Life-Cycle Fertility and Human Capital Accumulation*

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ABSTRACT: The proposed research analyzes the impact of public policy expenditures directed to mothers and their children, for instance subsidized child care expenditures, on life cycle fertility and female labor supply. It also investigate interventions that decrease the opportunity cost of the time spent rearing children. Decreases in the opportunity cost are attained both through a wage paid to women who bear children or directly through the provision of child care. Finally, the proposed research investigates the effects of retraining women when they reenter the labor force after a hiatus spent raising children. To analyze these policies we formulate and estimate a structural dynamic model of labor supply and fertility. The model accounts for maternal time spent raising children of different ages. We take the model to the data using the PSID.

KEYWORDS: Fertility, Labor Market, Continuous Choice.
JEL CLASSIFICATION:

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1 Introduction

Both female labor supply and fertility choices are topical issues of public interest. For example, declining rates of fertility worldwide, especially amongst educated women, affect intergenerational wealth transfers as well as the demand for public infrastructure and privately produced goods. Additionally, female labor market supply may be affected by the persistence of a gender wage gap in the U.S., remaining after a long period of shrinking. Sociologists, demographers and economists recognize that both female labor supply and fertility behavior are intertwined. Hence, it is reasonable to expect public policies affecting fertility to also have an effect on female labor supply, and vice versa. However, quantifying the effects of such policies and their implementation can be challenging.

Social scientists have drawn upon many tools in their attempts to predict how public policies affect fertility and female labor supply.[1] Public opinion, as elicited in survey responses to hypothetical counterfactuals and ideal family sizes, has been used to provide a first view at how populations might react to policy innovations (Goldstein, Lutz, and Testa, 2003). Time series analysis has being used to estimate the role of substitution and wealth effects caused by increasing female wages on labor supply and fertility (Butz and Ward, 1979, 1980; Buttner and Lutz, 1990). In addition, cross sectional studies have compared the effects of different policies addressing labor supply and fertility across countries (Billari and Kohler, 2004; Kögel, 2004) and event studies have analyzed the adoption of new programs (Milligan, 2005; Laroque and Salanié, 2008; Cohen, Dehejia, and Romanov, 2013).

Our work joins a handful of studies that recognize the dynamic interactions between female labor supply and fertility by modeling and estimating the sequential determination of these joint events with panel data (Hotz and Miller, 1988; Francesconi, 2002; Keane and Wolpin, 2010; Adda, Dustmann, and Stevens, 2017). The latter two also conduct counterfactual policy simulations. Keane and Wolpin investigate changes to the welfare system, while Adda, Dustmann, and Stevens simulate the effects of increasing child allowances. We conduct counterfactual simulations on four policies: paying for expenditures on offspring, providing child care, paying women a wage to bear children, and retraining mothers who quit the labor force when they reenter it.

To analyze these policies we formulate and estimate a dynamic model of labor supply and fertility. The model accounts for maternal time spent raising children and the effect of time spent on current and summed discounted expenditures on them. We estimate the model with data from the Panel Study of Income Dynamics (PSID), and solve for the policy functions with the estimated parameters perturbed by the counterfactual policy innovations.

[1] See for instance the survey by Gauthier (2007).

The next section provides the theoretical underpinnings to our empirical investigations, by laying out a life cycle model of labor supply and fertility. Then in Section 2 we briefly summarize the sample of households used in our empirical work, which is drawn from the PSID. Section **??** explains our estimation strategy, while Section 6 reports our structural estimates. In Section 7 we conduct several policy simulations and summarize our findings, and in Section 8 we conclude. All proofs and estimation details are contained in the Appendix.

2 Data

We use three main pieces of data for this paper. First, we consult a number of sources to build a collection of unique leave policies available for women in the United States since 1968 until 2017. Second, we bring 50 years of information from the Panel Study of Income Dynamics which includes labor and fertility choices of women across the country. Finally, we combine these data from the PSID with the NBER's TAXISM program (See Feenberg and Coutts (1993) for more details io the Taxism program.) to calculate the taxation and government transfers for each household in ours sample.

2.1 Leave Policies

We gather information on leave policies across the U.S. from 1968 to 2017. We employ 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.[2] The collection of state and federal leave policies we find are presented in detail in Table S1 in Appendix A. Table 1 presents the collection of unique policies in the U.S. during our sample period derived from the information in Table S1.

The leave policies in Table 1 have two main components: *eligibility* and *generosity*. Eligibility is based on the number of hours the individual worked last year. About half of the policies have two tiers of eligibility where the second tier grants women access to more generosity if they worked more hours during the prior year. On average, one-tier policies require 628 hours of prior work. For two-tier policies, the first tier requires 457 hours of prior work on average whereas the second tier requires 1,197 hours. 40 percent of all policies do not require any prior hours.

Generosity has itself two components: *protected time* and *paid time*. Protected time is not necessarily paid and vice versa. Protected time refers to leave that a woman can take while having her job protected. In other words, upon returning to the firm after a spell of protected leave a

[2]See Appendix A for an extensive list of our sources.

TABLE 1: Leave Policies in the U.S. 1968-2017

	One-tier Policies				*Two-tier Policies*						
					Tier 1			*Tier 2*			
	Eligibility	*Generosity*			*Eligibility*	*Generosity*		*Eligibility*	*Generosity*		
		Protected	*Paid*	*Rate*		*Protected*	*Paid*		*Protected*	*Paid*	*Rate*
	(hours)	*(weeks)*	*(weeks)*		*(hours)*	*(weeks)*	*(weeks)*	*(hours)*	*(weeks)*	*(weeks)*	
	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	1250	18	6	0.55
	1	10	0		0	6	12	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	1250	12	10	0.50
	560	6	6	0.58	400	10	10	1250	22	10	0.55
	643	24	0		400	14	10	1250	26	10	0.55
	800	0	10	0.67	400	10	10	1560	23	10	0.55
	1000	8	0		520	8	0	1250	12	0	
	1000	32	0		560	6	6	1250	18	6	0.58
	1040	6	0		800	0	10	1000	16	10	0.67
	1250	12	0		800	0	10	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	1197	17.1	4.7	0.57
SD	(590)	(7.7)	(3.9)	(0.05)	(341)	(3.5)	(5.0)	(280)	(4.3)	(5.5)	(0.06)

Notes: Collection of all 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 reimbursement 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.

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. The first tier of two-tier policies grants 6.3 weeks of protected leave on average while the second tier grants 17.1 weeks. Paid time refers to leave that is paid at a given proportion (*reimbursement rate*) of the woman's wage rate. One-tier policies grant 2.6 weeks of paid leave on average. The first tier of two-tier policies grants 4.4 weeks of paid leave on average while the second tier grants 4.7 weeks. The average reimbursement rate conditional on paid leave is 0.57.

The heterogeneous implementation of these unique polices over time and across states provides a rich source of policy variation that we present in Figure 1.[3] 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, year in which federal policy (FMLA) was introduced. During

[3] All statistics in Figure 1 and population weighted.

the 1980s and before 1993 there was a substantial difference between regions with high (North East and West) and low (North Central and South) proportion of leave availability. The top-right panel displays the average number of prior hours required for eligibility. Before FMLA there's 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). The difference in average hours after the introduction of FMLA is caused by the higher prevalence of two-tier policies in the North East and West, the first tier requiring less prior hours.

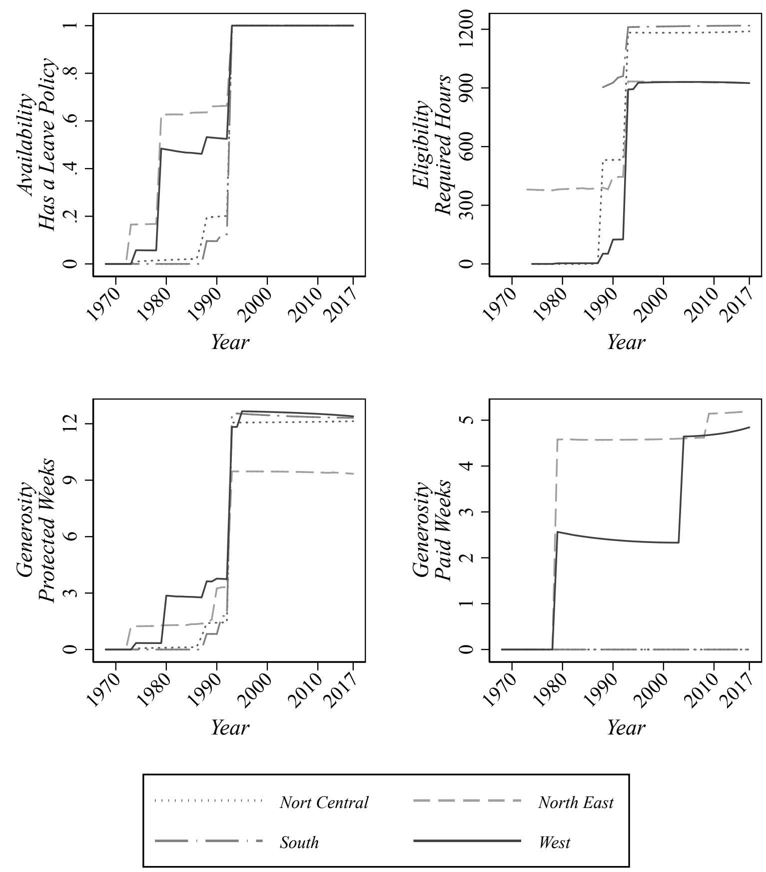

FIGURE 1: Variation in Leave Policies over Time and Across Regions.
Notes: Weighted averages across states within a region. Eligibility average computed using only states that have leave policies at that year. Generosity (protected and paid weeks) takes the value of zero if the state has no leave policy. 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.

The bottom panels of Figure 1 contain information regarding generosity. The left panel displays variation in generosity as measured by average protected weeks. It shows that the largest change in protected weeks is by far the introduction of FMLA. However, there is pre-FMLA variation in protected weeks driven mainly by the North East and West regions. Post-FMLA the North-East appears to have less protected weeks on average; this is a product of the prevalence of two-tier policies in the region. The right panel displays variation in generosity as measured by average paid weeks. On the one hand, neither the North Central region nor the South region have had paid leave policies up to the end of our sample period in 2017. On the other, the North East and West regions appear to start offering paid leave weeks in 1979. In practice this is a product of Temporary Disability Insurance (TDI) policies enacted before 1979 and the introduction of the Pregnancy Discrimination Act of October 30, 1978 which formally allowed for the TDIs to be used as paid maternity leave.[4] The North East region started off offering almost twice as much paid leave the West region; this gap continued up until the mid 2000s when both regions started offering more similar amounts of paid leave on average.

2.2 Women in the Sample

We use fifty years of data from the Panel Study of Income Dynamics (PSID) from the period between 1968 and 2017. Specifically, we use 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 fraction of hours worked by woman n at date t, h_{nt}; reported real average hourly earnings, $\widetilde{w}_{nt}$; real household food consumption expenditures, x_{nt}; number of household members, fam_{nt}; number of children less than six years of age, $ykid_{nt}$; number of children of ages between six and fourteen, $okid_{nt}$; age_{nt}; years of completed education, edu_n; whether the individual is black, $black_n$; region dummies ne_{nt}, nc_{nt}, and so_{nt} for north-east, north-central, and south, respectively; and whether a woman is married or not, mar_{nt}, . The construction of our sample and the definition of the variables is described in greater detail in Appendix [Appendix Label Here].

The PSID data files do not contain information on leave usage. Hence, for women who give birth in period t or $t-1$, we measure leave usage in t indirectly as a woman's decrease in hours in period t relative to her recent (during the last four periods) working hours when she did not have a birth.[5] Our measure of leave usage is bounded by the amount of leave that a woman has available given the policies of the state she lives in and her eligibility.[6] Our indirect measure does

[4] This approach to treating TDI policies is similar to the one in Stearns (2015).

