Reducing maternal labor market detachment: A role for paid family leave*

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Abstract

Nearly 30% of working women leave the labor force when they have a child. Access to paid family leave may allow some women to take temporary leave rather than quitting, which may have significant implications for their labor force participation in the long run. We test this hypothesis relying on two policy-based natural experiments: implementation of state-legislated paid family leave programs in California and New Jersey. We estimate an event-study difference-in-differences model comparing pre-to-post-policy trends in labor force participation between women with young children and women with no minor children in each state. We find that in the absence of paid leave, maternal labor market detachment is nearly 30% following a birth; it attenuates over time but remains significantly different from zero as much as eleven years later. We find that access to paid family leave at the time of a birth significantly increases labor market participation by more than 5% in the year of a birth; it attenuates over time but remains significantly different from zero as much as five years later. The impacts are the largest for women with higher educational attainment, indicating that paid leave policies induce the most productive workers to remain in the labor market.

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1 Introduction

Despite the fact that the labor force participation of women has nearly doubled since the 1950s, women's labor force participation continues to lag behind men. Today, 75% of prime-age women participate in the labor force, versus 89% of prime-age men, earning 63 cents for every dollar men make in 2019.[3] A significant share of these gaps are generated by motherhood. Mothers are 14% less likely than other women to participate in the labor force, and earn 36% less. For both participation and earnings, the gender gap triples with parenthood. Why is the arrival of a child such a changing point in women's work lives?

Quite simply someone must take care of an infant. Many child care facilities do not accept infants younger than six weeks, most households cannot afford a nanny. Despite significant cultural change in the past few decades, it remains true that women are more likely to modify their work schedule to care for a child Pew (2013). In the vast majority cases, a woman must stop working, at least temporarily, after the birth of a child. Many factors enter the decision about whether she will return to work, and if so, when. One critical factor may be whether she has a job to return to or was forced to quit in order to take time off.

The Family and Medical Leave Act of 1993 guarantees job-protected leave for up to 12 weeks over a 12 month period. Existing evidence has shown that FMLA increased the likelihood of mothers and fathers taking leave to care for a new child, and returning to work afterward (Waldfogel, 1999; Baum, 2003; Han et al., 2009; Schott, 2012; Kerr, 2016) . However, due to various exemptions, only 54% of working parents have access to FMLA.[4] Further, FMLA is unpaid, and many workers simply cannot afford to take unpaid leave. Use of FMLA is lower for those who have low incomes, less than a college education, or are unmarried (Han et al., 2009; Kerr, 2016). After accounting for parents that do not earn a wage high enough to ensure economic security, only 34% of working parents would be able to take FMLA (DDK, 2011).[5]

The United States is the only OECD[6] country without a national-level guarantee of paid

[3]Prime-age is 25 to 54. Participation in labor force is working or looking for work. Statistics based on the Current Population Survey, 2017-2019, March and June supplements.

[4]Based on analysis of the Current Population Survey March Supplement 2007-2011 (DDK, 2011). Note that in order to be eligible for FMLA leave, an employee must work for an employer with more than 50 employees, have worked for that employer for at least 12 months, have worked at least 1,250 hours over the past 12 months. Elected officials and highly compensated employees are also excluded or face limitations.

[5]Wages that ensure economic security are based on the Basic Economic Security Tables Index for a working parent in a family with two workers and two children . The BEST Index takes into account the full costs of raising children, public benefits received, and the earnings and assets workers need to ensure their family's economic security.

[6]Organisation for Economic Co-operation and Development

leave to care for a new or adopted child. Some employers offer private programs of paid parental leave, but these cover only 13% of U.S. workers (BLS, 2017). Those who are least able to afford to take unpaid leave are also less likely to have access to employer-provided paid leave. To address this gap, a growing number of states have enacted programs of mandatory, publicly-administered paid family leave (PFL). While eight states and the District of Columbia have adopted, the first adopters of paid family leave were California and New Jersey, which are the focus of this study.[7]

We estimate an event study difference in differences, comparing women with young children to women without children, across those who did and did not have access to PFL at the time of their child's birth. Because we rely on monthly data over many years, we observe women with children of the same age in the same state with different exposures to the policy. We document significant labor force detachment of women following the arrival of a child. While detachment declines over time, it is statistically significant for up to 11 years after the birth. In comparison, the arrival of a child has no immediate impact on men's labor force participation and instead has significantly positive effects beginning eight years later.

We next examine the impact of access to PFL on women's labor force detachment and test how this impact changes over time. We find that PFL significantly decreases labor force detachment in the year of the birth and up to five years afterward. These effects are stronger for women with college degrees for whom the effects are sustained for up to eight years. Effects are muted among Hispanic women and are not significantly different from zero among Black and Asian women, who have lower levels of parental labor market detachment than White women.

In the next section, we provide details on the state-level policies examined in this analysis and discuss existing evidence about their impacts. We then lay out a conceptual framework to fix ideas and describe our analysis. Section 5 presents the results and section 6 concludes.

2 Background and Existing Evidence

California's Paid Family Leave program (CA-PFL) was the first state program to implement paid leave entitlements in 2004. Any person who has been paid at least $300 in wages during the base period is eligible to take up to six weeks of leave in the 12 months following the birth or adoption of a child. The program is funded by mandatory employee payroll

[7] See Table 1 for a summary of existing paid leave legislation.

tax deductions, and pays new parents 60 to 70 percent of weekly wages during absences for caregiving.[8] Beginning in July 2020, the leave allowance will increase to eight weeks and wage replacement will increase to 90% for low-wage workers. Given the length of time this program has been in place, analysis of it offers a unique opportunity to examine impacts up to thirteen years after a birth. However, given that California is often an outlier state in many ways, we complement this analysis by also examining medium-run impacts in New Jersey.

New Jersey's Family Leave Insurance (NJ-FLI) Program was implemented in 2009. Eligibility requires a history of earnings subject to state taxes for minimum of five months. Entitlement includes six weeks of leave with up to 66% of normal wages, financed jointly by employee and employer payroll deductions. Entitlements will increase to 12 weeks in July 2020. For both CA-PFL and NJ-FLI, paid leave may be coupled with federal and state unpaid leave options that provide job protection, such as FMLA, California Family Rights Act, California New parent Leave Act, and New Jersey Family Leave Act.

Other states have more recently implemented PFL programs, including Rhode Island (2014), New York (2018), and Massachusetts (2019). However, not enough time has yet passed since the implementation of these programs to examine their impacts on longer-term labor force attachment.[9]

A growing body of research examines the immediate and short-run impacts of CA-PFL, and to a lesser extent, NJ-FLI. The primary outcome that has been examined is leave taking. Rossin-Slater et al. (2013) and Baum and Ruhm (2016) find that CA-PFL doubled the use of maternity leave, as well as increasing the length of leaves from an average of three to six weeks.

There is suggestive evidence that increased use of maternity leave improves mothers' and children's health. Bullinger (2019) finds that it improves mother's mental health. Oloomi (2016) finds that it encourages older women to have births sooner, reducing low birth weight and premature birth. Other channels through which infant health outcomes are potentially improved are breastfeeding and health checkups. PFL increased the likelihood and duration of breastfeeding (Huang and Yang, 2015) as well as adherence to

[8]More recently, California cities such as San Francisco offer a generous add on to state paid family leave ensuring that new parents receive 100 percent of wages during time off. Under the San Francisco Paid Family Leave Policy (SFO PFL) employers are required to provide employees receiving state paid family leave to care for new child with "Supplemental Coverage" equal to the difference between the employee's PFL benefit and gross weekly wages to ensure that wages are replaced at 100 percent while on leave. This policy took effect on January 1, 2017 and January 1, 2018 for employers with 50 or more and 20 or more employees, respectively.

[9]For example, even in Rhode Island less than 0.5% of children under age 5 in years 2010 to 2019 were born under the PFL policy, offering too little variation for meaningful analysis.

vaccination schedules (Choudhury and Polachek, 2019). These modified health behaviors contributed to a decline in infant mortality (Choudhury, 2018) and positive effects on the health of elementary school age children Lichtman-Sadot and Bell (2017).

Use of PFL has also been shown to impact short-run labor dynamics. Das and Polachek (2015) compare labor force participation rates and unemployment rates of state-by-gender-by-age groups and find that young women have increased rates of labor force participation after CA-PFL (relative to young men and older women). They also find that PFL increased the unemployment rate of young women. This unexpected effect may be a result of reduced hiring of women, as documented by Sarin (2016), who finds that employers who are required to offer job-protected leave reduce their hiring of women by 1.1%. However, other studies find no impact of PFL on women's unemployment (Rossin-Slater et al., 2013). Findings on job separations are also mixed, with Sarin (2016) finding that they decrease and Curtis et al. (2016) finding that job separations increase. Whatever the pathway, these changes add up to real economic impacts on households in the short-run. Stanczyk (2019) shows that, in the year following a birth, mothers with access to PFL have 4.1% higher incomes and 10.2% lower risk of poverty.

The studies most nearly related to this one are those that examine the impact of PFL on the labor force participation of new mothers. Unlike Das and Polachek, these analyses are conducted at the individual level and specifically examine labor market behaviors in the years immediately following a birth. While the primary outcome of interest in the article by Rossin-Slater et al. (2013) is leave-taking, they also examine working status and hours of work in the one to three years following a birth. In this analysis they find no impact on the probability of working, but find increased hours of work among those working.

Byker (2016) offers the only existing evidence of an impact of PFL on women's labor force participation at the individual level. Her analysis is also unique as it is the only existing study to consider the impacts of NJ-FLI. Byker finds that women having births in CA or NJ after the implementation of paid leave are about 10 percentage points more likely to be in the labor force during the six month period that is centered around a birth, relative to women with births occurring before the paid leave legislation. While this represents one of the most recent and highest quality studies on this topic, it is limited by data availability and only examines behaviors up to two years after a birth.[10]

This is the first study to document the longer-run impacts of PFL on women's labor force participation. Current data now allow for examination of mothers' labor market be-

[10] Byker (2016) relies on data from the Study of Income and Program Participation, which is a 4-year panel data set on individuals. This data allows for the use of within-woman estimation by employing individual fixed effects, but it limits her analysis to a narrow window of time for each individual.

haviors up to 13 years after the implementation of paid leave in CA, and up to 8 years in New Jersey. None of the existing work shows impact beyond 2 years after a birth nor tests for impacts beyond 3 years after a birth. We show that maternal labor market detachment is significant up to 11 years after a birth and document that PFL reduces this significantly during the first 5 years. In addition, our analysis by demographic sub-groups is the first to document evidence that some PFL benefits may be regressive in nature. While others have shown that some PFL benefits are driven by disadvantaged groups, we find that longer-term improvements in labor force participation are driven by those with higher education and greater social privilege. We further discuss these differential findings in section 6.

3 Conceptual Framework

Consider a multi-period framework where in each period a woman decides to work or be out of the labor force (OLF).[11] This decision is affected by several factors, including the age of her youngest child, whether or not she was working in the previous period, individual fixed effects, and other random shocks. In each period there is a utility cost for changing her work status from the previous period. That is, all else equal, a working woman would prefer to keep working and an OLF woman would prefer to continue OLF status. The age of her youngest child is negatively and exponentially related to her probability of working. Access to paid leave is negatively related to OLF status through a step-wise function, such that it increases the probability of being in the labor force only in the first year after a birth.

In the first year after a birth a woman on the margin of working vs. OLF may be induced to remain in the labor force by access to paid leave. Given the dynamic nature of the framework, preventing OLF status in any given year reduces the probability of OLF status in future years. As such, all else equal, those who had access to paid leave at the time of a birth would be more likely than others to be working not just in the first year or two after a birth, but for many years after. The time span at which this effect would dissipate would depend on the exact function that relates the decision in each period to the age of the youngest child. That is, as the youngest child gets older, the utility of working increases; at some point it will overcome the disutility of changing status and the impact of paid leave will dissipate.

[11] Without loss of generality, we assume full employment.

4 Analysis

4.1 Data

We employ individual-level data from the Basic Monthly Sample of the Current Population Survey (CPS) accessed through the Integrated Public Use Microdata Series (IPUMS) database. It is a representative sample of the civilian population in the United States. Over 65,000 households are selected into the sample and surveyed for four consecutive months, excluded from the sample for eight months, and then re-interviewed for four consecutive months. The data provide comprehensive information on labor force participation, employment, full-time employment status, occupation type, and other demographic and labor force characteristics over time. Our primary sample contains the first interview from civilian, prime-age women (aged 25 to 54) for twenty years of data (1999 to 2019).

Table 2 provides descriptive statistics about the samples of women with young children (under age 5) (group Y) and women with no minor children (group N) for California and New Jersey separately. Both groups are equally as likely to be in their 20's, but group Y is more concentrated in their 30's, while group N has a higher concentration in their 40's and 50's. All specifications include a quadratic function of age to control for these differences. The groups are comparable in terms of race and education, but Y is more likely to be Hispanic and married than N. Unsurprisingly, Y is much less likely to participate in the labor force, with rates of approximately 60% versus 77% for group N. Among those who are employed, Y are less likely than N to be working fulltime (64% vs. 78%) or in a managerial or professional occupation as well (37-38% vs 41%). Racial composition is comparable across groups Y and N. Notably, race differs considerably across the two states, with black women making up 6-8% of the sample in California and 15-18% in New Jersey. New Jersey's population has relatively fewer Asian women (8-11% versus 16-17% in California). In terms of ethnicity, we do see significantly more Hispanic women in group Y than in group N in both states (45% vs. 27% in CA, and 23% vs. 17% in NJ), with California having significantly more than New Jersey. Educational attainment is comparable across groups Y and N, and across states.

4.2 Methods

We employ an event study difference-in-differences methodology that exploits changes in access to PFL through family leave insurance programs in California and New Jersey. We estimate,

$$O_{iy} = \alpha + \beta_1 Child_{iy}^a + \beta_2 PFL_{y-a} \times Child_{iy}^a + \sum_{n=0}^{a-1} \delta_n Child_{iy}^n + X_{iy}\gamma + \nu_y + \varepsilon_{iy} \quad (1)$$

where O_{iy} is the outcome of interest for woman i interviewed in year y. Our primary outcome of interest is labor force participation last week. Estimations are conducted separately by state.

