\right]^{\chi_{t+1}(s)}\right)q_k(h|x_t)dh \end{aligned} \tag{30}$$

Proof: See Appendix B.

Corollary 1.1. *For $k \in \{2,3,4\}$ the log-odds ratio relative to alternative 1 can be written as:*

$$\begin{aligned} \ln\left(\frac{p_{kt}(x_t)}{p_{1t}(x_t)}\right) =& \overline{u}_k(x_t) - \overline{u}_1(x_t) \\ &- (B_t-1)\ln\int\left(\prod_{s=0}^{T-t-1}\left[p_{1t+1+s}(x^{(kh,1)}_{t+1+s})\exp\left\{-\overline{u}_1(x^{(kh,1)}_{t+1+s})\right\}\right]^{\chi_{t+1}(s)}\right)q_k(h|x_t)dh \\ &+ (B_t-1)\sum_{s=0}^{T-t-1}\chi_{t+1}(s)\left[\ln p_{1t+1+s}(x^{(1,1)}_{t+1+s}) - \overline{u}_1(x^{(1,1)}_{t+1+s})\right] \end{aligned} \tag{31}$$

Therefore $\overline{u}_k(x_t)$ is identified up to the normalizing constant defined as:

$$\begin{aligned} &\overline{u}_1(x_t) + (B_t-1)\ln\int\left(\prod_{s=0}^{T-t-1}\left[p_{1t+1+s}(x^{(kh,1)}_{t+1+s})\exp\left\{-\overline{u}_1(x^{(kh,1)}_{t+1+s})\right\}\right]^{\chi_{t+1}(s)}\right)q_k(h|x_t)dh \\ &+ (B_t-1)\sum_{s=0}^{T-t-1}\chi_{t+1}(s)\overline{u}_1(x^{(1,1)}_{t+1+s}) \end{aligned} \tag{32}$$

The representation of the household capital value index $A_t(x_t)$ in Proposition 1 helps us establish identification in Corollary 1.1, which shows that if the utility from alternative 1 is known for every state and time period, then expected utility from alternative k is identified. This is a standard result in the discrete choice literature, except here we account for the preference shock to the continuous choice.

To identify the marginal utility we use the first order condition in (27) along with standard exclusion restrictions used in static selection models. We assume the demand shifters $\widetilde{\nu}_t \subset \nu_t$ satisfy $E\left[\xi_t \left|\widetilde{\nu}_t\right.\right] = 0$. Such instruments can be differences in policy regimes or changes in aggregate wage productivity and bond prices, all affecting the demand for labor, but not the contemporaneous preference shock for leisure, in other words, not affecting the supply side. Without loss of generality we set the normalizing constant in (32) equal to zero for the rest of the identification analysis.

Proposition 2. *Assuming there exists at least one demand side instrument $\widetilde{\nu}_t$ with at least two points in its support $\widetilde{\nu}_1, \widetilde{\nu}_2$:*

$$\frac{\partial u_k\left(h^*, \widetilde{x}_t\right)}{\partial h_t} + \alpha E\left[w(x_t)\left(1 + \iota(\pi)\frac{\partial h^{\ell}_{2t}}{\partial h_t}\right)\left[1 - \pi^{tax}_{1k}(x_t)\pi^{tax}_{2k}(x_t)W_k(h^*, x_t)^{\pi^{tax}_{2k}(x_t)-1}\right] \middle| \widetilde{\nu}_j, \widetilde{x}_t, h_t\right] =$$
$$(B_t - 1)\sum_{s=0}^{T-t-1}\chi_{t+1}(s)E\left[\frac{1}{p_{1t+1+s}(x^{(kh,1)}_{t+1+s})}\frac{\partial p_{1t+1+s}(x^{(kh,1)}_{t+1+s})}{\partial h} - \frac{\partial \overline{u}_1(x^{(kh,1)}_{t+1+s})}{\partial h}\middle| \widetilde{\nu}_j, \widetilde{x}_t, h_t\right] \qquad \textit{for } j = 1, 2. \tag{33}$$

Therefore for every value h^* of hours worked observed in the data and every $\widetilde{x}_t$, then $\frac{\partial u_k(h^*, \widetilde{x}_t)}{\partial h}$ and α are identified. Proof: See Appendix B.

Corollary 2.1. *For $k \in \{2, 3, 4\}$ and any $\widetilde{h}$, current utility $u_k(\widetilde{h}, \widetilde{x})$ can be expressed as:*

$$\begin{aligned} u_k(\widetilde{h}, \widetilde{x}_t) &= \int \left\{ u_k(h^*, \widetilde{x}) + \int_{h^*}^{\widetilde{h}} \frac{\partial u_k(h, \widetilde{x}_t)}{\partial h} dh \right\} q_k(h^* | \widetilde{x}_t) dh^* \\ &= E\left[u_k\left(h^*, \widetilde{x}_t\right) | \widetilde{x}_t\right] + \int \left[\int_{h^*}^{\widetilde{h}} \frac{\partial u_k\left(h, \widetilde{x}_t\right)}{\partial h} dh\right] q_k(h^* | \widetilde{x}_t) dh^* \end{aligned} \tag{34}$$

and from our definition in (24):

$$E\left[u_k\left(h^*, \widetilde{x}_t\right) | \widetilde{x}_t\right] = \int \left\{\overline{u}_k\left(x_t\right) - E\left[h_k\left(x_t, \xi^*_{kt}\right)\xi^*_{kt} | x_t\right] - \alpha E[\Upsilon_k(h_k\left(x_t, \xi^*_{kt}\right), x_t) | x_t]\right\} dF\left(\nu_t \left| \widetilde{x}_t\right.\right) \tag{35}$$

Therefore $u_k(h_t, \widetilde{x}_t)$ is identified since $\overline{u}_k(x_t)$, $\frac{\partial u_k(h, \widetilde{x}_t)}{\partial h}$, and α are identified, and Υ_k is known. Hence, from equation (27), ξ^*_t is also identified.

Combining the results of Corollary 1.1 and Proposition 2 establishes the identification of the utility function in Corollary 2.1. Notice that the utility function evaluated at any (potentially not optimal) hours, $u_k(\widetilde{h}, \widetilde{x})$, is not a central object of analysis. Instead, the relevant objects are the expected flow utility $\overline{u}_k\left(x_t\right)$ and the marginal utility $\partial u_k(h, \widetilde{x}_t) / \partial h$.

6 Estimation

6.1 Empirical Specification

To facilitate the implementation of the model, instead of including the vector of children's ages $\underline{a}_t$, the state vector contains the first $\rho_1 \equiv \max\{\rho_b, \rho_l + \rho_c\}$ lags of birth indicators $\{b_{t-\rho_1}, \ldots, b_{t-1}\}$, the woman's age at first birth t_{b_1}, and the number of underage children older than ρ_1 years, denoted $\bar{n}_t$.[16] The transition function of the number of children is specified in Appendix C. The wage equation in (12) and the preferences for leisure in (21) imply that the state vector must contain the first $\rho_2 \equiv \max\{\rho_l, \rho_w\}$ lags of work hours and the first ρ_w lags of protected take-up. We set $\rho_b = 4$, $\rho_l = 3$, $\rho_c = 3$, and $\rho_w = 4$. Hence, $\rho_1 = 6$ and $\rho_2 = 4$.

All processes determining $G(m_t, z'_t | m_{t-1}, z_{t-1}, z'_{t-1}, x_{t-1})$, the distribution of partnership dynamics, depend on the state of the problem including fertility and labor history and the policy environment. We also include two race-specific, state-level ratios to measure the tightness of the married market over time: men to women with less than college, and men to women with college or more. These ratios are included in the aggregate vector $\underline{\omega}_t$ and we assume women have perfect foresight over them. We simplify partnership dynamics as follows: there are no mix-race partnerships, the difference between a woman's age and her partner's is constant across women, and there are no transitions from marriage to cohabitation. The partner characteristic z'_t is his education type (high school or less, some college, college or more). The probability of full-time work is estimated separately for partnered and single men.[17] Full-time work hours for men, h' in (14), are the scaled equivalent of 2,080 hours. Concretely, binary processes (separation if partnered, married if cohabiting, full-time partner work) are specified as logistic regressions and multiple-outcome processes (partnership type if single, partner type if newly partnered) are specified as multinomial logistic regressions.

Base hours to determine policy benefits, h^B_t in (7), are the number of hours she worked

[16] The value of ρ_1 depends on preferences in (20) and (21) and on the time constraint in (5). ρ_1 encompasses the value of $\rho_l + \rho_c$ because leisure is defined as the residual of work and child nurturing time going back ρ_l periods, while nurturing time itself depends on previous birth decisions going back ρ_c periods.

[17] Men's full-time work depends on their prior work. Hence, single women taking expectations over future partners' work must integrate over their probability of working in $t-1$, when they were single men.

most recently while not having a birth:

$$h_t^B(\underline{h}_{t-1}, \underline{b}_{t-1}) \equiv \max_{r \in \{1,...\rho_w\}} \left\{ h_{t-r} \prod_{s=1}^{r} \left[1 - d_{t-s}\left(1 - b_{t-s}\right)\right] \right\} \tag{36}$$

where ρ_w determines the relevant time window of human capital in (12) and $\underline{b}_{t-1}$ is her recent birth history. Hence, the base hours for policy benefits correspond to typical, recent work hours in non-birth years, thereby capturing the nature of the labor contract with her employer (e.g. part time versus full time). Whenever a woman has not worked recently in non-birth years ($h_t^B = 0$) we predict h_t^B using a regression on age, race, and education, estimated on women who worked recently in non-birth years.

We assume the reported wage rate, denoted $\widetilde{w}_t$, measures a woman's marginal product in the labor market with error so that $\widetilde{w}_t \equiv w_t \exp(\widetilde{\epsilon}_t)$, where the multiplicative error term is conditionally independent over individuals, covariates, and labor supply decisions. We assume the same for male wages. To tractably capture employer responses to leave policies in the women's wage equation we let the parameters in (12) to change only across three broad regime types: regimes with no leave, regimes with only protected leave, and regimes with paid leave. In addition, we interact all the wage equation parameters with race to capture differences in returns to human capital that can generate different responses to leave and tax-transfer policies.

Additionally, since 36% of household observations had zero non-labor income, we complement the specification in (15) with an extensive margin regression for non-labor income; both margins are estimated separately for single and partnered women. Finally, nurturing time in (4) is obtained by regressing reported housework hours on birth history, controlling for mother's race, partnership status, and years of education.

6.2 Estimation Process

Estimation proceeds in three stages. First, we estimate the process of partnership dynamics, the wage and non-labor income equations, the nurturing time equation, and the CCPs. Second, we use the Euler equation in (27) to obtain the marginal utility of work and leisure. Finally, we use the conditional value functions implied by (26) to obtain the remaining utility parameters. We correct our standard errors to account for the three-stage estimation process using subsampling.

Stage I: wage, non-labor income, partnership dynamics, nurturing time, and CCPs. Estimation of the wage equation proceeds by substituting (12) into reported wages $\widetilde{w}_t$, taking logarithms, and first differencing to eliminate individual fixed effects. This first differences estimator embeds the common trend assumption by not allowing the aggregate component $\omega(\tau_t)$ to vary with the policy regimes. Then we obtain consistent estimates of aggregate wages $\omega(\tau_t)$ and individual wage fixed effects μ using the residuals from the first differences estimator. (See Appendix C for details.) Importantly, since we identify local average treatment effects in the wage equation, counterfactual extrapolation outside of the observed policy variation, which we do not do in this paper, would rely on the functional assumptions and remain local relative to the general equilibrium response of firms to these policy changes.[18] Estimation of all other first-stage processes is standard. Similar to the causal inference drawn from the wage equation, we rely on the quasi-experimental policy variation to draw causal inference for other first-stage processes, including non-linear processes such as partnership formation (Athey and Imbens, 2006; Blundell and Costa Dias, 2009).

Stage II: marginal utility of leisure. The Euler equation in (27) depends only on a subset of the structural parameters $\theta_1 = \{B_1, \delta_0, ..., \delta_{\rho_l}, \alpha\}$ and on the idiosyncratic shock ξ_t whose distribution is characterized by θ_ξ. Taking as given the first-stage parameters, estimation proceeds using the Simulated Method of Moments (SMM). For each candidate vector $\{\theta_1, \theta_\xi\}$ the search algorithm entails three main steps. First, we solve for the $A_{t+1}(x_{t+1})$ index recursively. Second, we obtain 10 draws of ξ_t for each of the observations of women who worked in the sample and use the Euler equation to solve for their implied optimal hours. Third, we construct a vector of simulated moments $M^S(\theta_1, \theta_\xi)$. The moments we use include: the mean, standard deviation and selected percentiles of hours, unconditional and conditional on birth, and the mean of hours conditional on age, race, education, marital status, prior work hours and wages. Consistent with the identification analysis, our moments also include the mean of hours conditional on leave and tax-transfer policies, these demand shifters affect net income directly but are orthogonal to labor supply preferences. The estimator minimizes the relative distance between simulated moments and data moments using the variance of the data moments to con-

[18]The first differences estimator does not yield consistent estimates of the average treatment effect (ATE) unless we assume that the impact of policy changes is homogenous across households. This assumption of course contradicts our structural model which predicts the opposite. In that sense, the best we can hope to identify is the local average treatment effect (LATE).

struct the weighting matrix. Finally, we impose two estimation restrictions: risk-aversion ($\alpha > 0$) and decreasing utility returns from leisure ($\delta_0 < 0$). (See Appendix C for details.)

Stage III: utility from participation and birth. The remaining structural parameters, denoted $\theta_2 = (B_0, \gamma_0, \tilde{\gamma}_0, \gamma_1, ..., \gamma_6)$, capture the utility cost of labor market participation and the lifetime expected utility from births. Estimation of θ_2 is based on the four discrete choices of the problem and it takes as given the first- and second-stage parameters. It uses standard maximization of a quasi log-likelihood function where the conditional probability of each discrete choice is written as a function of the differences in conditional value functions implied by (26). (See Appendix C for details.)

7 Empirical Results

The model fits very well both the discrete and continuous choices. Taking the state of each observation in the data as given, Figure 3 shows the model fits current choices very well with a slight understatement of the full-time peak in the distribution of work hours and an understatement of the probability of birth while working at ages 20-22.[19] Appendix Tables S3 and S4 confirm the excellent fit of the model across various subgroups (age, education, race, and partnership status) in both discrete and continuous choices. To provide a more stringent measure of fit we create subsamples of individuals who are observed continuously from t to $t + 10$. For these subsamples we simulate forward using the model taking as given the state at t. Appendix Figures S6 and S7 further confirm the excellent fit of the model. In the remainder of this section we highlight the main estimated mechanisms through which leave and tax-transfer policies affect women's labor market and fertility choices, including wages, partnership dynamics, the marginal utility of leisure, the disutility from labor market participation, and the utility from births and birth spacing. Further details of the estimates are in Appendix D.

Time cost of children. Estimates in Table 5 indicate that the nurturing time cost is the lowest for new-borns (103 annual hours) and the highest for children 1 to 3 years old (249 to 381 annual hours). Consequently, mothers with two children in the age range 1-3 face a nurturing time cost of around 28% of full-time hours. For children 4 years and above the nurturing time cost falls to 139 annual hours (7% of full-time hours).

[19] We have limited power for working women who have children in ages 20-22.

Women's wages. Table 6 shows the parameters of the wage equation. Adding the coefficients on lagged hours ($\delta_{11}, \ldots, \delta_{14}$) for each of the three regimes yields the marginal contribution of hours to wages for women who are continuously attached to the labor market.[20] This measure indicates the marginal returns to human capital are larger for white women in all regimes (10, 8 and 24 percent larger in no leave, only protected, and any paid, respectively). Comparing within races, black women enjoy higher returns in regimes with no leave and the opposite is true for white women. A salient feature of the wage equation estimates in Table 6 is the part-time penalty on wages implied by the negative coefficients on recent participation. Adding the coefficients on lagged participation ($\delta_{21}, \ldots, \delta_{24}$) yields the penalty for women who are continuously attached to the labor market. Relative to white women, the part-time penalty is 64 and 72 percent higher for black women in no leave and paid leave regimes, respectively. In regimes with only protected leave the penalty is 18 percent higher for white women. Finally, there is significant human capital depreciation, evidenced by the sharp decay over time in the marginal contribution of hours to future wages. Appendix Figure S2 shows the wage equations for women and men fit well the life cycle profiles.

Men's participation and wages. We relegate the estimates of men's labor market processes to Appendix D but highlight some key features here. Appendix Figure S3 shows that men's wage returns to human capital are higher for those with higher completed education, especially among black men, and that the returns decrease over the life cycle. Importantly, Tables S6 and S7 show that men's full-time participation in the labor market is significantly affected by the policy environment. In general, tax-transfer and leave policies affect more strongly the full-time participation of single men who have a much lower rate of full-time participation (80.8%) than men in partnerships (93.3%). For instance, a one standard deviation increase in the lump sum transfer for unmarried (married) individuals significantly decreases (increases) the likelihood of full-time participation among single men by 2.2 pp (0.17 pp).[21] The slope and progressivity of the tax schedule also affect the full-time participation of single men more strongly. The presence of leave policy in their state of residence significantly increases the likelihood of full-time participation of single men. For married men, being partnered to a woman who is eligible for leave policy significantly increases the likelihood of full-time participation between 0.39 and

[20] Recall that the *Only Protected* and *Any Paid* coefficients must be added to the *Baseline* coefficients to obtain the corresponding regime coefficients.

[21] Recall that the lump sum part of the tax-transfer schedule is negatively signed.

0.76 pp. In addition, a one standard deviation increase in the amount of protected hours available for their partner decreases full-time participation by 0.25 pp.

Non-labor income. Single women are about 6 pp more likely to have non-labor income than partnered women (70.3% vs 64.4 %). Appendix Table S8 shows that regardless of partnership status, this likelihood is very persistent, lower for black women, and higher for older women and those with higher completed education. For partnered women, having partners with higher completed education increases the likelihood of having non-labor income. Conditional on having non-labor income, Appendix Table S9 shows that, regardless of partnership status, the log of non-labor income is very persistent, increasing and concave on age and education, and higher for black women. For partnered women, the log of non-labor income decreases with their partners' completed education.

Partnership. Both policy and choices affect partnership dynamics. Conditional on being single, Table 7 shows women who are eligible for leave policies are 0.44-0.57 pp more likely to stay single. Surprisingly, higher transfers in the unmarried (married) tax-transfer schedule decrease the probability of staying single (transitioning to marriage). Notably, lower child-related advantages in tax rates (higher π_{11}^{tax}) for the unmarried increase the likelihood of transitioning into a partnership. Single women's prior labor market and fertility choices also affect their partnership transition. Women more strongly attached to the labor market are less likely to stay single as well as those who have had births in the recent past. Conditional of forming a new partnership, Appendix Table S10 shows the estimates of the probability of match type. Women with higher completed education and wage productivity (μ) are more likely to match with men with higher completed education, revealing assortative mating. Women with part-time recent attachment to the labor market and those with more children are less likely to match with college-educated men. Higher protected or paid leave available and higher child transfers for married women also reduce the likelihood of matching with college-educated men, while higher tax slopes in the married schedule increase this likelihood.

Partnership separation is strongly affected by policy. Table 8 shows that partnered women who are eligible for leave and those with more paid leave available are less likely to become single. However, partnered women with higher protected leave available and higher replacement rates are more likely to become single. Tax policies also affect separation. For instance, a one standard deviation increase in the lump sum transfer for married individuals decreases the probability of separation by 0.78 pp. Higher progressivity of the married tax schedule also decreases the likelihood of separation. In addition, women in married partnerships and recent mothers are much less likely to transition into separation, women who worked recently are more likely to become single. Conditional on not separating, Appendix Table S11 shows that cohabiting women with higher completed education, with highly educated partners, or with higher wage productivity are more likely to transition from cohabitation to marriage.

Utility. Table 9 presents the estimates of the utility function. Women's level of risk aversion yields a static certainty equivalent of (-$3,219), indicating higher risk aversion than the estimated for managerial executives in Gayle, Golan, and Miller (2015), but lower than the estimated for men in Hincapié (2020).[22] Parameter vector B_0 indicates that there is a fixed cost of participation that declines with age and education, and is higher for black and partnered women. The marginal utility of leisure is concave in age, increases with education, and is lower for black women and for partnered women. Current leisure has strong complementarity with prior adjacent leisure ($\delta_1 > 0$) and weak substitutability with leisure further back ($\delta_2, \delta_3 < 0$). Women who do not have a contemporaneous birth tend to have larger idiosyncratic shocks to the disutility from work. For these women, the distribution of the shock, F_{ξ}, is effectively discrete with a much more likely negative value (-3.66 with probability 0.96). For women who do have a contemporaneous birth, the distribution F_{ξ} is continuous, centered on a negative but smaller value (-.091), and has a low standard deviation.

The baseline lifetime expected utility from birth is higher when the mother is not currently working (γ_0) than when she is ($\tilde{\gamma}_0$). Relative to not working and not having a birth (the normalized alternative), having a birth yields less utility in most cases. An exception are women under 28 who are not contemporaneously working; for these women the baseline lifetime expected utility from birth is higher relative to not working and not having a birth. Regardless of labor status, the baseline utility from birth increases with education, and is higher for black women and for partnered women. Regarding spacing, adjacent births decrease the lifetime expected utility of birth ($\gamma_1 < 0$) as well as births more than four years apart ($\gamma_b < 0$). Births 2-4 years apart are preferred.

[22] The static certainty equivalent is computed using a lottery of equal probability between winning and losing $50,000. See Table A.6 in Hincapié (2020).

8 National Implementation of Leave and Taxation Policies

8.1 Setup

We counterfactually implement leave and tax-transfer policies nation-wide and assess their impact on women's labor market and fertility decisions, the labor market motherhood penalty, family structure, tax revenue, and policy costs. Crucially, all the policies we evaluate are part of the quasi-experimental variation in our data, which is included in the state of women's dynamic problems. Hence, we do not need to solve the model backwards to evaluate the policies.[23] Instead, we forward simulate using the function describing the continuation value of women's dynamic problems (the index $A(x_t)$) obtained in the second stage of estimation. In order to construct the initial condition for simulation we focus on observations of women in the estimation sample who are as close as possible to the beginning of their labor market careers, which ensures that the initial state for simulation, x_0, captures well women's characteristics and prior history at the onset.[24] This results in 1,970 unique women with their corresponding initial state for simulation. Each of these women is then replicated 30 times creating a simulation sample of 59,100 individuals whose decisions and outcomes are simulated forward until age 64. Appendix Table S12 confirms the simulation sample is balanced relative to the full estimation sample.