[5] We include women who gave birth in $t-1$ as well because very often unused leave time can be rolled over for one period.

[6] We treat protected and paid leave differently. On the one hand, the benefits from protected leave are reaped *after* the woman's reduction in working time, when she returns to the workplace. Hence, we assume that protected leave is not binding if the woman reduces her working hours more than the amount of protected leave time available to her. On the other, paid leave benefits are reaped *during* the woman's reduction in time. Hence, we assume paid leave is always binding.

not assume that women always use the leave they have available. As Rossin-Slater, Ruhm, and Waldfogel (2013) and Baum and Ruhm (2014) show, this is not the case. Instead, our indirect measure makes the much weaker assumption that if a woman, for whatever reason, does reduce her working hours upon birth in a state where leave policies are available, she utilizes any protected or paid leave she has available; this is equivalent to assuming that preferences are monotonically increasing in income.[7]

Table 2 presents the characteristics of fertile-age women, those between ages 15 and 45, in our sample. The observations are split in three groups: women observed prior to FMLA residing in states with no leave policy, women observed prior to FMLA residing in states with leave policy, and women observed after FMLA. In only 15% of the observations before FMLA women had leave policies available. Compared to women not exposed to leave policies before FMLA, those who were exposed to leave policies before FMLA are slightly older, are much less likely to be black (24% versus 45%), were more likely to participate in the labor market (48% versus 39%), worked more hours per year (743 vs 589), had higher hourly wages (19.5$ versus 15.6$), and were less likely to have a birth during the year (6.6% versus 7.7%). The main differences between women exposed to leave policies before and after FMLA is that the women after FMLA are older, are more likely to be married (0.59 versus 0.50), follow the racial and geographical distribution of the full sample, are more likely to participate in the labor market (78% versus 48%) and work more hours per year (1391 vs 743)

2.3 Leave Availability and Take-up

As it is well known, most women who have births are not exposed to paid leave policies and exposure to protected leave policies only became universal with the introduction of FMLA. Table 2 presents summary statistics of leave availability, generosity and usage among women who gave birth. Most births in the sample are not covered by protected or paid leave. In only 24% (6%) of births women were granted protected (paid) leave. This is not surprising given that federal policy was only introduced in 1993 and paid leave policies remain extremely scarce in the country. Since federal policy was introduced, in only 56% of births women have satisfied the eligibility requirements for protected leave policy. Both policy generosity and labor market participation have increased over time. Consequently, conditional on any protected (paid) leave being granted, the number of protected (paid) leave hours being granted on average has gone from 225 (231)

[7] If a woman reduces hours but does not use available protected leave she is allowing her future wages to decrease because she could have protected her previous job. If a woman reduces hours but does not use available paid leave she is explicitly leaving money on the table.

TABLE 2: Descriptive Statistics of Women in Fertile Age, U.S. 1968-2017

	All		*Before FMLA*				*After FMLA*	
			no leave policy		*leave policy*			
	mean	sd	mean	sd	mean	sd	mean	sd
Observations	243,644		126,016		22,539		95,089	
Age	29.6	(8.4)	27.1	(8.3)	28.7	(8.1)	33.0	(7.4)
Black	0.42		0.45		0.24		0.41	
Married	0.53		0.49		0.50		0.59	
Years of education	13.5	(2.5)	13.0	(2.6)	13.8	(2.5)	14.0	(2.3)
North Central	0.25		0.27		0.09		0.26	
North East	0.14		0.10		0.42		0.13	
South	0.41		0.48		0.07		0.41	
West	0.20		0.15		0.41		0.21	
Participation$_t$	0.55		0.39		0.48		0.78	
Hours worked$_t$	916	(972)	589	(851)	743	(912)	1391	(944)
Wage$_t$	17.8	(14.5)	15.6	(12.6)	19.5	(13.5)	18.9	(15.6)
Birth$_t$	0.073		0.077		0.066		0.068	
***Conditional on Birth at** t*								
Observations	17,685		9,729		1,485		6,471	
Protected Leave								
Any granted$_t$	0.24				0.35		0.56	
Hours granted$_t$	443	(193)			225	(143)	474	(179)
% of granted leave at t used	63.5	(43.4)			78.7	(39.0)	61.3	(43.5)
Paid Leave								
Any granted$_t$	0.06				0.30		0.08	
Hours granted$_t$	292	(148)			231	(109)	343	(157)
% of granted leave at t used	74.1	(40.6)			79.2	(38.4)	69.9	(41.8)

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 places with (without) leave policies. Hours worked and wages conditional on participation. Wages are in real dollars of year 2015. Top 0.1% wages are truncated. *Leave granted* refers to the leave (protected or paid) that a woman is entitled to given the policy in her state or residency as well as her labor market participation and prior working hours. *Hours of leave granted* and *Percent of granted leave at t used* are both conditional on any leave being granted. *Percent of granted leave at t used* is computed used our definition of leave usage in Section 2.2.

before FMLA to 474 (343) hours after.

Although leave availability has increased since the introduction of FMLA, leave take-up has moved in the opposite direction falling from 78.7% (79.2%) of protected (paid) leave granted being used before FMLA, to only 61.3% (69.9%) 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 (conditional on availability) than their counterparts in conservative-leaning states such as Alabama, Iowa and Mississippi. There is less variation in paid-leave take-up among the states that offer it, in particular New York, New

Jersey and California.[8] Paid leave take-up is consistently similar to the highest levels of protected leave take-up.

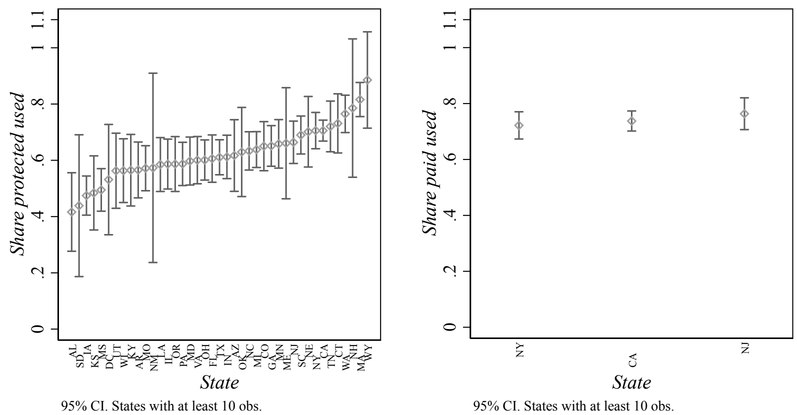

FIGURE 2: Average of share of leave available that is used by state, (1968-2017).
Notes: Left: protected leave. Right: paid leave.

We also find that the distribution of leave take-up is bimodal. Women often either do not use any of the protected or paid leave available or use it all. Figure 3 shows that while 25% (19%) of women who have births do not use any protected (paid) leave available, 54% (68%) of women who have births use all of the the protected (paid) leave that is available to them. Since FMLA made it easier to obtain protection over previously unprotected, paid leave, it is not surprising that paid leave has a higher take-up than protected leave.

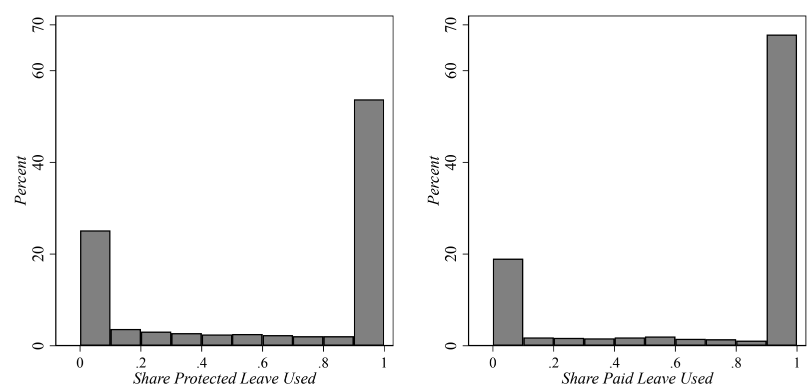

FIGURE 3: Distribution of leave usage, (1968-2017).
Notes: Left: protected leave. Right: paid leave.

We further explore the association between leave take-up and demographics, birth and work

[8]We do not have enough data from births in Hawaii and Rhode Island so we exclude those from the figure.

history in Table 3.[9] Regardless of marital status, black women use less protected leave than white women, 4.1 pp (percent points) less for married black women and 5.7 pp less for unmarried black women. [10] Women with college education or more use 7.1 pp less protected leave. Consistent with Figure 2, women in conservative-leaning regions use less protected leave, 11.4 pp less in the South and 13.3 pp less in the North Central region. For the most part there are no statistically significant correlations between birth history and protected leave take-up, only women who also had a birth two years ago use 4.6 pp less protected leave in the current period. Work history both at the extensive and intensive margins is much more strongly associated with protected leave take-up. Women who are heavily attached to the labor market use less protected leave, women who have worked full-time during the last four years use 10.2 pp less protected leave. While the contribution from the extensive margin is -23.9 pp, the contribution from the intensive margin is 13.7 pp. However, conditional on working last period, the more attached women are the less protected leave they use.

Our descriptive results in Table 3 show that the gap in leave take-up between married white women and everyone else more than doubles for paid leave. Married black women use 8.8 pp less paid leave, unmarried black women use 17.3 pp less, and unmarried white women use 19.6 less.There are no statistically significant correlations between paid leave take-up and education, region (North East or West) or birth history. Similar to our findings for protected leave, work history both at the extensive and intensive margins is much more strongly associated with paid leave take-up. Women who have worked full-time during the last four years use 5.9 pp less protected leave. While the contribution from the extensive margin is -16.3 pp, the contribution from the intensive margin is 10.4 pp.

2.4 The Motherhood Penalty and the Impact of Leave Policies

For obvious biological reasons women often choose to leave their jobs either temporarily or permanently in the weeks prior to having birth. For women who return to the labor market this gap in their careers can have a lasting effect. In order to estimate the size of this "motherhood penalty" we use the following standard event-study specification where $t = 0$ denotes the year in which an individual has their first child, the event study runs for $t = -3, -2, \cdots, 10$, and separately for men

[9] Given the distribution of leave take-up in Figure 3, Table S3 in Appendix A extends the results in Table 3 including regressions for two additional, binary outcomes: zero take-up and full take-up. Results are consistent with the results in Table 3.

[10] Using data from the CPS and the NLSY, respectively, Rossin-Slater, Ruhm, and Waldfogel (2013) and Baum and Ruhm (2014) study the effect of the introduction of paid family leave in California on leave take-up. Rossin-Slater, Ruhm, and Waldfogel (2013) find that women with high school or less, black women, and unmarried women have lower leave take-up before the introduction of the policy in 2004. When we restrict our sample to Californian women before 2004 we find the same results.