$Child_{iy}^a$ is an indicator that the woman has a child of age $a = \{0, 1, 2, ...a_s\}$ in year y, and PFL_{y-a} indicates that the paid family leave law was in place at the time that child was born. The maximum age examined, a_s, is state-specific. In NJ, given the 2009 policy change, we have very no variation in policy exposure among children older than eight years. In CA, the 2004 policy onset allows us to examine the impacts until children are as old as thirteen years.

Each specification employs a single-state sample that contains all women with a child of age a, and all women with no children under age 18 in the home.[12] For robustness, we also estimate the equation employing alternative comparison groups.

We do not require that $Child^a$ be the youngest child of woman i, as that would introduce endogenous selection. Instead we include $\sum_{n=0}^{a-1} \delta_n Child_{iy}^n$, which is a set of indicators for having a child of each younger age from 0 to $a-1$. The specification also includes year-fixed effects, ν_y, which absorb year-specific variations in labor markets and other relevant trends. Note that year-fixed effects also absorb the term PFL_{y-a} that would otherwise be included.

X_{iy} is a vector of individual and household characteristics, including a quadratic function of age, indicators for completing high school, bachelor's degree, and advanced degree, Hispanic ethnicity, race (white, black, Asian, or other), residing in a metropolitan area, total number of children, and, to control for childcare help, number of related teens in the household and number of related adults (e.g. grandparents, aunts, etc.). Estimated standard errors are heteroskedasticity-robust.

We note that we have only the child's age at the time of the survey, not the child's birth date (or birth month). For children born near to the policy change, this induces uncertainty regarding whether the birth occurred before or after the policy. We code $PFL_{y-a} = 1$ if we are certain that the child was born after the policy and $PFL_{y-a} = 0$ if we are certain that the child was born before the policy. For the small subset with some ambiguity, we leave PFL_{y-a} as missing and thus exclude these from the estimation. Therefore each

[12]This includes both women with no children, and women whose children are over 18 or not living with her.

estimation includes all women with $Child^a = 1$ for who PFL_{y-a} is not missing, and all women with no children, as the comparison group. Women with children who do not have a child of age a are also excluded. In an robustness check, we employ as an alternative control group women with a youngest child aged 7 to 17 rather than women with no children.

The coefficient β_1 indicates the impact of having a child of age a who was born prior to PFL, relative to having no children under age 18 in the household. The coefficient β_2 indicates the amount by which access to PFL at the child's birth offsets the impact of having a child of age a.

To interpret β_2 as a causal effect, the key required assumption is that the trend in labor force participation over time would have been similar between women with young children (group Y) and women without minor children (N) in the absence of the policy. A standard test of the validity of this assumption is to examine the trends in the outcome of interest over the time period before the policy implementation. These trends are presented in Figure 1 for California and New Jersey separately. In both states, the pre-policy trends are almost perfectly parallel between groups Y and N. This provides evidence that the assumption of common trends in the absence of the policy is reasonable. The figure also shows the post-policy trends (to the right of the vertical line). In both states, following policy implementation we see a continuation of the pre-policy trend for group N, and an significant increase in slope for group Y, creating distinctly different trends and much more similar levels of labor market participation between the groups in the post-policy period.

Heterogeneous effects

We additionally explore how the effects pf PFL vary by demographic sub-groups. In order to test this we estimate

$$\begin{aligned} O_{iy} = \alpha + \beta_1 Child^a_{iy} + \beta_2 \left(PFL_{y-a} \times Child^a_{iy}\right) + \beta_3 \left(Child^a_{iy} \times notG_i\right) \\ + \beta_4 \left(PFL_{y-a} \times Child^a_{iy} \times notG_i\right) + \beta_5 notG_i + \sum_{n=0}^{a-1} \delta_n Child^n_{iy} + X_{iy}\gamma + \nu_y + \varepsilon_{iy} \end{aligned} \quad (2)$$

where all parameters are as described above and $notG_{iy}$ is an indicator for not being in the group of interest, so that now β_1 and β_2 indicate the impact of a child and of PFL, respectively, specifically for the group G. We test this for the disjoint education groups: with vs. without bachelor's degree. We also consider subsets of these groups: those without a high school diploma, and those with an advanced degree. We consider two disjoint ethnic groups: Hispanic and non-Hispanic. We consider three disjoint race groups: Black, White, and Asian/Pacific Islander. We also examined potential heterogeneities by age and marital status but found none.

5 Results

5.1 Parental labor market detachment

We first examine the impact of a child's arrival on the labor force participation of women and men in the absence of paid family leave legislation and how this evolves over time. We define the labor market detachment rate ($LMDR_a$) as the decline in the probability of participating in the labor force for a parent with child of age a, relative to the comparison group of individuals of the same gender in the same state who have no children in the home. Note that $LMDR = -1 \times \beta_1$. This reflects the degree to which parents quit their jobs or stop looking for work; parents who remain employed while on parental leave (whether paid or not) do not impact the $LMDR$.

We present estimates of mothers' $LMDR$ for all values of a in Tables 3 and 7. To illustrate how detachment changes over time, we plot β_1 estimates in Figures 2 and 4 against values of a, with error bars showing 90% confidence intervals.

California

In California, we find $LMDR_0 = 0.285$ for women. That is, the arrival of an infant reduces the probability of the mother participating in the labor force by 28.5 percentage points, or 41% relative to the 69.5% participation rate of women without children at home.

This effect dissipates as mothers return to work over time. Year-over-year changes are largest in the first two years, with a slight discontinuity at age four and then more gradual decreases. Nonetheless, even when the child is as much as 11 years old, mothers still have $LMDR_{11} = 0.048$, statistically different from zero at the 1% level. Only at age 12 and 13 does women's $LMDR$ no longer differ from zero at a standard level of significance.

For comparison, we also estimate $LMDR$s for men. In contrast to women, $LMDR_0 = 0.029$ for men. While we can reject that this effect is zero at 1% significance, we also note that this $LMDR$ is only 10% of the figure for women. The $LMDR$ for men is fairly consistent for $0 \leq a \leq 3$;at $a = 4$, $LMDR_4$ drops to 0.009 and is no longer statistically different from zero. This indicates that a very small share of men step away from the labor force as a result of having a child under age four; children aged four and older have no significant impact on their fathers' labor force participation.

We examine heterogeneous labor market detachment of women by education, ethnicity, and race. These are plotted in Figure 3, Panels A and B, and presented in Tables 4 to 6. Among women who did not complete high school, we see a large discontinuity at age three. This likely reflects the association between low education and poverty, as age three is when children from poor households become eligible for Head Start programs. In contrast, among women with advanced degrees, initial detachment is lower than for other groups ($LMDR_0 = 0.213$), but return to work happens more gradually. Among the highly educated, $LMDR_3$ remains at 0.184, and then drops considerably to $LMDR_4 = 0.064$, likely reflecting the fact that many preschool programs begin at age four. While these differences in estimated $LMDR$ by education are suggestive and interesting, we note that given the confidence intervals we cannot reject that the $LMDR$ is the same across all groups for any level of a.

In Panel B and Tables 5 and 6, we consider ethnicity and race. Initially, we see higher $LMDR_0$ among Hispanic women (0.323 vs 0.260 for non-Hispanic). But Hispanic women return to work more quickly, with a strong discontinuity at $LMDR_2 = 0.179$, lower than for non-Hispanic women. We also note that Asian women have an $LMDR_0 = 0.179$ that is lower than for white women (0.319) and this difference is statistically significant ($p = 0.012$). Despite imprecision of the wide confidence internals for Asian women, it is clear that the point estimates of $LMDR$ are higher than for white women at every value of a. While estimations for Black women are excluded from Figure 3 due wide confidence intervals arising from the small population share of this group (6%), these results are included in Table 6. For this group we find a statistically $LMDR$ only when $a = 0$. Black women return to work by $a = 1$, and when $a \geq 4$, we observe positive and statistically significant impacts of a child on labor force participation.

New Jersey

We now consider the parallel findings for New Jersey. Given the 2009 implementation of the program in New Jersey, we are able to examine impacts up to eight years after the birth of a child. There is no variation in exposure among nine year old's in our data. As we have already discussed the findings from California, in this section we focus on how the findings from New Jersey corroborate or differ from what has already been found. These are presented in Tables 7 through 9 and Figures 4 and 5.

We find strongly consistent patterns of maternal labor market detachment across the two states. In New Jersey, $LMDR_0 = 0.264$, indicating a 26.4 percentage point decline in labor force participation in the year of a birth or adoption. This represents a 33% drop relative to prime-age women who do not have children at home. As before, we see a slow but steady decline in $LMDR$ over time, but it remains statistically different from zero even eight years after the birth, at $LMDR_8 = 0.087$, which is comparable to and slightly higher than what is observed in California. Also consistent is the finding that paternal labor market detachment does not exist, with men's labor force participation unaffected or significantly increasing as a result of fatherhood.

We similarly examine heterogeneities in $LMDR$ in New Jersey. Fewer than 10% of new mothers in this population did not complete high school, so the confidence intervals for this group are very wide and the group is not included in Figure 5. However, similar to CA, we find that the $LMDR$ decreases suddenly when the child reaches age three; from that point onward it is not distinguishable from zero for this group. Otherwise, we find no substantial differences across other education groups in the levels or trends of $LMDR$s in New Jersey.

Examining by ethnicity, findings are consistent with those from California. Hispanic women return to work sooner than other women; this occurs even earlier in New Jersey ($a = 7$) than in California ($a = 12$). Among Black and Asian women we also observe similar patterns across the two states. Black women do not leave the labor force following a birth at the same rate as other women, and they return to work sooner. $LMDR$ first becomes insignificant for Black women at $a = 1$ in CA and $a = 3$ in NJ. Asian women also return to work sooner, with insignificant LMDR beginning at $a = 7$ in CA and $a = 5$ in NJ. In contrast, White women exhibit statistically significant $LMDR$s in all years observed in both states.

5.2 Impact of paid family leave on maternal labor market detachment

We now examine the impact of paid family leave legislation at the time of a birth on women's labor market detachment a years later. This effect is estimated by β_2 in equations 1 and 2. We interpreted $\beta_1$as the decline in the probability of labor force participation as a result of having a child a years ago in the absence of paid family leave (that is, -1$\times LMDR_a$). In contrast, β_2 represents the increase in the probability of labor force participation resulting from having access to paid family leave a years ago, relative to women who have a child of age a who was born without access to PFL. β_2 can also be interpreted as the reduction in $LMDR_a$ that results from implementation of PFL.

Estimates of β_2 are also presented in the tables previously discussed, and are plotted in Figures 6 through 9. Note that variation in treatment status wanes as a approaches a_s, reducing statistical power and increasing confidence intervals considerably. For this reason, estimations for $a_s - 1$ and a_s are included in the tables, but are not shown in the figures that are disaggregated by demographic group.

California

We find that the implementation of paid family leave legislation significantly increased the labor force participation of mothers. This effect is evident not just in year zero, when access to paid, job-protected leave would prevent some women from quitting their jobs, but continues up to five years later. $LMDR_0$ is reduced by 0.058, or 20%. The proportional effect is relatively constant over the first six years, with $LMDR_5$ reduced by 0.026, or 22%. When the child is age six, the impact is drastically reduced to 0.006, or 5.6%, and is not statistically different from zero.

This indicates that access to paid family leave increases the labor force participation of women in the first year after a birth, and that increase is sustained throughout the preschool years of the child. By the time the child enters first grade, his mother's labor force participation is no longer significantly affected by whether she had PFL at the time of his birth. Nonetheless, it is striking that a policy that officially affects no more than the first 12 months following a birth can have impacts that are sustained up to five years after. In section 6 we discuss the implications of a six year absence from the labor market for women's career trajectories and earnings.

We additionally consider heterogeneous impacts of paid leave legislation. Figure 7 shows estimates of β_2 from equation 2 for the same groups as presented in Figure 3. We find no statistically significant impact of the policy for women without a high school diploma. Not only are the confidence intervals wide due to the small sample size, but the estimates are also very close to zero, and in some cases negative. Among the two-thirds of women who do not have a bachelor's degree, effects are concentrated in years zero through five, but only years zero, one and three are significantly different from zero.

The strongest effects are observed among women with higher education. Those with bachelor's degrees experience positive and significant effects that are sustained until the child is eight years old (with one exception at age 4). The level effects are quite stable for this group, with a reduction in $LMDR_0$ of 0.064 and a reduction in $LMDR_8$ of 0.052. This amounts to increasing proportional effects ranging from 24.7% in year zero to 51% in year eight. Beginning in year nine, effect for this group are also indistinguishable from zero. Women with advanced degrees represent only 12% of the population, so the confidence intervals for this group are very wide. Nonetheless, the estimated effect sizes during years zero to four are larger for this group than for other highly educated women. While we acknowledge that there is no a for which we can reject that the effects are the same across these demographic groups, the pattern of estimated coefficients does suggest that the benefit of PFL is increasing in a women's level of education.

When disaggregating the results by ethnicity and race, we also find suggestive evidence of differential impacts. Among Hispanic women, impacts of PFL on labor force participation are large when $0 \leq a \leq 1$ but then reduce considerably and are generally no longer statistically different from zero. After year six, point estimates are actually negative, though generally we cannot reject that they are zero. In contrast, non-Hispanic women exhibit consistently positive and significant effects for $0 \leq a \leq 4$. When we disaggregate by race we find the strongest evidence of impact among White women. In this case, significant effects extend until $a = 5$, with proportional reductions in $LMDR$ trending from a 21% decrease in $LMDR_0$ to a 24% decrease in $LMDR_5$. In contrast, point estimates are much smaller (and not significantly different from zero) for Asian women at any value of a. This is not surprising given that $LMDR$s were generally smaller for Asian women (significantly so when $a = 0$), so there is less scope for impact of PFL in this population. Likewise, there are no significant impacts on Black women. Nonetheless, we note that we cannot statistically reject in any case that the impacts of PFL on $LMDR$ are the same across all demographic groups.

New Jersey

We now turn to the impact of the New Jersey Family Leave Insurance program, as plotted in Figures 8 and 9. Given the relatively recent implementation of the program, we have lower variation in exposure and the estimates are noisier and less precise than for California. While the pattern is not strictly monotonic, we do observe significant positive impacts on labor force participation for nearly all values of a between zero and five (except two). Despite a wide confidence interval, even the estimated impact at $a = 8$ is statistically significant at the 10% level. Proportionally, the effects are larger in New Jersey than in California, with paid leave offsetting 50% or more of the maternal labor market detachment in most of the first six years after a birth.