A grid of leave and tax-transfer policies. From the observed policies we create a grid of 7 leave policies by 4 tax-transfer policies, resulting in 28 policy regimes. For the same initial sample of 59,100 women we forward simulate decisions and outcomes under each of the 28 regimes. The leave policy grid points in Table 10 capture variation in type (paid and/or protected) and eligibility tiers (one or two) including: no-leave (LP1), which serves as the baseline for comparison and was present in states such as Texas and Florida before the introduction of federal policy; FMLA (LP2), which has only one tier of protected leave; a New Jersey one-tier policy with only paid leave (LP3), which resulted from a TDI policy accessible through the PDA; a Rhode Island one-tier policy with both

[23] Assessing the impact of out-of-sample policies (for instance, reducing the nurturing time costs of children by providing childcare), would entail counterfactual extrapolation that requires solving the model backwards. Naturally, such an exercise will rely more heavily on the estimated structural utility parameters.

[24] The main selection criterion is based on potential experience. For a given level e of completed education, potential experience at age t equals $t - e - 6$. We first select observations of women in the estimation sample with zero to three years of potential experience. For each woman in this subsample we then select the observation with the lowest level of potential experience.

paid and protected leave (LP4), also resulting form a TDI; a Washington early version of FMLA with two tiers of protected leave (LP5); a New Jersey two-tier policy with only paid leave in the first tier and with both paid and protected leave in the second tier (LP6); and a relatively generous two-tier policy with paid and protected leave in both tiers (LP7), present in California since the state introduced the 2004 Paid Family Leave Act.

The four tax-transfer policy grid points in Table 11, denoted TP1 to TP4, capture various combinations of tax-transfer features for married and unmarried individuals. Regime TP1, present in states such as Georgia and North Carolina during the G. H. Bush presidency, has child transfers of $275 and $527 for married and unmarried parents, lump sum transfers of $4,158 and $1,443, and marginal tax rates of 29.4% and 26.7%.[25] Regime TP2, present in states such as New Mexico and Arizona during the second Reagan presidency, has child transfers of $284 and $535 for married and unmarried parents, lump sum transfers of $7,318 and $1,080, and marginal tax rates of 31.1% and 26.1%. Regime TP3, present in states such as California and New York during the Carter years, has child transfers of $1,575 and $2,005 for married and unmarried parents, lump sum transfers of $8,563 and $3,018, and marginal tax rates of 44.2% and 35.5%. Finally, regime TP4, present in states such as Wisconsin and California during the George W. Bush era, has child transfers of $1,330 and $731 for married and unmarried parents, lump sum transfers of $11,668 and $2,771, and marginal tax rates of 33.0% and 28.8%.

8.2 Policy Effects

Take-up. Consistent with the data, Table 12 shows that paid leave take-up is higher than protected leave take-up. Across all regimes, protected leave take-up ranges between 12 and 45 percent while paid leave take-up fluctuates between 56 and 70 percent. Regardless of leave type, two-tier regimes are the most effective at increasing leave take-up as they are able to attract women at two different margins of prior attachment. Notably, tax-transfer regimes with higher child transfers (TP3-TP4) induce lower protected leave take-up and slightly higher paid leave take-up. This is driven by a higher share of eligible mothers decreasing working hours beyond available protection under these regimes.[26]

[25] Marginal tax rate for married women is computed for a woman with two children, income $50,000, and husband's income $62,500 (hence assuming an income gap of 0.8). Marginal tax rate for unmarried women is computed for a woman with two children and income $50,000.

[26] For instance, under leave regime LP4, which has both paid and protected leave, the share of women who reduce hours beyond available protection is 0.30 under tax-transfer regimes TP1 and TP2, and 0.32 under regimes TP3 and TP4. Consistently, the share of eligible women who return to work the next year

These mothers, who lose their protection, decrease average protected leave take-up. At the same time, since they do not lose their paid leave, these mothers increase average paid leave take-up. The higher decrease in working hours in regimes with higher child transfers likely follows from the decrease in the marginal utility of consumption caused by the transfers, which decreases the incentive to work and produce labor income.

Partnership. While partnership dynamics are not directly chosen in the model, the distributions determining this process depend on endogenous choices and policy variables. Table 13 shows across all policies marriage rates fluctuate between 58 and 74 percent, and cohabitation rates vary between 1.0 and 6.6 percent. Relative to no-leave (LP1), two-tier policies generate the largest gains in marriage rates (up to 3.0 pp) and the largest decline in cohabitation rates (up to 1.6 pp). While only having one tier of eligibility, FMLA also increases the marriage rate by up to 0.6 pp and it decreases the cohabitation rate by up to 0.9 pp. Notably, for any given tax-transfer regime, leave policies generally decrease the likelihood of separation relative to no-leave. Assortative mating is common across policies. The share of same-education partnerships ranges between 52.8 and 55.3 percent across all policies. Relative to no-leave, leave policies slightly decrease the prevalence of assortative mating by up to 1.9 pp (under the two-tier, paid and protected regime LP7). Among tax-transfer policies in the grid, regime TP3, which has the highest lump sums, child transfers and marginal tax rates, generates the highest rates of marriage, the lowest rates of cohabitation, and the lowest likelihood of separation.

Fertility. Table 14 shows that given any of the tax-transfer regimes, all leave policies in the grid decrease completed fertility relative to no-leave (LP1). In particular, two-tier policies that combine paid and protected leave decrease completed fertility the most (by up to 40 children per 100 women) under tax-transfer regimes with low child transfers (TP1-TP2). This negative effect of leave policies on completed fertility is consistent with the negative effect of protected leave on medium term fertility found by Flores, Gayle, and Hincapié (2024) in the US. Comparing across tax-transfer regimes, those with high child transfers (TP3-TP4) generate the highest levels of completed fertility. Relative to a regime with low child transfers (TP1), TP3 and TP4 generate gains in completed fertility of up to 32 children per 100 women. Notably, tax-transfer regimes with high child transfers

after being granted protected leave is 0.76-078 under regimes TP1 and TP2, but it drops to 0.70 under regimes TP3 and TP4.

mitigate the negative effects of leave policies on completed fertility. For instance, relative to no-leave, the drop in completed fertility from the generous LP7 (two tiers of paid and protected leave) goes from 15.5 to 9.8 percent.

All leave policies delay the age of first birth for new mothers and, with the exception of FMLA, tend to marginally increase the spacing between their first two children.[27] Tax-transfer policies with high child transfers decrease the age of first birth for new mothers although the effects are smaller in magnitude. Two-tier leave policies that combine both types of leave (LP6-LP7) increase the mothers' age of first birth the most (by up to 8 months). In general, the effects on birth spacing from all policies are small, indicating that mothers' preferences for spacing (Table 9) are likely the dominating force.

The motherhood penalty. Table 15 indicates that all leave policies, especially policies that contain protected leave, increase the motherhood penalty in labor income, worked hours, and wages, although they decrease the motherhood penalty on participation.[28] Relative to no-leave (LP1), leave policies increase the motherhood penalty in labor income between $198 (LP3) and $7,803 (LP5), in worked hours between 3 (LP3) and 177 (LP5) hours, and in wages between $0.11 (LP2) and $0.74 (LP5), and they decrease the penalty in participation between 0.3 pp (LP3) and 7.8 pp (LP5). Notably, two-tier policies (LP5-LP7) coupled with low child transfer regimes (TP1-TP2) sharply decrease the motherhood penalty in participation. This is likely due to the post-birth participation of mothers with lower prior labor attachment who are now eligible for protection, coupled with more incentives to stay in the labor market given lower child transfers. The effects of leave policies on the motherhood penalty in earnings, hours and wages are consistent (even in magnitude to a reasonable degree) with the causal reduced-form results in Flores, Gayle, and Hincapié (2024) regarding protected leave. This is important as we do not target in estimation the reduced-form causal effect or even the motherhood penalty itself; and it is also reassuring, as the quasi-experimental variation we use in this paper is a superset of the pre-FMLA variation the authors employ in their difference-in-differences design.

Moving across tax-transfer policies in the grid reveals less variation in the motherhood penalty. Nevertheless, tax-transfer policies with high child transfers (TP3-TP4) generate lower motherhood penalties in labor income and hours, and higher penalties in participation. This is because mothers who receive higher child transfers are more willing to drop

[27] *New mothers* refers to those who had no children when they entered the labor market.

[28] Our measure of the motherhood penalty is standard and follows the specifications in Flores, Gayle, and Hincapié (2024) and Kleven, Landais, and Søgaard (2019). We provide further details in Appendix E.

from the labor market, but conditional on participating, these mothers work longer hours to avoid the part-time penalty in wage returns to human capital (Section 7). While high child transfer policies induce lower motherhood penalties on wages under one-tier leave regimes, the opposite is true under two-tier leave regimes. This is likely explained by the following. Relative to low child transfer policies (TP1-TP2), high child transfer policies (TP3-TP4) yield both a larger decrease in the penalty in hours and a lower increase in the penalty in participation when combined with one-tier leave regimes (LP2-LP4). The lower penalty in hours is enough to counteract the human capital effect of the higher decline in participation. The opposite is true under two-tier leave regimes (LP5-LP7), where the marginally lower penalties in hours from TP3 and TP4 are not enough to counteract the larger penalties on participation, and ultimately on wages via lower human capital.

Labor market outcomes of all women. Table 16 shows that all leave policies in the grid increase life cycle labor market outcomes. Concretely, relative to no-leave, the leave policies in the grid increase the participation rate between 1.3 and 10.2 pp, average working hours between 4 and 618 hours, average wages between $0.4 and $3.6, and the average present value of labor income between 15 and 490 thousand dollars. Among one-tier policies, FMLA (LP2) is generally the most effective at raising labor outcomes relative to no-leave, increasing the participation rate by up to 3.4 pp, hours by up to 219 hours, wages by up to $1.2, and the present value of labor income by up to $146,000. Two-tier leave policies are even more effective at improving labor market gains. For example, the generous two-tier policy with paid and protected leave in both tiers (LP7) increases the participation rate by up to 5.8 pp, hours by up to 336 hours, wages by up to $2.6, and the present value of labor income by up to $263,000.

Table 12 suggest that higher take-up of protected leave under two-tier policies, resulting from the two tiers of eligibility, allow more women to reduce their hours while protecting their human capital. This increases women's future wages relative to no-leave (LP1) and induces them to participate and work more, a process that is also fueled by the adjacent complementarity in the marginal utility of leisure (Table 9). This is consistent with the fact that the only leave policy that does not provide any protected leave (LP3) yields the smallest gains in participation, hours, and wages relative to no-leave. Since all the leave policies in the grid increase the motherhood penalty in labor income, hours and wages (Table 15), their effects on life cycle labor market outcomes can appear surprising. However, while there is indeed a larger decline in outcomes upon birth, the level from which they decline is generally higher that under no-leave, which results on higher life cycle labor market outcomes under leave policies.

Among tax-transfer regimes, all policies in the grid reduce life cycle labor market outcomes relative to the regime with the lowest lump sum, child transfers and marginal tax rates for the married (TP1). In particular, the tax-transfer regime with the highest child transfers and marginal tax rates (TP3) reduces labor market outcomes the most. This happens because higher child transfers lower the marginal utility of consumption, which reduces incentives to work as women are able to substitute labor income with transfer income. This substitution operates during a long stretch in women's careers while they can still claim their children as dependents. Moreover, its long term consequences are sustained by the complementarity in the marginal utility of adjacent leisure. Finally, comparing the two regimes with high child transfers (TP3 and TP4) reveals the higher marginal tax rates in TP3 further weaken incentives to work and generate labor income.

Policy cost and tax revenue. Given any of the tax-transfer regimes, Table 17 shows all leave policies in the grid generate gains in tax revenue, relative to no-leave, that exceed the costs of the policies over the life cycle by a minimum of $7,052 per household in present value.[29] This happens primarily because the financial costs of providing leave are fairly temporary while the gains, as shown earlier, are long-term. The cost of protected leave corresponds to the labor income resulting from protected human capital accumulated through protected take-up. Due to human capital depreciation, this cost is effective only during the four years following take-up; even within those four years, the wage returns to human capital quickly flatten (Table 6). The cost of paid leave corresponds to the replacement income (paid take-up times replacement rate times wage). This cost is paid only during the current period or the following (if paid leave was rolled over). Relative to no-leave, two-tier policies, the most effective at keeping women in the labor market, increase tax revenue (net of policy costs) the most, by at least $50,728 per household in present value (LP7, TP4). Unsurprisingly, tax-transfer regimes with higher child transfers (TP3-TP4) generally reduce the gains in tax revenue from leave policies.

[29]This computation excludes single-men households as their income generating process is not included in the model. We do not expect their income to change much in response to the various leave polices.

9 Conclusion

We combine vast quasi-experimental variation in leave policies and tax-transfer policies in the US between 1968-2017, a similarly long panel of individual data, and a rich structural dynamic discrete-continuous choice model to assess the impact of the counterfactual national implementation of a large subset of 28 combinations of policies observed in the data. After showing that the utility function is identified, we focus on the impact of the policies on life cycle measures of policy take-up, labor market supply and outcomes, fertility, partnership dynamics, policy costs and tax revenue.

When it comes to fostering women's labor supply and fertility, our results suggest, policies cannot have it all. On the one hand, all leave policies decrease completed fertility. In fact, two-tier leave policies, the most effective at fostering women's labor participation, decrease completed fertility the most. On the other, the policies that are most effective at increasing completed fertility, those with high child transfers, are also the ones that hinder life cycle labor market outcomes the most. Given the objectives of these policies, our results reveal a policy trade-off. However, the opposing forces of these policies can be balanced to increase women's labor market outcomes while only moderately affecting fertility, if at all. Combining two-tier leave structures with high child transfers is a promising alternative. Strikingly, the policy trade-off is one in which the government's budget stands to increase following any course of action that includes leave, let it be protected, paid, or both, no matter the tax-transfer arrangement.

10 Figures and Tables

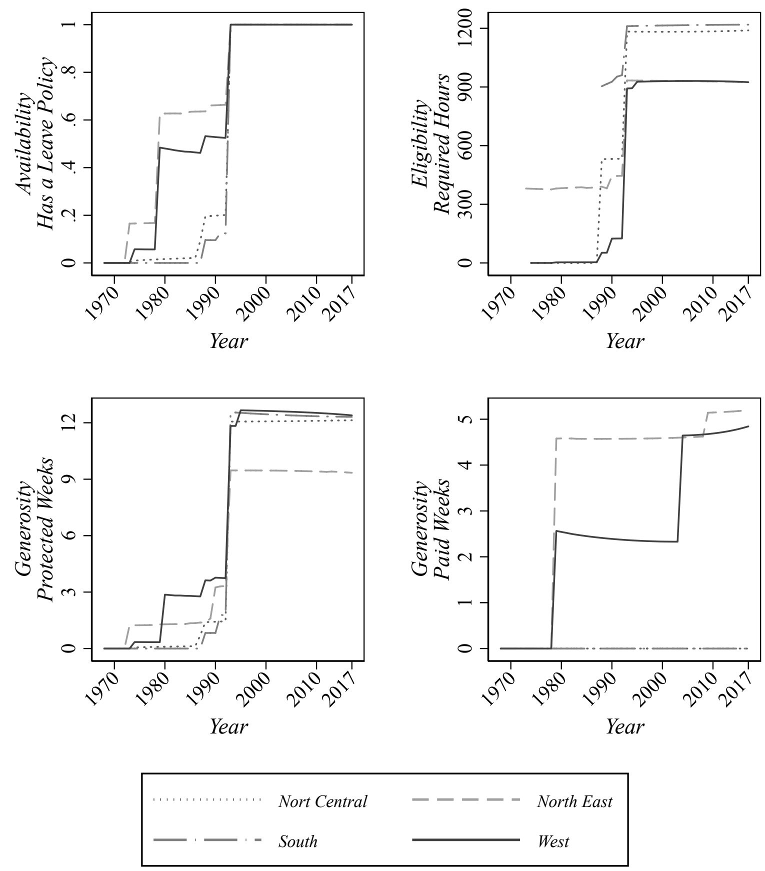


Figure 1: Variation in Leave Policies over Time and Across Regions

Notes: Weighted averages across states within a region. Average eligibility is computed using only states that have leave policies at that year. Generosity (protected and paid weeks) takes the value of zero if the state has no leave policy. Weights are built using each state's sample of women in the age range [15, 45] relative to the region's in each year. State-specific second degree polynomials are used to smooth population dynamics. For states with two-tier policies we compute the simple average of the two tiers before computing the regional average. *North Central*: Illinois, Indiana, Iowa, Kansas, Michigan, Minnesota, Missouiri, Nebraska, North Dakota, Ohio, South Dakota, Wisconsin. *North East*: Connecticut Maine, Massachusetts, New Hampshire, New Jersey, New York, Pennsylvania, Rhode Island, Vermont. *West*: Arizona, California, Colorado, Idaho, Montana, Nevada, New Mexico, Oregon, Texas, Utah, Washington, Wyoming, Alaska, Hawaii. All other states are in the *South* region.

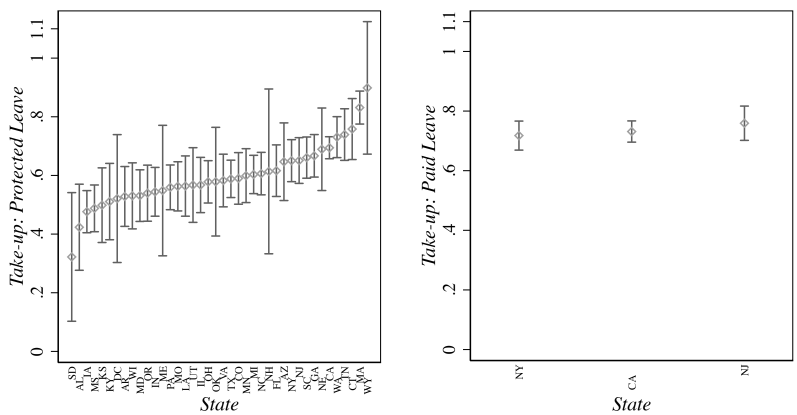
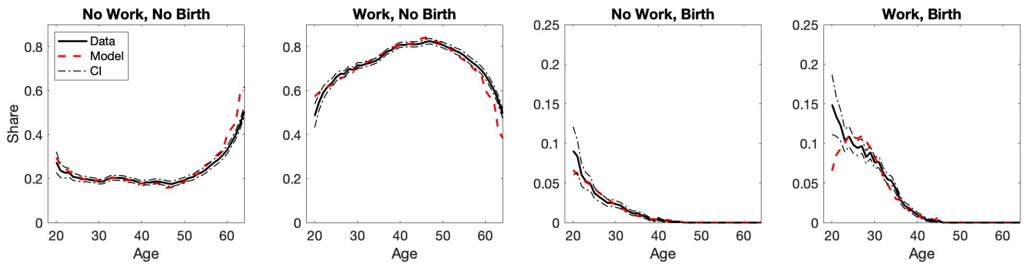
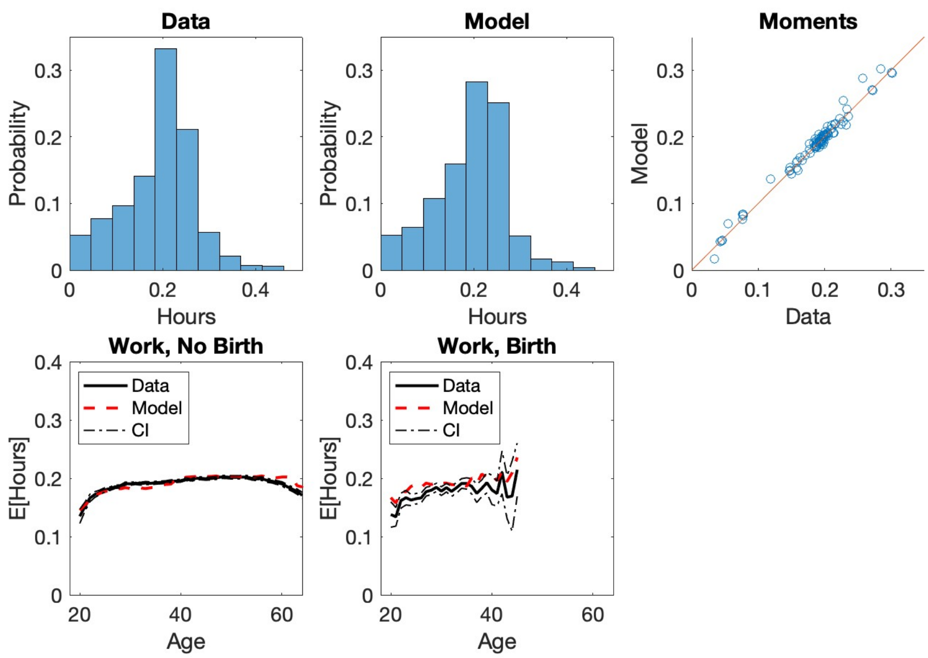


Figure 2: Average Leave Take-up, (1968-2017)
Notes: *Take-up* % is backed out from changes in worked hours and leave policies available. Bars represent 95% confidence intervals. Only states with at least 10 observations are included.



(a) Discrete Choices



(b) Hours

Figure 3: Model Fit

Notes: These measures of fit take the state of each observation in the data as given and simulate current discrete and continuous choices. Hours are scaled as a fraction of annual hours by dividing them by (24*365). The *moments* panel corresponds to the fit of the estimation moments in the second stage, which are all in terms of scaled hours.

Table 1: Leave Policies in the US, 1968-2017

	One-tier Policies				*Two-tier Policies*							
					Tier 1				*Tier 2*			
	Eligibility	*Generosity*			*Eligibility*	*Generosity*			*Eligibility*	*Generosity*		
	(hours)	*Protected (weeks)*	*Paid (weeks)*	*Rate*	*(hours)*	*Protected (weeks)*	*Paid (weeks)*	*Rate*	*(hours)*	*Protected (weeks)*	*Paid (weeks)*	*Rate*
	0	0	6	0.55	0	6	0		360	18	0	
	0	6	0		0	6	0		1000	18	0	
	0	6	6	0.55	0	6	0		1000	22	0	
	0	8	0		0	6	0		1250	12	0	
	1	8	0		0	6	6	0.55	1250	18	6	0.55
	1	10	0		0	6	12	0.55	1250	18	12	0.55
	160	0	10	0.50	0	6	0		1250	18	0	
	360	12	0		0	8	0		1250	20	0	
	400	10	10	0.55	0	6	0		1820	12	0	
	520	8	0		1	10	0		1250	12	0	
	560	0	6	0.58	160	0	10	0.50	1250	12	10	0.50
	560	6	6	0.58	400	10	10	0.55	1250	22	10	0.55
	643	24	0		400	14	10	0.55	1250	26	10	0.55
	800	0	10	0.67	400	10	10	0.55	1560	23	10	0.55
	1000	8	0		520	8	0		1250	12	0	
	1000	32	0		560	6	6	0.58	1250	18	6	0.58
	1040	6	0		800	0	10	0.67	1000	16	10	0.67
	1250	12	0		800	0	10	0.67	1000	16	16	0.67
	1250	14	0		1040	6	0		1250	12	0	
	1560	12	0									
	2080	12	0									
Mean	628	9.2	2.6	0.57	267	6.3	4.4	0.57	1197	17.1	4.7	0.57
SD	(590)	(7.7)	(3.9)	(0.05)	(341)	(3.5)	(5)	(0.06)	(280)	(4.3)	(5.5)	(0.06)

Notes: Unique leave policies effective between 1968-2017 in the United States (40 in total). Out of all the policies 19 have two tiers with increasing eligibility requirements. *Eligibility* refers to the number of prior hours worked. *Protected* corresponds to the number of leave weeks during which the job is protected. *Paid* corresponds to the number of leave weeks that are paid. *Rate* corresponds to the replacement rate, i.e. the share of the wage rate at which paid leave weeks are compensated. We do not distinguish between leave weeks that are awarded for birth or adoption and those awarded for pregnancy related disability. The policies in this table are coded from the extensive list of federal and state policies in Table S1 in Appendix A.