TABLE 3: Take-up of Available Leave in the U.S. 1968-2017

	Share Used			
	Protected		*Paid*	
	est.	se	est.	se
Age	-0.0001	(0.0020)	-0.0015	(0.0035)
Black and married	-0.041	(0.023)	-0.088	(0.041)
Black and unmarried	-0.057	(0.027)	-0.173	(0.050)
White and unmarried	-0.043	(0.032)	-0.196	(0.077)
Some college	-0.019	(0.021)	0.039	(0.037)
College or more	-0.071	(0.021)	-0.027	(0.040)
North Central	-0.133	(0.024)		
South	-0.114	(0.025)		
West	-0.039	(0.023)	-0.002	(0.028)
$Birth_{t-1}$	-0.021	(0.040)	-0.098	(0.076)
$Birth_{t-2}$	-0.046	(0.027)	-0.054	(0.050)
$Birth_{t-3}$	0.006	(0.025)	-0.020	(0.043)
$Birth_{t-4}$	-0.033	(0.028)	-0.017	(0.056)
Number of kids	-0.012	(0.010)	0.013	(0.019)
$Worked_{t-1}$	-0.347	(0.051)	-0.324	(0.074)
$Worked_{t-2}$	0.065	(0.041)	0.212	(0.067)
$Worked_{t-3}$	-0.045	(0.039)	-0.105	(0.063)
$Worked_{t-4}$	0.088	(0.036)	0.054	(0.057)
Hours $worked_{t-1}$	1.605	(0.143)	1.422	(0.268)
Hours $worked_{t-2}$	-0.386	(0.150)	-0.800	(0.268)
Hours $worked_{t-3}$	-0.207	(0.154)	0.386	(0.289)
Hours $worked_{t-4}$	-0.414	(0.144)	-0.554	(0.268)
Constant	0.922	(0.066)	0.906	(0.101)
Observations	2,859		801	

Notes: Dependent variables are the share of protected and paid leave granted that was used. Base demographic group is *white and married*, base region is *North East*. Work hours are scaled by (365*24), hence full-time hours (2000) corresponds to approximately 0.223 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.

and women:[11]

$$Y_{ist} = \sum_{j \neq -1} \alpha_j \mathbb{I}[j = t] + \sum_k \beta_k \mathbb{I}[k = age_{is}] + \sum_y \gamma_y \mathbb{I}[y = s] + \sum_{i=1}^{5} \theta X_{is} + \nu_{ist}, \tag{1}$$

where Y_{ist} is the outcome of interest (earnings, hours worked, participation rate and wage rate) for individual i in year s and at event time t, $\sum_{j \neq -1} \alpha_j \mathbb{I}[j = t]$ are event time dummies, $\sum_k \beta_k \mathbb{I}[k = age_{is}]$ are age dummies, $\sum_y \gamma_y \mathbb{I}[y = s]$ are year dummies, and X_{is} is a vector of controls.[12] The event time base is $t = -1$, hence the event time coefficients measure the impact of having a first child relative to the year immediately before the first child's birth.

Figure 4 replicates for the USA the results of Kleven, Landais, and Sgaard (2018) in Denmark. Upon having their first child women face a significant and permanent drop in participation rates, hours worked, labor market earnings, and wages. There is no similar drop for men, instead there

[11] See for example Kleven, Landais, and Sgaard (2018).

[12] X_{is} contains education, education squared, black, white, marital status, and state fixed effects.

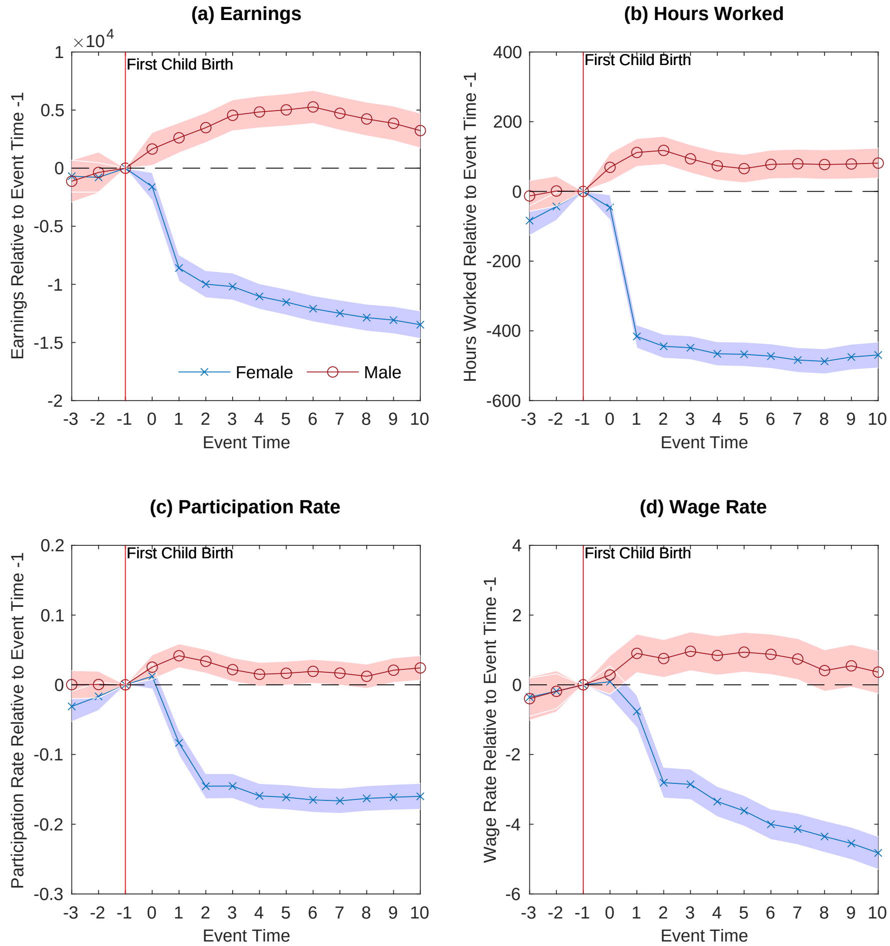

FIGURE 4: Motherhood Labor Market Penalty.

Notes: The shaded regions represent 95 percent confidence intervals for the estimated effect at each duration. Event study coefficients from the regression in equation (1) run separately for men and women. Base period is $t = -1$, hence the event time coefficients measure the impact of having a child relative to the year immediately before the first child's birth. Earnings and wages are in real dollars of year 2015.

is a temporary increase. We then focus on women and employ the quasi-experimental variation in policy exposure from the staggered introduction of parental leave entitlement across states and over time in the USA (Figure 1) to obtain the causal effect of the introduction of these policies on the motherhood penalty.

The results are presented in Figure 5. The casual effect of parental leave policies can be obtained by taking the difference between the red and blue line after event time 0. Before event time 0, there is no statistical difference between the red, blue, and dash lines. Results for earnings shows that there is a significant negative effect of the introduction of the parental leave from event time 5 that increases over time. This effects is largely due to a permanent reduction in hours worked and wage rates. As Figure 6 shows, we do not find a causal effect of the introduction of these policies on the labor market outcomes of men upon fatherhood.

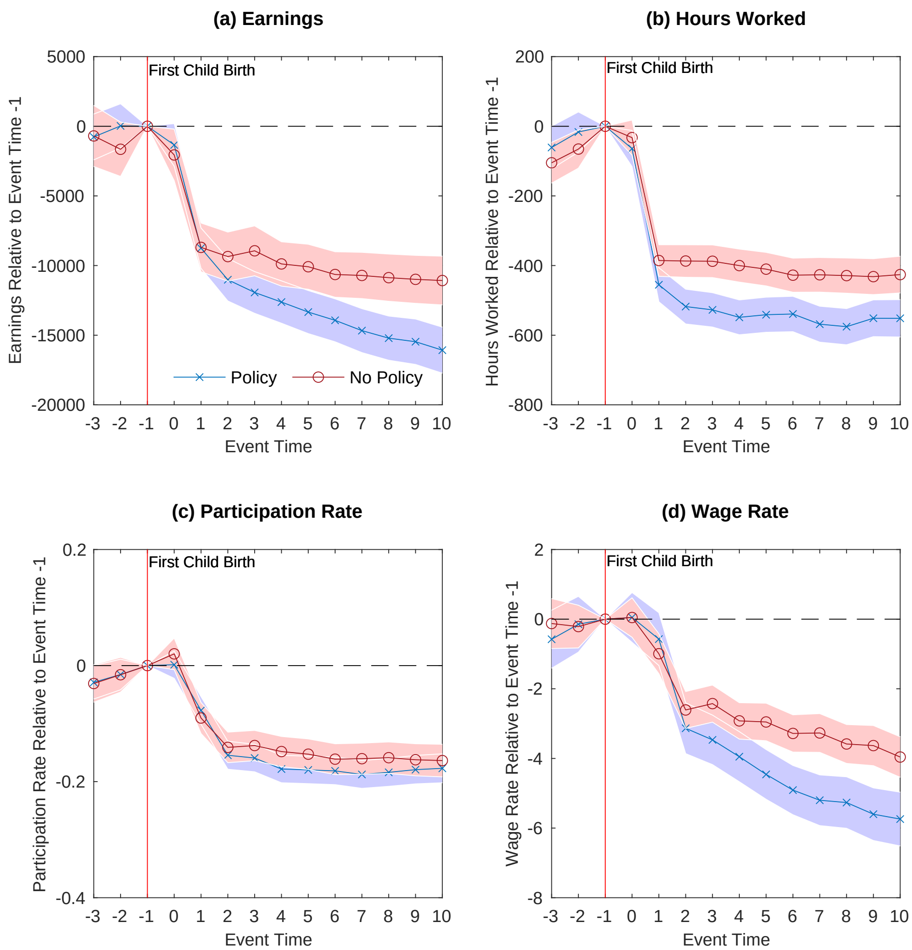

FIGURE 5: The Effect of Job-Protected Parental Leave on Women's Labor Market Outcomes upon Motherhood.

Notes: The shaded regions represent 95 percent confidence intervals for the estimated effect at each duration. Event study coefficients from the regression in equation (1) run separately for women in places with and without protected parental leave entitlement (either paid or unpaid). Base period is $t = -1$, hence the event time coefficients measure the impact of having a child relative to the year immediately before the first child's birth. Earnings and wages are in real dollars of year 2015.

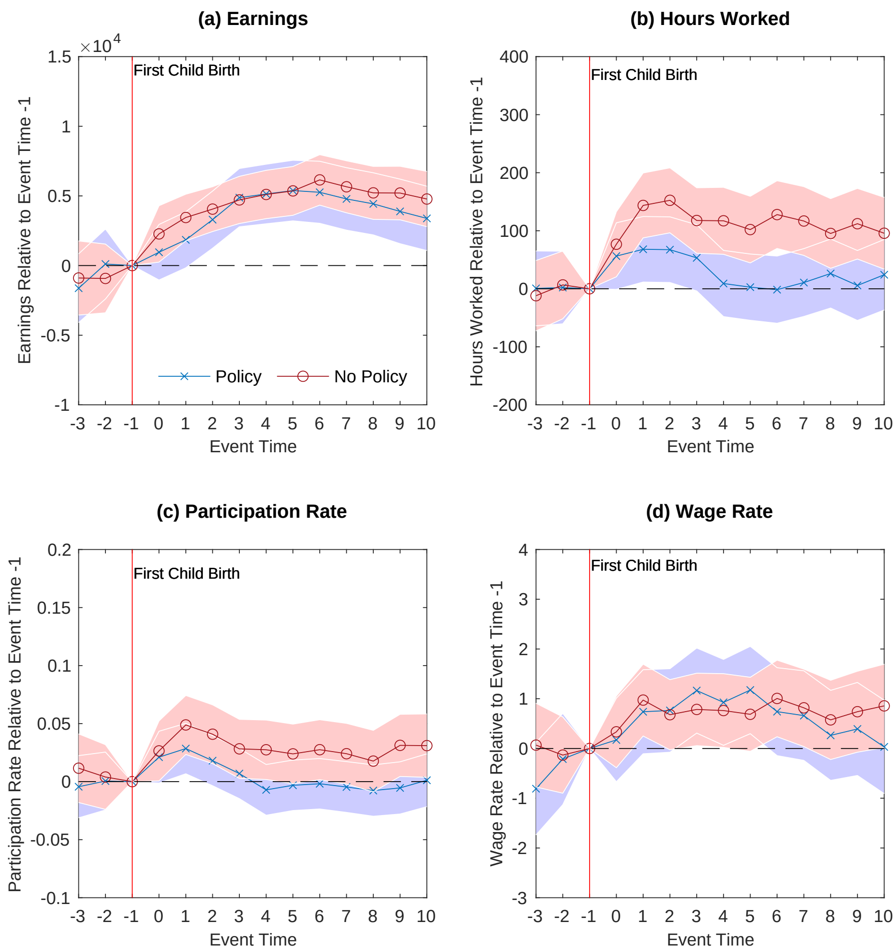

FIGURE 6: The Effect of Job-Protected Parental Leave on Men's Labor Market Outcomes upon Fatherhood.