We also examine impacts of the program by demographic group. There is no effect among the small group of women without a high school diploma, which is not surprising given their low levels of labor market detachment in the absence of the program (this small group is excluded from Figure 9 but is included in Table 8). As in California, impacts are larger and more consistent among women with higher education. Women with college degrees show positive and significant impacts of PFL in all years zero through four, whereas those without a degree show some signs of benefits that are smaller and less consistent. The largest estimates are among women with advanced degrees in years three through six, with PFL increasing labor force participation by as much as 22 percentage points.

In New Jersey we estimate striking differences in impact of the program by ethnicity. We observe no significant effect of the program on the labor force participation of Hispanic women for any value of a. In contrast, non-Hispanic women have statistically significant effects for eight of the nine years observed. The proportional effect sizes for non-Hispanic women are very large: in years zero through two these range from 29% to 48%, while effects in years three through eight range from 56% to 172%. Findings for White women closely mirror the effects for non-Hispanic women. In contrast, we find almost no statistically significant effects on Asian or Black women. We note however that the small population shares of these groups generate very wide confidence intervals; the point estimates do suggest the possibility of positive impacts on Black women, though the estimates for Asian women are much closer to zero (and in some cases negative).

5.3 Impact on other labor outcomes

The primary focus of this research is labor force participation, as we expect the most direct impacts of a paid leave policy on this outcome. However, we also examine whether the policy affects a limited set of other labor market indicators.

We find no evidence that access to paid leave affects unemployment, conditional on being in the labor force. This is true despite significant fluctuations in unemployment rates during our data period due to the Great Recession.

We also examine whether it impacts full-time working status, conditional on being employed (Tables 10 and 11). We find that impacts on full time status are consistently positive in both states, with effect sizes in California of 2 to 4 percentage points (on a base of 72%) during the first four years after a birth, and larger effects in New Jersey of 7 to 11 percentage points during the first three years, with positive but smaller effects in later years. In New Jersey, we can reject that these effects are zero in three of the first four years. In California, we can reject the null only when $a = 1$ and $a = 8$.

Finally, we also consider as an outcome whether or not a woman is working in a professional or managerial occupation at the time of the interview. The results for this indicator are mixed, with both positive and negative coefficients in both states. However, we do find statistically significant positive effects in California when $a = 4$ and $a = 8$. This is somewhat suggestive that preventing temporary labor market detachments can have knock-on benefits in terms of career advancement 4 to 8 years later.

6 Discussion

In this work we have explored how the arrival of a child impacts the trajectory of women's labor force participation over time. We confirm that while it has no significant impact on men's participation, a child has an immediate and sustained negative impact on women's labor force participation. In the year of a birth, women's labor force participation rates decline 0.26 to 0.28, representing declines in participation of 33% to 37%. While maternal labor market detachment shrinks over time, it remains significantly different from zero up to eleven years after the birth.

We test the impact of paid family leave legislation on maternal labor market detachment, and how this impact evolves over time. We note that legislation of this sort increases access to paid family leave only for a subset of the population. An estimated 13% of the population has access to PFL through their employer, and those who are unemployed in the year before the birth would not have access to benefits. Additionally, many workers are employed at small firms that are exempt from FMLA, so any paid leave taken may not be job-protected. While the legislation would affect PFL access for the majority of parents, we note that our estimates are attenuated by the fact that the policy does not affect all parents' leave access.

We find that access to PFL partially closes the labor force participation gap between mothers of young children and other women. As expected, we see a significant impact in the year of the birth, when PFL may allow a woman to take time away from work to care for the infant without having to quit her job to do so. What is striking is that access to PFL at the time of a birth continues to significantly reduce maternal labor market detachment for up to five years. This finding is consistent across both California and New Jersey.

We find that PFL reduces maternal labor market detachment (LMD) by 20% in the year of a birth. This indicates that the majority of LMD in the year of a birth is unaffected by PFL legislation. This partly reflects the fact that a non-negligible portion of the population have a PFL status that is unchanged by the legislation. More significantly, it reflects the fact that access to PFL does not prevent all women from exiting the labor force upon the arrival of a child. Reasons why a woman may choose to leave the labor force even when she has access to PFL may include: the length of the PFL is too short, the cost of quality childcare is too high, or a personal desire to engage in childcare rather than paid work.

Interestingly, we find that the proportional impact of PFL on women's labor force participation is constant or increasing during the five years following a birth. In California PFL continues to reduce LMD by about 20% in each of the following five years; in New Jersey, its proportional effects increase over time, averaging 46% in this period. This suggests that, in the absence of PFL, the labor market detachments prevented in year zero may have continued for up to five additional years.

In the absence of paid family leave, approximately 5 in 20 working women will step away from paid work entirely in the year of a birth. By the time the child is age six, 2 of those 5 will remain out of the labor force. Giving (some) women access to paid family leave at birth means that about 1 of those 5 will choose to keep her job when the child arrives. In every year in the first six years after a birth, we observe an additional 1 in 20 women in the labor force as a result of PFL. For this 1 women (in 20), PFL has prevented a six year absence from the labor market.

What does a six year absence from the labor market during prime working years cost a woman? Lost wages for the median working woman would be $253,344.[13] Foregone wage increases (assumed at 2% per year) set a woman back in her wage trajectory, amounting to an additional loss of $266,325 over her remaining 35 years in the labor force. It is more difficult to quantify the foregone human capital development that would have occurred during those years, and how such an absence would affect her career trajectory. Suggestive evidence presented here indicates that labor market detachments prevented by PFL may have impacts on the probability of being in a professional or managerial role five years in the future. For at least 20% of women, paid family leave legislation can prevent these significant costs in terms of lost earnings and dampened career trajectory.

What are the broader economic implications of these findings? To consider the potential economic impact of maternal labor market detachment, and potential economic benefits of PFL, we consider the educational profile of these 5 women who would leave the labor market and this 1 woman who is prevented from doing so by PFL. We find that the 5 in 20 women who exit the labor force when a birth occurs are distributed across the educational spectrum, from no high school diploma to advanced degrees. However, we find that the 1 in 20 women whose labor market detachment is prevented is unlikely to be women without a high school diploma, and is most likely to have a college degree. This suggests that among women who might leave the labor force as a a result of a birth, access to PFL acts to keep the most productive workers in the labor market.

[13] Median weekly earnings of full-time working women in the U.S. was $812 in the 2nd quarter of 2019 (BLS, 2019).

What are the distributional implications of these findings? We find that the benefits of PFL in terms of labor market attachment do not accrue evenly across racial and ethnic groups. PFL is substantially less likely to reduce LMD of women who are in the smallest racial and ethnic minorities in their state. We find that PFL does not significantly improve labor force participation of Black and Asian women in CA, nor of Hispanic and Asian women in NJ, in any of the years examined. (We note that we do see some positive impacts of PFL among Black women in NJ and among Hispanic women in CA). Among Black women in CA, the lack of impact is likely explained by the general lack of maternal labor market detachment in the absence of PFL among this population; in essence, there is little to offset. This is not the case for Hispanic women in NJ, nor for Asian women in either state; for these groups we do see significant maternal LMD, but no significant offsetting effects of PFL. This may reflect the fact that these women may be more likely to work in informal jobs, without access to the paid leave programs, or may be more likely to work for small employers who are exempt from FMLA, meaning their paid leave would not be job-protected.

How do these findings compare with existing evidence? Das and Polacheck find that PFL increased labor force participation by 0.0137 among women aged 18-41. This estimation is for all women in this age range, regardless of motherhood status. Naturally, this is lower than our estimates, which focus on impacts for women with recent births.

Byker focuses on women with births and estimates the effect in each of the 24 months before and after a birth. In year zero, her estimates of the impact of PFL on labor force participation range from 0 to 0.13, averaging about 0.06.[14] This is highly consistent with our estimates from CA and NJ, which are 0.058 and 0.056 for year zero, respectively. In year one, her estimates range from 0 to 0.06, averaging about 0.04. This is somewhat lower than our year one estimates, which are 0.056 in CA and 0.114 in NJ. For our estimates in years 2 through 13, there are no existing comparable estimates.

Another interesting point of comparison is the evidence regarding which subgroups are most benefited by these policies. Existing evidence suggests that these policies are progressive, providing the greatest benefits to the most disadvantaged groups. Rossin-Slater et al (2013) note that the increases in leave-taking are particularly large for less advantaged groups. Stanczyk (2019) finds that benefits of PFL such as increases in income and decreases in poverty in the year following a birth are concentrated among women with low-education, and low-income single mothers. Similarly, Byker finds that the PFL-induced gains in labor force participation in the first two years after a birth are entirely

[14] Note that Byker's results are presented graphically only, so it is impossible to know exact values.

driven by women without college degrees. In contrast, evidence presented here suggests that labor force participation gains from PFL are largest, most consistent, and longest lasting among women who are college graduates.[15] Effects are significantly different from zero in only 2 or 3 years for women without degrees, versus 8 out of 9 years after a birth (or 6 of 8 years in NJ) among women with degrees. While we cannot reject that the effects are the same across these groups, these findings suggest that the impacts on labor force participation are increasing in education, at least in the longer run.

What can explain such starkly different findings about the distributional impacts? Existing evidence suggests that disadvantaged women have bigger increases in leave-taking as a result of PFL and are are more benefited in terms of increased income and reduced poverty. These findings are actually not inconsistent with our finding that PFL has greater impacts on the labor force participation of more advantaged women. If disadvantaged women are financially unable to leave the labor force, PFL may increase their leave-taking but will not affect their labor force participation. We see some evidence of this in our data. While labor market detachment in the absence of PFL is not significantly different across education groups, we do see that $LMDR$s are increasing with education, especially in NJ were women without a high school degree have very inconsistent $LMDR$s. We also find that Black women in CA exhibit almost no maternal labor market detachment, and that of Hispanic women in NJ is also smaller and of shorter duration than for other women. Because of this, it is not surprising to find that "upstream" benefits like leave-taking and income may be higher among the disadvantaged, while "downstream" benefits such as longer term labor force participation may be higher among the more advantaged.

However, our findings are still at odds with those of Byker, who finds that even impacts on labor force participation are greater among those with less education. We note here that Byker's findings are focused on months -3 to +3 surrounding a birth. It may be the case that labor force participation just prior to a birth is strongly affected for those with lower education, which could be driving the difference. This is supported by Byker's secondary analysis, which shows that the largest gains in employment for women without degrees are observed in the months just prior to the birth. We are unable to test this in our cross-sectional data, with which we cannot examine impacts before a birth. We note that in our analysis, the differences across education groups primarily appear after year 2, which is outside the scope of Byker's analysis.

What are the policy implications? The existing body of evidence has documented that paid family leave offers many important short-run benefits. It increases leave-taking,

[15]Note also that we find no differences in impact at all across marital statuses.

which improves the health of mothers and children. Leave-taking of fathers has also been shown to reduce gender gaps in household responsibilities and improve father-child bonding in both the short and long term (Tamm, 2018; Patnaik, 2019; Petts et al., 2019). Given that it is paid leave, it also increases income and reduces poverty following a birth. These benefits alone are enough reason to ensure every parent has access to paid leave. Further, existing evidence has shown that these short-run benefits may be greater for women who are disadvantaged in terms of educational attainment or minority status.

This study adds a further economic rationale for prioritizing this social safety net. Temporary labor market detachments have inertia and often lead to much longer labor market detachments. Access to paid leave reduces this by 20%, primarily by returning highly-educated women to the workforce. While many of the short run benefits in terms of leave-taking, income, and health are progressive in nature, we find that the longer-run impacts on labor force participation are higher for more advantaged women. In order to address maternal labor market detachments among more disadvantaged populations, adjustments may be required regarding details such as the length of leave, the size of the benefit, and the degree to which many employers are exempt from FMLA.

In sum, we find that the arrival of a child significantly reduces the participation of mothers in the labor market, not just during infancy and preschool but for more than a decade. The longevity of this effect may be related to an inertia in working preferences and ability to find work, such that temporary absences make returning to work more difficult. State-based administration of a paid family leave program can significantly reduce the impact of childbearing on women's labor force participation by 20% or more for up to five years. This approach offers significant economic benefits, as our findings indicate that it is the most educated workers that are kept in the labor market by PFL. However, gaps in programs need to be examined to improve the impacts among minority race and ethnic groups. Minority women have lower incomes on average and are more likely to be the primary earner in their households, meaning that access to wage replacement during maternity leaves is even more important for these women.