Table 2: Tax-Transfer Regimes in the US, 1968-2017

	Married						*Not Married*					
	Lump sum ($) π_0^{tax}		*Slope* (%) π_1^{tax}		*Prog.* π_2^{tax}	*Marginal Tax* (%)	*Lump sum ($)* π_0^{tax}		*Slope* (%) π_1^{tax}		*Prog.* π_2^{tax}	*Marginal Tax* (%)
	Base	n_t	*Base*	n_t			*Base*	n_t	*Base*	n_t		
	-9,966	-2,397	15.5	0.455	1.05	31.7	-2,924	-878	9.7	0.392	1.08	28.3
	-3,859	-1,789	0.4	0.005	1.32	22.7	-3,274	-439	7.2	-0.107	1.10	22.5
	-8,563	-1,575	5.5	0.355	1.16	44.2	-3,018	-2,005	0.9	-0.023	1.32	35.5
	-8,244	-1,336	4.4	-0.047	1.15	27.8	-1,775	-826	1.5	0.026	1.23	24.6
	-11,668	-1,330	15.8	-0.018	1.06	33.0	-2,771	-731	8.2	0.216	1.10	28.8
	-2,872	-1,325	0.9	0.011	1.26	24.8	-897	-559	1.7	0.064	1.21	20.8
	-12,138	-1,253	11.4	-0.148	1.08	31.8	-3,450	-251	6.4	-0.323	1.13	25.8
	-4,272	-1,208	3.1	0.028	1.18	29.4	-1,843	-400	10.0	-0.299	1.08	24.3
	-6,002	-1,015	2.8	-0.081	1.17	22.7	-5,326	92	21.4	-1.152	1.03	26.5
	-4,437	-905	2.1	-0.035	1.21	28.4	-1,187	-560	1.8	-0.033	1.23	24.0
	-5,330	-706	4.0	0.060	1.16	29.3	-2,002	586	5.0	-1.267	1.14	13.5
	-4,051	-562	0.3	0.004	1.39	38.5	-1,678	-2,217	0.2	0.013	1.42	36.3
	-5,836	-546	1.5	0.063	1.25	38.5	-678	-381	0.2	-0.001	1.45	30.1
	-3,756	-329	0.5	0.017	1.31	26.0	-688	-201	0.2	-0.004	1.40	21.5
	-2,626	-289	0.8	0.002	1.27	23.2	-516	-223	0.2	-0.004	1.40	20.0
	-7,318	-284	4.9	0.105	1.14	31.1	-1,080	-535	1.1	0.007	1.27	26.1
	-5,691	-277	0.8	0.014	1.31	41.2	-1,125	-191	0.3	-0.005	1.41	31.8
	-4,158	-275	1.6	-0.020	1.23	29.4	-1,443	-527	2.4	-0.009	1.21	26.7
	-7,324	-251	3.1	0.018	1.19	33.4	-1,421	-459	1.2	-0.003	1.27	28.4
	-2,817	-143	0.1	0.000	1.46	32.8	-929	-1,224	0.1	0.000	1.51	29.0
	-5,001	238	0.4	0.003	1.35	33.5	-713	-75	0.2	-0.003	1.44	25.6
Mean	-5,997	-836	3.8	0.038	1.22	31.1	-1,845	-572	3.8	-0.120	1.26	26.2
SD	2,791	656	4.7	0.133	0.11	5.9	1,216	633	5.3	0.390	0.15	5.2

Notes: Unique tax-transfer regimes between 1968-2017 sorted by child transfers for the married (second column). Tax-transfer specification is $T(y) = \left(\pi_0^{tax} + \pi_1^{tax} y^{\pi_2^{tax}}\right)$ for gross-income y. *Prog.* stands for progressivity. All parameters of the regime vary by marital status and parameters π_1^{tax} and π_2^{tax} also vary by the number of dependent children n_t. Marginal tax rate for married women is computed for a woman with two children, income $50,000, and husband's income $62,500 (hence assuming an income gap of 0.8). Marginal tax rate for unmarried women is computed for a woman with two children and income $50,000.

Table 3: Descriptive Statistics of Women in Fertile Age, US 1968-2017

	All		*Before FMLA*				*After FMLA*	
			No Leave Policy		*Leave Policy*			
	mean	sd	mean	sd	mean	sd	mean	sd
Age	31.1	(8.0)	28.6	(8.3)	30.0	(7.9)	33.7	(7.0)
Black	0.41		0.44		0.22		0.40	
Years of education	13.6	(2.3)	13.1	(2.2)	14.0	(2.1)	14.0	(2.3)
Married	0.61		0.60		0.62		0.62	
Cohabiting	0.05		0.02		0.04		0.08	
Participation	0.72		0.62		0.72		0.82	
Hours worked	1,150	(937)	883	(899)	1,084	(909)	1,421	(901)
Wage	18.2	(14.3)	14.7	(10)	18.6	(12.2)	20.6	(16.6)
Birth	0.077		0.086		0.077		0.067	
Observations	187,382		84,669		15,538		87,175	
Conditional on Birth								
Observations	14,378		7,308		1,195		5,875	
Protected Leave								
Any granted	0.28				0.47		0.59	
Hours granted	429	(190)			215	(138)	464	(174)
Take-up (%)	61.6	(44.0)			78.4	(39.2)	58.9	(44.1)
Paid Leave								
Any granted	0.07				0.41		0.09	
Hours granted	278	(145)			222	(113)	333	(151)
Take-up (%)	73.6	(41.0)			79.8	(38)	67.7	(42.9)

Notes: Women in fertile age defined as women with age $\in [15, 45]$. The *leave policy* (*no leave policy*) columns correspond to observations of individuals prior to the introduction of FMLA who resided in states with (without) leave policies. Hours worked and wages are conditional on participation. Wages are in real dollars indexed to 2015. *Leave granted* refers to the leave (protected or paid) that a woman is entitled to given the policy in her state of residency as well as her labor market participation and prior work hours. *Hours granted* and *Take-up %* are both conditional on any leave being granted and are backed out from changes in worked hours and leave policies available.

Table 4: Take-up of Protected and Paid Leave in the US 1968-2017

	Protected Take-up		Paid Take-up	
	est.	se	est.	se
Age	0.0010	(0.002)	-0.0002	(0.004)
Black and partnered	-0.040	(0.025)	-0.096	(0.043)
Black and single	-0.084	(0.031)	-0.222	(0.062)
White and single	-0.011	(0.044)	-0.178	(0.109)
Some college	-0.021	(0.023)	0.070	(0.042)
College or more	-0.082	(0.023)	-0.007	(0.044)
North Central	-0.139	(0.026)		
South	-0.110	(0.027)		
West	-0.039	(0.025)	0.011	(0.031)
Birth_{t-1}	-0.013	(0.043)	-0.022	(0.072)
Birth_{t-2}	-0.066	(0.028)	-0.049	(0.052)
Birth_{t-3}	0.000	(0.027)	0.009	(0.049)
Birth_{t-4}	-0.035	(0.029)	0.034	(0.058)
Number of kids	-0.013	(0.011)	-0.026	(0.023)
Worked_{t-1}	-0.302	(0.063)	-0.267	(0.083)
Worked_{t-2}	-0.168	(0.056)	0.036	(0.083)
Worked_{t-3}	0.084	(0.049)	-0.048	(0.07)
Worked_{t-4}	0.019	(0.041)	-0.042	(0.061)
$\text{Hours worked}_{t-1}$	0.922	(0.177)	0.858	(0.281)
$\text{Hours worked}_{t-2}$	0.603	(0.199)	-0.026	(0.304)
$\text{Hours worked}_{t-3}$	-0.535	(0.189)	0.299	(0.276)
$\text{Hours worked}_{t-4}$	-0.378	(0.164)	-0.572	(0.262)
Observations	2,496		694	

Notes: Dependent variables are protected and paid leave take-up expressed as shares. Base demographic group is *white and partnered* (married or cohabiting), base region is *North East*. Work hours are scaled by diving by (365*24), hence full-time hours (2,000 hours) correspond to approximately 0.23 scaled hours. *North Central* and *South* region dummies are excluded of the paid leave take-up regression because states in these regions do not offer paid leave in our time period. "est." stands for estimate, "se" stands for standard error.

Table 5: Nurturing Time Cost

$$\varsigma_t = \sum_{s=0}^{\rho_c} \phi_s b_{t-s} + \phi \cdot \left(\sum_{s=\rho_c+1}^{18} b_{t-s} \right)$$

Variable	Parameter	est.	se	Hours	% of Full Time
New born child	ϕ_0	0.012	(3.2E-04)	103	5.1
1 year old child	ϕ_1	0.036	(3.5E-04)	318	15.9
2 year old child	ϕ_2	0.032	(2.9E-04)	282	14.1
3 year old child	ϕ_3	0.028	(3.1E-04)	249	12.5
Children 4 and over	ϕ_4	0.016	(1.1E-04)	139	6.9

Notes: We add a constant and controls for race, partnership status, and education. $\phi_s \equiv \phi$ for $4 \leq s < 18$, and $\phi_s \equiv 0$ for $s > 18$. "est." stands for estimate and "se" stands for standard errors. Last column indicates the magnitude of coefficient as a percentage of full time work (2000 hours). Standard errors corrected for three-stage estimation.

Table 6: Wage Equation (Women)

$$\ln(w_t) = \ln(\omega_t) + \ln(\mu) + z_t B_3 + \sum_{s=1}^{4} (\delta_{1s} h^*_{t-s} + \delta_{2s} d_{t-s})$$

Black

		Baseline		Only Protected		Any Paid	
variable	parameter	est.	se	est.	se	est.	se
Lags of participation							
d_{t-1}	δ_{21}	-0.097	(0.006)	0.130	(0.014)	0.154	(0.024)
d_{t-2}	δ_{22}	-0.090	(0.006)	0.039	(0.014)	0.018	(0.018)
d_{t-3}	δ_{23}	-0.053	(0.005)	-0.024	(0.012)	0.005	(0.018)
d_{t-4}	δ_{24}	-0.013	(0.005)	-0.064	(0.011)	-0.077	(0.018)
Lags of hours worked							
h^*_{t-1}	δ_{11}	1.451	(0.024)	-0.734	(0.043)	-0.281	(0.078)
h^*_{t-2}	δ_{12}	0.587	(0.023)	0.234	(0.040)	0.203	(0.067)
h^*_{t-3}	δ_{13}	0.412	(0.021)	0.194	(0.040)	-0.327	(0.076)
h^*_{t-4}	δ_{14}	0.187	(0.020)	0.296	(0.039)	0.277	(0.076)
Age and education							
$Age_t \times Education$	B_{31}	4.32E-03	(1.96E-04)	-2.90E-04	(7.20E-05)	-5.23E-04	(1.50E-04)
$Age_t^2 \times Education$	B_{32}	-2.49E-05	(2.09E-06)	3.65E-06	(1.25E-06)	9.67E-06	(3.07E-06)

White

		Baseline		Only Protected		Any Paid	
variable	parameter	est.	se	est.	se	est.	se
Lags of participation							
d_{t-1}	δ_{21}	-0.027	(0.006)	0.053	(0.011)	0.045	(0.014)
d_{t-2}	δ_{22}	-0.044	(0.006)	-0.058	(0.008)	0.006	(0.010)
d_{t-3}	δ_{23}	-0.050	(0.005)	-0.021	(0.009)	-0.020	(0.012)
d_{t-4}	δ_{24}	-0.034	(0.004)	-0.025	(0.007)	0.035	(0.008)
Lags of hours worked							
h^*_{t-1}	δ_{11}	1.579	(0.023)	-0.314	(0.039)	-0.118	(0.052)
h^*_{t-2}	δ_{12}	0.593	(0.024)	0.174	(0.030)	0.337	(0.038)
h^*_{t-3}	δ_{13}	0.406	(0.021)	0.092	(0.032)	0.067	(0.042)
h^*_{t-4}	δ_{14}	0.207	(0.019)	0.114	(0.031)	-0.067	(0.036)
Age and education							
$Age_t \times Education$	B_{31}	4.33E-03	(1.82E-04)	8.97E-05	(5.27E-05)	-3.98E-04	(7.02E-05)
$Age_t^2 \times Education$	B_{32}	-2.43E-05	(1.53E-06)	-7.36E-07	(8.68E-07)	6.07E-06	(1.10E-06)

Notes: Estimation of the wage equation for women in (12) using wage-equivalent hours and the econometric strategy in (S10). Estimation accounts for three policy regimes: *baseline* column are the baseline parameters, applicable to women in all regimes (they are also the parameters of the regime with no leave available); *Protected* column is the interaction of the coefficients with the regime where there is only protected leave; *Any Paid* column is the interaction of the coefficients with the regime where there is paid leave (either protected or not). See Table 1 for details on the regimes. Total observations: 130,765 total, 47,126 black, 83,639 white. "est." stands for estimate, "se" stands for standard error. Standard errors corrected for three-stage estimation.

Table 7: Partnership Type Conditional on Single

	Partnership Alternative						
	Single	Married			Cohabiting		
variable	Δp (%)	est.	se	Δp (%)	est.	se	Δp (%)
Constant		-4.722	(1.074)		2.625	1.566	
Age	2.816	0.063	(0.005)	-2.615	0.107	(0.008)	-0.201
Age^2		-0.002	(6.7E-05)		-0.002	(1.0E-04)	
Education	0.152	0.110	(0.077)	0.027	-0.356	(0.100)	-0.179
Education^2		-0.005	(0.001)		-0.002	(0.003)	
Black	6.876	-0.976	(0.016)	-5.216	-0.980	(0.034)	-1.661
$d_{n,t-1}$	-0.301	0.017	(0.020)	0.049	0.257	(0.043)	0.252
$d_{n,t-2}$	0.163	-0.001	(0.021)	0.004	-0.140	(0.047)	-0.167
$d_{n,t-3}$	-0.487	0.052	(0.019)	0.162	0.345	(0.039)	0.325
$d_{n,t-4}$	-0.355	0.071	(0.024)	0.230	0.121	(0.041)	0.125
$h_{n,t-1}$	-0.814	1.655	(0.131)	0.629	1.545	(0.196)	0.185
$h_{n,t-2}$	-0.261	0.356	(0.125)	0.133	1.041	(0.234)	0.128
$h_{n,t-3}$	0.395	-0.393	(0.133)	-0.142	-2.048	(0.269)	-0.254
$h_{n,t-4}$	0.278	-0.448	(0.121)	-0.168	-0.899	(0.228)	-0.110
$b_{n,t-1}$	-2.476	0.166	(0.031)	0.536	1.027	(0.039)	1.939
$b_{n,t-2}$	-1.211	0.174	(0.021)	0.625	0.431	(0.050)	0.586
$b_{n,t-3}$	-0.744	0.029	(0.030)	0.077	0.473	(0.050)	0.667
$b_{n,t-4}$	-0.460	0.045	(0.025)	0.146	0.251	(0.047)	0.314
Number of kids	-0.196	0.071	(0.006)	0.244	-0.041	(0.013)	-0.048
Individual productivity, μ	0.175	-0.084	(0.012)	-0.169	-0.012	(0.028)	-0.006
Marriage Market							
Men to women ratio ($\geq$ college)	0.224	1.642	(0.240)	-0.312	0.167	(0.383)	0.089
Education $\times$ Men to women ratio ($\geq$ college)		-0.144	(0.018)		0.007	(0.030)	
Men to women ratio ($<$ college)	0.116	-2.716	(0.871)	-0.249	-2.639	(1.615)	0.133
Education $\times$ Men to women ratio ($<$ college)		0.132	(0.059)		0.310	0.111	
Maternity Leave Variables							
Protected leave rolled	-0.126	9.616	(1.378)	0.103	7.048	(1.718)	0.023
Paid leave rolled	0.025	-4.828	(6.538)	-0.012	-16.197	(10.116)	-0.013
Applies for tier 1	0.438	-0.057	(0.024)	-0.192	-0.202	(0.040)	-0.246
Applies for tier 2	0.567	-0.090	(0.042)	-0.289	-0.289	(0.072)	-0.278
Protected hours available	-0.003	1.268	(0.485)	0.131	-3.918	(0.898)	-0.128
Paid hours available	0.083	-1.346	(1.426)	-0.048	-2.900	(1.919)	-0.034
Replacement rate	-0.039	-0.096	(0.074)	-0.057	0.530	(0.143)	0.097
Tax Policy Unmarried							
Lump sum (π_{00}^{tax})	-0.750	-1.5E-04	(2.6E-05)	0.516	-2.2E-04	(4.2E-05)	0.233
Lump sum*kids (π_{01}^{tax})	0.334	1.4E-05	(1.5E-05)	-0.027	3.5E-04	(3.3E-05)	-0.307
Slope (π_{10}^{tax})	0.080	0.457	(0.440)	0.075	-3.127	(0.661)	-0.154
Slope*kids (π_{11}^{tax})	-0.383	7.361	(3.332)	0.094	63.289	(5.097)	0.289
Progressivity (π_{2}^{tax})	-0.408	1.407	(0.146)	0.677	-1.698	(0.289)	-0.269
Tax Policy Married							
Lump sum (π_{00}^{tax})	0.602	4.4E-05	(1.1E-05)	-0.386	7.6E-05	(2.2E-05)	-0.217
Lump sum*kids (π_{01}^{tax})	-0.175	-9.1E-06	(2.3E-05)	0.015	-2.2E-04	(4.2E-05)	0.160
Slope (π_{10}^{tax})	-0.372	1.551	(0.469)	0.265	1.977	(0.922)	0.108
Slope*kids (π_{11}^{tax})	0.238	15.68	(8.96)	0.098	-187.74	(14.83)	-0.336
Progressivity (π_{2}^{tax})	0.021	0.508	(0.207)	0.205	-1.775	(0.379)	-0.226
Observations	68,825						

Notes: Estimates from a multinomial logit regression of partnership type for single women. "est." stands for estimate and "se" stands for standard errors. Standard errors corrected for three-stage estimation. Column Δp is the approximated change in the probability (in percentage points) from an increase of one standard deviation in the regressor (or a unit change from zero for binary variables) evaluated at the average for continuous variables. Lump sump variables are negatively signed. Unconditional transition probabilities: single 93.0, married 5.4, cohabiting 1.6.

Table 8: Separation Conditional on Partnership

variable	est.	se	Δp (%)
Constant	-2.686	(1.115)	
Married$_{t-1}$	1.876	(0.278)	-15.931
Age	-0.086	(0.003)	-0.541
Age^2	0.001	(4.0E-05)	
Education	0.061	(0.076)	0.224
Education^2	0.004	(0.001)	
Black	0.233	(0.014)	0.561
$d_{n,t-1}$	0.133	(0.026)	0.335
$d_{n,t-2}$	-0.024	(0.024)	-0.064
$d_{n,t-3}$	0.049	(0.027)	0.128
$d_{n,t-4}$	0.035	(0.023)	0.093
$h_{n,t-1}$	0.762	(0.127)	0.212
$h_{n,t-2}$	-0.119	(0.121)	-0.033
$h_{n,t-3}$	0.017	(0.120)	0.005
$h_{n,t-4}$	-0.219	(0.104)	-0.061
$b_{n,t-1}$	-0.884	(0.036)	-1.599
$b_{n,t-2}$	-0.436	(0.026)	-0.957
$b_{n,t-3}$	-0.294	(0.022)	-0.687
$b_{n,t-4}$	-0.084	(0.022)	-0.217
Number of kids	0.005	(0.004)	0.022
Individual Productivity, μ	-0.162	(0.014)	-0.258
Marriage Market			
Men to women ratio ($\geq$ college)	-0.091	(0.255)	0.091
Education $\times$ Men to women ratio ($\geq$ college)	0.017	(0.019)	
Men to women ratio ($<$ college)	2.453	(0.918)	0.133
Education $\times$ Men to women ratio ($<$ college)	-0.136	(0.064)	
Spouse Type			
Spouse has some college	0.067	(0.114)	-0.384
Education $\times$ Spouse has some college	-0.016	(0.121)	
Spouse has college or more	1.099	(0.008)	-0.868
Education $\times$ Spouse has college or more	-0.109	(0.009)	
Maternity Leave Variables			
Protected leave rolled	1.876	(1.522)	0.028
Paid leave rolled	-51.95	(22.10)	-0.252
Applies for tier 1	-0.119	(0.027)	-0.337
Applies for tier 2	-0.294	(0.047)	-0.688
Protected hours available	1.533	(0.472)	0.120
Paid hours available	-8.143	(0.937)	-0.253
Replacement rate	0.588	(0.076)	0.272
Tax Policy Unmarried			
Lump sum (π_{00}^{tax})	-8.0E-05	(1.8E-05)	0.226
Lump sum*kids (π_{01}^{tax})	1.2E-04	(1.7E-05)	-0.238
Slope (π_{10}^{tax})	0.265	(0.317)	0.034
Slope*kids (π_{11}^{tax})	22.598	(2.190)	0.264
Progressivity (π_{2}^{tax})	0.436	(0.129)	0.161
Tax Policy Married $\times$ Married$_{t-1}$			
Lump sum (π_{00}^{tax})	1.1E-04	(9.4E-06)	-0.772
Lump sum*kids (π_{01}^{tax})	-4.3E-05	(2.1E-05)	0.078
Slope (π_{10}^{tax})	1.753	(0.424)	0.249
Slope*kids (π_{11}^{tax})	-61.48	(6.297)	-0.269
Progressivity (π_{2}^{tax})	-2.793	(0.200)	-0.822
Observations	135,791		

Notes: Estimates from a logit regression of the probability of separation for women in partnerships (either married or cohabiting). "est." stands for estimate and "se" stands for standard errors. Standard errors corrected for three-stage estimation. Column Δp is the approximated change in the probability (in percentage points) from an increase of one standard deviation in the regressor (or a unit change from zero for binary variables) evaluated at the average for continuous variables. Married tax policy is interacted with a married indicator because cohabiting individuals face no change in taxes upon separation. Lump sump variables are negatively signed. Unconditional probability is 2.7.