Notes: The shaded regions represent 95 percent confidence intervals for the estimated effect at each duration. Event study coefficients from the regression in equation (1) run separately for men in places with and without protected parental leave entitlement (either paid or unpaid). Base period is $t = -1$, hence the event time coefficients measure the impact of having a child relative to the year immediately before the first child's birth. Earnings and wages are in real dollars of year 2015.

3 A Model of Fertility and Female Labor Supply

To explain the economics behind these empirical patterns and show how they relate to different child care policies, we develop a dynamic optimization model of life-cycle fertility and female labor supply that recognizes the several different phases of nurturing offspring, relationships with their siblings, the effects of accumulating work experience on wages, and time spent at home on household production. Since these polices directly affect the income taxation of both parents, as well as including provisions for a mother to return a job she held before taking leave to give birth, we endogenize both the extensive and intensive margins of the mother's labor supply, and also account for their effects on the father's net income.

Choice set Let $t \in \{0, 1, \ldots, T\}$ denote a female's age in years beyond adolescence, τ_t denote the calendar year when the female is of age t, and $r \in \{0, 1, \ldots, \rho_r\}$ and the policy environment to which she is exposed.[13] Each period she chooses two continuous variables, consumption, denoted c_t, and hours worked in the labor force, denoted by h_t. We capture nonlinearities in leisure and returns to labor market experience using the following discrete-choice indicator function that captures the labor force participation decision of an individual:

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

where $d_t = 0$ indicates that she stayed out of the workforce in period t. In addition to consumption and hours of work, she makes fertility choices captured by the indicator b_t, which takes the value of 1 if she decides to have a child. Hence, at every period she chooses one of four discrete alternatives $k \in \{1, \ldots, 4\}$. She can choose neither to work nor to have a child by setting $k = 1$, to work and not to have a child by setting $j = 2$, to have a child and not to work by setting $k = 3$, and both to work and to have a child by setting $k = 4$. Let the indicator for whether she chooses alternative k at t be given by:

$$d_{kt} = \mathbf{1}\{1 + d_t + 2b_t = k\} \tag{3}$$

The amount of time a woman can spend working in a period is limited by the total available time, here normalized to one, and the demands of her offspring. We assume the time cost of nurturing an s year old is ϕ_s, up until age ρ_c, and ϕ for offspring aged between ρ_c and 18, and zero beyond that age. Letting ς_t denote The total amount of time the mother of age t spends nurturing

[13] For notational convenience we model a situation where the policy environment does not change throughout the lifecycle, but in estimation and prediction we adapt this framework to cases where it does.

her children is therefore:[14]

$$\varsigma_t \equiv \sum_{s=0}^{\rho_c} \phi_s b_{t-s} + \phi \sum_{s=\rho_c+1}^{18} b_{t-s} \tag{4}$$

This implies $h_t \in [0, 1-\varsigma_t]$. Defining leisure l_t as the residual time not spent at work h_t or nurturing children ς_{nt} implies $l_t = 1 - h_t + \varsigma_t$.

Human Capital and Protected Leave Current wages depend on accumulated human capital, measured in two ways because of family leave policies. First, *actual* human capital, denoted by h_t, is a function of the vector of hours the woman has worked in previous periods, and thus measures how much her experience increases her productivity. Second, we define *wage-equivalent* human capital by:

$$h_t^* = h_t + h_t^\ell \tag{5}$$

where the number of protected leave hours used, $h_t^\ell \geq 0$, augments h_t by crediting the worker with additional experience if she reduces her labor supply upon giving birth. Calculating h_t^ℓ follows institutional rules. Conditional on having a child a woman is granted a number of protected leave hours h_t^{LB} that depends on the policy environment π_t and her recent work history:

$$h_t^{LB} = b_t \kappa(\pi_t, h_{t-1}) h_t^B \tag{6}$$

where $\kappa \in [0,1)$ captures the policy's eligibility criteria and generosity, and h_t^B captures the intensity of the woman's recent work history and is defined as:

$$h_t^B \equiv \max_{r \in \{1,\ldots \rho_B\}} \left\{ h_{t-r} \prod_{s=1}^{r} \left[1 - d_{t-s}(1 - b_{t-s})\right] \right\} \tag{7}$$

In other words, h_t^B is the number of hours the woman worked most recently while not having a birth in the same year, within the last ρ_B years; it captures the nature of the woman's contract with her employer (e.g. part time versus full time).[15] Women can use protected leave hours granted at t in either t or $t+1$. Hence, the total number of protected leave hours available is the sum of h_t^{LB}, newly granted protected leave from a birth at t, and the residual protected leave not used in the

[14] 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. The evidence on the importance of such scale economies is mixed; Lazear and Michael (1980) find evidence of large scale economies while Espenshade (1984) finds them to be small.

[15] If $d_{t-s}(1-b_{t-s}) = 0 \; \forall s = 1, \ldots, \rho_B$, h_t^B is determined as a function of the woman's age, race, and education level. The function is estimated using the women that are observed working and not having kids at some point in the last ρ_B years. We set $\rho_B = 4$.

previous period, h_t^{LR}, given by:

$$h_t^{LR} = h_{t-1}^{LB}\mathbf{1}\{h_{t-1}^B - h_{t-1} \leq h_{t-1}^{LB} + h_{t-1}^{LR}\} - (h_{t-1}^{\ell} - h_{t-1}^{LR})\mathbf{1}\{h_{t-1}^{\ell} - h_{t-1}^{LR} \geq 0\} \tag{8}$$

The first term in (8) implies that the entire base of protected leave from the previous period can be carried over into period t as long as the woman did not reduce her hours beyond her previous amount of protected leave available. The second term subtracts from the base the amount of protected leave used that came out of the base. We assume that women who decrease their hours in response to a recent birth (current or last period) always use their available protected leave. Hence, the amount of protected leave used at t is given by:

$$h_t^{\ell} = (h_t^B - h_t)\mathbf{1}\{0 \leq h_t^B - h_t \leq h_t^{LB} + h_t^{LR}\} \tag{9}$$

The first factor in (9) is the woman's reduction in hours (if any). The second factor is an indicator capturing two facts: if the woman increases hours no protected leave is used, and if she reduces hours for longer than the amount of protected leave available employers are not required to protect her job.

Paid leave Individual income is affected by the amount of paid leave hours used $h_t^{P\ell}$. Similar to the eligibility criteria in (6), the base for paid leave is:

$$h_t^{PLB} = b_t \kappa^P(\pi_t, h_{t-1}) h_t^B \tag{10}$$

Women can also carry over their paid leave one period. Paid leave carried over into the current period are the residual paid leave hours that were not used in the previous period:

$$h_t^{PLR} = h_{t-1}^{PLB} - (h_{t-1}^{P\ell} - h_{t-1}^{PLR})\mathbf{1}\{h_{t-1}^{P\ell} - h_{t-1}^{PLR} \geq 0\} \tag{11}$$

We make the same assumption here as we did for protected leave: individuals who decrease their hours in response to a recent birth (current or last period) always use their available paid leave hours. Hence, the number of paid leave hours used at t is given by:

$$h_t^{P\ell} = (h_t^B - h_t)\mathbf{1}\{0 \leq h_t^B - h_t \leq h_t^{PLB} + h_t^{PLR}\} + (h_t^{PLB} + h_t^{PLR})\mathbf{1}\{h_t^B - h_t > h_t^{PLB} + h_t^{PLR}\} \tag{12}$$

Equations (10) and (12) for paid leave differ from their counterparts for protected leave, equations (6) and (9), because paid leave is guaranteed regardless of whether the woman reduces her hours for longer than the amount of paid leave available.

Female Wages Real wages are the product of the current wage for one efficiency unit of labor ω and the number of efficiency units a worker embodies, determined by the wage-equivalent labor market experience accumulated by the woman up to ρ_w periods ago, and demographic characteristics z_t. Since firms may adjust how they compensate their employees in response to changes in leave policies, and during the time span of our study different groups of individuals are exposed to various policies, we allow the parameters of the wage equation to vary across policy regimes $r(\pi_t) \in \{1, \ldots, \rho_r\}$ which are collections of policy environments. Following a literature on female labor supply that explicitly incorporates dependence of current wages on past recent participation and/or hours, her wage rate in year τ_t is given by:

$$w_t = \omega(\tau_t)\,\mu \exp\left\{\sum_{r=1}^{\rho_r} \mathbf{1}\{r(\pi_t) = r\}\left[z_t' B_{r,3} + \sum_{s=1}^{\rho_w}\left(\delta_{r,1s} h_{t-s}^* + \delta_{r,2s} d_{t-s}\right)\right]\right\} \tag{13}$$

where μ is a fixed individual-specific productivity.

Income and wealth Net income is the after tax income from husband labor income, household non-labor income, transfer income, and women labor market earnings. We assume men always work and have earnings as function of their characteristics. However, given the marriage matching and transition function defined below we can write husband labor market earnings as a function of the wife's state variable, $e(x_t)$. In order to account for the differential tax treatment between labor and non-labor income we specify an exogenous process for non-labor income which also depends on the woman's state vector, $e^{NL}(x_t)$. Although, the federal and state parental leave laws only guarantee unpaid leave, some states do provide a partial replacement via Short-Term Disability Insurance (STDI) conditional on working full time. The replacement income from paid leave is given by $\zeta(\pi_t) w_t h_t^{P\ell}$, where $0 \leq \zeta(\pi_t) \leq 1$ is the replacement rate under policy π_{nt}. The premium for STDI are included in the state taxes. Taking these different sources of income into account, we define total household income, denoted by $W_k(h, x)$, as:

$$W_k(h_t, x_t) \equiv w(x_t) h_t + \zeta(\pi_t) w(x_t) h_t^{P\ell} + e(x_t) + e^{NL}(x_t). \tag{14}$$

Tax and transfer policies vary with the source of the income (i.e. labor and non-labor income are taxed at different rates), the marital status of household (joint versus individual taxation implying that the marginal tax rates for married and single women differ), the number of children, and the state and calendar year. Let $\Upsilon_k(h_t, x_t)$ denote the net household income conditional on working h_t hours, making decision $d_k = 1$, and having state x_t. To capture the progressivity of the actual tax schedule the tax and transfer policies are defined by the function:

$$\Upsilon_k(h_t, x_t) = W_k(h_t, x_t) - \lambda_k(x_t) W_k(h_t, x_t)^{1-\tau_k(x_t)} \tag{15}$$

The class of tax and transfer policies embedded in the net household income in (15) has a long tradition in public finance going back to Feldstein (1969). We modify the standard specification in the literature in order to account for the nine major tax and transfer policy changes during the time period our data covers.

Aside from the current wage of one efficiency unit of labor $\omega(\tau)$, aggregate effects are transmitted through interest rates. We denote by $\lambda(\tau_t)$ the value of a consumption unit discounted back t periods. In other words, $\lambda(\tau_t)$ is the price of consuming in period τ_t denominated in τ_0 consumption units, a notational convention we adopt so that the model reflects our emphasis on the life-cycle rather than on aggregate factors. Valued at calendar date τ_0, net transfers to the woman at age t are given as consumption minus net income:

$$\lambda(\tau_t)(c_t - \Upsilon_k(h_t, x_t)) \tag{16}$$

Marriage To account for the distinction between married households single households in terms of their tax liabilities and transfers, we model income at the household level, which accounts for income, welfare transfers and taxes to both spouses in a married household. Married households are modeled as unitary decisions makers, where males invariably work, earning gross income that is a function of the married households' state variables. Marriage and divorce are random events generated by a stochastic process that depends on state variables.