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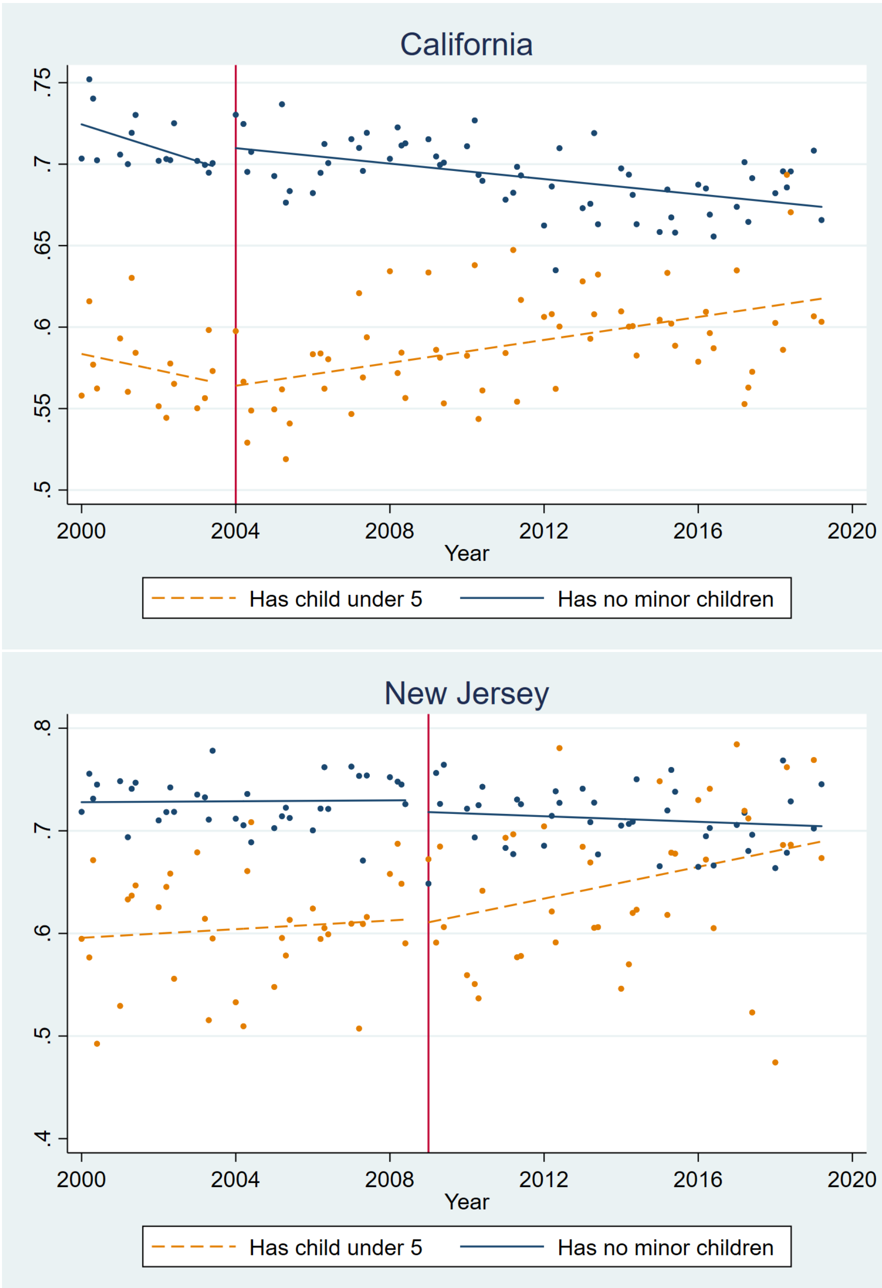
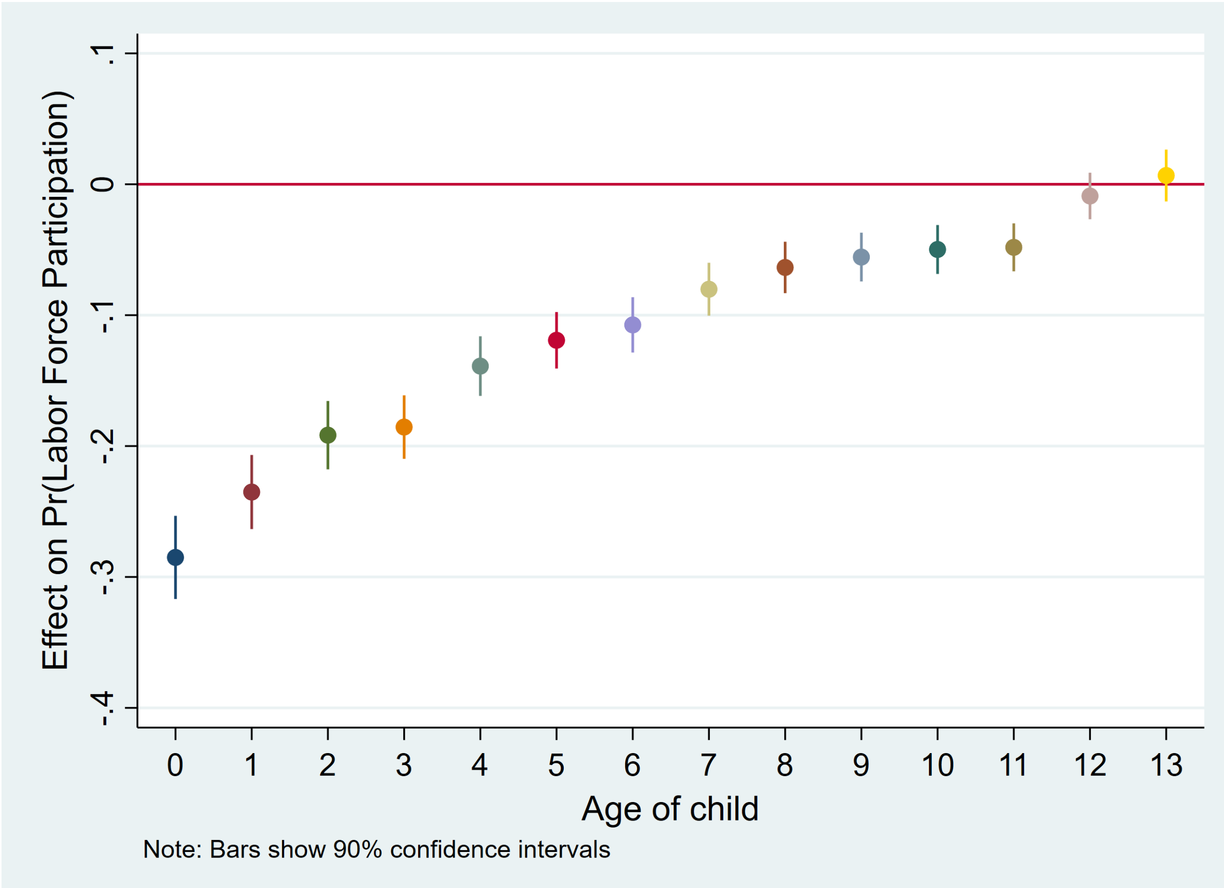
Figures

Figure 1: Common Trends in Labor Market Participation prior to policy



Note: Figures plot labor force participation by quarter, separately for women with a child under age 5 and women with no children under age 18. Lines of best fit are estimated separately before and after the policy implementation, indicated with a vertical line.

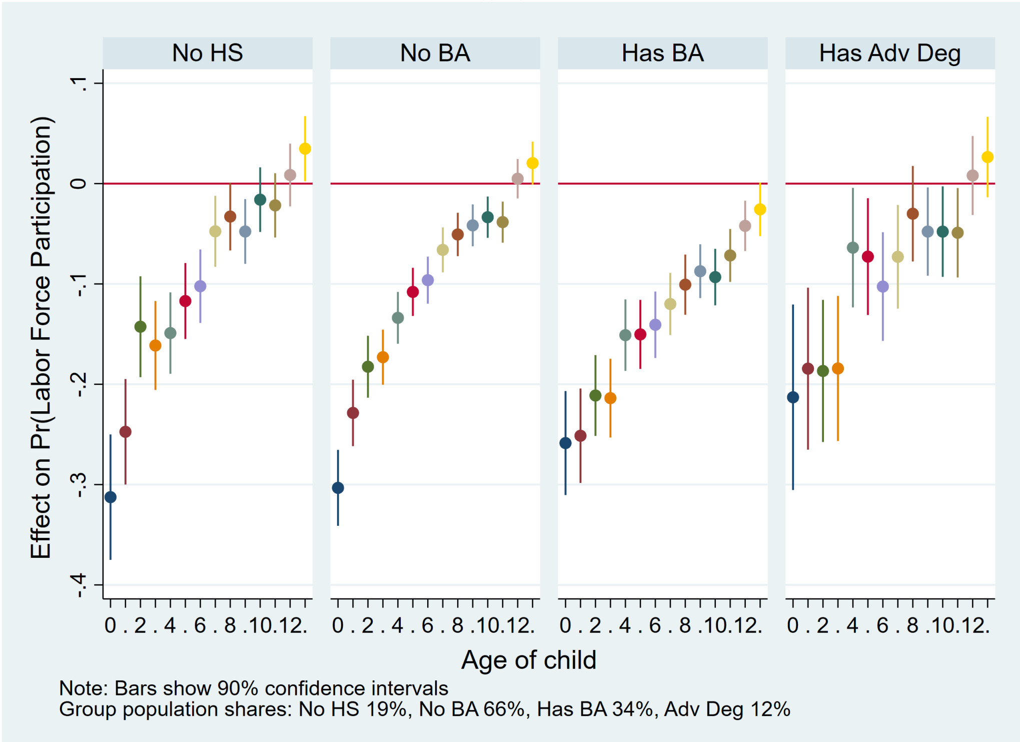
Figure 2: Labor Market Detachment Rates (CA)



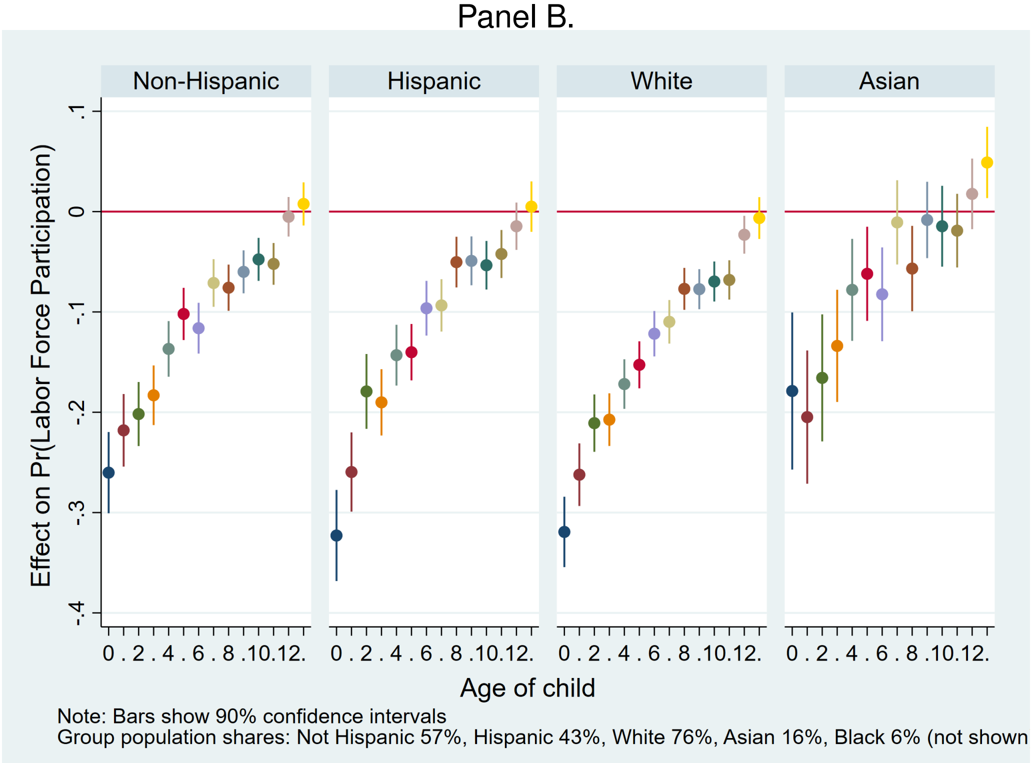
Note: Figure plots estimates of β_1 from equation 1, separately for women with a child aged $a \in [0, X]$. Note that in equation 1, the coefficient β_1 indicates the impact of having a child of age a who was born prior to PFL, relative to having no children under age 18 in the household. The coefficient β_2 indicates the amount by which access to PFL at the child's birth offsets the impact of having a child of age a.

Figure 3: Heterogeneous Labor Market Detachment Rates (CA)

Panel A.

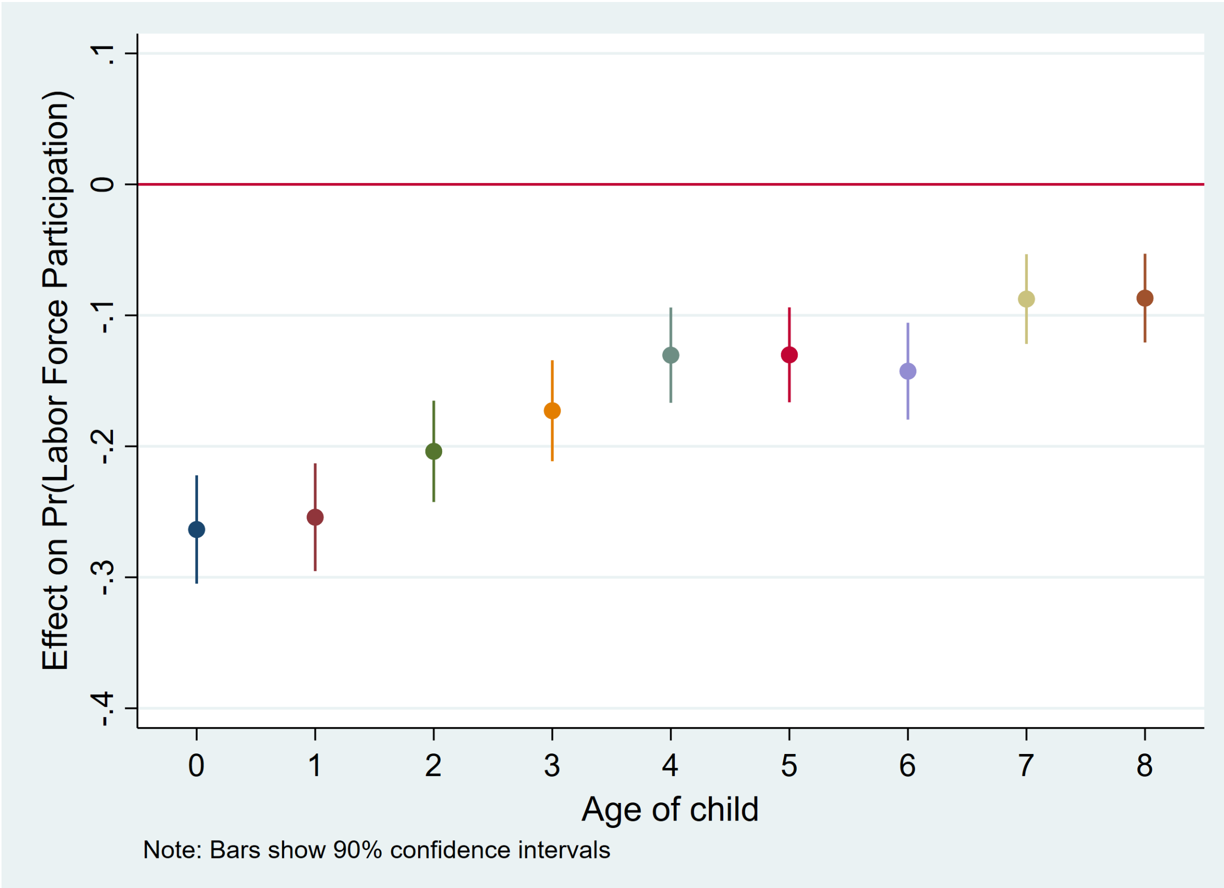


Panel B.