Table 9: Utility Function

Variable	Parameter	est.	se	Variable	Parameter	est.	se
Labor force participation: $\tilde{x}_t' B_0 d_t$				*Birth and labor force participation*: $\tilde{x}_t' \tilde{\gamma}_0 b_t d_t$			
d_t	B_{00}	-6.029	(0.157)	d_t	$\tilde{\gamma}_{00}$	-10.737	(0.233)
$d_t \cdot age_t$	B_{01}	0.128	(0.006)	$d_t \cdot b_t \cdot age_t$	$\tilde{\gamma}_{01}$	0.606	(0.015)
$d_t \cdot age_t^2$	B_{02}	-0.002	(7.4E-05)	$d_t \cdot b_t \cdot age_t^2$	$\tilde{\gamma}_{02}$	-0.013	(2.4E-04)
$d_t \cdot edu$	B_{03}	0.124	(0.007)	$d_t \cdot b_t \cdot edu$	$\tilde{\gamma}_{03}$	0.125	(0.003)
$d_t \cdot black$	B_{04}	-0.270	(0.026)	$d_t \cdot b_t \cdot black$	$\tilde{\gamma}_{04}$	0.105	(0.012)
$d_t \cdot married_t$	B_{05}	-0.309	(0.036)	$d_t \cdot b_t \cdot married_t$	$\tilde{\gamma}_{05}$	1.047	(0.028)
$d_t \cdot cohabiting_t$	B_{06}	-0.448	(0.071)	$d_t \cdot b_t \cdot cohabiting_t$	$\tilde{\gamma}_{06}$	0.666	(0.041)
Leisure: $\tilde{x}_t' B_1 l_t + \sum_{s=0}^{\rho_l} \delta_s l_t l_{t-s}$				*Birth and no labor force participaiton*: $\tilde{x}_t' \gamma_0 b_t (1-d_t)$			
l_t	B_{10}	4.881	(0.101)	b_t	γ_{00}	-4.522	(0.337)
$l_t \cdot age_t$	B_{11}	0.118	(0.006)	$b_t \cdot age_t$	γ_{01}	0.311	(0.023)
$l_t \cdot age_t^2$	B_{12}	-0.002	(7.1E-05)	$b_t \cdot age_t^2$	γ_{02}	-0.008	(3.6E-04)
$l_t \cdot edu$	B_{13}	0.123	(0.015)	$b_t \cdot edu$	γ_{03}	0.080	(0.005)
$l_t \cdot black$	B_{14}	-0.487	(0.048)	$b_t \cdot black$	γ_{04}	0.049	(0.017)
$l_t \cdot marriel_t$	B_{15}	-0.085	(0.029)	$b_t \cdot married_t$	γ_{05}	0.556	(0.029)
$l_t \cdot cohabiting_t$	B_{16}	-0.399	(0.061)	$b_t \cdot cohabiting_t$	γ_{06}	0.516	(0.049)
$l_t \cdot l_t$	δ_0	-22.349	(0.217)				
$l_t \cdot l_{t-1}$	δ_1	21.010	(0.167)				
$l_t \cdot l_{t-2}$	δ_2	-0.061	(0.133)	*Birth spacing*: $b_t \left(\sum_{s=1}^{\rho_b} \gamma_k b_{t-s} + \gamma_b \sum_{s=\rho_b+1}^{17} b_{t-s} \right)$			
$l_t \cdot l_{t-3}$	δ_3	-0.668	(0.137)	$b_t \cdot b_{t-1}$	γ_1	-0.998	(0.027)
				$b_t \cdot b_{t-2}$	γ_2	0.245	(0.025)
				$b_t \cdot b_{t-3}$	γ_3	0.370	(0.023)
Risk aversion				$b_t \cdot b_{t-4}$	γ_4	0.526	(0.012)
	α	0.0258	(0.008)	$b_t \cdot (\sum_{s=5}^{17} b_{t-s})$	γ_b	-0.337	(0.016)
Mixture distribution of idiosyncratic shock to marginal utility of work, F_ξ							
If no birth, $b_t = 0$				*If birth*, $b_t = 1$			
	$\mu_{\xi 01}$	2.255	(0.128)		$\mu_{\xi 11}$	6.703	(0.288)
	$\mu_{\xi 02}$	-3.664	(0.097)		$\mu_{\xi 12}$	-0.091	(0.166)
	$\sigma_{\xi 0}$	0.000	(0.008)		$\sigma_{\xi 1}$	0.055	(0.079)
	$p_{\xi 0}$	0.037	(0.003)		$p_{\xi 1}$	3.E-05	(2.3E-03)

Notes: Estimates of the utility function in equation (19) and its empirical implementation specifications in (20) and (21). The conditional (on birth) mixtures distributions have different means but constant variance. The mixture probability $p_{\xi k}$ for $k = 0, 1$ is the probability that the idiosyncratic shock to marginal utility of work comes from distribution 1. For instance, conditional on no birth, $p_{\xi 0}$ is the probability that the draw of ξ comes from a distribution with mean $\mu_{\xi 01}$ and standard deviation $\sigma_{\xi 0}$. "est." stands for estimate and "se" stands for standard errors. Standard errors corrected for three-stage estimation.

Table 10: Leave Policies in the Simulation Grid

Policy ID	*Tier 1*				*Tier 2*				*Place-Time*
	Eligibility	*Generosity*			*Eligibility*	*Generosity*			
	(hours)	*Protected (weeks)*	*Paid (weeks)*	*Rate*	*(hours)*	*Protected (weeks)*	*Paid (weeks)*	*Rate*	
LP1	0	0	0	0					Texas before 1993
LP2	1250	12	0	0					Florida after 1993
LP3	800	0	10	0.67					New Jersey 1979-1989
LP4	400	10	10	0.55					Rhode Island 1979-1986
LP5	0	6	0	0	1820	12	0	0	Washington 1990-1992
LP6	800	0	10	0.67	1000	16	10	0.67	New Jersey 1990-2008
LP7	0	6	12	0.55	1250	18	12	0.55	California 2004-2017

Notes: Column *Place-Time* is an example of a place and time in which the policy regime was active.

Table 11: Tax-Transfer Policies in the Simulation Grid

Policy ID	*Married*							*Not Married*							*Place-Time*
	Lump sum (\$) π_0^{tax}		*Slope (%)* π_1^{tax}		*Progr.* π_2^{tax}	*Marginal Rate (%)*		*Lump sum (\$)* π_0^{tax}		*Slope (%)* π_1^{tax}		*Progr.* π_2^{tax}	*Marginal Rate (%)*		
	Base	n_t	*Base*	n_t				*Base*	n_t	*Base*	n_t				
TP1	-4,158	-275	1.61	-0.020	1.230	29.4		-1,443	-527	2.40	-0.009	1.206	26.7		Georgia 1991-1996
TP2	-7,318	-284	4.92	0.105	1.143	31.1		-1,080	-535	1.07	0.007	1.272	26.1		New Mexico 1987-1990
TP3	-8,563	-1,575	5.52	0.355	1.156	44.2		-3,018	-2,005	0.90	-0.023	1.319	35.5		California 1968-1981
TP4	-11,668	-1,330	15.8	-0.018	1.059	33.0		-2,771	-731	8.15	0.216	1.103	28.8		Wisconsin 2002-2010

Notes: The parameters correspond to the tax-transfer function in equation (1), n_t corresponds to the interaction with the number of dependent children. *Progr.* stands from progressivity. Marginal tax rate for married women is computed for a woman with two children, income \$50,000, and husband's income \$62,500 (hence assuming an income gap of 0.8). Marginal tax rate for unmarried women is computed for a woman with two children and income \$50,000. Column *Place-Time* is an example of a place and time in which the policy regime was active.

Table 12: Policy Effects: Take-up

Protected Leave					Paid Leave				
	Tax-Transfer Policy					Tax-Transfer Policy			
Leave Policy	TP1	TP2	TP3	TP4	Leave Policy	TP1	TP2	TP3	TP4
LP1					LP1				
LP2	0.300	0.281	0.211	0.212	LP2				
LP3					LP3	0.562	0.575	0.640	0.641
LP4	0.147	0.146	0.120	0.120	LP4	0.655	0.661	0.688	0.686
LP5	0.398	0.383	0.296	0.298	LP5				
LP6	0.447	0.427	0.343	0.344	LP6	0.684	0.682	0.698	0.696
LP7	0.417	0.397	0.308	0.308	LP7	0.662	0.658	0.662	0.657

Notes: Leave take-up is measured as the total amount of leave granted across all women and all ages, divided by the total amount of leave used. *Leave Policies*: LP1: no-leave; LP2: FMLA; LP3: one-tier policy with only paid leave; LP4: a one-tier policy with both paid and protected leave; LP4: two-tier version of FMLA with only protected leave in both tiers; LP6: two-tier policy with only paid leave in the first tier and both types in the second tier; LP7: two-tier policy with paid and protected leave in both tiers. *Tax-Transfer Policies*: TP1 and TP2 are low lump sum and low child transfer policies. TP3 and TP4 are high lump sum and high child transfer policies. Policies are described in detail in Tables 10 and 11.

Table 13: Policy Effects: Partnership

Marriage Rate

Leave Policy	Tax-Transfer Policy TP1	TP2	TP3	TP4
LP1	0.635	0.641	0.717	0.589
LP2	0.641	0.646	0.722	0.595
LP3	0.627	0.631	0.705	0.581
LP4	0.631	0.634	0.707	0.583
LP5	0.665	0.670	0.739	0.616
LP6	0.649	0.651	0.722	0.599
LP7	0.664	0.664	0.723	0.606

Cohabitation Rate

Leave Policy	Tax-Transfer Policy TP1	TP2	TP3	TP4
LP1	0.032	0.022	0.012	0.063
LP2	0.024	0.018	0.011	0.053
LP3	0.034	0.024	0.013	0.066
LP4	0.029	0.021	0.012	0.061
LP5	0.021	0.015	0.010	0.047
LP6	0.024	0.018	0.011	0.054
LP7	0.023	0.017	0.011	0.053

Ever Separated if Partnered

Leave Policy	Tax-Transfer Policy TP1	TP2	TP3	TP4
LP1	0.655	0.608	0.498	0.695
LP2	0.650	0.604	0.495	0.687
LP3	0.635	0.595	0.497	0.692
LP4	0.634	0.594	0.498	0.692
LP5	0.614	0.569	0.468	0.656
LP6	0.610	0.573	0.481	0.671
LP7	0.568	0.535	0.462	0.648

Equal Education Partnership

Leave Policy	Tax-Transfer Policy TP1	TP2	TP3	TP4
LP1	0.551	0.552	0.542	0.553
LP2	0.548	0.549	0.540	0.553
LP3	0.546	0.550	0.539	0.550
LP4	0.541	0.544	0.535	0.549
LP5	0.550	0.549	0.539	0.552
LP6	0.541	0.541	0.531	0.548
LP7	0.532	0.534	0.528	0.542

Notes: *Married* and *Cohabitation* rates are the shares of all simulated observations in which women were married or cohabiting. *Ever Separated if Partnered* is the share of women who ever transitioned into singlehood as a proportion of women who were ever partnered. *Equal Education Partnership* is the share of partnerships in which both partners had the same education level. *Leave Policies*: LP1: no-leave; LP2: FMLA; LP3: one-tier policy with only paid leave; LP4: a one-tier policy with both paid and protected leave; LP4: two-tier version of FMLA with only protected leave in both tiers; LP6: two-tier policy with only paid leave in the first tier and both types in the second tier; LP7: two-tier policy with paid and protected leave in both tiers. *Tax-Transfer Policies*: TP1 and TP2 are low lump sum and low child transfer policies. TP3 and TP4 are high lump sum and high child transfer policies. Policies are described in detail in Tables 10 and 11.

Table 14: Policy Effects: Fertility

Completed Fertility

Leave Policy	Tax-Transfer Policy TP1	TP2	TP3	TP4
LP1	2.45	2.48	2.64	2.54
LP2	2.33	2.37	2.60	2.50
LP3	2.26	2.31	2.53	2.45
LP4	2.23	2.26	2.48	2.39
LP5	2.24	2.26	2.45	2.36
LP6	2.04	2.08	2.36	2.28
LP7	2.07	2.11	2.38	2.30

Share of New Mothers

Leave Policy	Tax-Transfer Policy TP1	TP2	TP3	TP4
LP1	0.858	0.862	0.896	0.874
LP2	0.809	0.815	0.877	0.851
LP3	0.810	0.819	0.872	0.854
LP4	0.799	0.807	0.862	0.842
LP5	0.787	0.787	0.832	0.805
LP6	0.730	0.735	0.811	0.785
LP7	0.734	0.742	0.820	0.796

Age of First Birth (New Mothers)

Leave Policy	Tax-Transfer Policy TP1	TP2	TP3	TP4
LP1	27.26	27.20	26.96	27.06
LP2	27.53	27.43	27.13	27.21
LP3	27.60	27.52	27.20	27.26
LP4	27.59	27.51	27.23	27.30
LP5	27.62	27.56	27.36	27.45
LP6	27.78	27.78	27.65	27.71
LP7	27.78	27.77	27.52	27.57

Spacing between First Two Children (New Mothers)

Leave Policy	Tax-Transfer Policy TP1	TP2	TP3	TP4
LP1	3.73	3.75	3.77	3.76
LP2	3.72	3.74	3.74	3.75
LP3	3.82	3.80	3.82	3.82
LP4	3.80	3.80	3.79	3.79
LP5	3.77	3.80	3.73	3.72
LP6	3.78	3.81	3.82	3.78
LP7	3.79	3.78	3.73	3.73

Notes: *Share of new mothers* is the share of women who were not mothers at the beginning of their labor market careers but who eventually became mothers. The age of first birth and spacing is conditional on these new mothers. *Leave Policies*: LP1: no-leave; LP2: FMLA; LP3: one-tier policy with only paid leave; LP4: a one-tier policy with both paid and protected leave; LP4: two-tier version of FMLA with only protected leave in both tiers; LP6: two-tier policy with only paid leave in the first tier and both types in the second tier; LP7: two-tier policy with paid and protected leave in both tiers. *Tax-Transfer Policies*: TP1 and TP2 are low lump sum and low child transfer policies. TP3 and TP4 are high lump sum and high child transfer policies. Policies are described in detail in Tables 10 and 11.

Table 15: Policy Effects: Motherhood Penalty

Labor income ($)

Leave Policy	Tax-Transfer Policy TP1	TP2	TP3	TP4
LP1	-4,061	-4,107	-3,446	-3,454
LP2	-8,005	-7,426	-5,221	-5,276
LP3	-4,715	-4,548	-3,746	-3,652
LP4	-5,350	-5,069	-4,352	-4,197
LP5	-11,858	-11,910	-10,229	-9,833
LP6	-8,900	-8,601	-7,552	-7,341
LP7	-9,700	-9,086	-7,475	-7,314

Participation

Leave Policy	Tax-Transfer Policy TP1	TP2	TP3	TP4
LP1	-0.083	-0.098	-0.119	-0.116
LP2	-0.061	-0.073	-0.116	-0.112
LP3	-0.065	-0.077	-0.101	-0.102
LP4	-0.066	-0.077	-0.104	-0.096
LP5	-0.008	-0.020	-0.085	-0.081
LP6	-0.023	-0.028	-0.063	-0.060
LP7	-0.026	-0.033	-0.097	-0.091

Hours

Leave Policy	Tax-Transfer Policy TP1	TP2	TP3	TP4
LP1	-191	-193	-181	-181
LP2	-317	-310	-259	-258
LP3	-204	-203	-188	-184
LP4	-236	-234	-213	-207
LP5	-348	-359	-358	-352
LP6	-335	-331	-314	-307
LP7	-360	-351	-315	-311

Wages

Leave Policy	Tax-Transfer Policy TP1	TP2	TP3	TP4
LP1	-0.526	-0.583	-0.532	-0.535
LP2	-0.916	-0.873	-0.647	-0.650
LP3	-0.816	-0.796	-0.716	-0.700
LP4	-0.810	-0.801	-0.837	-0.767
LP5	-1.016	-1.146	-1.280	-1.169
LP6	-0.798	-0.854	-1.058	-1.009
LP7	-1.036	-1.010	-1.125	-1.083

Notes: The motherhood penalty of first birth for new mothers is estimated using the same event study specification as Flores, Gayle, and Hincapié (2024) (equation (S35) in Appendix E) which takes into account three periods before birth and 10 periods after. The penalty is computed using only women who were not mothers at the initial condition. *Leave Policies*: LP1: no-leave; LP2: FMLA; LP3: one-tier policy with only paid leave; LP4: a one-tier policy with both paid and protected leave; LP4: two-tier version of FMLA with only protected leave in both tiers; LP6: two-tier policy with only paid leave in the first tier and both types in the second tier; LP7: two-tier policy with paid and protected leave in both tiers. *Tax-Transfer Policies*: TP1 and TP2 are low lump sum and low child transfer policies. TP3 and TP4 are high lump sum and high child transfer policies. Policies are described in detail in Tables 10 and 11.

Table 16: Policy Effects: Labor Market Outcomes

Participation Rate

	Tax-Transfer Policy			
Leave Policy	TP1	TP2	TP3	TP4
LP1	0.826	0.790	0.682	0.709
LP2	0.860	0.823	0.707	0.738
LP3	0.842	0.806	0.697	0.722
LP4	0.855	0.820	0.717	0.745
LP5	0.900	0.872	0.781	0.811
LP6	0.900	0.870	0.771	0.800
LP7	0.884	0.852	0.750	0.778

Mean Hours

	Tax-Transfer Policy			
Leave Policy	TP1	TP2	TP3	TP4
LP1	1,929	1,745	1,380	1,487
LP2	2,147	1,948	1,503	1,624
LP3	1,936	1,759	1,399	1,491
LP4	1,971	1,792	1,427	1,535
LP5	2,546	2,356	1,855	1,960
LP6	2,304	2,125	1,706	1,808
LP7	2,265	2,081	1,646	1,751

Mean Wage ($)

	Tax-Transfer Policy			
Leave Policy	TP1	TP2	TP3	TP4
LP1	17.5	16.7	15.2	15.6
LP2	18.7	17.7	15.7	16.3
LP3	18.2	17.3	15.6	16.1
LP4	18.4	17.4	15.7	16.3
LP5	21.1	20.1	17.5	18.0
LP6	20.3	19.2	17.1	17.6
LP7	20.1	19.1	16.8	17.4

Present Value Labor Income (Million $)

	Tax-Transfer Policy			
Leave Policy	TP1	TP2	TP3	TP4
LP1	0.476	0.406	0.253	0.279
LP2	0.622	0.531	0.314	0.348
LP3	0.500	0.428	0.270	0.294
LP4	0.523	0.449	0.287	0.317
LP5	0.967	0.858	0.540	0.580
LP6	0.779	0.687	0.449	0.485
LP7	0.739	0.646	0.407	0.442

Notes: The *Participation Rate*, *Mean Hours*, and *Mean Wage* are computed across all simulated observation; hours and wages are conditional on participating. *Present Value Labor Income* is computed at entry and using an interest rate of 5%. *Leave Policies*: LP1: no-leave; LP2: FMLA; LP3: one-tier policy with only paid leave; LP4: a one-tier policy with both paid and protected leave; LP4: two-tier version of FMLA with only protected leave in both tiers; LP6: two-tier policy with only paid leave in the first tier and both types in the second tier; LP7: two-tier policy with paid and protected leave in both tiers. *Tax-Transfer Policies*: TP1 and TP2 are low lump sum and low child transfer policies. TP3 and TP4 are high lump sum and high child transfer policies. Policies are described in detail in Tables 10 and 11.

Table 17: Policy Effects: Policy Cost and Tax Revenue

Present Value Protected Income ($ Per Household)

Leave Policy	Tax-Transfer Policy TP1	TP2	TP3	TP4
LP1				
LP2	988	785	300	296
LP3				
LP4	261	238	114	111
LP5	3,087	2,617	1,176	1,145
LP6	2,296	1,976	1,019	994
LP7	2,101	1,778	830	803

Present Value Replacement Income ($ Per Household)

Leave Policy	Tax-Transfer Policy TP1	TP2	TP3	TP4
LP1				
LP2				
LP3	1,396	1,297	986	950
LP4	1,434	1,340	1,005	967
LP5				
LP6	2,837	2,631	1,982	1,909
LP7	2,727	2,524	1,925	1,854

Present Value Tax Revenue (Million $ Per Household)

Leave Policy	Tax-Transfer Policy TP1	TP2	TP3	TP4
LP1	0.297	0.250	0.280	0.167
LP2	0.336	0.285	0.304	0.187
LP3	0.305	0.258	0.287	0.175
LP4	0.308	0.261	0.292	0.179
LP5	0.441	0.383	0.397	0.260
LP6	0.382	0.330	0.356	0.231
LP7	0.372	0.319	0.339	0.218

Excess Revenue Relative to No-Leave ($ Per Household)

Leave Policy	Tax-Transfer Policy TP1	TP2	TP3	TP4
LP1				
LP2	38,675	34,485	24,008	19,854
LP3	8,239	7,293	7,052	7,152
LP4	10,842	10,609	12,259	12,084
LP5	143,594	132,944	116,446	92,758
LP6	84,665	79,264	75,635	63,306
LP7	75,172	68,871	59,216	50,728

Notes: This computations exclude single-men households as their income generating process is not included in the model. *Protected Income* is the labor income generated by protected human capital gained through take-up of protected leave (h^{ℓ}_{1t} in equation (16)) multiplied by the wage. *Replacement Income* is the take-up of paid leave (h^{ℓ}_{2t} in equation (**??**)) multiplied by the reimbursement rate and by the wage. *Present Value* for either type of income is computed at entry and using an interest rate of 5%. *Leave Policies*: LP1: no-leave; LP2: FMLA; LP3: one-tier policy with only paid leave; LP4: a one-tier policy with both paid and protected leave; LP4: two-tier version of FMLA with only protected leave in both tiers; LP6: two-tier policy with only paid leave in the first tier and both types in the second tier; LP7: two-tier policy with paid and protected leave in both tiers. *Tax-Transfer Policies*: TP1 and TP2 are low lump sum and low child transfer policies. TP3 and TP4 are high lump sum and high child transfer policies. Policies are described in detail in Tables 10 and 11.

A Data Appendix

A.1 State and Federal Leave Policies

During the half a century spanned by our data set many states changed policies and the Federal Maternity Leave Act (FMLA) was enacted and became effective. Table S1 summarizes the policies in place that covered both private and public employees during these years describing them in terms of their effective year, work requirements, minimum size of firms required to comply, leave length, job protection status, type of leave, whether leave is paid and replacement rate.

We code the policies in Table S1 into a set of unique policies presented in Table 1. We make the following coding decisions:

- ↪ "Reasonable" and/or not specified length is coded as 6 weeks.
- ↪ Not specified prior work is coded as zero hours required.
- ↪ Not specified job protection is coded as not job protected.
- ↪ All women obtain the minimum level of pregnancy disability upon child birth. Hence, both leave types (pregnancy disability and birth or adoption) are treated equally and aggregated into a single leave length.
- ↪ Individuals select to have their unprotected paid leave run concurrently with their protected unpaid leave whenever both are available.