In each period a woman is either married or single. At the beginning of period t, before any labor market or fertility decisions are made, a marriage shock is realized. If a woman was single in period $t-1$ then her marital status in period t is determined according to the matching function $G_0(.)$ that maps the state variable of the woman, x_t, into marital status and characteristics of a husband, $\tilde{x}'_t$. Let $\emptyset$ denote the spouse characteristics of a single woman and $x'_t = \tilde{x}'_t \cup \emptyset$. Therefore, with some abuse of notation, $G_0(x'_t|x_t)$ represent both the marriage matching function and the marital status of a woman who is single entering period t.

For a woman that was married in period $t-1$ her marital status is determined at the beginning of period t before making labor market and fertility decisions. She could remain married to the same spouse or get divorced. If she gets divorce, she has to remain single for at least one period. The evolution of her marital status and husband characteristics follows the distribution $G_1(x'_{t+1}|x_{t+1})$. Therefore generically we denote the matching and transition processes as $G(x'_{nt}|x_{nt})$.

Male employment, male earnings, and non-labor earnings Following Blundell, Costa Dias, Meghir, and Shaw (2016) we assume that male either work full time or not all. The employment status of men are given by

$$Prob[h'_t = \overline{h}'|x_t] = \begin{cases} \varepsilon'_{1t} > \Lambda_1(t, ed', ed, h_{t-1}, h'_{t-1}, \mathbf{b_{t-1}}, \pi_\mathbf{t}) & \text{if } m_t = 1 \\ \varepsilon'_{0t} > \Lambda_0(t, ed', h'_{t-1}, \pi_t) & \text{if } m_t = 0 \end{cases} \tag{17}$$

where ed' and ed is the education of the man and woman respectively; $\mathbf{b_{t-1}}$ is the birth history of the woman, and m_t is the marriage indicator equal one if married and zero otherwise. The hourly wage of the men are given by

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

where $\mu(ed', race)$ is a deterministic fixed individual-specific productivity as a function of education and race . Non-labor household earnings follows an AR(1) process with log normal innovations and is given by

$$lne^{NL}_{t,\tau_t} = \begin{cases} \omega^{NL}_{1,\tau_t}(ed, ed') + B_1 X_t + u_{1,\tau_t} & \text{if } m_t = 1 \\ \omega^{NL}_{0,\tau_t}(ed) + B_0 X_t + u_{0,\tau_t} & \text{if } m_t = 0 \end{cases} \tag{19}$$

where$\omega^{NL}_{m_t,\tau_t}$ are the aggregate component of non-labor earnings; X_t include a polynomial in age as well as other characteristics including region, race, and education level; and u_{m_t,τ_t} are normally distributed innovation to process with mean zero and variance $\sigma^2_{m_t,e}$.

Marriage, divorce, and matching The Family formation dynamics is modelled as a stochastic and predetermined process that is set to match the observed data including any causal policy treatment effect. The transition probability is given by

$$G(x'_{nt}|x_{nt-1}) \equiv Prob[m_t, ed'|t, ed, m_{t-1}, ed' \times m_{t-1},, \mathbf{b_{t-1}}, \pi_\mathbf{t}] \tag{20}$$

where ed' is only observed if $m_{t-1} = 1(m_t = 1)$.

Preferences Utility is determined by consumption, labor supply and fertility choices in ways that depend on socioeconomic demographics. To account for covariation in the data we flexibly model interactions between the age distribution of the households' stock of children, current births, along with lagged and current labor supply. Setting $\rho_1 \equiv \max\{\rho_b, \rho_l + \rho_c\}$ and $\rho_2 \equiv \max\{\rho_l, \rho_w\}$, we denote by x_t the vector of state variables that captures the demographics of women as well as the dependence of her current state on lagged labor supply and birth choices for the optimization problem are:[16]

$$x_t \equiv \left(t, \pi, z_t', h_{t-\rho_2}, \ldots, h_{t-1}, h_{t-\rho_2}^{\ell}, \ldots, h_{t-1}^{\ell}, h_{t-1}^{LR}, h_{t-1}^{PLR}, \sum_{r=1}^{t-1} b_r, b_{t-\rho_1}, \ldots, b_{t-1} \right)' \tag{21}$$

z_{nt} is a vector that includes individual characteristics (age, formal education, race and marital status) In addition to these state variables we posit disturbance for each of the four discrete choices denoted by and ε_{0t} is identically and independently distributed across t. Idiosyncratic factors also affect the utility from each discrete choice k through an alternative-specific disturbance ε_{kt} that is identically and independently distributed across (k,t) is distributed Type 1 Extreme Value. . modeling lifetime utility as:

$$-E\left\{ \sum_{t=0}^{T} \sum_{k=1}^{4} \beta^t d_{kt} \exp\left[-\alpha c_t - u_k\left(h_t + \varsigma_t, x_t\right) - h_t \xi_t + \varepsilon_{kt}\right] \right\} \tag{22}$$

Equation (22) implies that siblings k years apart are complementary in lifetime utility if:

$$u_k\left(h_t + \varsigma_t, x_t\right) - u_{k-}\left(h_t + \varsigma_t, x_t\right) > u_k\left(h_t + \varsigma_t, x_t\right) - u_{k-}\left(h_t + \varsigma_t, x_t\right).$$

Similarly leisure are substitutes in household production or utility if:

$$u_k\left(h_t + \varsigma_t, x_t\right) - u_{k-}\left(h_t + \varsigma_t, x_t\right) > u_k\left(h_t + \varsigma_t, x_t\right) - u_{k-}\left(h_t + \varsigma_t, x_t\right).$$

3.1 Optimization

We denote the optimal choices maximizing (22) as $\{c_{nt,}^o h_{nt}^o, b_{nt}^o\}_{t=0}^T$, d_{knt}^o as the value of d_{knt} implied by (h_{nt}^o, b_{nt}^o), and $h_{knt} \equiv h_k\left(x_{nt}, \xi_{nt}\right)$ as the optimal choice of hours given choice k. (By definition, $h_{knt} = h_{nt}^o$ if $d_{knt}^o = 1$, and $h_{1nt} = h_{3nt} = 0$.) The woman sequentially chooses consumption, labor supply and births (c_t, h_t, b_t) at each age t to maximize (22) subject to the constraints defined in (16). We denote by $d_t^o = \left(d_{1t}^o, \ldots, d_{4t}^o\right)$ the discrete choices that along with the consumption and labor supply choices, (c_t^o, h_t^o), solve this individual optimization problem.

Our representation of the optimality conditions adapts and extends previous related work by Altuğ and Miller (1998), Gayle, Golan, and Miller (2015) and Khorunzhina and Miller (2019) to our framework. Let $p_{kt}\left(x_t\right) \equiv E\left[d_{kt}^o \left| x_t\right.\right]$ denote the conditional choice probability (CCP) of making

[16] The values of ρ_1 and ρ_2 depend on how far back the definition of the state variables in the utility function go. For instance, 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.

discrete choice k at year t conditional on the value of the household state variable vector x_t, and denote by ε^*_{jt} the truncated variable that takes on the value of ε_{jt} only when $d_{jt}=1$. Similarly, Let $h_{kt}(x_t) \equiv E\left[h^o_{kt}|x_t\right]$ denote the conditional hour choice of choosing to work h^o_{nt} if $d^o_{knt}=1$ conditional on the value of the household observed state variable vector x_t, and denote by ξ^*_{jt} the marginal value of ξ_{jt} that makes the choice of hours, h^o_{kt}, optimal. Adapting the results in Gayle, Golan and Miller (2015) to our framework, let $A_{T+1}(x_{T+1}) \equiv 1$, and recursively define an index of household capital for a household at year t as:

$$A_t(x_t) \equiv \sum_{k=1}^{4} p_{kt}(x_t) \exp\left(\frac{-E[u_k(h_k(x_t,\xi^*_{kt}),x_t)|x_t] - E[h_k(x_t,\xi^*_{kt})\,\xi^*_{kt}|x_t] - \rho E[\Upsilon_k(h_k(x_t,\xi^*_{kt}),x_t)|x_t]}{B_t}\right)$$
$$\times E\left[\exp\left(\frac{-\varepsilon^*_{kt}}{B_t}\right)|x_t\right]\left[\int A_{t+1}(x_{t+1})\, g_k(x_{t+1}|x_t)dx_{t+1}\right]^{1-\frac{1}{B_t}} \tag{23}$$

where $g_k(x_{t+1}|x_t)$ is the transition function of the state vector at $t+1$ following the choice k in period t applied to x_t, the value of the state vector in period t. The index is strictly positive; lower values of $A_t(x_t)$ come from higher current income and lower rent, both incorporated within y_{jt}, as well as less distasteful x_t values that increase $u_k(h_t,x_t)$. Following Khorunzhina and Miller (2019), at each age $t \in \{1,2,\ldots\}$ the optimal discrete choices d^o_t and continuous labor supply choice h^o_t maximize:

$$\sum_{k=1}^{4} d_{jt}\left[\rho\Upsilon_k(h_t,x_t) + u_k(h_t,x_t) + h_t\xi_t - (B_t-1)\ln\left(\int A_{t+1}(x_{t+1})\, g_j(x_{t+1}|x_t)dx_{t+1}\right) + \varepsilon_{jt}\right] \tag{24}$$

Intuitively, the household maximizes a weighted sum of net current income, current utility from choices made at that time, as well as adjustments to household capital that reflect the impact of gaining work experience, and changes to family composition. Given the functional form of $A_{t+1}(x_{t+1})$ and optimal labor supply conditional on working, this is a standard discrete choice problem. The optimal hours of a working female satisfy the first order condition:

$$-\xi_t = \rho w(x_t)[1 - \frac{(1-\tau_j(x_t))\lambda_j(x_t)}{W_j(h_t,x_t)^{\tau_j(x_t)}}] + \frac{\partial u_j(h_t,x_t)}{\partial h_t} - \frac{(B_t-1)}{\int A_{t+1}(x_{t+1})\, g_j(x_{t+1}|x_t)dx_{t+1}}$$
$$\times \int\left[\frac{\partial A_{t+1}(x_{t+1})}{\partial h_t} + A_{t+1}(x_{t+1})\frac{\partial g_j(x_{t+1}|x_t)/\partial h_t}{g_j(x_{t+1}|x_t)}\right] g_j(x_{t+1}|x_t)dx_{t+1} \tag{25}$$

for $j \in \{2,4\}$.Describe the state here too and how the FOC are affected by the leave policies: today it affects wages because it affects current leave hours hl_{nt}, tomorrow it affects the available leave tomorrow as well as future wages up to $t+4$.

The model is written as though women can carry residual leave time. We may want to check in *the data if they always max their leave time in the birth year, that way we wouldn't have to model the carry over.*

4 Identification

Following the terminology of Arcidiacono and Miller (2019) we assume that the data is a long panel, that is in each regime r a synthetic panel can be constructed to string together comprehensive histories of the life cycle fertility and labor supply for each demographic group. The structure of our model exhibit finite dependence hence we do not need long panel. The data used in this paper is a long panel as we have 50 years of data hence the model estimated in this paper will be grossly over-identified. Let $x_{t+1+s}^{(k,1)}$ for $s = 0,...,T-t$ be the (perfectly anticipated) value of the state vector at $t+1+s$ following the choice k in period t applied to x_t and the choosing choice 1 from period $t+1$ to $t+1+s$[17]. For notational ease define the expected per-period utility as

$$\bar{u}_k(x_t) = E[u_k(h_k(x_t, \xi_{kt}^*), x_t)|x_t] + E[h_k(x_t, \xi_{kt}^*)\xi_{kt}^*|x_t] + \rho E[\Upsilon_k(h_k(x_t, \xi_{kt}^*), x_t)|x_t], \tag{26}$$

and define a accumulative discount factor as:

$$\chi_t(s) = \frac{1}{B_{t+s}}\left[\prod_{r=1}^{s-1}\left(1-\frac{1}{B_{t+r}}\right)\right]^{I\{s>0\}}. \tag{27}$$

The following representation theorem is very useful in establishing identification of the model.