Note: Figures plots estimates of β_1 from equation 2, women with a child aged $a \in [0, X]$, separately by education, ethnicity and race groups.

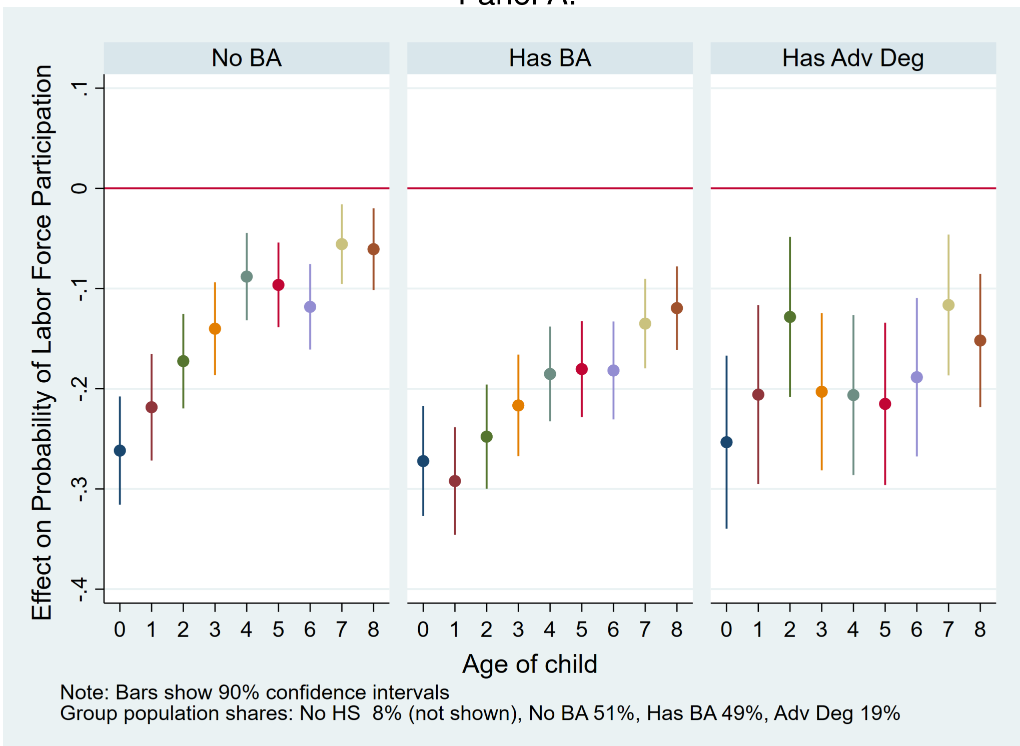
Figure 4: Labor Market Detachment Rates (NJ)



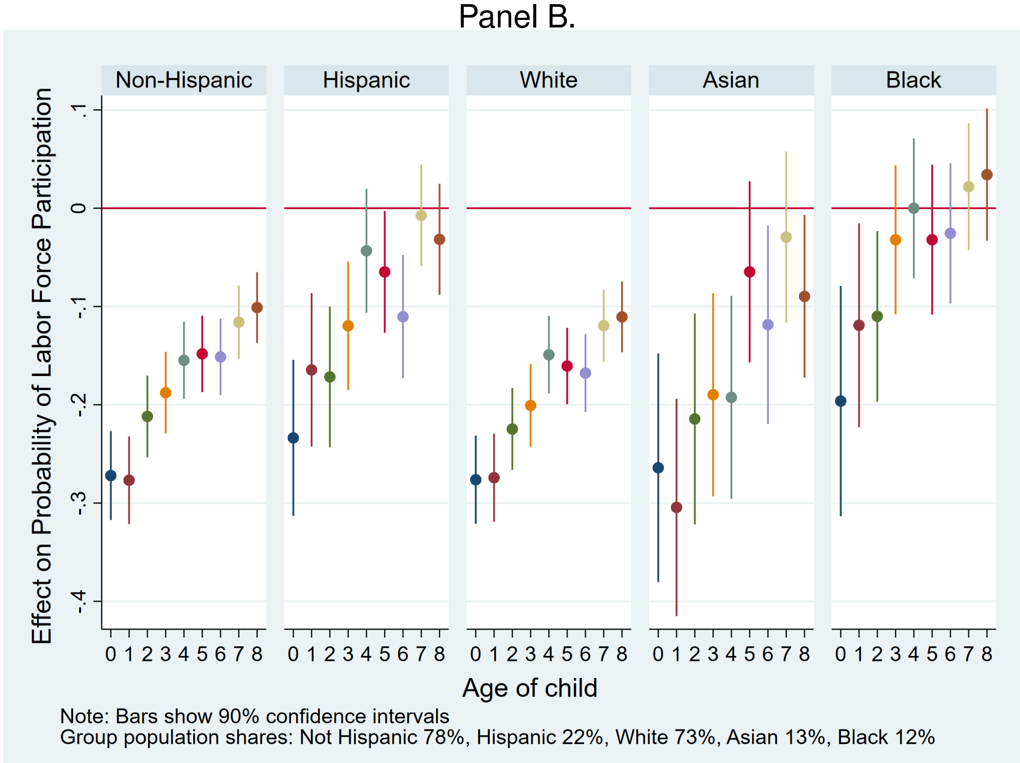
Note: Figure plots estimates of β_1 from equation 1, separately for women with a child aged $a \in [0, X]$. Note that in equation 1, the coefficient β_1 indicates the impact of having a child of age a who was born prior to PFL, relative to having no children under age 18 in the household. The coefficient β_2 indicates the amount by which access to PFL at the child's birth offsets the impact of having a child of age a.

Figure 5: Heterogeneous Labor Market Detachment Rates (NJ)

Panel A.

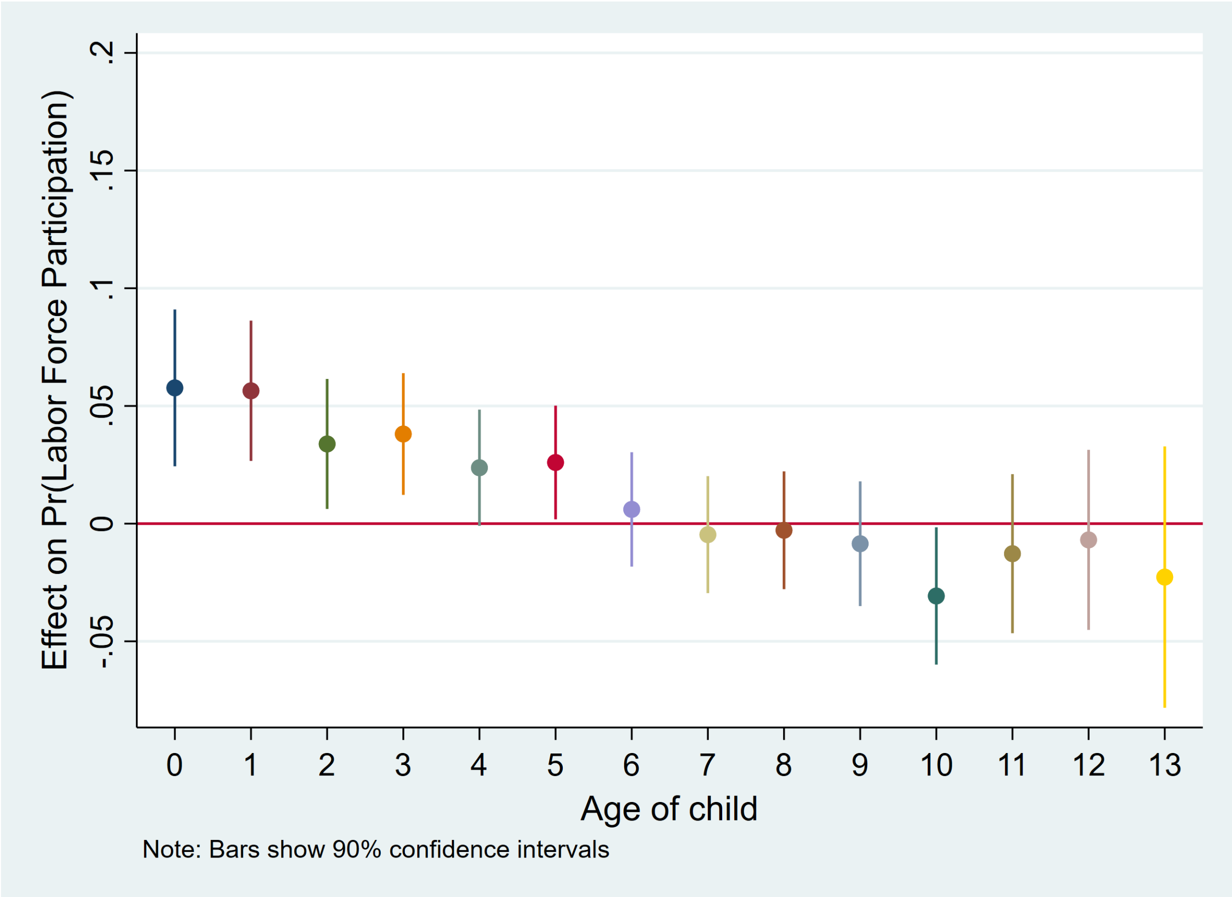


Panel B.



Note: Figures plots estimates of β_1 from equation 2, women with a child aged $a \in [0, X]$, separately by education, ethnicity and race groups.

Figure 6: Impact of PFL on labor force participation (CA)

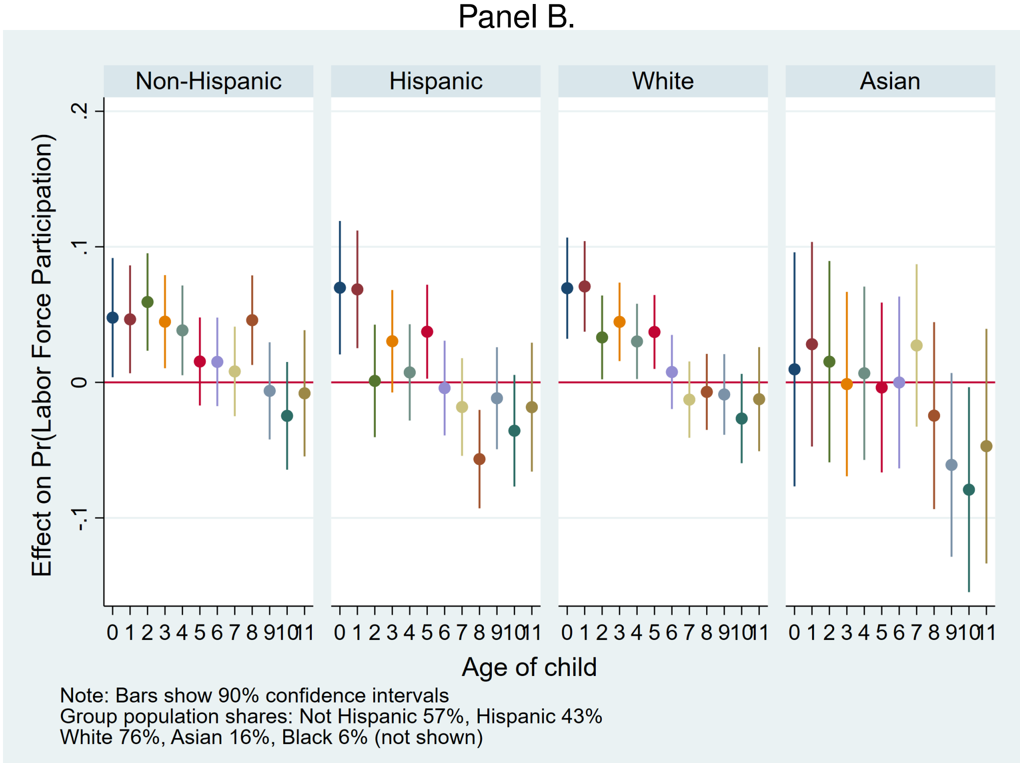


Note: Figure plots estimates of β_2 from equation 1, separately for women with a child aged $a \in [0, X]$. Note that in equation 1, the coefficient β_1 indicates the impact of having a child of age a who was born prior to PFL, relative to having no children under age 18 in the household. The coefficient β_2 indicates the amount by which access to PFL at the child's birth offsets the impact of having a child of age a.