Appendix Table S1: State and Federal Leave Policies

state	policy name	effective year	min work eligibility	min firm size	leave length (weeks)	protected	type	paid	rate
California	Temporary Disability Insurance (TDI)	1946	-	1	6	no	pregnancy disability	yes	0.55
	California's Fair Employment and Housing Act	1980	-	5	reasonable, max 4 months	yes	pregnancy disability	no	
	California's Family Rights Act (CFRA)	1993	1,250 hours	50	12	yes	birth or adoption	no	
	Family TDI Program	2004	-	1	6	no, unless covered by CFRA or FMLA	birth or adoption	yes	0.55
Connecticut	Connecticut Fair Employment Practices Act	1973	-	75	reasonable	yes	pregnancy disability	no	
	Connecticut Family and Medical Leave Act	1990	1,000 hours	3	12; 16 (1994)	yes	birth or adoption	no	
Hawaii	TDI	1969	14 weeks	1	max 26	no, unless covered by FMLA	pregnancy disability	yes	0.58
	Sex and Marital Status Discrimination Regulations	1983	-	1	reasonale	yes	pregnancy disability	no	

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Appendix Table S1 – *Continued from previous page*

state	policy name	effective year	min work eligibility	min firm size	leave length (weeks)	protected	type	paid	rate
	Hawaii Family Leave Law	1994	6 months	100	4	yes	birth or adoption	no	
Iowa	Iowa Civil Rights Act	1987	-	4	max 8	yes, if other disabled protected	preg-nancy disability	no	
Kansas	Guidelines on Discrimination Because of Sex	1974	-	4	reasonable	yes	preg-nancy disability	no	
Louisiana	Pregnancy Disability Louisiana	1988	-	26	min 6, max 4 months	yes	preg-nancy disability	no	
Maine	Maine Family and Medical Leave Act	1989	employed with employer	25; 15 (1997)	8; 10 (1991)	yes	birth or adoption	no	
Mas-sachusetts	Massachusetts Maternity Leave Act	1973	3 months full time	6	8	yes	birth or adoption	no	
Minnesota	Minnesota Parental Leave Act	1988	20 hours per week	21	6	yes	birth or adoption	no	
Montana	Montana Maternity Leave Act	1985	-	1	reasonable	yes	preg-nancy disability	no	

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Appendix Table S1 – *Continued from previous page*

state	policy name	effective year	min work eligibility	min firm size	leave length (weeks)	protected	type	paid	rate
New Hampshire	Equal Employment Opportunity	1985	-	6	based on doctor's certification	yes	preg-nancy disability	no	
New Jersey	TDI	1948	20 weeks	1	usual length 10, max 26	no, unless covered by FMLA	preg-nancy disability	yes	0.67
	New Jersey Family Leave Act	1990	1,000 hours	100; 75 (1991); 50 (1993)	16	yes	birth or adoption	no	
	New Jersey's Paid Family Leave	2009	1,000 hours	50	6	no, unless covered by FMLA	birth or adoption	yes	0.67
New York	TDI	1949	4 prior weeks	1	4 to 6 before delivery, 4 to 6 after, max 26	no, unless covered by FMLA	birth or adoption & disability	yes	0.50
Oregon	Oregon Family and Medical Leave Act	1988	90 days; 180 days (1995)	25	12 weeks	yes	birth or adoption	no	
	Oregon Family and Medical Leave Act	1990	not specified; 25 hours per week (1995)	25	reasonable; 12 (1995)	yes	preg-nancy disability	no	

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Appendix Table S1 – *Continued from previous page*

state	policy name	effective year	min work eligibility	min firm size	leave length (weeks)	protected	type	paid	rate
Rhode Island	TDI	1942	20 weeks	-	max 30	yes	preg-nancy disability	yes	0.55
	Rhode Island Parental and Family Leave Act	1987	30 hours per week	50	13	yes	birth or adoption	no	
	Temporary Caregiver Insurance	2013	-	-	4	yes	birth or adoption	yes	0.55
Tennessee	Tennessee Human Rights Act	1988	12 months full time	100	max 4 months	yes	birth or adoption	no	
Vermont	Parental and Family Leave Act	1989	30 hours per week	10	12	yes	birth or adoption	no	
Washington	Washington State Human Rights Commission Regulations against Discrimination	1974	-	8	reasonable	yes	preg-nancy disability	no	
	Washington State Family Leave Act	1990	35 hours per week; 1250 hours (2010)	100; 50 (2010)	12	yes	birth or adoption	no	
Wisconsin	Wisconsin Family and Medical Leave Act	1988	1,000 hours	50	6, 2 may be added for pregnancy disability	yes	birth or adoption	no	

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Appendix Table S1 – *Continued from previous page*

state	policy name	effective year	min work eligibility	min firm size	leave length (weeks)	protected	type	paid	rate
District of Columbia	District of Columbia Family and Medical Leave Act	1991	1,000 hours	50; 20 (1994)	16, 16 may be added for pregnancy disability	yes	birth or adoption	no	
All	Family and Medical Leave Act (FMLA)	1993	1,250 hours	50	12	yes	birth or adoption	no	

Notes: *Min work eligibility* column corresponds to the minimum work requirements, most often during the prior year, for a woman to be eligible to the program. *Min firm size* column corresponds to the minimum size of firms that must comply to the policy. *Protected* column corresponds to whether the leave granted is job-protected. *Rate* column corresponds to the replacement rate, i.e. the share of the wage rate that is paid during paid leave. Dates in parenthesis indicate changes in policy; for instance, Connecticut's Family and Medical Leave Act changed in 1994 to give 16 weeks of leave instead of 12. Sources: Skolnik (1952), Women's Legal Defense Fund (1991), Women's Bureau (1993), Table 1 in Essay 1 in Kallman Kane (1998), Appendix Table in Waldfogel (1999), Appendix Table A.1 in Han, Ruhm, and Waldfogel (2009), Grant, Hatcher, and Patel (2005), Presagia (2012), Gault et al. (2014), Bartel et al. (2014), Table 15 in Appendix B in Thomas (2019). In addition to the literature cited we consulted several web sources (in March 2019) to obtain information regarding the nature of the leave and replacement policies. Below are the sources we consulted:

- ↪ State family and medical leave laws: http://www.ncsl.org/research/labor-and-employment/state-family-and-medical-leave-laws.aspx
- ↪ California: https://ca.db101.org/ca/situations/workandbenefits/rights/program2c.htm
- ↪ Connecticut: https://www.cwealf.org/i/assets/FMLA_14765.pdf
- ↪ Hawaii: http://labor.hawaii.gov/dcd/home/about-tdi/
- ↪ Maine: http://www.mainelegislature.org/legis/statutes/26/title26sec844.html
- ↪ New Jersey: https://myleavebenefits.nj.gov/labor/myleavebenefits/worker/tdi/
- ↪ Rhode Island: http://www.dlt.ri.gov/tdi/
- ↪ FMLA: https://www.dol.gov/whd/fmla/

Other relevant notes to policies in Table S1:

- California
  - *Family TDI Program*: (also called Paid Family Leave) does not subtract from SDI leave.
- Hawaii
  - *Hawaii Family Leave Law*: runs concurrently with FMLA if eligible for both.
- Iowa
  - *Iowa Civil Rights Act*: Code of Iowa, Title XXIX, Chapter 601A, Section 601A.6; same job protection as given to other disabled employees.
- Louisiana
  - *Pregnancy Disability Louisiana*: Revised Statutes, Title 23, Chapter 9, Part VIII, Section 23:1008.
- New Jersey
  - *New Jersey Family Leave Act*: runs concurrently with FMLA if eligible for both.
  - *New Jersey's Paid Family Leave*: runs concurrently with FMLA if eligible for both.
  - *TDI*: women can use TDI and New Jersey's Paid Family Leave sequentially.
- Oregon
  - *Oregon Family and Medical Leave Act*: not counted against job-protected parental leave.
- Rhode Island
  - *Temporary Caregiver Insurance*: can be used in addition to TDI.
- All TDIs (California, Hawaii, New Jersey, New York, Rhode Island), whose enactment dates were all before the sample initial date (1968), were coded as available paid maternal/pregnancy leave starting from 1979, following the enactment of the Pregnancy Discrimination Act of October 30, 1978. This approach is similar to the one in Stearns (2015).

A.2 Tax-Transfer Policies

The calculation of taxation and government transfers uses data from the PSID on state of residence, marital status, dependents, annual earnings, and government transfers, in combination with the NBER's TAXISM program. We calculate gross household income (pre-tax and pre-government transfers) including labor earnings, self-employment income, private transfers (alimony, child support, help from relatives, miscellaneous transfers, private retirement income, annuities, and other retirement income), plus income from interest, dividends, and rents. Taxable income is gross income minus deductions. For each household in the data, we compute the five main deductible expenses in the U.S. tax code: medical expenses, mortgage interest, state taxes paid, charitable contributions, and children/dependents credits. TAXSIM calculates whether each household would be better off itemizing or taking the standard deduction. We obtain the actual government welfare transfers using individual data from the PSID. The TAXISM program calculates the state and federal tax payable.

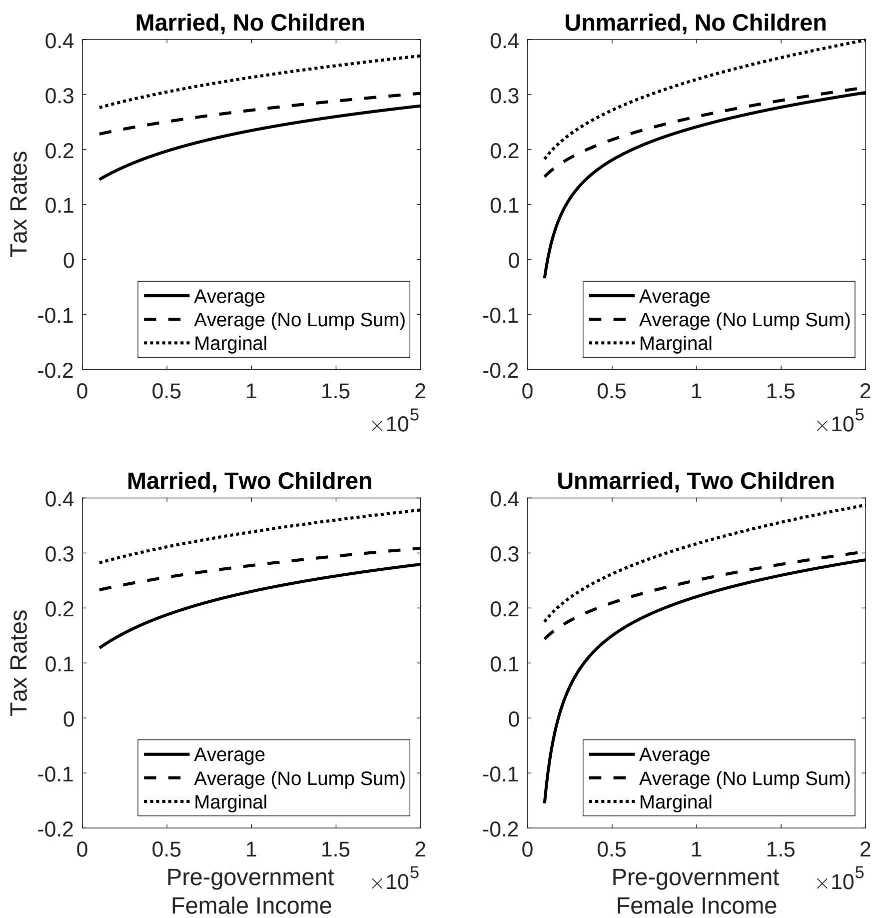
To back out the tax-transfer schedules (π^{tax}) in equation (17) we first grouped states into three categories according to their average income tax rate from 1978 to 2017. The low-tax category in Table S2 contains the nine states with zero average income taxes and the two states with average income tax rates of less than two percent. The medium-tax category contains the twenty-three states with average income tax rates between two and five percent. The high-tax category contains the District of Columbia and sixteen states that have average income tax rates greater than or equal to five percent.

Appendix Table S2: States by Income Tax Level

Category	Mean Rate	States
Low	$[0, 2)$	FL, NV, NH, SD, TN, TX, WA, WY, AK, LA, ND
Medium	$[2, 5)$	CT, IL IN, MS, PA, WV, AL, AZ, MO, NJ, OH, AR, CO, KS, KY, MD, MA, MI NE, NM, SC, VT, VA
High	≥ 5	DC, CA, DE, GA, ID, IA, ME, MT, NC, OK, RI, UT, MN, NY, OR, WI, HI

Notes: *Mean Rate* is the average income tax rate from 1978 to 2017.

Over time we split the tax and transfer policy variation into seven periods determined by the following six major tax and welfare reforms at the federal level: the Economic Recovery Tax Act of 1981 (ERTA), the Tax Reform Act of 1986 (TRA), the Omnibus Budget Reconciliation Act of 1990 (OBRA-90), the Personal Responsibility and Work Opportunity Reconciliation Act of 1996 (PRWORA), the Economic Growth and Tax Relief Reconciliation Act of 2001, and the Tax Relief Act of 2010. There are some other taxes and policy changes that we smoothed over because either they were in place for a short period, hence overlapping in a significant way with the major six changes, or they did not change our estimated tax and welfare function in any considerable way. Notable amongst these are the Jobs and Growth Tax Relief Reconciliation Act of 2003 (JGTRRA), the American Taxpayer Relief Act of 2012 (ATRA), and the American Recovery and Reinvestment Act of 2009 (ARRA). The tax/welfare policy variation across states (in average income tax) and over time (in tax-transfer reforms) creates 21 (3×7) tax and welfare policy regimes. We estimate tax-transfer parameters π^{tax} separately for each of the 21 regimes. The estimated regime parameters are presented in Table 2.



Appendix Figure S1: Average and Marginal Tax Rates Across Regimes: US, 1968-2017

Notes: Mean of the average and marginal tax rate across all 21 tax-transfer regimes (Table 2) at different levels of household income. Given the shape of our tax-transfer function $T(y)$, the average tax rate is $T(y)/y = \pi_0^{tax}/y + \pi_1^{tax} y^{\pi_2^{tax}-1}$, the average tax rate with no lump sum is $(T(y) - \pi_0^{tax})/y = \pi_1^{tax} y^{\pi_2^{tax}-1}$, and the marginal tax rate is $T'(y) = \pi_1^{tax} \pi_2^{tax} y^{\pi_2^{tax}-1}$. For married women husband's income is fixed at $65,000 (approximately median income for married men).

B Model and Identification Appendix

B.1 Proof of Proposition 1

Recall that for Proposition 1 we are using the perfect foresight version of the model (without $g_{kh}(x_{t+1}|x_t)$). Hence, we can rewrite the dynamic discrete choice problem in (26) as

$$\sum_{k \in C_t} d_{kt} \left[\overline{u}_k(x_t) - (B_t - 1) \ln \int A_{t+1}(x_{t+1}^{(kh)}) q_k(h|x_t) dh + \epsilon_{kt} \right] \tag{S1}$$

Using equation (S1) and noting that $\int A_{t+1}(x_{t+1}^{(1)}) q_k(h|x_t) dh = A_{t+1}(x_{t+1}^{(1)})$, the log ratio of conditional choice probabilities is:

$$\ln\left(\frac{p_{1t}(x_t)}{p_{kt}(x_t)}\right) = \overline{u}_1(x_t) - (B_t - 1) \ln A_{t+1}(x_{t+1}^{(1)}) - \left(\overline{u}_k(x_t) - (B_t - 1) \ln \int A_{t+1}(x_{t+1}^{(kh)}) q_k(h|x_t) dh\right) \tag{S2}$$

Applying the exponential function, elevating to the power of $1/B_t$, and rearranging terms yields:

$$\left(\frac{p_{1t}(x_t)}{p_{kt}(x_t)}\right)^{1/B_t} \exp\left\{\frac{-\overline{u}_1(x_t)}{B_t}\right\} A_{t+1}(x_{t+1}^{(1)})^{1-1/B_t} = \exp\left\{\frac{-\overline{u}_k(x_t)}{B_t}\right\} \left(\int A_{t+1}(x_{t+1}^{(kh)}) q_k(h|x_t) dh\right)^{1-1/B_t} \tag{S3}$$

Substituting the left hand side of (S3) into the perfect-foresight version of (25) yields:

$$A_t(x_t) = \sum_{k \in C_t} p_{kt}(x_t)\, E\left[\exp\left(\frac{-\varepsilon_{kt}^*}{B_t}\right) \middle| x_t\right] \left(\frac{p_{1t}(x_t)}{p_{kt}(x_t)}\right)^{1/B_t} \exp\left\{\frac{-\overline{u}_1(x_t)}{B_t}\right\} A_{t+1}(x_{t+1}^{(1)})^{1-1/B_t} \tag{S4}$$

From the Online Appendix of Gayle, Golan, and Miller (2015) we know that:

$$E\left[\exp\left(\frac{-\varepsilon_{kt}^*}{B_t}\right) \middle| x_t\right] = p_{kt}(x_t)^{1/B_t} \Gamma\left(\frac{B_t + 1}{B_t}\right) \tag{S5}$$

Substituting into (S4) yields:

$$A_t(x_t) = p_{1t}(x_t)^{1/B_t} \Gamma\left(\frac{B_t + 1}{B_t}\right) \exp\left\{\frac{-\overline{u}_1(x_t)}{B_t}\right\} A_{t+1}(x_{t+1}^{(1)})^{1-1/B_t} \tag{S6}$$

Using (S6) to substitute recursively onto its right hand side yields equation (28). Hence, given choice k and hours h_{kt} at t, the index capturing the future continuation value is:

$$A_{t+1}(x_{t+1}^{(kh)}) = \prod_{s=0}^{T-t-1} \left[p_{1t+1+s}(x_{t+1+s}^{(kh,1)}) \Gamma \left(\frac{B_{t+1+s}+1}{B_{t+1+s}} \right)^{B_{t+1+s}} \exp\left\{ -\overline{u}_1(x_{t+1+s}^{(kh,1)}) \right\} \right]^{\chi_{t+1}(s)} \tag{S7}$$

Substituting in equation (S1) and using the fact that the alternative-specific preference shocks are distributed Type I Extreme Value to write the conditional value function finishes the proof. *Q.E.D.*

B.2 Proof of Proposition 2

Computing expectations of the perfect-foresight version of equation (27) over ζ_t and ν_t conditional on $\widetilde{\nu}_t$, $\widetilde{x}_t$, and h_t yields:

$$\begin{aligned} 0 =& \alpha E \left[w(x_t) \left(1 + \iota(\pi) \frac{\partial h_{2t}^{\ell}}{\partial h_t} \right) \left[1 - \pi_{1k}^{tax}(x_t) \pi_2^{tax}(x_t) W_k(h_{kt}, x_t)^{\pi_2^{tax}(x_t)-1} \right] \middle| \widetilde{\nu}_j, \widetilde{x}_t, h_t \right] \\ &+ \frac{\partial u_k(h_{kt}, x_t)}{\partial h_t} - (B_t - 1) E \left[\frac{\partial \ln A_{t+1}(x_{t+1}^{(kh)})}{\partial h} \middle| \widetilde{\nu}_j, \widetilde{x}_t, h_t \right] \end{aligned} \tag{S8}$$

Substituting for the future value index $A_{t+1}(x_{t+1}^{(kh)})$ using (28) in Proposition 1 and rearranging terms yields equation (33). Given the normalization of $\overline{u}_1$ implied in Corollary 1.1, separate identification of $\frac{\partial u_k(h^*, \widetilde{x}_t)}{\partial h}$ and ρ follows from the system of two equations with two unknowns in (33). *Q.E.D.*

C Estimation Appendix

C.1 Empirical Specification

Law of motion of old underage children $\bar{n}_t$. In the state of the problem we carry the vector $\{b_{t-1}, \ldots, b_{t-\rho_1}\}$, the number of old underage children $\bar{n}_t$, defined as the number of children whose age is in the interval (ρ_1, 18) at t, and the woman's age at first birth t_{b_1}. Recall that the last age of fertility is 45. The law of motion of the number of old underage children is given by:

$$\bar{n}_{t+1} = \begin{cases} 0 & \text{if } t \geq 63 \\ \bar{n}_t + b_{t-\rho_1} & \text{if } t < 63,\, \bar{n}_t = 0 \\ \bar{n}_t + b_{t-\rho_1} & \text{if } t < 63,\, \bar{n}_t > 0,\, t < t_{b_1} + 18 \\ \bar{n}_t + b_{t-\rho_1} - 1 & \text{if } t < 63,\, \bar{n}_t > 0,\, t = t_{b_1} + 18 \\ \bar{n}_t + b_{t-\rho_1} - adult_{t+1} & \text{if } t < 63,\, \bar{n}_t > 0,\, t > t_{b_1} + 18 \end{cases} \tag{S9}$$

where $adult_{t+1} \in \{0, 1\}$ is an indicator of whether an old kid *other than the first child* enters adulthood. $adult_{t+1}$ is a random variable with $Pr(adult_{t+1} = 1) = \phi_a$. The cases in equation (S9) are as follows:

1. Since last year of fertility is 45 and age of adulthood is 18, by age 63 all children would have entered adulthood.

2. For women younger than 63 with no old underage children, $\bar{n}_t$ can increase if she had a child ρ_1 years ago who becomes an old underage child at $t + 1$.

3. For women younger than 63, with old underage children, and also younger than the age of first birth plus 18, $\bar{n}_t$ can increase via an oldest recent birth ($b_{t-\rho_1}$) turning old.

4. For women younger than 63, with old underage children, and whose age equals the age of first birth plus 18, $\bar{n}_t$ can increase via an oldest recent birth ($b_{t-\rho_1}$) turning old, and it will decrease with certainty by one child since the first child will enter adulthood.

5. For women younger than 63, with old underage children, and also older than the age of first birth plus 18, $\bar{n}_t$ can increase via an oldest recent birth ($b_{t-\rho_1}$) turning old, and it can decrease if the draw of the adulthood random variable is equal to one. It is in this last case, after the first child enters adulthood, where we approximate the transition of old underage children.

We estimate ϕ_a (the probability that an older kid, who is younger than the first kid, turns into adulthood) by regressing an indicator of having a kid who is entering adulthood at t (which is equivalent to the indicator of birth 18 periods ago, b_{t-18}) on mother's age, age of first birth, race and education using the sample of women who satisfy the following three conditions: $t < 63, \bar{n}_t > 0$, $t > t_{b_1} + 18$; that is, women who could still have children younger than 18, who have at least one old child, and whose first child has already entered adulthood.