Lemma 1. *Let $p_k(x_t)$ be the probability, before observing ε_t, that alternative k is chosen conditional on state x_t, and assume that the distribution of preference shocks ε is Type I extreme value. For $k \in \{1,2,3,4\}$ define:*

$$A_{t+1}(x_{t+1}^{\{k\}}) = \prod_{s=0}^{T-t}\left[\Gamma\left(\frac{B_{t+1+s}+1}{B_{t+1+s}}\right)^{B_{t+1+s}} p_1(x_{t+1+s}^{(k,1)})\exp\left(\frac{-\bar{u}_1(x_{t+1+s}^{(k,1)})}{B_{t+1+s}}\right)\right]^{\chi_{t+1}(s)} \tag{28}$$

Then the ex-ante conditional valuation function for choice $k \in \{1,2,3,4\}$ is defined as:

$$V_k(x_{nt}) = \bar{u}_k(x_t) - (B_t - 1)\sum_{s=0}^{T-t}\chi_{t+1}(s)\left[\ln\Gamma\left(\frac{B_{t+1+s}+1}{B_{t+1+s}}\right)^{B_{t+1+s}} + \ln p_1(x_{t+1+s}^{(k,1)}) - \frac{\bar{u}_1(x_{t+1+s}^{(k,1)})}{B_{t+1+s}}\right] \tag{29}$$

The above representation is useful in establishing semi-parametric identification and for estimation.

[17] This assumption is made for notational easy and the more general stochastic formulation is used in estimation.

Corollary 1.1. *For $k \in \{2,3,4\}$ the following equation is true:*

$$\ln\left(\frac{p_k(x_t)}{p_1 x_t}\right) = \overline{u}_k(x_t) - \overline{u}_1(x_t) - (B_t - 1)\sum_{s=0}^{T-t}\chi_{t+1}(s)\left[\ln\left(\frac{p_1(x_{t+1+s}^{(k,1)})}{p_1(x_{t+1+s}^{(1,1)})}\right) + \frac{\left(\overline{u}_1(x_{t+1+s}^{(1,1)}) - \overline{u}_1(x_{t+1+s}^{(k,1)})\right)}{B_{t+1+s}}\right] \tag{30}$$

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

$$\overline{u}_1(x_t) + (B_t - 1)\sum_{s=0}^{T-t}\chi_{t+1}(s)\left[\frac{\left(\overline{u}_1(x_{t+1+s}^{(1,1)}) - \overline{u}_1(x_{t+1+s}^{(k,1)})\right)}{B_{t+1+s}}\right]. \tag{31}$$

Hence, if the utility from the first action is known for every state and time period then expected utility from action k is identified. This a standard results in the discrete choice model except here we have account for the preference shock from the continuous choice hence only the expected utility is identified.

To disentangle the actually utility we use the FOC in equation (25) along with a the standard exclusion restrictions used in static selection models. We assume there exist instruments z_{kt} satisfying $E[\xi_t | z_{kt}] = 0$ (such as differences in regimes, changes in aggregate wage rates and bond prices, all affecting the demand for labor, but not the preferences for leisure, the supply side). Then let us decompose the observed state variables in the pure demand shifters and the rest by letting $x_t = (\widetilde{x}_t, z_t)$. Without loss of generality we set equation (31) equal to zero for the rest of the identification analysis.

Lemma 2. *Assuming there exist at least two demand side instruments then:*

$$\frac{\partial u_k(h^*, \widetilde{x}_t)}{\partial h} + \rho E\left[w(x_t)\left(1 - \frac{(1-\tau_k(x_t))\lambda_k(x_t)}{W_k(h_t,x_t)^{\tau_k(x_t)}}\right)|z_t\right] = \prod_{s=0}^{T-t} E\left[\frac{(B_t-1)}{p_1(x_{t+1+s}^{(k,1)})}\frac{\partial p_1(x_{t+1+s}^{(k,1)})}{\partial h_t}|z_t\right] \tag{32}$$

and therefore for very value h^* of hours worked observed in the data then $\frac{\partial u_k(h^*,\widetilde{x}_t)}{\partial h}$ and ρ are identified.

Then combining the results Corollary (1.1) and Lemma (2) we established the identification of the utility function.

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

$$\begin{aligned} u_k(\overline{h}, x) &= \int\left\{u_k(h_t^*, x) + \int_{h_t^*}^{\overline{h}}\frac{\partial u_k(h, x_t)}{\partial h}dh\right\}dF(h_t^* | x_t) \\ &= E[u_k(h_t^*, x_t) | x_t] + \int\left[\int_{h_t^*}^{\overline{h}}\frac{\partial u_k(h, x_t)}{\partial h}dh\right]dF(h_t^* | x_t). \end{aligned} \tag{33}$$

with

$$E\left[u_k\left(h_t^*,x_t\right)|x_t\right] = \int \{\bar{u}_k\left(x_t,z_t\right) - E\left[\,h_t^*\xi_t^*\,|x_t,z_t\right]$$
$$-\rho E\left[w(x_t)\left(1-\frac{\left(1-\tau_k(x_t)\right)\lambda_k(x_t)}{W_k(h_t,x_t)^{\tau_k(x_t)}}\right)|z_t\right]dF\left(z_t\,|x_t\right). \quad (34)$$

Therefore $u_k(x_t)$ since $\bar{u}_k\left(x_t,z_t\right)$, $\frac{\partial u_k(h,x_t)}{\partial h}$, and ρ are identified hence from the equation() ξ_t^* is also identified.

Counterfactuals are identified and computed the same way as in the dynamic discrete choice model, after adding in an extra step at each stage that uses the first order condition to derive hours worked. Notice that $u_k\left(\bar{h},x\right)$ is not a central object of analysis, rather $\bar{u}_k\left(x_t,z_t\right)$ and $\partial u_k\left(h,x_t\right)/\partial h$. The results in the section relies on two functional form assumption, the Type I extreme of the discrete choice preference sock and the absolute risk aversion utility function for consumption. These results goes through if we would have made other functional form assumptions. In the Appendix we derive these results for a unspecified distribution of preference shock and CARA utility functions. Note we do have to specify the functional form of the distribution of ξ.

5 Estimation

The estimation will proceed in multiple steps following the steps in the identification analysis. The identification analysis was done without specifying the functional form of the utility function, however, the estimation is done using a fully specified model. This allows out of sample counterfactual analysis but the parametric functional form of the utility function can be tested against the nonparametric version because as showed the int previous section it semi-parametrically identified. Below we specify the functional form of the utility function used in estimation.

5.1 Empirical Specification

5.1.1 Preferences

Her utility function is determined by consumption as well as her labor supply and fertility choices. Births contribute directly to her utility and she has preferences over the age distribution of its children, which determines the spacing of births. More specifically, let γ_0 denote the additional lifetime expected utility that she receives for her first child ($\tilde{\gamma}_0$ if she works), let $\gamma_0+\gamma_k$ denote the utility from having a second child when the first born is k years old, let $\gamma_0+\gamma_k+\gamma_j$ denote the utility from having a third child when the first two are aged k and j years old, and so on. Thus her deterministic benefits from having a child in period t are:

$$u_{nt}^{(b)} \equiv b_{nt} \left(\gamma_0(1 - d_{nt}) + \tilde{\gamma}_0 d_{nt} + \sum_{k=1}^{\rho_b} \gamma_k b_{n,t-k} + \gamma_b \sum_{k=\rho_b+1}^{t} b_{n,t-k} \right) \tag{35}$$

Equation (35) implies that siblings k years apart are complementary in lifetime utility if $\gamma_k > 0$.

In addition to obtaining utility for children, she gets utility from household consumption of market goods—which she decides—denoted c_{nt}, leisure time denoted $l_{nt} \in [0, 1]$, and taste shocks. We allow for both fixed and variable utility costs associated with working. We assume her utility loss from working in period t is given by:

$$u_{nt}^{(\ell)} \equiv z_{nt}' B_0 d_{nt} + z_{nt}' B_1 l_{nt} + \sum_{s=0}^{\rho_l} \delta_s l_{nt} l_{n,t-s} \tag{36}$$

where z_{nt} is a vector that includes individual characteristics (age, formal education, race and marital status), B_0 captures fixed-costs of participating in the work force and B_1 captures the marginal utility of leisure. Utility is increasing in leisure if:

$$z_{nt}' B_1 + 2\delta_0 l_{nt} + \sum_{s=1}^{\rho_l} \delta_s l_{n,t-s} > 0 \tag{37}$$

and concave if $\delta_0 < 0$. Intertemporal non-separabilities in preferences with respect to leisure are captured by δ_s for $s > 0$. A value of $\delta_s > 0$, for $s = 1, ..., \rho_l$, indicates that leisure s periods ago increases the marginal utility of current leisure. In other words, current and past leisure time are complements. In turn, current and past leisure time are substitutes if $\delta_s < 0$, for $s = 1, ..., \rho_l$.

5.2 Outline of Estimator

The estimation of the model proceed in three stages. In the first stage we estimation the conditional choice probability, transition transition of the stage variables, wages and earnings equations and the tax-transfer functions, all accounting for the quasi-experimental variation across state and time. This gives us the treatment effect is in the reduced form equations. In the second stage we combine the reduced estimates, the instruments from the demand side (i.e. policy variation), with hours worked equaler equation to estimate the marginal utility of leisure us a optimal instrumental variable estimation. In the third stage with us a pseudo-maximum likelihood estimator the estimate the remaining parameters of the model.

5.2.1 Stage I: Conditional choice probabilities, Transition functions, Wage equation, and Tax-transfer parameters

Taxation and government transfer The calculation of taxation and government transfer uses data from the PSID on state of residence, marital status, dependents, annual earnings, and government transfers, in combination the NBER's TAXISM program. We calculates pre tax and government transfer gross household income to include 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 in individual used from the PSID. The TAXISM program calculates the state and federal tax payable.

Leave Policies In the model section we simplified the structure of leave policies to facilitate exposition. Here we describe in more detailed how we model leave policies.

Wages. We assume that reported wage rate $\widetilde{w}_{nt}$ measures the marginal product of a woman in the market sector with error. Hence, using (13) we define $\widetilde{w}_{nt}$ as

$$\widetilde{w}_{nt} = w_{nt} \exp(\widetilde{\varepsilon}_{nt}) \tag{38}$$

where the multiplicative error term in (38) is conditionally independent over individuals, covariates in the wage equation, and labor supply decisions.

The policy variables are divided into two main categories. The first is the policies changes that are related to family and medical leave and the second are those policies related to taxation and welfare. One of the identifying exclusion assumptions maintained throughout the paper is that family does not only affect household optimal behavior but only the wage equation directly. While taxation and welfare policy does not affect the wage equation directly. Taxation still affects that the household budget constraint via its impact on net income. The intuition behind why family leave policy would affect the marginal product of labor is via the rental rate of human capital. If the government mandates that a woman is entitled to maternal leave and upon returning from said leave she is guaranteed the same job at the same pay as if she did not have a break in work experience then firm will optimally react by adjusting the rental rate of human capital in anticipation of the actual reduction in human capital. We will not directly model the firm side in this paper (see Gayle and Golan (2012) for a paper that does model the firm side.). We will however identify the causal effect of any such policy change on the marginal product of labor function via a quasi-experimental design.