Figure 7: Heterogeneous Impact of PFL on labor force participation (CA)

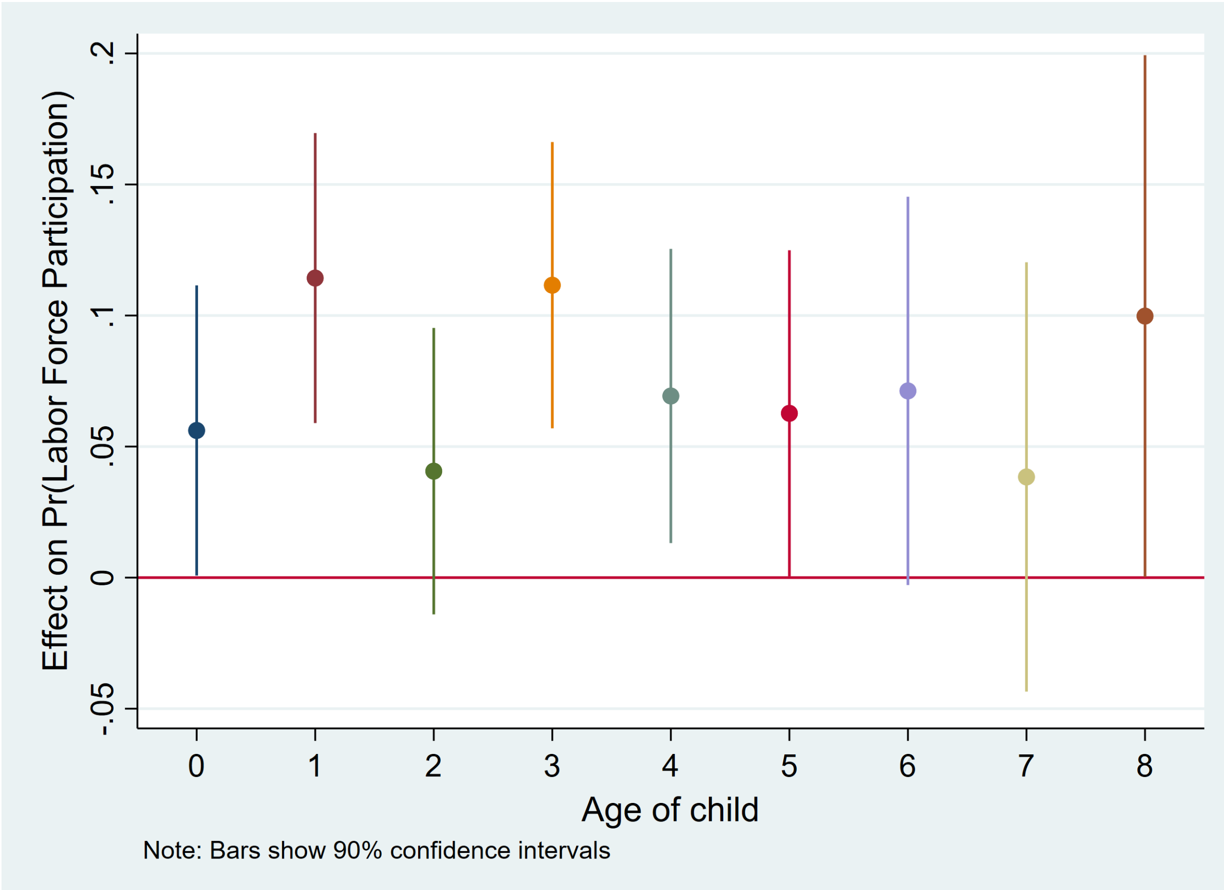
Panel A.

Panel B.



Note: Figures plots estimates of β_2 from equation 2, women with a child aged $a \in [0, X]$, separately by education, ethnicity and race groups.

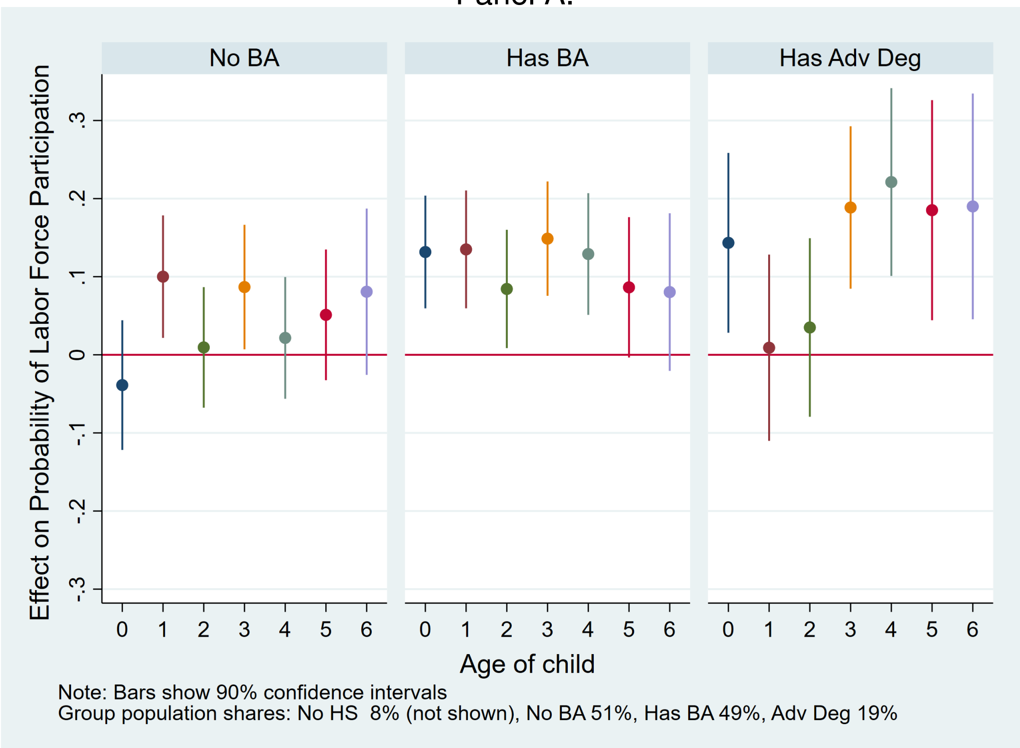
Figure 8: Impact of PFL on labor force participation (NJ)



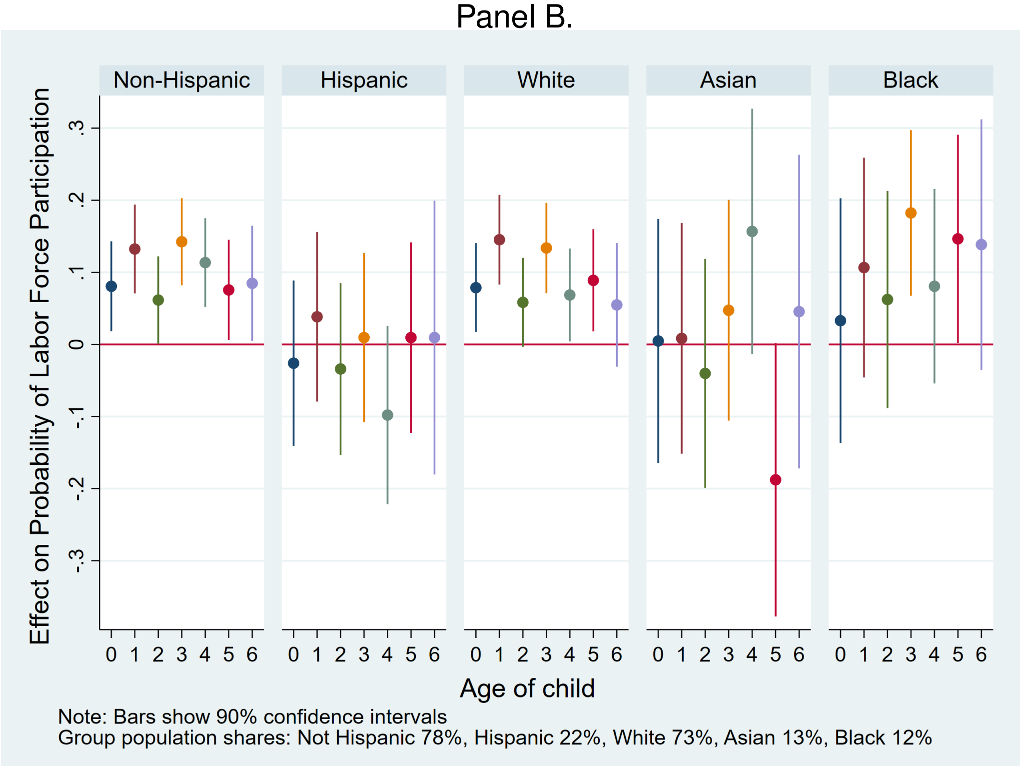
Note: Figure plots estimates of β_2 from equation 1, separately for women with a child aged $a \in [0, X]$. Note that in equation 1, the coefficient β_1 indicates the impact of having a child of age a who was born prior to PFL, relative to having no children under age 18 in the household. The coefficient β_2 indicates the amount by which access to PFL at the child's birth offsets the impact of having a child of age a.

Figure 9: Heterogeneous Impact of PFL on labor force participation (NJ)

Panel A.



Panel B.



Note: Figures plots estimates of β_2 from equation 2, women with a child aged $a \in [0, X]$, separately by education, ethnicity and race groups.

Tables

Table 1: State legislation of paid family leave

State	Effective Year	Contributor(s)	Weeks of leave	Max benefit per week	Job protected
California	2004	Workers	6	$1,252	No
New Jersey	2009	Workers	6	$650	No
Rhode Island	2014	Workers	4	$852	Yes
New York	2018	Workers	10 to 12	$746.41	Yes
Massachusetts	2019	Workers	12	$850	Yes*
District of Columbia	2020	Employers	8	$1,000	No
Washington	2020	Employers & qualifying workers	12	$1,000	Yes*
Connecticut	2022	Workers	12	$900	Yes
Oregon	2022	Employers & qualifying workers	12	$1,215	Yes

*with exceptions

Other Notes: Workers' contributions are via payroll taxes. Weeks of leave are the maximum for paid family/medical leave; this varies by type for some states (e.g. parental, family, medical). Maximum benefits per week are shown; actual benefits per week are calculated as a percentage of recent earnings.

Table 2: Summary of Sample

	Women in California				Women in New Jersey			
	With child under age 5		With no minor children		With child under age 5		With no minor children	
Sample size	**18557**		**85718**		**4315**		**21931**	
Labor force	**Mean**	**SE**	**Mean**	**SE**	**Mean**	**SE**	**Mean**	**SE**
Participation	0.596	(0.004)	0.771	(0.002)	0.596	(0.004)	0.771	(0.002)
If employed,								
Fulltime	0.639	(0.008)	0.783	(0.003)	0.637	(0.005)	0.779	(0.002)
Mnger/Pro	0.373	(0.008)	0.409	(0.004)	0.380	(0.005)	0.408	(0.003)
Age (Years)								
25-29	0.282	(0.004)	0.234	(0.002)	0.224	(0.004)	0.227	(0.007)
30-34	0.314	(0.004)	0.152	(0.002)	0.138	(0.003)	0.314	(0.008)
35-39	0.252	(0.004)	0.108	(0.001)	0.097	(0.003)	0.285	(0.007)
40-44	0.114	(0.003)	0.117	(0.002)	0.114	(0.003)	0.133	(0.006)
45-49	0.03	(0.001)	0.17	(0.002)	0.18	(0.004)	0.032	(0.003)
50-54	0.008	(0.001)	0.22	(0.002)	0.247	(0.004)	0.009	(0.002)
Race								
Asian/PI	0.156	(0.003)	0.174	(0.002)	0.117	(0.005)	0.083	(0.003)
Black	0.064	(0.002)	0.079	(0.001)	0.152	(0.007)	0.178	(0.004)
White	0.714	(0.002)	0.747	(0.004)	0.716	(0.008)	0.727	(0.005)
Ethnicity								
Hispanic	0.445	(0.004)	0.274	(0.002)	0.228	(0.007)	0.172	(0.004)
Education								
HS but no BA	0.489	(0.002)	0.485	(0.004)	0.485	(0.004)	0.489	(0.002)
BA only	0.275	(0.002)	0.219	(0.003)	0.219	(0.003)	0.275	(0.002)
Adv Degree	0.121	(0.002)	0.104	(0.002)	0.104	(0.002)	0.121	(0.002)
Marital Status								
Never	0.138	(0.003)	0.395	(0.002)	0.147	(0.006)	0.393	(0.005)
Currently	0.777	(0.003)	0.417	(0.002)	0.787	(0.007)	0.438	(0.005)
Previously	0.085	(0.002)	0.188	(0.002)	0.066	(0.004)	0.169	(0.004)
Children								
Has infant	0.097	(0.002)			0.101	(0.005)		
Has 1 yr old	0.273	(0.004)			0.266	(0.007)		
Has 2 yr old	0.287	(0.004)			0.293	(0.008)		
Has 3 yr old	0.299	(0.004)			0.303	(0.008)		
Has 4 yr old	0.312	(0.004)			0.314	(0.008)		

Table 3: Impact of child on women's labor force participation, and mitigating impact of PFL (CA)

	Impact of child		Impact of PFL				Mean when $Child_{iy}^{a} = 1$
a	β_1	$se(\beta_1)$	β_2	$se(\beta_2)$	N	R^2	& $PFL_{y-a} = 0$
0	-0.285***	[0.019]	0.058***	[0.020]	49738	0.069	0.501
1	-0.235***	[0.017]	0.056***	[0.018]	50159	0.063	0.539
2	-0.192***	[0.016]	0.034**	[0.017]	50358	0.060	0.569
3	-0.186***	[0.015]	0.038**	[0.016]	50566	0.065	0.555
4	-0.139***	[0.014]	0.024	[0.015]	50753	0.063	0.586
5	-0.119***	[0.013]	0.026*	[0.015]	50904	0.063	0.587
6	-0.107***	[0.013]	0.006	[0.015]	50963	0.062	0.601
7	-0.080***	[0.012]	-0.005	[0.015]	51104	0.059	0.625
8	-0.064***	[0.012]	-0.003	[0.015]	51165	0.059	0.633
9	-0.051***	[0.011]	-0.007	[0.016]	51349	0.058	0.648
10	-0.050***	[0.011]	-0.031*	[0.018]	51260	0.060	0.635
11	-0.048***	[0.011]	-0.013	[0.021]	51134	0.057	0.651
12	-0.009	[0.011]	-0.007	[0.023]	51274	0.055	0.682
13	0.007	[0.012]	-0.023	[0.034]	51115	0.054	0.684

Note: Each row is a separate estimation of equation 1. The dependent variable is labor force participation. The comparison group is women without co-resident children under age 18. The mean of the dependent variable for the comparison group is 0.771. Estimations include women in California interviewed between 2000 and 2019 who either have a child of age a or are in the comparison group. Estimations include year fixed effects and woman-level controls as described in Section 4.2. Statistical significance indicated by *** 1%, ** 5%, * 10%.