C.2 Estimation Process

Stage I: wage equation. Let $\triangle$ denote first differences between variables and recall that we only allow for three broad policy regimes in the wage equation (no policy, only protected available, paid available). Substituting w_t from (12) into reported wages $\widetilde{w}_t \equiv w_t \exp(\widetilde{\epsilon}_t)$, taking logarithms, and first differencing to eliminate individual fixed effects yields:

$$\triangle\widetilde{\epsilon}_t = \triangle \ln \widetilde{w}_t - \triangle \ln \omega(\tau_t) - \sum_{r=1}^{3} \left\{ \triangle z_{rt} B_{r,3} + \sum_{s=1}^{\rho_w} \left(\delta_{r,1s} \triangle h^*_{r,t-s} + \delta_{r,2s} \triangle d_{r,t-s} \right) \right\} \quad \text{(S10)}$$

where $z_{rt} = z_t \times \mathbf{1}\{\pi_t = \pi_r\}$, $h^*_{r,t-s} = h^*_{t-s} \times \mathbf{1}\{\pi_t = \pi_r\}$, and $d_{r,t-s} = d_{t-s} \times \mathbf{1}\{\pi_t = \pi_r\}$. To obtain consistent estimates of aggregate wages and individual wage fixed effects define the log wage residuals from (S10) as:

$$\hat{u}^w_t = \ln \widetilde{w}_t - \sum_{r=1}^{3} \left\{ \triangle z_{rt} \hat{B}_{r,3} + \sum_{s=1}^{\rho_w} \left(\hat{\delta}_{r,1s} \triangle h^*_{r,t-s} + \hat{\delta}_{r,2s} \triangle d_{r,t-s} \right) \right\} \quad \text{(S11)}$$

Adding the individual subindex n to the notation, we begin by obtaining a biased estimate of the aggregate effect at the initial year τ_0:

$$\widehat{\ln \omega}_{\tau_0} = \frac{\sum_n \sum_t \mathbf{I}\{d_{nt} = 1, \tau_{nt} = \tau_0\} \hat{u}^w_{nt}}{\sum_n \sum_t \mathbf{I}\{d_{nt} = 1, \tau_{nt} = \tau_0\}} \quad \text{(S12)}$$

This estimator is biased because the residual wages also contain the individual fixed effect and $E[\ln \mu_n | d_{nt} = 1, \tau_{nt} = \tau_0]$ may not be equal to zero. We will correct for the bias at the end of the procedure. For any $\tau > \tau_0$, we estimate the aggregate effect sequentially as:

$$\widehat{\ln \omega}_\tau = \widehat{\ln \omega}_{\tau-1} + \widehat{\triangle \ln \omega}_\tau \quad \text{(S13)}$$

Next we estimate individual fixed effects as:

$$\widehat{\ln \mu}_n = \frac{\sum_t \mathbf{I}\{d_{nt} = 1\} (\hat{u}^w_{nt} - \widehat{\ln \omega}(\tau_{nt}))}{\sum_t \mathbf{I}\{d_{nt} = 1\}} \quad \text{(S14)}$$

Finally, we correct for the estimation bias using the following estimators:

$$\widetilde{\ln \omega_\tau} = \widehat{\ln \omega_\tau} + \sum_{n'} \widehat{\ln \mu_{n'}} \tag{S15}$$

$$\widetilde{\ln \mu_n} = \widehat{\ln \mu_n} - \sum_{n'} \widehat{\ln \mu_{n'}} \tag{S16}$$

Stage II: dynamic index $A_t(x_t)$. Using equation (26) the log ratio of conditional choice probabilities is:

$$\begin{aligned}\ln\left(\frac{p_{1t}(x_t)}{p_{kt}(x_t)}\right) =& \overline{u}_1(x_t) - (B_t - 1)\ln\left[\int A_{t+1}(x_{t+1})g_1(x_{t+1}|x_t)dx_{t+1}\right] \\ &- \left(\overline{u}_k(x_t) - (B_t - 1)\ln\left[\int\left(\int A_{t+1}(x_{t+1})g_{kh}(x_{t+1}|x_t)dx_{t+1}\right)q_k(h|x_t)dh\right]\right)\end{aligned} \tag{S17}$$

Applying the exponential function, elevating to the power of $1/B_t$, and rearranging terms yields:

$$\begin{aligned}&\left(\frac{p_{1t}(x_t)}{p_{kt}(x_t)}\right)^{1/B_t} \exp\left\{\frac{-\overline{u}_1(x_t)}{B_t}\right\}\left[\int A_{t+1}(x_{t+1})g_1(x_{t+1}|x_t)dx_{t+1}\right]^{1-1/B_t} = \\ &\exp\left\{\frac{-\overline{u}_k(x_t)}{B_t}\right\}\left[\int\left(\int A_{t+1}(x_{t+1})g_{kh}(x_{t+1}|x_t)dx_{t+1}\right)q_k(h|x_t)dh\right]^{1-1/B_t}\end{aligned} \tag{S18}$$

Substituting the left hand side of (S18) into equation (25) yields:

$$A_t\left(x_t\right) = \sum_{k\in C_t} p_{kt}\left(x_t\right) E\left[\exp\left(\frac{-\varepsilon^*_{kt}}{B_t}\right)\middle| x_t\right]\left(\frac{p_{1t}(x_t)}{p_{kt}(x_t)}\right)^{1/B_t}\exp\left\{\frac{-\overline{u}_1(x_t)}{B_t}\right\}\left[\int A_{t+1}(x_{t+1})g_1(x_{t+1}|x_t)dx_{t+1}\right]^{1-1/B_t} \tag{S19}$$

Using the results in the Online Appendix of Gayle, Golan, and Miller (2015) further yields:

$$A_t\left(x_t\right) = p_{1t}(x_t)^{1/B_t}\Gamma\left(\frac{B_t+1}{B_t}\right)\exp\left\{\frac{-\overline{u}_1(x_t)}{B_t}\right\}\left[\int A_{t+1}(x_{t+1})g_1(x_{t+1}|x_t)dx_{t+1}\right]^{1-1/B_t} \tag{S20}$$

Using (S20) to substitute recursively onto its right hand side yields A_t as a recursive integration over the distribution of observables:

$$
\begin{aligned}
A_t\left(x_t\right) = &\prod_{s=0}^{T-t}\left[\Gamma\left(\frac{B_{t+s}+1}{B_{t+s}}\right)\exp\left\{-\bar{\bar{u}}_1(x_t^{(1,s)})\right\}\right]^{\chi_t(s)} p_{1t}(x_t)^{\frac{1}{B_t}} \\
&\times\left[\int p_{1t+1}^{1/B_{t+1}}\exp\left\{-\tilde{\tilde{u}}_1(x_{t+1})\right\}\times\left[\int p_{1t+2}^{1/B_{t+2}}\exp\left\{-\tilde{\tilde{u}}_1(x_{t+2})\right\}\times\cdots\right.\right. \\
&\times\left[\int p_{1T}^{1/B_T}\exp\left\{-\tilde{\tilde{u}}_1(x_T)\right\}dG_1(x_T|x_{T-1})\right]^{1-\frac{1}{B_{T-1}}}\times dG_1(x_{T-1}|x_{T-2})\Bigg]^{1-\frac{1}{B_{T-2}}}\times\cdots \\
&\left.\left.\times\, dG_1(x_{t+2}|x_{t+1})\right]^{1-\frac{1}{B_{t+1}}}\times dG_1(x_{t+1}|x_t)\right]^{1-\frac{1}{B_t}}
\end{aligned}
\tag{S21}
$$

where $\bar{\bar{u}}_1(x_t^{(1,s)}) \equiv \sum_{r=0}^{\rho_l}\delta_r l_{t+s}^{(1)} l_{t+s-r}^{(1)}$, $l_{t+s}^{(1)}$ is the leisure at period $t+s$ that results from not working from t until $t+s$ given state x_t at t, $\tilde{\tilde{u}}_1(x_{t+s}) \equiv z_{t+s}B_1 l_t + \rho Y_1(x_{t+s})$; and $dG_1(x_{t+s}|x_{t+s-1}) \equiv g_1(x_{t+s}|x_{t+s-1})dx_{t+s}$.

Stage II: estimation process. Here we explain further the second stage of the estimator process. For each guess in the parameter space $\{\theta_1, \theta_\xi\}$ the estimator entails three main steps:

1. *Obtain the index $A_t(x_t)$.* We do this recursively using equation (S20) in Appendix C and the fact that $A_{T^R+1}(x_{T^R+1}) \equiv 1$. At each age t, we project the index on the state and obtain a vector of ancillary parameters. We then use this ancillary parameters to compute future expectations when calculating the index at age $t-1$. This procedure results in a matrix of age-specific ancillary parameters describing the index $A_{t+1}(x_{t+1})$.

2. *Solve for optimal hours h_t^o.* In order to reduce simulation noise we first obtain 10 independent draws of ξ_{kt} for each of the N_1 observations of working women in the sample. Then we use the Euler equation in (27) to define the function:

$$S_{kt}(h;x_t,\xi_{kt},\theta_1,\theta_\xi) = -\xi_{kt} - \alpha w(x_t)\left(1+\iota(\pi)\frac{\partial h^{\ell}_{2t}}{\partial h}\right)\left(1-\pi_2^{tax}(x_t)\pi_{1k}^{tax}(x_t)W_k(h,x_t)^{\pi_2^{tax}(x_t)-1}\right)$$
$$+\left(z_t'B_1 + 2\delta_0 l_{kt} + \sum_{s=1}^{\rho_l}\delta_s l_{t-s}\right)$$
$$+\left(\frac{(B_t-1)}{\int A_{t+1}(x_{t+1};\theta_1)g_{kh}(x_{t+1}|x_t)dx_{t+1}}\times \int\left[\frac{\partial A_{t+1}(x_{t+1};\theta_1)}{\partial h} + \frac{A_{t+1}(x_{t+1};\theta_1)}{g_{kh}(x_{t+1}|x_t)}\frac{\partial g_{kh}(x_{t+1}|x_t)}{\partial h}\right]g_{kh}(x_{t+1}|x_t)dx_{t+1}\right), \quad \text{for } k=2,4 \tag{S22}$$

which yields the deviation of the Euler equation from zero, for a given value of hours h. The optimal value of hours h^o is obtained when $S_{kt}(h^o;x_t,\xi_{kt},\theta_1,\theta_\xi)=0$. To reduce computational time, for each observation coupled with each of its ten draws of ξ_{kt} we solve for the function S_{kt} in a grid of hours using numerical derivatives for $\frac{\partial A_{t+1}}{\partial h}$ and $\frac{\partial g_{kh}}{\partial h}$, and using a smoothed derivative for $\frac{\partial h^{\ell}_{2t}}{\partial h}$ (see details below). Then we interpolate between the points h and h' in the grid around the change in sign of S_{kt} (that is, around the root of the first order condition).

3. *Obtain relative differences*. Using the implied optimal hours we construct a $[R\times 1]$ vector of simulated moments $M^S(\theta_1,\theta_\xi)$. Let M be the $[R\times 1]$ vector of data moments. Then we obtain the $[R\times 1]$ vector of relative differences $E(\theta_1,\theta_\xi;M)$ with rth component equal to $(M_r^S(\theta_1,\theta_\xi)-M_r)/M_r$.

Let W be the $[R\times R]$ diagonal weighting matrix that has on its diagonal the inverse of the variance of the data moments, which we obtain using 200 subsamples with replacement. Hence, the estimator of the parameter vector $\{\theta_1,\theta_\xi\}$ is:

$$\{\hat\theta_1,\hat\theta_\xi\} = \arg\min \; E(\theta_1,\theta_\xi;M)'WE(\theta_1,\theta_\xi;M) \tag{S23}$$

Stage III: differences in conditional value functions. Let $dF_\xi = f_\xi d\xi$ and let ς_{1t} be the current time cost of children conditional on not having a birth today. Hence according to (4):

$$\varsigma_{1t} \equiv \sum_{s=1}^{\rho_c}\phi_s b_{t-s} + \phi\sum_{s=\rho_c+1}^{17} b_{t-s} \tag{S24}$$

The difference in conditional value functions for alternative 2 {work, no birth} is:

$$
\begin{aligned}
V_2(x_t;\theta_2,\cdot) - V_1(x_t;\theta_2,\cdot) = {} & z_t B_0 + \int \Bigg(-z_t \hat{B}_1 h_{2t}(x_t,\xi) + \hat{\delta}_0 \left(h_{2t}^2(x_t,\xi) - 2(1-\varsigma_{1t}) h_{2t}(x_t,\xi) \right) \\
& - \sum_{s=1}^{\rho_l} \hat{\delta}_s h_{2t}(x_t,\xi) l_{t-s} + h_{2t}(x_t,\xi)\xi + \hat{\rho} \left(\Upsilon_2(h_{2t}(x_t,\xi), x_t) - \Upsilon_1(0,x_t) \right) \\
& - (B_t - 1) \ln \frac{\int A_{t+1}(x_{t+1};\hat{\theta}_1) g_{2h}(x_{t+1}|x_t) dx_{t+1}}{\int A_{t+1}(x_{t+1};\hat{\theta}_1) g_1(x_{t+1}|x_t) dx_{t+1}} \Bigg) dF_\xi(\xi;\hat{\theta}_\xi)
\end{aligned} \tag{S25}
$$

The difference in conditional value functions for alternative 3 (no work, birth) is:

$$
\begin{aligned}
V_3(x_t;\theta_2,\cdot) - V_1(x_t;\theta_2,\cdot) = {} & z_t \gamma_0 + \sum_{k=1}^{\rho_b} \gamma_k b_{t-k} + \gamma_b \left(\sum_{k=\rho_b+1}^{17} b_{t-k} \right) - z_t \hat{B}_1 \hat{\phi}_0 \\
& + \hat{\delta}_0 \left(\hat{\phi}_0^2 - 2(1-\varsigma_{1t}) \hat{\phi}_0 \right) - \sum_{s=1}^{\rho_l} \hat{\delta}_s \hat{\phi}_0 l_{t-s} + \hat{\rho} \left(\Upsilon_3(0,x_t) - \Upsilon_1(0,x_t) \right) \\
& - (B_t - 1) \ln \frac{\int A_{t+1}(x_{t+1};\hat{\theta}_1) g_3(x_{t+1}|x_t) dx_{t+1}}{\int A_{t+1}(x_{t+1};\hat{\theta}_1) g_1(x_{t+1}|x_t) dx_{t+1}}
\end{aligned} \tag{S26}
$$

The difference in conditional value functions for alternative 4 (work, birth) is:

$$
\begin{aligned}
V_4(x_t;\theta_2,\cdot) - V_1(x_t;\theta_2,\cdot) = {} & z_t(B_0 + \tilde{\gamma}_0) + \sum_{k=1}^{\rho_b} \gamma_k b_{t-k} + \gamma_b \left(\sum_{k=\rho_b+1}^{17} b_{t-k} \right) \\
& + \int \Bigg(-z_t \hat{B}_1 (\hat{\phi}_0 + h_{4t}(x_t,\xi)) + \hat{\delta}_0 \left((\hat{\phi}_0 + h_{4t}(x_t,\xi))^2 - 2(1-\varsigma_{1t})(\hat{\phi}_0 + h_{4t}(x_t,\xi)) \right) \\
& - \sum_{s=1}^{\rho_l} \hat{\delta}_s (\hat{\phi}_0 + h_{4t}(x_t,\xi)) l_{t-s} + h_{4t}(x_t,\xi)\xi + \hat{\rho} \left(\Upsilon_4(h_{4t}(x_t,\xi), x_t) - \Upsilon_1(0,x_t) \right) \\
& - (B_t - 1) \ln \frac{\int A_{t+1}(x_{t+1};\hat{\theta}_1) g_{4h}(x_{t+1}|x_t) dx_{t+1}}{\int A_{t+1}(x_{t+1};\hat{\theta}_1) g_1(x_{t+1}|x_t) dx_{t+1}} \Bigg) dF_\xi(\xi;\hat{\theta}_\xi)
\end{aligned} \tag{S27}
$$

The integrals over the marginal utility shocks ξ are obtained using Monte Carlo integration with 1,000 independent draws.

Stage III: estimation process. Estimation of $\theta_2 = (B_0, \gamma_0, \tilde{\gamma}_0, \gamma_1, ..., \gamma_6)$ is based on the four discrete choices of the problem and it takes as given the first- and second-stage parameters. We maximize the following quasi log-likelihood function:

$$
\ln L(\theta_2,\cdot) = \sum_i \sum_t \sum_{k \in C_t} d_{kit} \ln p_{kit}(x_{it}|\theta_2,\cdot) \tag{S28}
$$

where the second argument of the likelihood and CCPs are the parameters from previous stages. For any available alternative $k \in C_t$ the CCPs implied by the model are:

$$p_{kit}(x_{it}|\theta_2,\cdot) = \frac{\exp\left(V_{kit}\left(x_{it}|\theta_2,\cdot\right) - V_{1it}\left(x_{it}|\theta_2,\cdot\right)\right)}{\sum_{j\in C_t}\exp\left(V_{jit}\left(x_{it}|\theta_2,\cdot\right) - V_{1it}\left(x_{it}|\theta_2,\cdot\right)\right)}. \tag{S29}$$

The differences in conditional value functions V_{kit} implied by (26) are presented in equations (S25), (S26) and (S27) in Appendix C.

Standard errors. We correct our standard errors to account for the three-stage estimation process using subsampling with 100 subsamples. Each subsample draws 90 percent of the unique individuals with replacement. During the correction of the standard errors we take the tax-welfare schedules as given and fix the ancillary parameters (tightness of the marriage market, adulthood transition, individual wage effects, aggregate wage effects, and aggregate non-labor income effects). For each of the 100 subsamples we repeat the three-stage estimation process. Since the second-stage of estimation uses a parallelized global optimization search algorithm (particle swarm) with 100 cores, each of the 100 subsamples repeats this procedure, hence requiring a total of 10,000 (100 x 100) cores in parallel. The corrected standard errors are

$$SE(\hat{\Theta}) \approx SDV(\hat{\Theta}^{(s)})\sqrt{0.9} \tag{S30}$$

where $SDV(\hat{\Theta}^{(s)})$ is the standard deviation across all 100 subsample estimates $\hat{\Theta}^{(s)}$.

Smoothed derivatives of indicator functions. We smooth the derivatives of indicator functions (e.g. for paid leave takeup) using the smoothing function:

$$J(x \geq a) \equiv \left(1 + e^{(-\tilde{m}*(x-a))}\right)^{-1} \tag{S31}$$

with smoothing parameter $\tilde{m}$ (which we set at 200). We smooth indicator functions as follows:

$$\mathbf{I}\{x \geq a\} \approx J(x \geq a) \tag{S32}$$

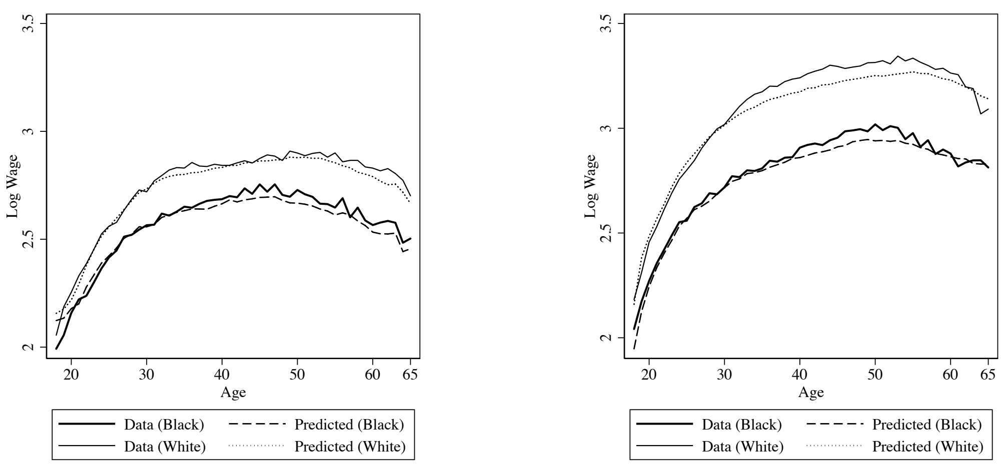
$$\mathbf{I}\{a \leq x \leq b\} \approx J(x \geq a) - J(x \geq b) \tag{S33}$$

Hence, the smoothed derivative of an indicator function is given by:

$$\frac{d}{dx}\mathbf{I}\{x \geq a\} \approx \frac{d}{dx}J(x \geq a)$$
$$= \tilde{m} * e^{(-\tilde{m}*(x-a))} * \left(1 + e^{(-\tilde{m}*(x-a))}\right)^{-2} \quad \text{(S34)}$$

D Results Appendix

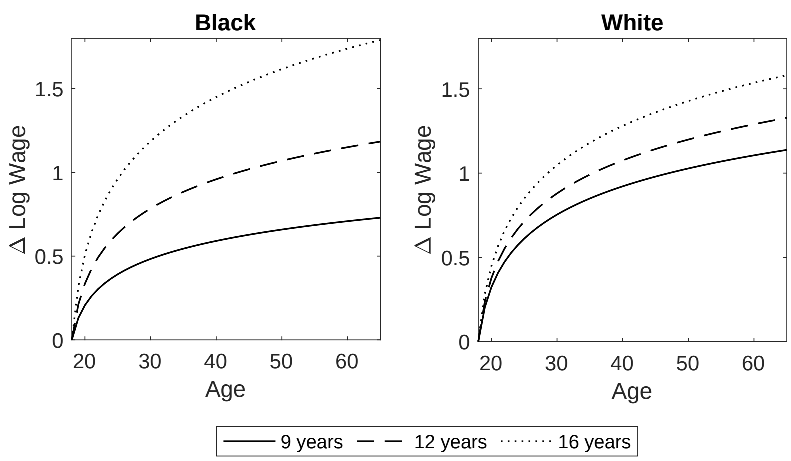
D.1 First-Stage Results



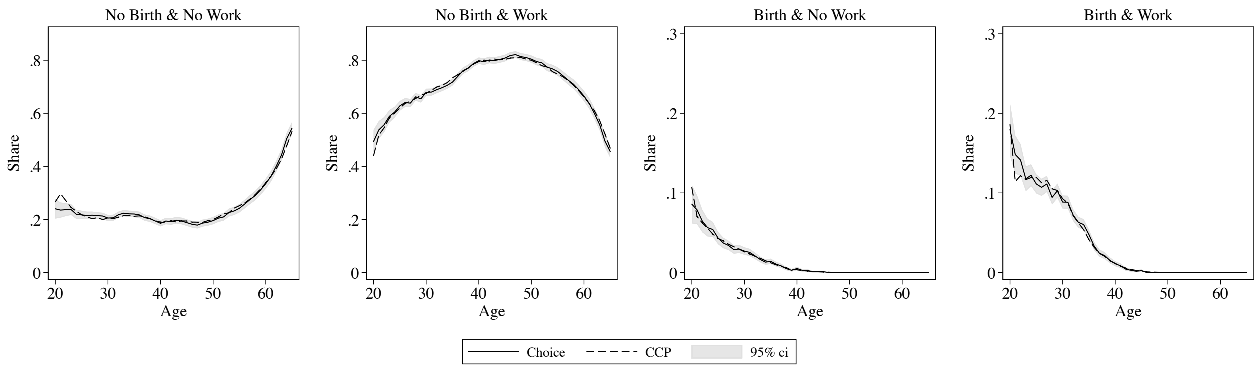
(a) Women (b) Men

Appendix Figure S2: Log Wage Equation Fit

Notes: Predicted log wages (women and men) over the life cycle given the estimates in Tables 6 and S5. Log wages in dollars indexed to 2015.



Appendix Figure S3: Log Wages Returns to Human Capital by Years of Education (Men)
Notes: Contribution to log wages from years of potential experience (age - 17) indexed to 2015, by years of education.