The variation of family/maternal leave policy can be characterized by four main features. Namely, the date of the enactment of the family leave policy, the length of leave entitled to, the work requirement to qualify for maternity leave, and the income replacement when on leave. The federal law (FMLA) was enacted in 1993 and offer job protection for leave up to 12 weeks conditional previous full time work with no income replacement. However, the variation this paper relies on for identification is differences across states in the date of the enactment, length of leave, hours worked requirement for leave qualification, and income replacement while on leave. About of a third of all states had a maternity leave law before the FMLA was enacted. For example, California enacted a family leave policy in 1991 with 16 weeks of job protection and partial income replacement while on leave paid for by Short-Term Disability Insurance (STDI). Maine, along with a group of states we refer to as the 1987 early group, enacted a family policy in 1987. New Jersey and a handfull of other states, called the 1989 group, enactment a family law in 1989 while DC enacted a family leave law in 1990. Along with California, 4 other states (Hawaii, New Jersey, New York, and Rhode Island) family leave laws provides partial income replacement via STDI.

Let $\triangle$ denote first differences between variables. Taking logarithms of equation (13) and first differencing yields:

$$\triangle\widetilde{\varepsilon}_{nt} = \triangle\ln\widetilde{w}_{nt} - \sum_{r=0}^{\rho_\pi}\left\{\sum_{s=1}^{\rho_w}\left(\delta_{r,1s}\triangle h^{\pi,r}_{n,t-s} + \delta_{r,2s}\triangle d^{\pi,r}_{n,t-s}\right) + \triangle z^{(\pi,r)\prime}_{nt}B_{r,3}\right\} - \triangle\ln\omega(\tau_{nt}) \quad (39)$$

where $h^{\pi,r}_{n,t-s} = h_{n,t-s}\times I^{\pi}_{nt}(r)$, $d^{\pi,r}_{n,t-s} = d_{n,t-s}\times I^{\pi}_{nt}(r)$, and $z^{\pi,r}_{nt} = z_{nt}\times I^{\pi}_{nt}(r)$. Estimation implicitly imbeds the common trend assumption by not allowing ω_τ to vary with the policy regimes. However, using equation (39) as the estimating equation does not yields consistent estimates of the average treatment effect (ATE) unless we assume that impact of the policy changes are homogenous across households. An assumption that is in direct contradiction with structural model specified in Section 3,which predicts that the response to the policy would be heterogeneous. Hence the best we can hope to identify is the local average treatment effect (LATE). Which means any counterfactual policy evaluation of policy variation observed in the data are semi-parametrically identified, while extrapolation outside of the data are relying on the functional assumption and are still local relative to the general equilibrium response of firms to these policy changes. Finally, equation (39) yields consistent estimates of $\triangle\ln\omega_\tau$ and using the residuals from estimation we obtain consistent estimates of aggregate wages $\ln\omega_\tau$ and individual wage fixed effects $\ln\mu_n$. (See Appendix **??**.)

Time costs of nurturing. We estimate the parameters of (4) by regressing the number of home hours reported in the survey on a collection of indicator functions capturing whether the household has a new born or a child of ages one to five, $(b_{nt}, \ldots, b_{n,t-5})$ in our notation, and on the number of children above age five. We also control for race, marital status, and years of education.

5.2.2 Stage II: Marginal utilities

Combining equations yields the following moment conditions:

$$\xi_{t,k}(\theta_1, x_t) = \prod_{s=0}^{T-t} \frac{(B_t - 1)}{p_1(x_{t+1+s}^{(k,1)})} \frac{\partial p_1(x_{t+1+s}^{(k,1)})}{\partial h_t} - \widetilde{x}_t' B_1 - 2\delta_0 l_{nt} - \sum_{s=1}^{\rho_l} \delta_s l_{n,t-s} - \rho w(x_t) \left(1 - \frac{(1-\tau_k(x_t))\,\lambda_k(x_t)}{W_k(h_t, x_t)^{\tau_k(x_t)}}\right) \tag{40}$$

for $k \in \{2,4\}$ and $\theta_1 = [B_1, \delta_0, ..., \delta_{\rho_l}, \rho]$. The define the $2T \times 1$ vector

$$\xi_n(\theta_1, \widetilde{x}_n) = [\xi_{1,2}(\theta_1, x_n, 1), \xi_{1,4}(\theta_1, x_n, 1), ..., \xi_{T,2}(\theta_1, x_{n,T}), \xi_{T,4}(\theta_1, x_{n,T})] \tag{41}$$

The estimate θ_1 via the linear instrumental variable estimator from the orthogonality condition $E[Z_n' \xi_n(\theta_1, \widetilde{x}_n)] = 0$.

5.2.3 Stage III: Participation cost and utility of birth

The estimation of the labor market participation cost and the utility come from the decision to work or have a birth given that θ_1 is already estimated. We will use a quasi-maximum likelihood base on the log likelihood function:

$$\ln L(\theta_2, \widehat{\theta}_1) = \sum_{n=1}^{N} \sum_{t=1}^{T} \sum_{j=1}^{4} d_{njt} \ln p_j(x_{nt} | \theta_2, \widehat{\theta}_1) \tag{42}$$

where

$$p_k(x_{nt} | \theta_2, \widehat{\theta}_1) = \frac{\exp\left(V_k\left(x_{nt} | \theta_2, \widehat{\theta}_1\right) - V_1\left(x_{nt} | \theta_2, \widehat{\theta}_1\right)\right)}{1 + \sum_{j=2}^{4} \exp\left(V_j\left(x_{nt} | \theta_2, \widehat{\theta}_1\right) - V_1\left(x_{nt} | \theta_2, \widehat{\theta}_1\right)\right)} \tag{43}$$

for $\{k = 2, 3, 4\}$ and,

$$p_1(x_{nt} | \theta_2, \widehat{\theta}_1) = \frac{1}{1 + \sum_{j=2}^{4} \exp\left(V_j\left(x_{nt} | \theta_2, \widehat{\theta}_1\right) - V_1\left(x_{nt} | \theta_2, \widehat{\theta}_1\right)\right)}. \tag{44}$$

The value function is linear in $\theta_2 = (B_0, \gamma_0, \tilde{\gamma}_0, \gamma_1, ..., \gamma_6)$ and is given by

$$
\begin{aligned}
V_2\left(x_{nt}|\theta_2,\widehat{\theta}_1\right)-V_1\left(x_{nt}|\theta_2,\widehat{\theta}_1\right)=&\tilde{x}_{nt}B_0-\left[\tilde{x}_{nt}-(B_t-1)\sum_{s=0}^{T-t}\chi_{t+1}(s)\frac{\tilde{x}_{n,t+1+s}}{B_{t+1+s}}\right]\hat{B}_1 h_2\left(x_{nt}\right)\\
&-\hat{\delta}_0\left[h_2^2\left(x_{nt}\right)-2(1-\hat{\varsigma}_{n.t-1})h_2\left(x_{nt}\right)\right]\left[1-(B_t-1)\sum_{s=0}^{T-t}\frac{\chi_{t+1}(s)}{B_{t+1+s}}\right]\\
&+\hat{\delta}_1\left[l_{n,t-1}+(B_t-1)\left[h_2^2\left(x_{nt}\right)-2(1-\hat{\varsigma}_{n.t-1})h_2\left(x_{nt}\right)\right]\sum_{s=0}^{T-t}\frac{\chi_{t+1}(s)}{B_{t+1+s}}\right]\\
&+\sum_{r=2}^{4}\hat{\delta}_r h_2\left(x_{nt}\right)\left[l_{nt-r}-(B_t-1)\sum_{s=0}^{T-t}\chi_{t+1}(s)\frac{l_{n,t+1+s-r}^{(2,1)}}{B_{t+1+s}}\right]\\
&-(B_t-1)\sum_{s=0}^{T-t}\chi_{t+1}(s)\ln\left(\frac{p_1(x_{t+1+s}^{(2,1)})}{p_1(x_{t+1+s}^{(1,1)})}\right)+h\otimes\xi_{t,2}^{*}\left(x_{nt},\hat{\theta}_1\right)\\
&+\hat{\rho}\left[\Upsilon_2\left(x_{nt}\right)-\Upsilon_1\left(x_{nt}\right)-(B_t-1)\sum_{s=0}^{T-t}\chi_{t+1}(s)\frac{\Upsilon_1(x_{t+1+s}^{(2,1)})-\Upsilon_1(x_{t+1+s}^{(1,1)})}{B_{t+1+s}}\right]
\end{aligned}
$$

where

$$
l_{n,t+1+s-r}^{(2,1)}=\begin{cases}1-\hat{\varsigma}_{n,t-1}-h_2(x_{nt})) & \text{if } 1+s-r=0\\ (1-\hat{\varsigma}_{n,t-1}) & \text{if } 1+s-r>0\\ (1-\hat{\varsigma}_{n,t+1+s}-h_{n,t+1+s}) & \text{otherwise}\end{cases} \tag{45}
$$

$$
\begin{aligned}
V_3\left(x_{nt}|\theta_2,\widehat{\theta}_1\right)-V_1\left(x_{nt}|\theta_2,\widehat{\theta}_1\right) =& \gamma_0+\sum_{s=1}^{5}\gamma_s b_{n,t-5}+\gamma_6\sum_{k=6}^{t} b_{n,t-k} \\
& -\left[\tilde{x}_{nt}-(B_t-1)\sum_{s=0}^{T-t}\phi_{t+1}(s)\frac{\tilde{x}_{n,t+1+s}}{B_{t+1+s}}\right]\hat{B}_1\hat{\phi}_0 \\
& -\hat{\delta}_0\left[\hat{\phi}_0^2-2(1-\hat{\varsigma}_{n.t-1})\hat{\phi}_0\right]\left[1-(B_t-1)\sum_{s=0}^{T-t}\frac{\phi_{t+1}(s)}{B_{t+1+s}}\right] \\
& +\hat{\delta}_1\left[l_{n,t-1}+(B_t-1)\left[\hat{\phi}_0^2-2(1-\hat{\varsigma}_{n.t-1})\hat{\phi}_0\right]\sum_{s=0}^{T-t}\frac{\phi_{t+1}(s)}{B_{t+1+s}}\right] \\
& \sum_{r=2}^{4}\hat{\delta}_r\hat{\phi}_0\left[l_{nt-r}-(B_t-1)\sum_{s=0}^{T-t}\phi_{t+1}(s)\frac{l_{n,t+1+s-r}^{(3,1)}}{B_{t+1+s}}\right] \\
& -(B_t-1)\sum_{s=0}^{T-t}\phi_{t+1}(s)\ln\left(\frac{p_1(x_{t+1+s}^{(3,1)})}{p_1(x_{t+1+s}^{(1,1)})}\right) \\
& -(B_t-1)\hat{\rho}\sum_{s=0}^{T-t}\chi_{t+1}(s)\frac{\Upsilon_1(x_{t+1+s}^{(3,1)})-\Upsilon_1(x_{t+1+s}^{(1,1)})}{B_{t+1+s}}
\end{aligned}
$$

where

$$
l_{n,t+1+s-r}^{(3,1)}=\begin{cases}1-\hat{\varsigma}_{n,t-1}-\hat{\phi}_0 & \text{if } 1+s-r=0\\ 1-\hat{\varsigma}_{n,t-1} & \text{if } 1+s-r>0\\ 1-\hat{\varsigma}_{n,t+1+s}-h_{n,t+1+s} & \text{otherwise}\end{cases} \tag{46}
$$