Table 4: Impacts by education group (CA)

a	Impact of child β_1	$se(\beta_1)$	Impact of PFL β_2	$se(\beta_2)$	N	R^2	Mean when $Child^a_{iy} = 1$ & $PFL_{y-a} = 0$
NO HIGH SCHOOL DIPLOMA							
0	-0.313***	[0.038]	0.006	[0.042]	49738	0.069	0.548
1	-0.247***	[0.032]	0.038	[0.038]	50159	0.063	0.591
2	-0.143***	[0.031]	-0.001	[0.037]	50358	0.061	0.602
3	-0.161***	[0.027]	-0.010	[0.034]	50566	0.065	0.594
4	-0.149***	[0.025]	0.001	[0.033]	50753	0.063	0.640
5	-0.117***	[0.023]	0.011	[0.032]	50904	0.063	0.638
6	-0.102***	[0.022]	-0.006	[0.033]	50963	0.062	0.654
7	-0.048**	[0.022]	0.004	[0.034]	51104	0.059	0.670
8	-0.033	[0.021]	-0.090***	[0.034]	51165	0.060	0.679
9	-0.043**	[0.020]	0.013	[0.037]	51349	0.058	0.704
10	-0.016	[0.020]	-0.035	[0.041]	51260	0.060	0.686
11	-0.022	[0.019]	-0.037	[0.047]	51134	0.057	0.700
12	0.009	[0.019]	-0.083	[0.055]	51274	0.055	0.732
13	0.035*	[0.020]	-0.017	[0.089]	51115	0.054	0.733
NO BACHELOR'S DEGREE							
0	-0.303***	[0.023]	0.051**	[0.025]	49738	0.069	0.622
1	-0.229***	[0.020]	0.044**	[0.022]	50159	0.063	0.627
2	-0.183***	[0.019]	0.022	[0.021]	50358	0.060	0.646
3	-0.173***	[0.017]	0.032*	[0.019]	50566	0.065	0.618
4	-0.134***	[0.016]	0.023	[0.018]	50753	0.063	0.674
5	-0.108***	[0.015]	0.018	[0.017]	50904	0.063	0.664
6	-0.096***	[0.014]	-0.008	[0.018]	50963	0.062	0.682
7	-0.066***	[0.014]	-0.023	[0.018]	51104	0.059	0.702
8	-0.051***	[0.013]	-0.021	[0.018]	51165	0.060	0.711
9	-0.037***	[0.013]	-0.003	[0.019]	51349	0.058	0.734
10	-0.033***	[0.013]	-0.037*	[0.021]	51260	0.060	0.715
11	-0.038***	[0.012]	-0.002	[0.024]	51134	0.057	0.743
12	0.005	[0.012]	-0.021	[0.029]	51274	0.055	0.763
13	0.020	[0.013]	-0.005	[0.041]	51115	0.054	0.766

Continued on next page

Table 4 continued

a	Impact of child β_1	$se(\beta_1)$	Impact of PFL β_2	$se(\beta_2)$	N	R^2	Mean when $Child^a_{iy} = 1$ & $PFL_{y-a} = 0$
BACHELOR'S DEGREE							
0	-0.259***	[0.032]	0.064*	[0.034]	49738	0.069	0.441
1	-0.251***	[0.029]	0.082***	[0.031]	50159	0.063	0.502
2	-0.211***	[0.024]	0.059**	[0.028]	50358	0.060	0.534
3	-0.214***	[0.024]	0.057**	[0.028]	50566	0.065	0.530
4	-0.151***	[0.022]	0.029	[0.026]	50753	0.063	0.554
5	-0.150***	[0.021]	0.053**	[0.026]	50904	0.063	0.563
6	-0.141***	[0.020]	0.048*	[0.026]	50963	0.062	0.577
7	-0.120***	[0.019]	0.048*	[0.026]	51104	0.059	0.602
8	-0.101***	[0.018]	0.052*	[0.027]	51165	0.060	0.610
9	-0.084***	[0.016]	-0.007	[0.028]	51349	0.058	0.620
10	-0.093***	[0.017]	-0.001	[0.031]	51260	0.060	0.613
11	-0.072***	[0.016]	-0.037	[0.037]	51134	0.057	0.623
12	-0.042***	[0.015]	0.036	[0.037]	51274	0.055	0.657
13	-0.026	[0.016]	-0.047	[0.057]	51115	0.054	0.660
ADVANCED DEGREE							
0	-0.213***	[0.056]	0.088	[0.061]	49738	0.069	0.483
1	-0.184***	[0.049]	0.080	[0.053]	50159	0.063	0.522
2	-0.187***	[0.043]	0.093*	[0.048]	50358	0.061	0.558
3	-0.184***	[0.044]	0.091*	[0.050]	50566	0.065	0.547
4	-0.064*	[0.036]	-0.046	[0.045]	50753	0.063	0.571
5	-0.073**	[0.035]	0.023	[0.044]	50904	0.063	0.576
6	-0.103***	[0.033]	0.060	[0.042]	50963	0.062	0.591
7	-0.073**	[0.031]	0.014	[0.044]	51104	0.059	0.615
8	-0.030	[0.029]	0.031	[0.043]	51165	0.060	0.622
9	-0.046*	[0.027]	0.006	[0.044]	51349	0.058	0.638
10	-0.048*	[0.027]	0.009	[0.048]	51260	0.060	0.626
11	-0.049*	[0.027]	0.013	[0.066]	51134	0.057	0.642
12	0.008	[0.024]	-0.019	[0.061]	51274	0.055	0.672
13	0.026	[0.024]	-0.021	[0.082]	51115	0.054	0.674

Note: Each row is a separate estimation of equation 1. The dependent variable is labor force participation. The comparison group is women without co-resident children under age 18. The mean of the dependent variable for the comparison group is 0.771. Estimations include women in California interviewed between 2000 and 2019 who either have a child of age a or are in the comparison group. Estimations include year fixed effects and woman-level controls as described in Section 4.2. Statistical significance indicated by *** 1%, ** 5%, * 10%.

Table 5: Impacts by ethnicity (CA)

a	Impact of child β_1	$se(\beta_1)$	Impact of PFL β_2	$se(\beta_2)$	N	R^2	Mean when $Child^a_{iy} = 1$ & $PFL_{y-a} = 0$
HISPANIC							
0	-0.323***	[0.0276]	0.0698**	[0.0299]	49738	0.069	0.556
1	-0.260***	[0.0240]	0.0686***	[0.0264]	50159	0.063	0.592
2	-0.179***	[0.0227]	0.00107	[0.0252]	50358	0.061	0.591
3	-0.190***	[0.0201]	0.0303	[0.0230]	50566	0.065	0.590
4	-0.143***	[0.0184]	0.00735	[0.0216]	50753	0.063	0.620
5	-0.140***	[0.0171]	0.0374*	[0.0211]	50904	0.063	0.637
6	-0.0963***	[0.0166]	-0.00420	[0.0212]	50963	0.062	0.625
7	-0.0935***	[0.0159]	-0.0182	[0.0219]	51104	0.059	0.669
8	-0.0504***	[0.0154]	-0.0566**	[0.0221]	51165	0.060	0.658
9	-0.0440***	[0.0148]	-0.0103	[0.0228]	51349	0.058	0.683
10	-0.0535***	[0.0147]	-0.0357	[0.0250]	51260	0.060	0.676
11	-0.0423***	[0.0146]	-0.0183	[0.0289]	51134	0.057	0.684
12	-0.0146	[0.0143]	0.00490	[0.0334]	51274	0.055	0.724
13	0.00495	[0.0153]	-0.0391	[0.0528]	51115	0.054	0.720
NON-HISPANIC							
0	-0.260***	[0.0246]	0.0478*	[0.0267]	49738	0.069	0.429
1	-0.218***	[0.0220]	0.0465*	[0.0242]	50159	0.063	0.472
2	-0.202***	[0.0194]	0.0593***	[0.0219]	50358	0.061	0.538
3	-0.183***	[0.0181]	0.0448**	[0.0209]	50566	0.065	0.510
4	-0.137***	[0.0169]	0.0384*	[0.0201]	50753	0.063	0.544
5	-0.102***	[0.0158]	0.0154	[0.0197]	50904	0.063	0.533
6	-0.116***	[0.0154]	0.0151	[0.0199]	50963	0.062	0.574
7	-0.0712***	[0.0144]	0.00807	[0.0201]	51104	0.059	0.576
8	-0.0759***	[0.0140]	0.0459**	[0.0201]	51165	0.060	0.605
9	-0.0561***	[0.0131]	-0.00453	[0.0217]	51349	0.058	0.607
10	-0.0476***	[0.0130]	-0.0247	[0.0242]	51260	0.060	0.590
11	-0.0521***	[0.0127]	-0.00808	[0.0283]	51134	0.057	0.613
12	-0.00517	[0.0120]	-0.0174	[0.0314]	51274	0.055	0.631
13	0.00764	[0.0131]	-0.0102	[0.0427]	51115	0.054	0.643

Note: See notes to Table 4.

Table 6: Impacts by race (CA)

a	Impact of child β_1	$se(\beta_1)$	Impact of PFL β_2	$se(\beta_2)$	N	R^2	Mean when $Child^a_{iy} = 1$ & $PFL_{y-a} = 0$
WHITE							
0	-0.319***	[0.0213]	0.0695***	[0.0227]	49738	0.069	0.606
1	-0.262***	[0.0190]	0.0708***	[0.0203]	50159	0.063	0.620
2	-0.211***	[0.0174]	0.0332*	[0.0188]	50358	0.061	0.619
3	-0.207***	[0.0160]	0.0446**	[0.0176]	50566	0.065	0.625
4	-0.172***	[0.0150]	0.0302*	[0.0169]	50753	0.064	0.675
5	-0.153***	[0.0143]	0.0372**	[0.0166]	50904	0.064	0.691
6	-0.122***	[0.0138]	0.00765	[0.0166]	50963	0.063	0.632
7	-0.110***	[0.0132]	-0.0127	[0.0171]	51104	0.060	0.712
8	-0.0770***	[0.0127]	-0.00703	[0.0170]	51165	0.060	0.661
9	-0.0729***	[0.0122]	-0.00739	[0.0180]	51349	0.058	0.710
10	-0.0697***	[0.0121]	-0.0267	[0.0200]	51260	0.061	0.691
11	-0.0681***	[0.0119]	-0.0124	[0.0233]	51134	0.057	0.710
12	-0.0231**	[0.0115]	-0.0196	[0.0269]	51274	0.056	0.717
13	-0.00642	[0.0127]	-0.0114	[0.0384]	51115	0.054	0.716
BLACK							
0	-0.140**	[0.0682]	-0.000161	[0.0784]	49738	0.069	0.493
1	-0.00812	[0.0603]	-0.0455	[0.0704]	50159	0.064	0.528
2	-0.0419	[0.0527]	-0.00871	[0.0665]	50358	0.061	0.562
3	-0.0634	[0.0484]	0.0394	[0.0612]	50566	0.065	0.547
4	0.102***	[0.0366]	-0.0734	[0.0534]	50753	0.064	0.571
5	0.0731*	[0.0380]	-0.0597	[0.0562]	50904	0.064	0.575
6	0.0356	[0.0347]	-0.0762	[0.0572]	50963	0.063	0.593
7	0.0807**	[0.0339]	-0.0928	[0.0601]	51104	0.060	0.615
8	0.0699**	[0.0324]	0.0391	[0.0546]	51165	0.060	0.625
9	0.0737**	[0.0302]	0.0668	[0.0580]	51349	0.059	0.641
10	0.0838***	[0.0290]	-0.0823	[0.0795]	51260	0.061	0.625
11	0.0843***	[0.0288]	0.0459	[0.0787]	51134	0.057	0.643
12	0.0544*	[0.0293]	0.0781	[0.0767]	51274	0.055	0.679
13	0.0748***	[0.0262]	0.124	[0.137]	51115	0.054	0.679
ASIAN							
0	-0.179***	[0.0476]	0.00961	[0.0525]	49738	0.069	0.482
1	-0.205***	[0.0404]	0.0281	[0.0459]	50159	0.063	0.530
2	-0.166***	[0.0385]	0.0153	[0.0452]	50358	0.060	0.564
3	-0.134***	[0.0340]	-0.00127	[0.0414]	50566	0.065	0.543
4	-0.0780**	[0.0309]	0.00672	[0.0389]	50753	0.063	0.575
5	-0.0620**	[0.0285]	-0.00379	[0.0381]	50904	0.063	0.577
6	-0.0824***	[0.0284]	-0.0000837	[0.0385]	50963	0.062	0.597
7	-0.0107	[0.0255]	0.0272	[0.0364]	51104	0.060	0.614
8	-0.0568**	[0.0259]	-0.0245	[0.0419]	51165	0.060	0.631
9	-0.00423	[0.0232]	-0.0601	[0.0412]	51349	0.058	0.639
10	-0.0146	[0.0245]	-0.0792*	[0.0460]	51260	0.060	0.630
11	-0.0190	[0.0223]	-0.0471	[0.0526]	51134	0.057	0.646
12	0.0176	[0.0214]	0.0138	[0.0560]	51274	0.055	0.676
13	0.0490**	[0.0216]	-0.188**	[0.0898]	51115	0.054	0.678

Note: See notes to Table 4.

Table 7: Impact of child on women's labor force participation, and mitigating impact of PFL (NJ)

	Impact of child		Impact of PFL				Mean when $Child_{iy}^{a} = 1$
a	β_1	$se(\beta_1)$	β_2	$se(\beta_2)$	N	R^2	& $PFL_{y-a} = 0$
0	-0.264***	[0.0251]	0.0561*	[0.0337]	12510	0.060	0.559
1	-0.254***	[0.0250]	0.114***	[0.0336]	12533	0.053	0.576
2	-0.204***	[0.0235]	0.0406	[0.0332]	12644	0.059	0.589
3	-0.173***	[0.0234]	0.112***	[0.0332]	12695	0.055	0.596
4	-0.130***	[0.0221]	0.0693**	[0.0341]	12742	0.052	0.632
5	-0.130***	[0.0220]	0.0627*	[0.0378]	12781	0.052	0.627
6	-0.143***	[0.0225]	0.0712	[0.0450]	12740	0.057	0.609
7	-0.0876***	[0.0208]	0.0384	[0.0498]	12817	0.053	0.651
8	-0.0869***	[0.0206]	0.0998*	[0.0605]	12818	0.048	0.676

Note: Each row is a separate estimation of equation 1. The dependent variable is labor force participation. The comparison group is women without co-resident children under age 18. The mean of the dependent variable for the comparison group is 0.794. Estimations include women in California interviewed between 2000 and 2019 who either have a child of age a or are in the comparison group. Estimations include year fixed effects and woman-level controls as described in Section 4.2. Statistical significance indicated by *** 1%, ** 5%, * 10%.