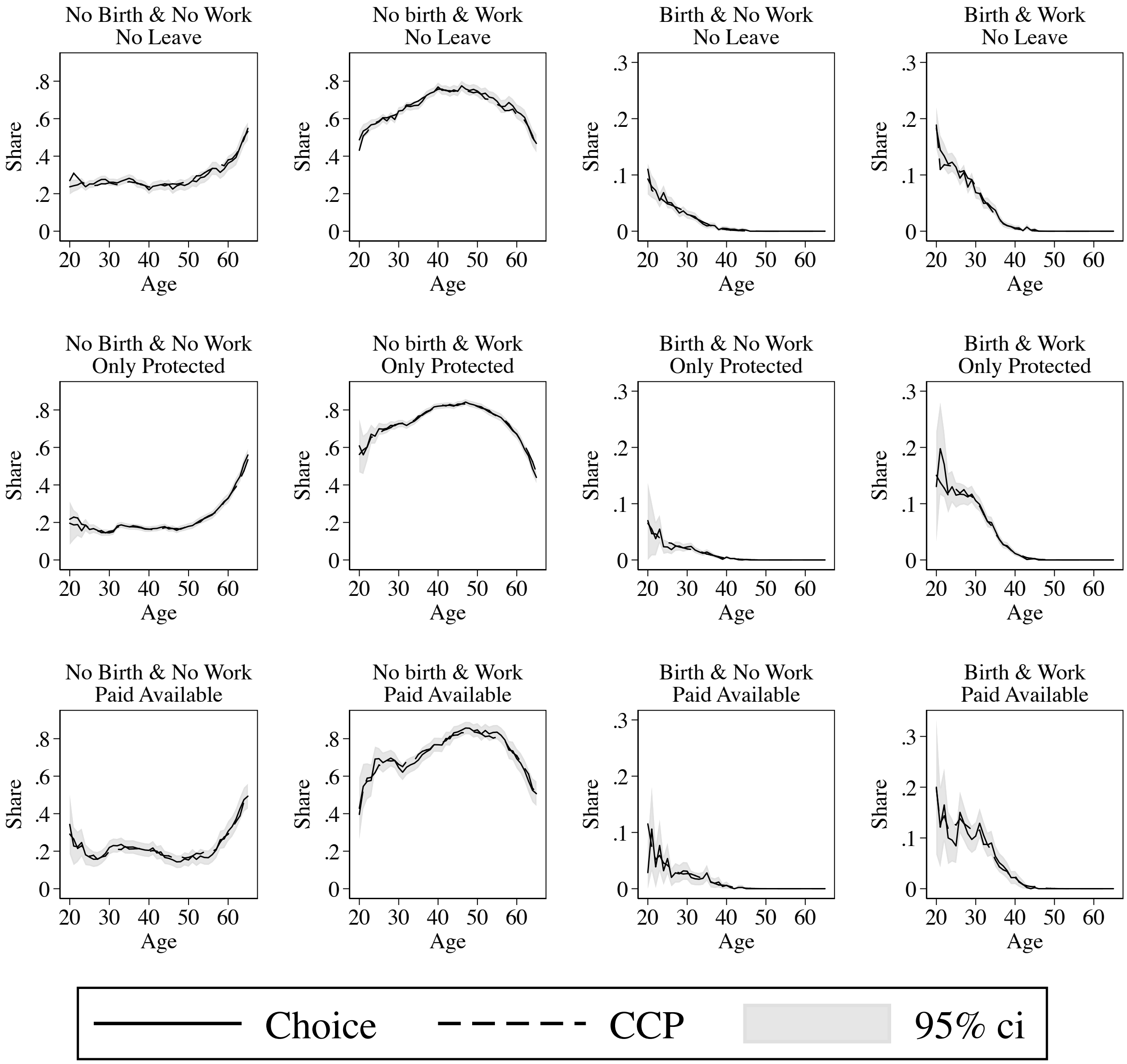
(a) Over the Life Cycle

(b) Over Time

Appendix Figure S4: Fit of Reduced Form CCPs

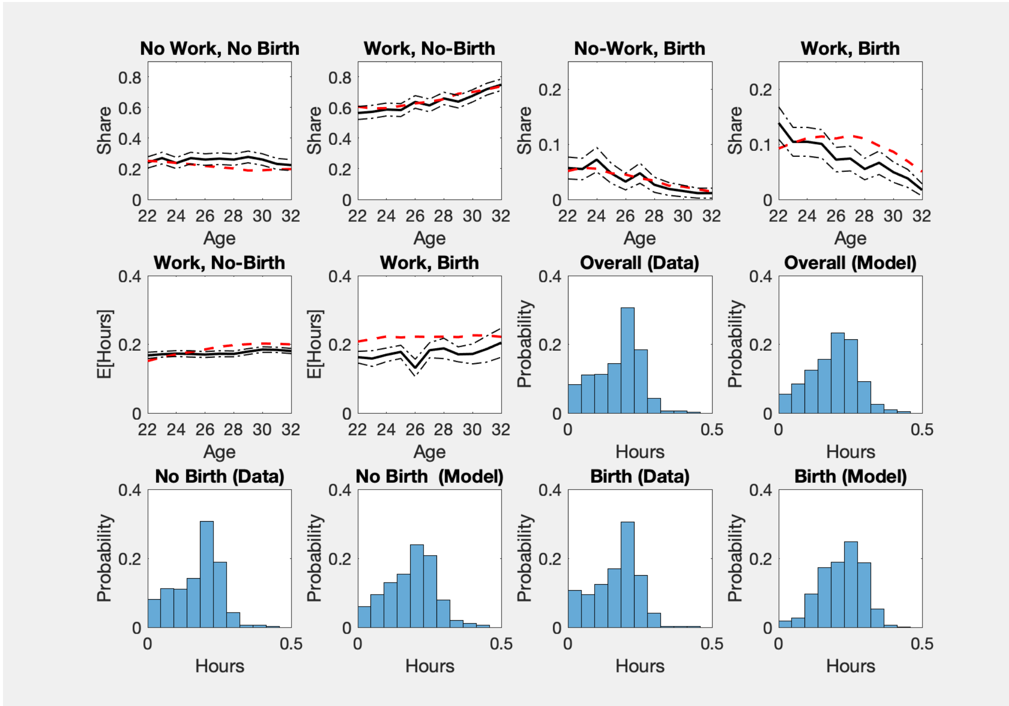
Notes: Estimated CCPs and observed shares of choices over the life cycle and over time.

Figure S4 shows that the ancillary reduced-form CCPs fully capture both the life cycle and the aggregate trends. The aggregate trend is particularly reassuring as we do not include year fixed effects. Instead, the close fit of the CCPs to the aggregate trends suggests that the variables describing the policy environment (π_t) and the additional aggregate components of the state vector, $\underline{\omega}_t$ in equation (18), sufficiently describe the aggregate environment. Crucially, the reduced-form CCPs also fit well the variation in choices caused by the quasi-experimental variation in leave policies (Figure S5).

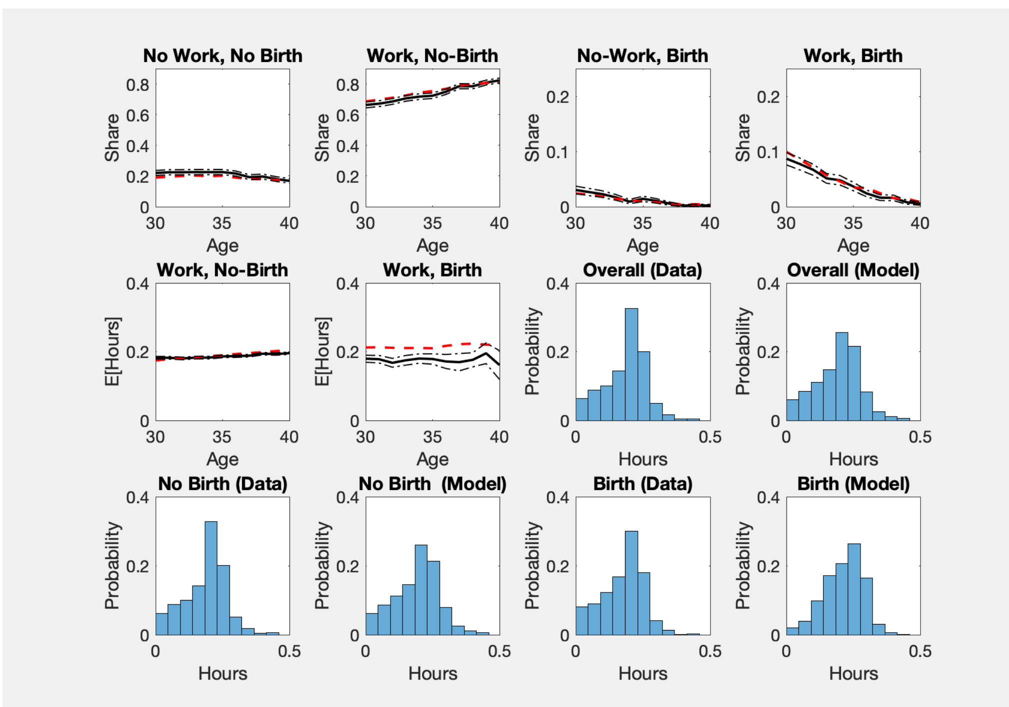


Appendix Figure S5: Fit of Reduced Form CCPs by Leave Policy Regime

Notes: Estimated CCPs and observed shares of choices over the life by leave policy regime.



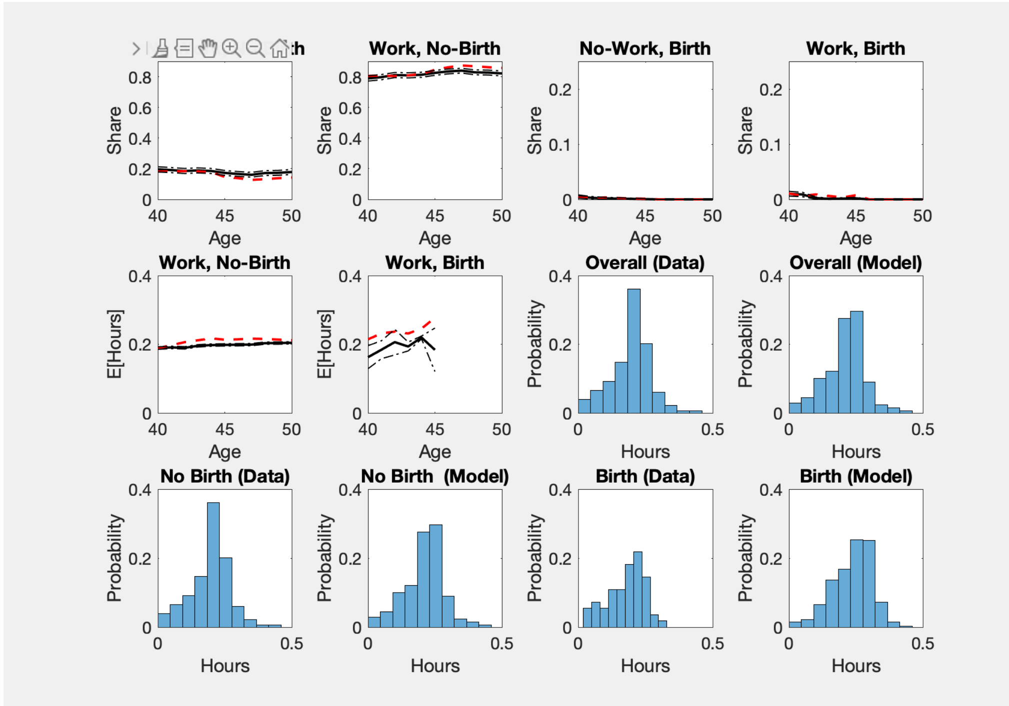
(a) Initial Condition at Age 22



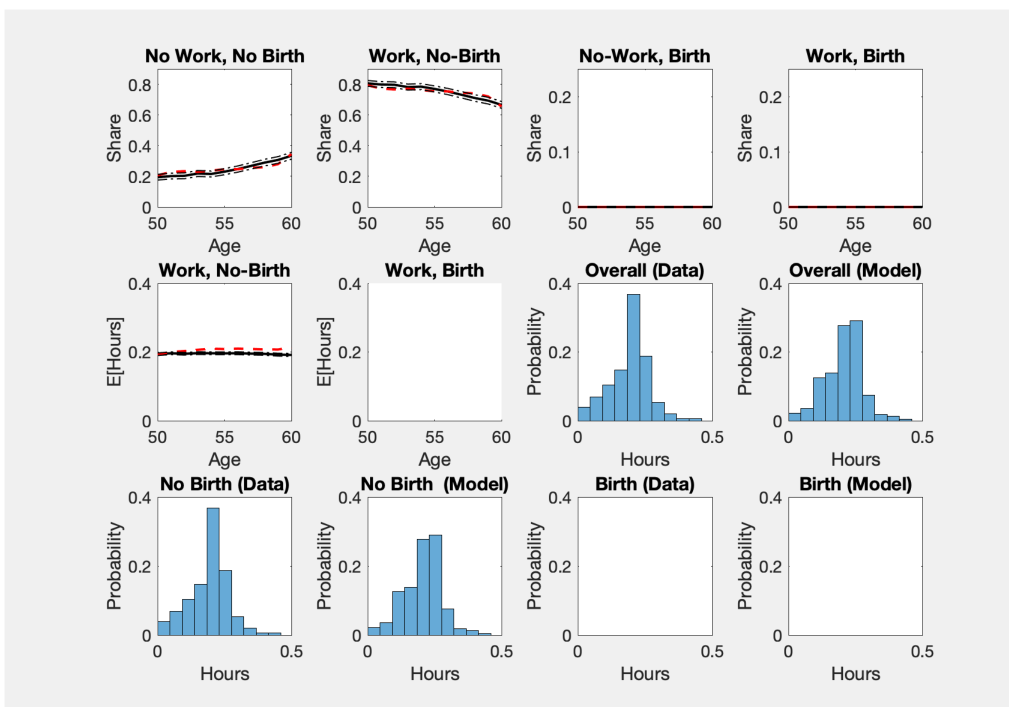
(b) Initial Condition at Age 30

Appendix Figure S6: Dynamic Model Fit I

Notes: To provide a more stringent measure of fit that takes into account the dynamics generated by the model, we create subsamples of individuals who are observed continuously from a given age *t* and ten years into the future. For this subsamples we take the initial state as given and simulate forward using the model. Hours are scaled to annual hours by dividing them by (24*365). We use age 22 as the first initial condition to guarantee enough observations.



(a) Initial Condition at Age 40



(b) Initial Condition at Age 50

Appendix Figure S7: Dynamic Model Fit II

Notes: To provide a more stringent measure of fit that takes into account the dynamics generated by the model, we create subsamples of individuals who are observed continuously from a given age *t* and ten years into the future. For this subsamples we take the initial state as given and simulate forward using the model. Hours are scaled to annual hours by dividing them by (24*365).

Appendix Table S3: Model Fit - Conditional Continuous Choices (Hours)

	Work		Work, No Birth		Work, Birth	
	Data	Model	Data	Model	Data	Model
All	0.193	0.193	0.193	0.193	0.177	0.189
$Age \leq 45$	0.191	0.189	0.192	0.189	0.177	0.189
$Age > 45$	0.197	0.200	0.197	0.200	-	-
$<$ *College*	0.190	0.190	0.190	0.190	0.172	0.188
$\geq$ *College*	0.200	0.200	0.201	0.200	0.186	0.192
Black	0.197	0.199	0.197	0.199	0.180	0.195
White	0.191	0.189	0.191	0.190	0.175	0.187
Single	0.205	0.201	0.206	0.202	0.178	0.183
Partnered	0.188	0.189	0.188	0.189	0.177	0.190

Notes: Average hours in the data versus averages simulated hours given the observed state. These measures of fit take the state of each observation in the data as given and simulate current choices. Hours are scaled to annual hours by dividing them by (24*365).

Appendix Table S4: Model Fit - Conditional Discrete Choices

	No Work, No Birth		Work, No Birth		No Work, Birth		Work, Birth	
	Data	Model	Data	Model	Data	Model	Data	Model
$Age \leq 45$	0.194	0.192	0.742	0.744	0.016	0.016	0.048	0.048
$Age > 45$	0.264	0.268	0.736	0.732	0.000	0.000	0.000	0.000
$<$ *College*	0.250	0.250	0.713	0.713	0.010	0.011	0.026	0.027
$\geq$ *College*	0.138	0.140	0.812	0.812	0.009	0.008	0.041	0.040
Black	0.231	0.231	0.733	0.733	0.010	0.010	0.027	0.027
White	0.214	0.214	0.744	0.744	0.010	0.010	0.032	0.032
Single	0.196	0.196	0.783	0.783	0.006	0.006	0.015	0.015
Partnered	0.229	0.229	0.723	0.723	0.012	0.012	0.036	0.036

Notes: Shares in the data versus averages choice probabilities evaluated at the observed state. These measures of fit take the state of each observation in the data as given and simulate current choices.

Appendix Table S5: Wage Equation (Men)

$$\ln(w'_{nt}) = \ln(\omega'_t) + \ln(\mu(ed'_n, race_n)) + B(ed')\ln(t-17)$$

		Black		*White*	
variable	parameter	est.	se	est.	se
Potential experience $(t-17)\times$					
High school or less	B_1	0.293	(0.011)	0.343	(0.008)
Some college	B_2	0.386	(0.014)	0.338	(0.011)
College or more	B_3	0.422	(0.028)	0.445	(0.011)

Notes: Estimation of the wage equation for men in (13). We tested for interactions of the parameters with policy regimes and found no statistically significant interactions. Total observations: 173,367 total, 48,850 black, 124,517 white. "est." stands for estimate and "se" stands for standard errors. Standard errors corrected for three-stage estimation.

Appendix Table S6: Full Time Work: Single Men

variable	est.	se	Δp (%)
Constant	-3.177	(0.155)	
Age	0.327	(0.004)	7.776
Age^2	-0.004	(5.1E-05)	
Some college	0.397	(0.017)	4.573
College or more	0.633	(0.022)	6.696
Black	-0.837	(0.018)	-8.233
Tax Policy			
Lump sum (π_{00}^{tax})	1.6E-04	(1.5E-05)	-2.222
Lump sum*kids (π_{01}^{tax})	-5.2E-05	(1.5E-05)	0.518
Slope (π_{10}^{tax})	4.122	(0.328)	2.473
Slope*kids (π_{11}^{tax})	-1.816	(2.069)	-0.100
Progressivity (π_{2}^{tax})	-0.389	(0.105	-0.709
Maternity Leave Policy			
State has a policy	0.334	(0.047)	4.943
Required hours	-6.1E-05	(3.7E-05)	-0.465
Protected weeks	-0.013	(0.003)	-1.033
Paid weeks	0.003	(0.008)	0.132
Replacement rate	-0.175	(0.137)	-0.443
Observations	56,687		

Notes: Estimates from a logit regression of the probability of full-time work for single men. "est." stands for estimate and "se" stands for standard errors. Standard errors corrected for three-stage estimation. Column Δp is the approximated change in the probability (in percentage points) from an increase of one standard deviation in the regressor (or a unit change from zero for binary variables) evaluated at the average for continuous variables. *Rows*: for states with two-tier leave policies we average the policy characteristics (required hours, protected or paid weeks, reimbursement rate) across both tiers. Lump sump variables are negatively signed. Unconditional probability is 80.8%.

Appendix Table S7: Full Time Work: Men in Partnership (Married or Cohabiting)

variable	est.	se	Δp (%)
Constant	-4.299	(0.220)	
Own Variables			
$d_{n,t-1}$	5.208	(0.016)	9.072
Age	0.072	(0.005)	-1.183
Age^2	-0.002	(5.2E-05)	
Some college	0.186	(0.019)	0.297
College or more	0.538	(0.020)	0.730
Black	-0.407	(0.017)	-0.586
Tax Policy			
Lump sum (π_{00}^{tax})	-3.5E-05	(4.4E-06)	0.172
Lump sum*kids (π_{01}^{tax})	-6.2E-06	(1.6E-05)	0.007
Slope (π_{10}^{tax})	-0.168	(0.268)	-0.015
Slope*kids (π_{11}^{tax})	14.421	(4.709)	0.046
Progressivity (π_{2}^{tax})	1.8613	(0.1169)	0.352
Spouse: Maternity Leave Variables			
Protected leave rolled	-3.564	(1.415)	-0.036
Paid leave rolled	-6.489	(2.563)	-0.022
Applies for tier 1	0.249	(0.027)	0.386
Applies for tier 2	0.569	(0.056)	0.762
Protected hours available	-4.839	(0.540)	-0.247
Paid hours available	-3.186	(1.355)	-0.065
Replacement rate	-0.056	(0.098)	-0.017
Spouse: Other Variables			
Education	0.044	(0.004)	0.178
$d_{n,t-1}$	0.001	(0.034)	0.002
$d_{n,t-2}$	0.172	(0.032)	0.325
$d_{n,t-3}$	-0.073	(0.035)	-0.123
$d_{n,t-4}$	0.252	(0.027)	0.497
$h_{n,t-1}$	0.498	(0.160)	0.089
$h_{n,t-2}$	-1.053	(0.162)	-0.189
$h_{n,t-3}$	0.512	(0.203)	0.092
$h_{n,t-4}$	-0.669	(0.132)	-0.121
$b_{n,t-1}$	0.089	(0.046)	0.162
$b_{n,t-2}$	-0.247	(0.032)	-0.485
$b_{n,t-3}$	-0.331	(0.030)	-0.679
$b_{n,t-4}$	-0.177	(0.031)	-0.337
Number of kids	3.3E-04	(0.004)	0.001
Labor productivity μ	-0.003	(0.014)	-0.003
Observations	112,504		

Notes: Estimates from a logit regression of the probability of full-time work for partnered men. "est." stands for estimate and "se" stands for standard errors. Standard errors corrected for three-stage estimation. Column Δp is the approximated change in the probability (in percentage points) from an increase of one standard deviation in the regressor (or a unit change from zero for binary variables) evaluated at the average for continuous variables. Lump sump variables are negatively signed. Unconditional probability is 93.3%.

Appendix Table S8: Any Non-Labor Income

Panel A: Singles

variable	est.	se	Δp (%)
Constant	-0.239	(0.086)	
Any Non-Labor Income$_{t-1}$	3.151	(0.008)	63.119
Age	-0.009	(0.001)	
Age^2	2.0E-04	(1.5E-05)	0.636
Education	-0.129	(0.012)	
Education^2	0.006	(4.7E-04)	0.367
Black	-0.373	(0.009)	-4.161
Observations	78,444		

Panel B: Partnered

variable	est.	se	Δp (%)
Constant	-0.587	(0.049)	
Any Non-Labor Income$_{t-1}$	2.639	(0.006)	57.593
Age	-0.035	(0.002)	2.617
Age^2	0.001	(2.0E-05)	
Education	-0.067	(0.006)	1.286
Education^2	0.004	(2.4E-04)	
Black	-0.428	(0.005)	-7.367
Spouse Type			
Spouse has some college	0.117	(0.008)	1.703
Spouse has college or more	0.349	(0.009)	4.721
Observations	178,812		

Notes: Estimates from two logit regressions of the probability of having any non-labor income conditional on being single or in a partnership (married or cohabiting) this period, respectively. "est." stands for estimate and "se" stands for standard errors. Standard errors corrected for three-stage estimation. Column Δp is the approximated change in the probability (in percentage points) from an increase of one standard deviation in the regressor (or a unit change from zero for binary variables) evaluated at the average for continuous variables. Unconditional probability: singles 70.3, partnered 64.4.