and

$$
\begin{aligned}
V_4\left(x_{nt}|\theta_2,\widehat{\theta}_1\right)-V_1\left(x_{nt}|\theta_2,\widehat{\theta}_1\right)=&\tilde{x}_{nt}B_0+\tilde{\gamma}_0+\sum_{k=1}^{5}\gamma_k b_{n,t-k}+\gamma_6\sum_{k=6}^{t}b_{n,t-k}\\
&-\left[\tilde{x}_{nt}-(B_t-1)\sum_{s=0}^{T-t}\chi_{t+1}(s)\frac{\tilde{x}_{n,t+1+s}}{B_{t+1+s}}\right]\hat{B}_1\left(h_4\left(x_{nt}\right)+\hat{\phi}_0\right)\\
&-\hat{\delta}_0\left[\left(h_4\left(x_{nt}\right)+\hat{\phi}_0\right)^2-2(1-\hat{\varsigma}_{n.t-1})\left(h_4\left(x_{nt}\right)+\hat{\phi}_0\right)\right]\\
&\otimes\left[1-(B_t-1)\sum_{s=0}^{T-t}\frac{\chi_{t+1}(s)}{B_{t+1+s}}\right]\\
&+\hat{\delta}_1[l_{n,t-1}+(B_t-1)\left[\left(h_4\left(x_{nt}\right)+\hat{\phi}_0\right)^2-2(1-\hat{\varsigma}_{n,t-1})\left(h_4\left(x_{nt}\right)+\hat{\phi}_0\right)\right]\\
&\otimes\sum_{s=0}^{T-t}\frac{\chi_{t+1}(s)}{B_{t+1+s}}]+\sum_{r=2}^{4}\hat{\delta}_r(h_4\left(x_{nt}\right)+\hat{\phi}_0)\\
&\otimes\left[l_{nt-r}-(B_t-1)\sum_{s=0}^{T-t}\chi_{t+1}(s)\frac{l^{(4,1)}_{n,t+1+s-r}}{B_{t+1+s}}\right]\\
&-(B_t-1)\sum_{s=0}^{T-t}\chi_{t+1}(s)\ln\left(\frac{p_1(x^{(4,1)}_{t+1+s})}{p_1(x^{(1,1)}_{t+1+s})}\right)+h\otimes\xi^*_{t,4}\left(x_{nt},\hat{\theta}_1\right)\\
&+\hat{\rho}\left[\Upsilon_4\left(x_{nt}\right)-\Upsilon_1\left(x_{nt}\right)-(B_t-1)\sum_{s=0}^{T-t}\chi_{t+1}(s)\frac{\Upsilon_1(x^{(4,1)}_{t+1+s})-\Upsilon_1(x^{(1,1)}_{t+1+s})}{B_{t+1+s}}\right]
\end{aligned}
$$

where

$$
l^{(4,1)}_{n,t+1+s-r}=\begin{cases}1-\hat{\varsigma}_{n,t-1}-\hat{\phi}_0-h_4(x_{nt})) & \text{if } 1+s-r=0\\(1-\hat{\varsigma}_{n,t-1}) & \text{if } 1+s-r>0\\(1-\hat{\varsigma}_{n,t+1+s}-h_{n,t+1+s}) & \text{otherwise}\end{cases}\tag{47}
$$

6 Results

Incomplete

7 Policy simulations

Incomplete

8 Conclusion

This paper develops a dynamic model of female labor supply and fertility behavior and estimates its structural parameters. Previous empirical research on female labor supply had shown that current labor supply choices affect future wages and utility through intertemporal nonseparabilites in the production function (such as through learning by doing or staying in practice), and in utility (for example, through the household production function and also possibly due to the intertemporal nature of utility from leisure). In addition, there are a small number of studies of fertility behavior that suggest the timing of later births is partly determined by economic factors. Our study nests both kinds of dynamic interactions within a unified structural model.

Our estimates reaffirm the importance of dynamic factors in labor supply and fertility choices. Wages increase with experience up to four years in the past, recent experience counting the most. Leisure taken in different periods are substitutes. Estimated preferences peg optimal birth gestation at about two years.

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9 Figures and Tables

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 consequently 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	reasobale	yes	pregnancy disability	no	
	Hawaii Family Leave Law	1994	6 months	100	4	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
Iowa	Iowa Civil Rights Act	1987	-	4	max 8	yes, if other disabled protected	pregnancy disability	no	
Kansas	Guidelines on Discrimination Because of Sex	1974	-	4	reasonable	yes	pregnancy disability	no	
Louisiana	Pregnancy Disability Louisiana	1988	-	26	min 6, max 4 months	yes	pregnancy disability	no	
Maine	Maine Family and Medical Leave Act	1989	employed with employer	25; 15 (1997)	8; 10 (1991)	yes	birth or adoption	no	
Massachusetts	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	pregnancy disability	no	
New Hampshire	Equal Employment Opportunity	1985	-	6	based on doctor's certification	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
New Jersey	TDI	1948	20 weeks	1	usual length 10, max 26	no, unless covered by FMLA	pregnancy 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 specifed; 25 hours per week (1995)	25	reasonable; 12 (1995)	yes	pregnancy disability	no	
Rhode Island	TDI	1942	20 weeks	-	max 30	yes	pregnancy disability	yes	0.55
	Rhode Island Parental and Family Leave Act	1987	30 hours per week	50	13	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
	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	pregnancy 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	
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	

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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
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/

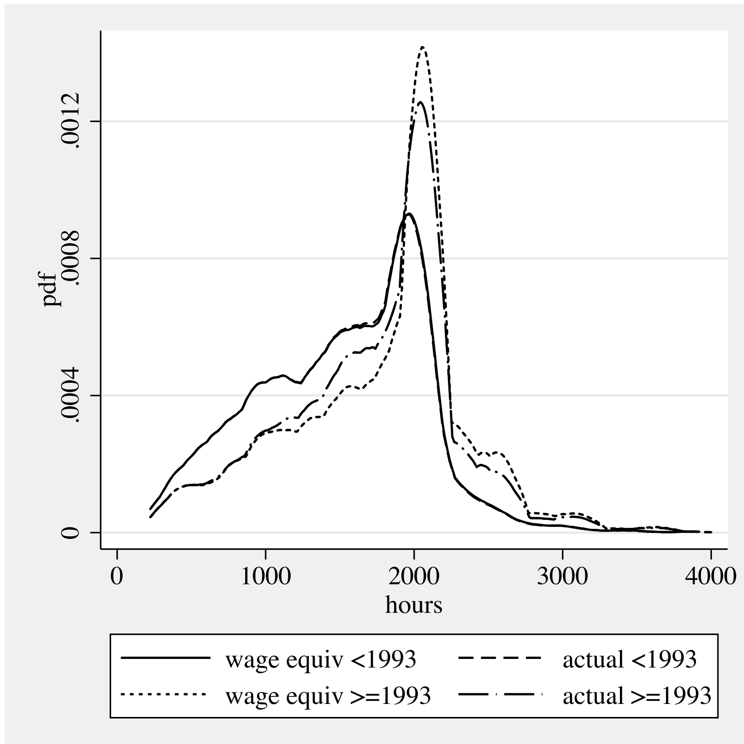
Other relevant notes to policies in Table S1:

- 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.1.1 Leave Hours and Wage-equivalent Working Hours

APPENDIX TABLE S2: Leave Hours in the U.S. 1968-2017

Notes: Leave granted, leaved rolled and leave used are computed using equations (6) to (9).



APPENDIX FIGURE S1: Actual and Wage-equivalent Working Hours of Women who Worked at t and Gave Birth at t or $t-1$, (1968-2017)

Notes: Wage-equivalent working hours are the sum of actual working hours and protected, leave hours taken. See equation (5).

A.1.2 Leave Usage

APPENDIX TABLE S3: Leave Usage in the U.S. 1968-2017

	Protected Leave						*Paid Leave*					
	Share Used		*All Used*		*None Used*		*Share Used*		*All Used*		*None Used*	
	est.	se	est.	se	est.	se	est.	se	est.	se	est.	se
Age	-0.0001	(0.002)	0.0005	(0.0023)	-0.0007	(0.0018)	-0.0015	(0.0035)	-0.0024	(0.004)	-0.0004	(0.0033)
Black and married	-0.041	(0.023)	-0.061	(0.027)	0.047	(0.021)	-0.088	(0.041)	-0.094	(0.049)	0.067	(0.038)
Black and unmarried	-0.057	(0.027)	-0.034	(0.03)	0.083	(0.025)	-0.173	(0.05)	-0.185	(0.058)	0.141	(0.048)
White and unmarried	-0.043	(0.032)	-0.034	(0.038)	0.062	(0.03)	-0.196	(0.077)	-0.202	(0.086)	0.143	(0.075)
Some college	-0.019	(0.021)	-0.017	(0.025)	0.02	(0.018)	0.039	(0.037)	0.015	(0.043)	-0.028	(0.034)
College or more	-0.071	(0.021)	-0.083	(0.025)	0.074	(0.019)	-0.027	(0.04)	-0.034	(0.046)	0.0240	(0.037)
North Central	-0.133	(0.024)	-0.135	(0.029)	0.096	(0.021)						
South	-0.114	(0.025)	-0.128	(0.03)	0.071	(0.021)						
West	-0.039	(0.023)	-0.039	(0.029)	0.028	(0.02)	-0.002	(0.028)	0.041	(0.034)	0.0110	(0.026)
$Birth_{t-1}$	-0.021	(0.04)	-0.005	(0.045)	0.075	(0.039)	-0.098	(0.076)	-0.108	(0.084)	0.092	(0.073)
$Birth_{t-2}$	-0.046	(0.027)	-0.014	(0.03)	0.035	(0.025)	-0.054	(0.05)	-0.079	(0.059)	0.029	(0.048)
$Birth_{t-3}$	0.006	(0.025)	0.003	(0.03)	0.004	(0.023)	-0.02	(0.043)	-0.066	(0.055)	-0.01	(0.038)
$Birth_{t-4}$	-0.033	(0.028)	-0.026	(0.032)	0.015	(0.026)	-0.017	(0.056)	-0.067	(0.066)	0.009	(0.054)
Number of kids	-0.012	(0.01)	-0.013	(0.012)	0.015	(0.009)	0.013	(0.019)	0.017	(0.023)	-0.013	(0.018)
$Worked_{t-1}$	-0.347	(0.051)	-0.358	(0.056)	0.322	(0.05)	-0.324	(0.074)	-0.255	(0.082)	0.387	(0.071)
$Worked_{t-2}$	0.065	(0.041)	0.081	(0.048)	-0.078	(0.039)	0.212	(0.067)	0.198	(0.076)	-0.238	(0.063)
$Worked_{t-3}$	-0.045	(0.039)	-0.055	(0.046)	0.028	(0.036)	-0.105	(0.063)	-0.134	(0.073)	0.077	(0.06)
$Worked_{t-4}$	0.088	(0.036)	0.082	(0.042)	-0.079	(0.033)	0.054	(0.057)	0.026	(0.068)	-0.029	(0.053)
Hours worked$_{t-1}$	1.605	(0.143)	1.44	(0.167)	-1.717	(0.144)	1.422	(0.268)	1.144	(0.29)	-1.738	(0.265)
Hours worked$_{t-2}$	-0.386	(0.15)	-0.601	(0.181)	0.332	(0.138)	-0.8	(0.268)	-0.914	(0.319)	0.815	(0.248)
Hours worked$_{t-3}$	-0.207	(0.154)	-0.209	(0.187)	0.063	(0.139)	0.386	(0.289)	0.426	(0.34)	-0.332	(0.267)
Hours worked$_{t-4}$	-0.414	(0.144)	-0.572	(0.172)	0.201	(0.132)	-0.554	(0.268)	-0.441	(0.322)	0.285	(0.248)
Constant	0.922	(0.066)	0.897	(0.076)	0.095	(0.061)	0.906	(0.101)	0.886	(0.116)	0.139	(0.094)
Observations	2,859		2,859		2,859		801		801		801	

Notes: *Shared Used* is the share of leave available that was used. *All Used* is an indicator for all leave available being used. *None Used* is an indicator for no leave available being used.

A.2 Taxes and Welfare

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