Table 8: Impacts by education group (NJ)

a	Impact of child β_1	$se(\beta_1)$	Impact of PFL β_2	$se(\beta_2)$	N	R^2	Mean when $Child_{iy}^a = 1$ & $PFL_{y-a} = 0$
NO HIGH SCHOOL DIPLOMA							
0	-0.189**	[0.077]	-0.156	[0.126]	12510	0.061	0.573
1	-0.172**	[0.079]	0.096	[0.135]	12533	0.053	0.587
2	-0.266***	[0.060]	0.008	[0.116]	12644	0.059	0.621
3	0.018	[0.065]	-0.212	[0.131]	12695	0.056	0.598
4	-0.043	[0.067]	-0.018	[0.136]	12742	0.052	0.641
5	-0.053	[0.060]	0.011	[0.142]	12781	0.052	0.638
6	-0.125**	[0.055]	0.101	[0.203]	12740	0.057	0.629
7	0.020	[0.052]	-0.198	[0.174]	12817	0.053	0.666
8	0.008	[0.054]	0.072	[0.270]	12818	0.048	0.687
NO BACHELOR'S DEGREE							
0	-0.262***	[0.033]	-0.039	[0.050]	12510	0.061	0.607
1	-0.218***	[0.032]	0.100**	[0.048]	12533	0.053	0.589
2	-0.172***	[0.029]	0.009	[0.047]	12644	0.060	0.604
3	-0.140***	[0.028]	0.087*	[0.048]	12695	0.055	0.602
4	-0.088***	[0.026]	0.022	[0.047]	12742	0.053	0.625
5	-0.096***	[0.026]	0.051	[0.051]	12781	0.053	0.631
6	-0.118***	[0.026]	0.081	[0.065]	12740	0.057	0.626
7	-0.056**	[0.024]	0.049	[0.068]	12817	0.054	0.664
8	-0.061**	[0.025]	0.008	[0.087]	12818	0.049	0.694
BACHELOR'S DEGREE							
0	-0.272***	[0.033]	0.132***	[0.044]	12510	0.061	0.518
1	-0.292***	[0.033]	0.135***	[0.046]	12533	0.053	0.565
2	-0.248***	[0.032]	0.084*	[0.046]	12644	0.060	0.579
3	-0.217***	[0.031]	0.149***	[0.045]	12695	0.055	0.592
4	-0.185***	[0.029]	0.129***	[0.047]	12742	0.053	0.637
5	-0.180***	[0.029]	0.086	[0.055]	12781	0.053	0.624
6	-0.182***	[0.030]	0.080	[0.061]	12740	0.057	0.599
7	-0.135***	[0.027]	0.046	[0.070]	12817	0.054	0.644
8	-0.119***	[0.025]	0.232***	[0.068]	12818	0.049	0.663
ADVANCED DEGREE							
0	-0.253***	[0.053]	0.143**	[0.070]	12510	0.061	0.545
1	-0.206***	[0.054]	0.009	[0.072]	12533	0.053	0.560
2	-0.128***	[0.049]	0.035	[0.069]	12644	0.060	0.568
3	-0.203***	[0.048]	0.189***	[0.063]	12695	0.055	0.591
4	-0.206***	[0.049]	0.221***	[0.073]	12742	0.053	0.632
5	-0.215***	[0.049]	0.185**	[0.086]	12781	0.053	0.630
6	-0.188***	[0.048]	0.190**	[0.088]	12740	0.057	0.606
7	-0.116***	[0.043]	0.096	[0.101]	12817	0.053	0.645
8	-0.152***	[0.040]	0.327***	[0.051]	12818	0.048	0.678

Note: See notes to Table 4.

Table 9: Impacts by ethnicity and race (NJ)

a	Impact of child β_1	$se(\beta_1)$	Impact of PFL β_2	$se(\beta_2)$	N	R^2	Mean when $Child^a_{iy} = 1$ & $PFL_{y-a} = 0$
HISPANIC							
0	-0.234***	[0.048]	-0.026	[0.070]	12510	0.060	0.569
1	-0.165***	[0.047]	0.038	[0.072]	12533	0.054	0.568
2	-0.172***	[0.044]	-0.034	[0.072]	12644	0.059	0.600
3	-0.120***	[0.040]	0.010	[0.071]	12695	0.055	0.594
4	-0.043	[0.038]	-0.098	[0.075]	12742	0.053	0.620
5	-0.065*	[0.038]	0.009	[0.080]	12781	0.053	0.622
6	-0.110***	[0.038]	0.010	[0.115]	12740	0.057	0.615
7	-0.007	[0.031]	-0.050	[0.100]	12817	0.054	0.642
8	-0.032	[0.034]	-0.145	[0.148]	12818	0.049	0.676
NON-HISPANIC							
0	-0.272***	[0.028]	0.081**	[0.038]	12510	0.060	0.523
1	-0.277***	[0.027]	0.132***	[0.037]	12533	0.054	0.606
2	-0.212***	[0.025]	0.062*	[0.037]	12644	0.059	0.549
3	-0.188***	[0.025]	0.142***	[0.037]	12695	0.055	0.604
4	-0.155***	[0.024]	0.113***	[0.037]	12742	0.053	0.679
5	-0.148***	[0.024]	0.076*	[0.042]	12781	0.053	0.646
6	-0.151***	[0.024]	0.085*	[0.049]	12740	0.057	0.588
7	-0.116***	[0.023]	0.068	[0.056]	12817	0.054	0.679
8	-0.101***	[0.022]	0.174***	[0.060]	12818	0.049	0.679
WHITE							
0	-0.276***	[0.027]	0.079**	[0.037]	12510	0.060	0.564
1	-0.274***	[0.027]	0.145***	[0.038]	12533	0.053	0.603
2	-0.225***	[0.025]	0.058	[0.038]	12644	0.059	0.618
3	-0.201***	[0.026]	0.134***	[0.038]	12695	0.055	0.649
4	-0.149***	[0.024]	0.069*	[0.039]	12742	0.053	0.650
5	-0.161***	[0.024]	0.089**	[0.043]	12781	0.053	0.680
6	-0.168***	[0.024]	0.055	[0.052]	12740	0.058	0.648
7	-0.119***	[0.022]	0.066	[0.062]	12817	0.054	0.711
8	-0.111***	[0.022]	0.121*	[0.067]	12818	0.049	0.708
BLACK							
0	-0.196***	[0.071]	0.033	[0.103]	12510	0.060	0.554
1	-0.119*	[0.063]	0.107	[0.093]	12533	0.054	0.559
2	-0.110**	[0.053]	0.062	[0.092]	12644	0.060	0.573
3	-0.032	[0.046]	0.182***	[0.070]	12695	0.057	0.568
4	-0.000	[0.043]	0.081	[0.082]	12742	0.054	0.610
5	-0.032	[0.046]	0.146*	[0.088]	12781	0.053	0.614
6	-0.025	[0.043]	0.138	[0.106]	12740	0.058	0.591
7	0.022	[0.039]	0.034	[0.109]	12817	0.054	0.633
8	0.034	[0.041]	-0.081	[0.187]	12818	0.049	0.660
ASIAN							
0	-0.264***	[0.071]	0.005	[0.103]	12510	0.060	0.566
1	-0.304***	[0.067]	0.008	[0.097]	12533	0.054	0.587
2	-0.214***	[0.065]	-0.040	[0.097]	12644	0.059	0.597
3	-0.190***	[0.063]	0.047	[0.093]	12695	0.055	0.604
4	-0.192***	[0.063]	0.157	[0.104]	12742	0.052	0.645
5	-0.065	[0.056]	-0.188	[0.115]	12781	0.053	0.625
6	-0.119*	[0.061]	0.045	[0.132]	12740	0.057	0.611
7	-0.029	[0.053]	-0.073	[0.121]	12817	0.053	0.649
8	-0.090*	[0.050]	0.360***	[0.069]	12818	0.048	0.683

Note: See notes to Table 4.

Table 10: Impacts on other outcomes (CA)

a	Impact of child β_1	$se(\beta_1)$	Impact of PFL β_2	$se(\beta_2)$	N	R^2	Mean when $Child^a_{iy} = 1$ & $PFL_{y-a} = 0$
FULLTIME STATUS, IF EMPLOYED							
0	-0.135***	[0.027]	0.033	[0.028]	34906	0.017	0.650
1	-0.149***	[0.023]	0.041*	[0.025]	35252	0.018	0.630
2	-0.128***	[0.020]	0.027	[0.022]	35385	0.018	0.650
3	-0.142***	[0.019]	0.022	[0.021]	35441	0.020	0.630
4	-0.089***	[0.018]	0.028	[0.020]	35604	0.017	0.666
5	-0.103***	[0.017]	0.005	[0.020]	35706	0.017	0.667
6	-0.106***	[0.017]	0.010	[0.020]	35769	0.019	0.643
7	-0.129***	[0.016]	0.027	[0.020]	35915	0.019	0.625
8	-0.100***	[0.015]	0.041**	[0.020]	36031	0.018	0.646
9	-0.110***	[0.015]	0.010	[0.021]	36201	0.018	0.643
10	-0.128***	[0.015]	0.017	[0.024]	36062	0.021	0.623
11	-0.092***	[0.014]	0.006	[0.027]	36081	0.019	0.656
12	-0.102***	[0.014]	0.011	[0.031]	36317	0.020	0.646
13	-0.075***	[0.016]	0.028	[0.042]	36255	0.020	0.645
MANAGER/PROFESSIONAL, IF EMPLOYED							
0	0.038*	[0.023]	0.002	[0.024]	37437	0.245	0.399
1	0.055***	[0.020]	-0.006	[0.021]	37829	0.246	0.383
2	0.042**	[0.017]	-0.018	[0.018]	37966	0.248	0.369
3	-0.002	[0.016]	0.027	[0.018]	38024	0.245	0.311
4	-0.001	[0.015]	0.034**	[0.016]	38236	0.248	0.307
5	0.025*	[0.014]	-0.004	[0.016]	38330	0.247	0.313
6	0.014	[0.014]	-0.001	[0.016]	38403	0.248	0.307
7	0.003	[0.013]	-0.003	[0.016]	38549	0.247	0.291
8	0.008	[0.013]	0.036**	[0.017]	38667	0.245	0.289
9	0.032***	[0.012]	0.009	[0.016]	38827	0.248	0.310
10	0.028**	[0.012]	-0.006	[0.018]	38704	0.247	0.299
11	0.020*	[0.012]	-0.041*	[0.021]	38717	0.245	0.312
12	0.012	[0.012]	0.010	[0.026]	38974	0.246	0.311
13	0.022*	[0.013]	-0.041	[0.035]	38879	0.246	0.302

Note: Each row is a separate estimation of equation 1. The dependent variables are shown in section headers: full time status if employed, and manager/professional occupation, if employed. The comparison group is women without co-resident children under age 18. The mean of the dependent variables for the comparison group are 0.757 (full time) and 0.410 (manager/professional). Estimations include women in California interviewed between 2000 and 2019 who either have a child of age a or are in the comparison group. Estimations include year fixed effects and woman-level controls as described in Section 4.2. Statistical significance indicated by *** 1%, ** 5%, * 10%.

Table 11: Impacts on other outcomes (NJ)

	Impact of child		Impact of PFL				Mean when
a	β_1	$se(\beta_1)$	β_2	$se(\beta_2)$	N	R^2	$Child^a_{iy} = 1$ & $PFL_{y-a} = 0$
FULLTIME STATUS, IF EMPLOYED							
0	-0.135***	[0.027]	0.033	[0.028]	34906	0.017	0.650
1	-0.149***	[0.023]	0.041*	[0.025]	35252	0.018	0.630
2	-0.128***	[0.020]	0.027	[0.022]	35385	0.018	0.650
3	-0.142***	[0.019]	0.022	[0.021]	35441	0.020	0.630
4	-0.089***	[0.018]	0.028	[0.020]	35604	0.017	0.666
5	-0.103***	[0.017]	0.005	[0.020]	35706	0.017	0.667
6	-0.106***	[0.017]	0.010	[0.020]	35769	0.019	0.643
7	-0.129***	[0.016]	0.027	[0.020]	35915	0.019	0.625
8	-0.100***	[0.015]	0.041**	[0.020]	36031	0.018	0.646
9	-0.110***	[0.015]	0.010	[0.021]	36201	0.018	0.643
10	-0.128***	[0.015]	0.017	[0.024]	36062	0.021	0.623
11	-0.092***	[0.014]	0.006	[0.027]	36081	0.019	0.656
12	-0.102***	[0.014]	0.011	[0.031]	36317	0.020	0.646
13	-0.075***	[0.016]	0.028	[0.042]	36255	0.020	0.645
MANAGER/PROFESSIONAL, IF EMPLOYED							
0	0.038*	[0.023]	0.002	[0.024]	37437	0.245	0.399
1	0.055***	[0.020]	-0.006	[0.021]	37829	0.246	0.383
2	0.042**	[0.017]	-0.018	[0.018]	37966	0.248	0.369
3	-0.002	[0.016]	0.027	[0.018]	38024	0.245	0.311
4	-0.001	[0.015]	0.034**	[0.016]	38236	0.248	0.307
5	0.025*	[0.014]	-0.004	[0.016]	38330	0.247	0.313
6	0.014	[0.014]	-0.001	[0.016]	38403	0.248	0.307
7	0.003	[0.013]	-0.003	[0.016]	38549	0.247	0.291
8	0.008	[0.013]	0.036**	[0.017]	38667	0.245	0.289
9	0.032***	[0.012]	0.009	[0.016]	38827	0.248	0.310
10	0.028**	[0.012]	-0.006	[0.018]	38704	0.247	0.299
11	0.020*	[0.012]	-0.041*	[0.021]	38717	0.245	0.312
12	0.012	[0.012]	0.010	[0.026]	38974	0.246	0.311
13	0.022*	[0.013]	-0.041	[0.035]	38879	0.246	0.302

Note: Each row is a separate estimation of equation 1. The dependent variables are shown in section headers: full time status if employed, and manager/professional occupation, if employed. The comparison group is women without co-resident children under age 18. The mean of the dependent variables for the comparison group are 0.807 (full time) and 0.416 (manager/professional). Estimations include women in New Jersey interviewed between 2000 and 2019 who either have a child of age a or are in the comparison group. Estimations include year fixed effects and woman-level controls as described in Section 4.2. Statistical significance indicated by *** 1%, ** 5%, * 10%.