Appendix Table S9: Log of Non-Labor Income

	Singles		*Partnered*	
	est.	se	est.	se
Any Non-Labor Income$_{t-1}$	-6.533	(0.019)	-6.117	(0.012)
Non-Labor Income$_{t-1}$ (if any)	0.789	(0.002)	0.751	(0.001)
Age	0.013	(4.7E-04)	0.016	(0.001)
Age^2	-6.2E-05	(4.3E-06)	-4.0E-06	(6.0E-06)
Education	0.040	(0.003)	0.014	(0.003)
Education^2	-0.002	(1.4E-04)	-3.9E-04	(1.3E-04)
Black	0.063	(0.004)	0.092	(0.004)
Spouse has some college			-0.017	(0.004)
Spouse has college or more			-0.018	(0.004)
Constant	7.603	(0.024)	7.401	(0.026)
Variance Residuals	1.116	(0.004)	1.323	(0.002)

Notes: Table presents separate regressions of the log of non-labor income for singles and partnered, respectively; "est." stands for estimate and "se" stands for standard errors. Standard errors corrected for three-stage estimation.

Appendix Table S10: Match Conditional on Newly-formed Partnership

	Spouse (Men) Education Types						
	Type I: ≤ 12	Type II: (12,16)			Type III: ≥ 16		
variable	Δp (%)	est.	se	Δp (%)	est.	se	Δp (%)
Constant		-15.528	(2.372)		12.649	(3.773	
Age	-6.226	0.059	(0.010)	2.017	0.095	(0.012)	4.209
Age^2		-0.001	(1.3E-04)		-0.001	(1.6E-04)	
Education	-20.359	1.104	(0.202)	10.574	-1.197	(0.279)	9.786
Education^2		-0.025	(0.005)		0.010	(0.005)	
Black	10.359	-0.244	(0.031)	-1.657	-0.844	(0.037)	-8.702
$d_{n,t-1}$	2.321	0.028	(0.047)	2.069	-0.420	(0.060)	-4.390
$d_{n,t-2}$	1.313	-0.023	(0.048)	-0.023	-0.150	(0.064)	-1.289
$d_{n,t-3}$	0.376	0.007	(0.054)	0.406	-0.086	(0.063)	-0.782
$d_{n,t-4}$	-0.301	-0.022	(0.052)	-0.854	0.135	(0.061)	1.155
$h_{n,t-1}$	0.006	-0.457	(0.287)	-1.577	1.504	(0.352)	1.572
$h_{n,t-2}$	-1.331	0.707	(0.299)	1.747	-0.194	(0.355)	-0.417
$h_{n,t-3}$	-0.452	-0.016	(0.311)	-0.296	0.793	(0.396)	0.748
$h_{n,t-4}$	2.050	-0.919	(0.252)	-2.049	-0.320	(0.361)	0.000
$b_{n,t-1}$	0.857	-0.013	(0.060)	0.059	-0.116	(0.098)	-0.916
$b_{n,t-2}$	-0.612	0.018	(0.060)	0.248	0.048	(0.107)	0.364
$b_{n,t-3}$	7.119	-0.312	(0.068)	-5.668	-0.280	(0.121)	-1.451
$b_{n,t-4}$	2.560	-0.018	(0.062)	0.772	-0.475	(0.122)	-3.332
Number of kids	4.747	-0.087	(0.013)	-1.334	-0.313	(0.020)	-3.413
Individual productivity, μ	-6.980	0.492	(0.031)	4.462	0.726	(0.038)	2.517
Marriage Market							
Men to women ratio ($\geq$ college)	-2.163	-0.594	(0.511)	1.517	-5.563	(0.913)	0.647
Education $\times$ Men to women ratio ($\geq$ college)		0.065	(0.041)		0.430	(0.064)	
Men to women ratio ($<$ college)	-0.395	2.702	(1.867)	1.721	-17.797	(2.757)	-1.326
Education $\times$ Men to women ratio ($<$ college)		-0.138	(0.136)		1.163	(0.187	
Maternity Leave Variables							
Protected leave rolled	0.050	-3.451	(3.029)	-0.500	9.621	(4.063)	0.451
Paid leave rolled	2.415	47.83	(65.28)	3.127	-511.01	(63.19)	-5.542
Applies for tier 1	-0.068	0.000	(0.056)	-0.036	0.012	(0.069)	0.104
Applies for tier 2	4.307	-0.162	(0.105)	-2.752	-0.249	(0.113)	-1.555
Protected hours available	0.188	1.014	(1.093)	0.984	-4.576	(1.179)	-1.172
Paid hours available	0.104	2.359	(2.680)	0.827	-9.609	(2.573)	-0.931
Replacement rate	-2.030	0.337	(0.161)	0.698	1.041	(0.198)	1.332
Tax Policy Unmarried							
Lump sum (π_{00}^{tax})	-11.077	-2.3E-04	(5.8E-05)	12.717	-4.9E-06	(6.6E-05)	-1.660
Lump sum*kids (π_{01}^{tax})	1.791	1.9E-04	(4.0E-05)	-2.792	-1.2E-04	(4.8E-05)	1.001
Slope (π_{10}^{tax})	3.995	-4.798	(1.000)	-4.880	0.551	(1.025)	0.884
Slope*kids (π_{11}^{tax})	-0.267	10.995	(7.185)	0.384	-5.119	(7.916)	-0.117
Progressivity (π_{2}^{tax})	-3.061	1.193	(0.343)	2.798	0.674	(0.399)	0.263
Tax Policy Married							
Lump sum (π_{00}^{tax})	4.567	8.1E-05	(2.1E-05)	-3.987	5.5E-05	(2.8E-05)	-0.593
Lump sum*kids (π_{01}^{tax})	0.274	-2.1E-05	(5.7E-05)	0.559	1.4E-04	(6.8E-05)	-0.835
Slope (π_{10}^{tax})	-4.774	4.486	(0.992)	4.010	3.477	(1.207)	0.765
Slope*kids (π_{11}^{tax})	-1.429	39.86	(17.29)	1.149	35.29	(18.80)	0.280
Progressivity (π_{2}^{tax})	-2.347	0.995	(0.453)	2.445	0.250	(0.533)	-0.098
Observations	4,337						

Notes: Estimates from a multinomial logit regression of spouse type (education) on state variables, conditional on being single in $t-1$ and being in a partnership in t. "est." stands for estimate and "se" stands for standard errors. Standard errors corrected for three-stage estimation. Column Δp is the approximated change in the probability (in percentage points) from an increase of one standard deviation in the regressor (or a unit change from zero for binary variables) evaluated at the average for continuous variables. Lump sump variables are negatively signed. Unconditional probabilities: Type I 52.3, Type II 24.6, Type III 23.1.

Appendix Table S11: Marriage Conditional on Cohabiting and Not Separating

variable	est.	se	Δp (%)
Constant	-3.702	(0.559)	
Age	-0.051	(0.010)	-1.584
Age^2	2.6E-04	(1.4E-04)	
Education	0.037	(0.026)	0.636
Education^2	0.001	(0.001)	
Black	-0.697	(0.029)	-4.183
Individual Productivity, μ	0.284	(0.034)	0.807
Spouse Type			
Spouse has some college	0.282	(0.035)	1.394
Spouse has college or more	0.607	(0.039)	3.489
Tax Policy Unmarried			
Lump sum (π_{00}^{tax})	-8.6E-05	(6.2E-05)	0.411
Lump sum*kids (π_{01}^{tax})	-1.4E-04	(4.3E-05)	0.350
Slope (π_{10}^{tax})	-2.347	(1.069)	-0.517
Slope*kids (π_{11}^{tax})	-41.78	(6.60)	-0.836
Progressivity (π_{2}^{tax})	0.629	(0.424)	0.346
Tax Policy Married			
Lump sum (π_{00}^{tax})	3.1E-05	(2.9E-05)	-0.397
Lump sum*kids (π_{01}^{tax})	6.6E-04	(4.1E-05)	-2.016
Slope (π_{10}^{tax})	4.175	(1.059)	1.045
Slope*kids (π_{11}^{tax})	204.55	(16.26)	1.630
Progressivity (π_{2}^{tax})	1.538	(0.579)	0.687
Observations	7,526		

Notes: Estimates from a logit regression of the probability of marriage at t from a logit regression conditional on cohabiting in $t-1$ and being in a partnership in t. "est." stands for estimate and "se" stands for standard errors. Standard errors corrected for three-stage estimation. Column Δp is the approximated change in the probability (in percentage points) from an increase of one standard deviation in the regressor (or a unit change from zero for binary variables) evaluated at the average for continuous variables. Lump sump variables are negatively signed. Unconditional probability is 9.3.

E Counterfactuals Appendix

Descriptives of the simulation sample Table S12 shows comparative descriptives between the simulation sample and the full sample. The simulation sample is balanced in race, education, region, and non labor income (both extensive and intensive margins). Naturally, since the observations of the unique women in the simulation sample are at younger ages, they are less likely to be partnered, have less children on average, are less likely to have worked in the recent past, and are likely to have worked less hours in the recent past conditional on working.

Appendix Table S12: Simulation and Estimation Samples

	Simulation Sample		*Estimation Sample*	
Variable	Mean	SD	Mean	SD
Observations	1,970		10,804	
Black	0.384		0.388	
Age observed	22.24	1.86	31.16	9.40
Education	13.76	2.24	13.51	2.42
Less than high school	0.101		0.105	
High school	0.311		0.325	
Some college	0.286		0.296	
College or more	0.303		0.274	
North Central region	0.235		0.254	
North East region	0.109		0.145	
South region	0.420		0.394	
West region	0.236		0.207	
Individual log-wage producivity μ	0.041	0.478	0.004	0.693
Married	0.591		0.652	
Cohabiting	0.051		0.069	
Partner Education: High school or less	0.575		0.495	
Partner Education: Some college	0.243		0.244	
Partner Education: College or more	0.181		0.261	
Partner participation d'_t	0.969		0.959	
Any non-labor income	0.551		0.575	
Log of non-labor income (given any)	8.597	1.586	8.821	1.750
Number of children	0.723	0.838	1.144	1.280
d_{t-1}	0.783		0.808	
d_{t-2}	0.668		0.773	
d_{t-3}	0.578		0.756	
d_{t-4}	0.447		0.704	
h_{t-1}	0.154	0.078	0.184	0.076
h_{t-2}	0.127	0.081	0.178	0.081
h_{t-3}	0.108	0.073	0.173	0.078
h_{t-4}	0.098	0.075	0.167	0.085

Notes: Comparison between the unique individual observations used for the initial condition of the policy simulations and the first observation for each unique individual in the full estimation sample.

The motherhood penalty. To compute the motherhood penalty we focus on new mothers, in other words, women who were not mothers in the baseline, at the beginning of their labor market career. We follow Flores, Gayle, and Hincapié (2024) and for each regime in the policy grid estimate the following event-study specification using the three years before and the ten years after a birth event:

$$Y_{istk} = \alpha_{PRE}\mathbb{1}_{[-3\leq k<-1]} + \alpha_{POST}\mathbb{1}_{[-1<k\leq 10]} + \sum_{a\in[15,55]} \gamma_l \mathbb{1}[age_{istk} = a] + \boldsymbol{\beta}\mathbf{X}_{it} + \eta_s + \eta_t + \epsilon_{istk} \quad \text{(S35)}$$

where Y_{istk} is the outcome of interest for mother i (earnings, hours worked, employment, and wage), living in state s, in calendar year t for event time k, $\mathbf{X}_{it}$ is a vector of controls at the time of birth, including a quadratic polynomial on education, race, and a categorical variable capturing marital status (married, single, or cohabiting), and η_s and η_t denote state and calendar-year fixed effects. The first two terms on the right-hand side of (S35) represent the pre and post event time indicators, omitting the event-time $k = -1$. Hence, these coefficients can be interpreted relative to the year before a parent's first childbirth. The motherhood penalty is then captured by coefficient α_{POST}.

References

Adda, Jérôme, Christian Dustmann, and Katrien Stevens. 2017. "The Career Costs of Children." *The Journal of Political Economy* 125 (2):293–337.

Albanesi, Stefania, Claudia Olivetti, and Barbara Petrongolo. 2022. "Families, Labor Markets, and Policy." Working Paper 30685, NBER.

Altuğ, Sumru and Robert A. Miller. 1998. "The Effect of Work Experience on Female Wages and Labour Supply." *Review of Economic Studies* 65:45–85.

Arcidiacono, Peter and Robert A. Miller. 2019. "Nonstationary Dynamic Models with Finite Dependence." *Quantitative Economics* 10 (3):853–890.

Athey, Susan and Guido W. Imbens. 2006. "Identification and Inference in Nonlinear Difference-in-Differences Models." *Econometrica* 74 (2):431–497.

Bailey, Martha J, Tanya Byker, Elena Patel, and Shanthi Ramnath. 2024. "The Long-run Effects of California's Paid Family Leave Act on Women's Careers and Childbearing: New Evidence from a Regression Discontinuity Design and U.S. Tax Data." .

Bartel, Ann, Charles Baum, Maya Rossin-Slater, Christoher Ruhm, and Jane Waldfogel. 2014. "California's Paid Family Leave Law: Lessons from the First Decade." Tech. rep., Prepared for the U.S. Department of Labor.

Baum, Charles a and Christoher Ruhm. 2014. *The Effects of Paid Family Leave in California on Labor Market Outcomes*. Cambridge, MA: National Bureau of Economic Research.

Baum, Charles L. 2003. "The effect of State Maternity Leave Legislation and the 1993 Family and Medical Leave Act on Employment and Wages." *Labour Economics* 10 (5):573–596.

Billari, Francesco and Hans-Peter Kohler. 2004. "Patterns of Low and Lowest-low Fertility in Europe." *Population Studies* 58 (2):161–176.

Blundell, Richard and Monica Costa Dias. 2009. "Alternative Approaches to Evaluation in Empirical Microeconomics." *Journal of Human Resources* 44 (3):565–640.

Blundell, Richard, Monica Costa Dias, Costas Meghir, and Jonathan Shaw. 2016. "Female Labor Supply, Human Capital, and Welfare Reform." *Econometrica* 84 (5):1705–1753.

Buttner, Thomas and Wolfgang Lutz. 1990. "Estimating Fertility Responses to Policy Measures on the German Democratic Republic." *Population and Development Review* 16 (3):539–555.

Butz, William P. and Michael P. Ward. 1979. "The Emergence of Countercyclical U.S. Fertility." *American Economic Review* 69 (3):318–328.

———. 1980. "Completed Fertility and its Timing." *The Journal of Political Economy* 88 (5):917–940.

Carneiro, Pedro, Katrine V Løken, and Kjell G Salvanes. 2015. "A Flying Start? Maternity Leave Benefits and Long-run Outcomes of Children." *Journal of Political Economy* 123 (2):365–412.

Cohen, Alma, Rajeev Dehejia, and Dmitri Romanov. 2013. "Financial Incentives and Fertility." *The Review of Economics and Statistics* 95 (1):1–20.

Committee on Women's Rights. 1990. "Report on the Proposal from the Commission to the Council for a Directive Concerning the Protection at Work of Pregnant Women or Women Who Have Recently Given Birth." Document A 3-0337/90, European Parliament.

Dustmann, Christian and Uta Schönberg. 2012. "Expansions in Maternity Leave Coverage and Children's Long-term Outcomes." *American Economic Journal: Applied Economics* 4 (3):190–224.

Espenshade, Thomas J. 1984. *Investing in Children: New Estimates of Parental Expenditures*. "An Urban Institute paperback". Urban Institute Press.

Feenberg, Daniel and Elisabeth Coutts. 1993. "An Introduction to the TAXSIM Model." *Journal of Policy Analysis and Management* 12 (1):189–194.

Feldstein, Martin S. 1969. "The Effects on Taxation on Risk Taking." *The Journal of Political Economy* 77 (5):755–764.

Flores, Andrea, George-Levi Gayle, and Andrés Hincapié. 2024. "The Intergenerational Effects of Parental Leave: Exploiting Forty Years of U.S. Policy Variation." Tech. rep., Working Paper.

Francesconi, Marco. 2002. "A Joint Dynamic Model of Fertility and Work of Married Women." *Journal of Labor Economics* 20 (2):336–380.

Gault, Barbara, Heidi Hartmann, Ariane Hegewisch, and Lindsey Milli, Jessica Reichlin. 2014. "Paid Parental Leave in the United States. What the Data Tell Us About Access, Usage, and Economic and Health Benefits." Tech. rep., Institute for Women's Policy Research, Washington, D.C.

Gayle, George-Levi, Limor Golan, and Robert A. Miller. 2015. "Promotion Turnover and the Compensation in the Executive Labor Market." *Econometrica* 83 (6):2293–2369.

Ginja, Rita, Jenny Jans, and Arizo Karimi. 2020. "Parental Leave Benefits, Household Labor Supply, and Children's Long-run Outcomes." *Journal of Labor Economics* 38 (1):261–320.

Goldstein, Joshua, Wolfgang Lutz, and Maria Rita Testa. 2003. "The emergence of Sub-Replacement Family Size Ideals in Europe." *Population Research and Policy Review* 22 (5):479–496.

Grant, Jodi, Taylor Hatcher, and Nirali Patel. 2005. "Expecting Better: A State-by-State Analysis of Parental Leave Programs." Tech. rep., National Partnership for Women & Families, Washington, D.C.

Guner, Nezih, Remzi Kaygusuz, and Gustavo Ventura. 2014. "Income Taxation of U.S. Households: Facts and Parametric Estimates." *Review of Economic Dynamics* 17:559–581.

Han, Wen-Jui, Christopher Ruhm, and Jane Waldfogel. 2009. "Parental Leave Policies and Parents' Employment and Leave-Taking." *Journal of Policy Analysis and Management* 28 (1):29–54.

Heathcote, Jonathan, Kjetil Storesletten, and Giovanni L. Violante. 2011. "Redistributive Taxation in a Partial Insurance Economy." Tech. rep., Working Paper.

———. 2017. "Optimal Tax Progressivity." *The Quarterly Journal of Economics* 132 (4):1693–1754.

Heathcote, Jonathan and Hitoshi Tsujiyama. 2021. "Optimal Income Taxation: Mirrlees Meets Ramsey." *The Quarterly Journal of Economics* 129 (11):3141–3184.

Hill, C. Russell and Frank Stafford. 1980. "Parental Care of Children: Time Diary Estimates of Quantity, Predictability, and Variety." *Journal of Human Resources* 15 (2):219–239.

Hincapié, Andrés. 2020. "Where are the Young Entrepreneurs? A Study of Entrepreneurship over the Life Cycle." *International Economic Review* 61 (2):617–681.

Hotz, V. Joseph and Robert A. Miller. 1988. "Empirical Analysis of Life Cycle Fertility and Female Labour Supply." *Econometrica* 56 (1):91–118.

Kallman Kane, Carol. 1998. *State Mandates for Maternity Leave: Impact on Wages, Employment, and Access to Leave*. Ph.D. thesis, Boston College.

Keane, Michael P. and Kenneth I. Wolpin. 2010. "The Role of Labor and Marriage Markets, Preference Heterogeneity, and the Welfare System in the Life Cycle Decisions of Black, Hispanic, and White Women." *International Economic Review* 51 (3):851–892.

Khorunzhina, Natalia and Robert A. Miller. 2022. "American Dream Delayed: Shifting Determinants of Homeownership." *International Economic Review* 63 (1):3–35.

Kleven, Henrik, Camille Landais, and Jakob Egholt Søgaard. 2019. "Children and gender inequality: Evidence from Denmark." *American Economic Journal: Applied Economics* 11 (4):181–209.

Kögel, Tomas. 2004. "Did the association between fertility and female employment within OECD countries really change its sign?" *Journal of Population Economics* 17 (1):45–65.

Lalive, Rafael and Josef Zweimüller. 2009. "How Does Parental Leave Affect Fertility and Return to Work? Evidence from Two Natural Experiments." *The Quarterly Journal of Economics* 124 (3):1363–1402.

Laroque, Guy and Bernard Salanié. 2008. "Does Fertility Respond to Financial Incentives?"

Lazear, Edward and Robert T Michael. 1980. "Family Size and the Distribution of Real Per Capita Income." *American Economic Review* 70 (1):91–107.

Margiotta, Mary M. and Robert A. Miller. 2000. "Managerial Compensation and the Cost of Moral Hazard." *International Economic Review* 41 (3):418–438.

Milligan, Kevin. 2005. "Subsidizing the Stork: New Evidence on Tax Incentives and Fertility." *The Review of Economics and Statistics* 87 (3):539–555.

Olivetti, Claudia and Barbara Petrongolo. 2017. "The Economic Consequences of Family Policies: Lessons from a Century of Legislation in High-income Countries." *Journal of Economic Perspectives* 31 (1):205–230.

Presagia. 2012. "U.S. Pregnancy Leave Guide: A State by State Look at Pregnancy Leave Legislation." Tech. rep.

Rossin-Slater, Maya, Christoher Ruhm, and Jane Waldfogel. 2013. "The Effects of California's Paid Family Leave Program on Mothers' Leave-taking and Subsequent Labor Market Outcomes." *Journal of Policy Analysis and Management* 32 (2):224–245.

Skolnik, Alfred M. 1952. "Temporary Disability Insurance Laws in the United States." *Social Security Bulletin* 15 (10):11–22.

Stearns, Jenna. 2015. "The effects of paid maternity leave: Evidence from Temporary Disability Insurance." *Journal of Health Economics* 43:85–102.

Thomas, Mallika. 2019. "The Impact of Mandated Maternity Benefits on the Gender Differential in Promotions: Examining the Role of Adverse Selection." Working Paper, Cornell University.

Thévenon, Olivier. 2016. "The Influence of Family Policies on Fertility in France: Lessons from the Past and Prospects for the Future." In *Low Fertility, Institutions, and their Policies*, edited by Ronald R. Rindfuss and Minja Kim Choe, chap. 3. Springer Cham, 49–76.

Waldfogel, Jane. 1999. "Family Leave Coverage in the 1990s." *Monthly Labor Review* :13–21.

Wang, Hanna. 2022. "Fertility and Family Leave Policies in Germany: Optimal Policy Design in a Dynamic Framework." Working Paper, Universitat Autonòma de Barcelona and Barcelona School of Economics.

Women's Bureau. 1993. "State Maternity/Family Leave Law." Tech. rep., U.S. Department of Labor, Washington, D.C.

Women's Legal Defense Fund. 1991. "State Laws and Regulations Guaranteeing Employees Their Jobs after Family and Medical Leaves." In *Parental Leave and Child Care. Setting a Reseach and Policy Agenda*, edited by Janet Shibley Hyde and Marilyn J. Essex, chap. Appendix B. Philadelphia: Temple University Press, 468–489.