The Distributional Effects of Paid Parental Leave Policies on Fertility and Child Human Capital*

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Abstract

This paper studies the implications of paid parental leave (PPL) policies on fertility and child human capital. Using micro-level data, I show that the introduction of PPL in New Jersey is associated with an increase in fertility. To investigate the implications of these policy-induced responses for children, I develop a heterogeneous agents model that combines endogenous fertility and multi-period parental investment in children's human capital. I structurally estimate the model parameters to match key moments characterizing the U.S. economy. I then use the model to conduct a counterfactual exercise consisting of simulating the introduction of the New Jersey policy at the national level. The model predicts an increase in higher order births in response to the policy implementation, mostly among middle income families and with marginally larger effects among low-educated women. Increases in fertility lead parents to dilute per-child investment, negatively affecting their human capital through the mechanism of the quantity-quality trade-off. Finally, I show that in the absence of fertility responses, PPL would lead to higher investment in children, with positive implications for their human capital, underscoring the central role of fertility in shaping policy effects.

JEL Classification: J13, J22, I20, D13

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1 Introduction

Over the past few decades, fertility rates have dropped to historically low levels across most high-income countries (Doepke et al., 2022; Goldin, 2025), raising concerns about the implications of aging populations for labor supply, fiscal sustainability, and economic growth (Jones, 2022). This demographic change, alongside a growing evidence of the long-term economic returns of child development (Schoellman, 2016), have directed policymakers' attention toward family policies and early childhood interventions (Dougherty and Morabito, 2023). Among these policies, paid parental leave (PPL) has gained increasing popularity among policymakers worldwide as a tool to support parents in providing care during the earliest stages of a child's life (OECD, 2023). PPL can enhance fertility by reducing the opportunity cost that working parents face when taking time away from paid work to care for a newborn (Olivetti and Petrongolo, 2017); by providing them with financial compensation, it also eases family budget constraints, making it more affordable to raise additional children. Furthermore, by incentivizing bonding time with a newborn, PPL can foster child development (Bono et al., 2016).

While the positive effects of PPL on fertility are well documented[1], the evidence on its long-term implications for children's cognitive outcomes is far less conclusive. Economic theory predicts that, by increasing parental time investment, PPL should enhance children's human capital during early childhood (Cunha and Heckman, 2007; Cunha et al., 2010).[2] Yet empirical findings are mixed, with limited evidence of positive impacts.[3] One possible explanation is that by raising fertility, PPL may trigger a quantity–quality trade-off (Becker and Lewis, 1973), whereby increased family size dilutes parental resources and investment per child, potentially undermining their human capital. Against the backdrop of global fertility decline and its adverse consequences for economic growth through slower human capital accumulation, understanding how family policies shape these outcomes is crucial for designing effective interventions.

This paper examines the joint effects of PPL on fertility and child skills formations. The analysis proceeds in three steps. First, I provide new empirical evidence showing that the introduction of PPL increases fertility. Reduced-form estimates cannot distinguish actual increases in completed fertility from shifts in the timing of births, nor can they inform on the broader implications of these effects for children's skill formation. Second, given these limitations, I build a quantitative model that incorporates paid

[1] See, for example, Golightly and Meyerhofer (2022); Lalive and Zweimüller (2009); Raute (2019)

[2] Evidence also suggests that substituting parental time with full-time daycare can adversely affect cognitive development (Baker et al., 2008; Belsky, 1988; Bernal, 2008; Fort et al., 2020).

[3] Some studies report positive effects (Albagli and Rau, 2019; Carneiro et al., 2015), others find no impact (Dahl et al., 2016; Rasmussen, 2010), some suggest negative consequences (Baker and Milligan, 2015; Dustmann and Schönberg, 2012), and some highlight heterogeneous effects by maternal education (Albagli and Rau, 2019; Danzer and Lavy, 2018; Liu and Skans, 2010).

leave, fertility, and parental investment across multiple phases of childhood and I estimate the model parameters to fit data from the U.S.— the only high-income country without widespread paid leave.[4] I use the model to analyze the PPL's effects on fertility decisions, and child development through changes in parental investment. Third, I clarify the underlying mechanisms through a counterfactual analysis that omits fertility responses to the policy.

In the first step, I empirically document the effects of PPL on fertility. I exploit the introduction of six weeks of PPL in New Jersey and use a difference-in-differences framework to estimate its effect on birth rates relative to a neighboring control state. Unlike Golightly and Meyerhofer (2022), who analyze the same reform using aggregated birth data, I rely on individual-level data to identify likely eligibility. This also allows me to control for individual demographic and labor market characteristics, enabling a more precise estimation and heterogeneity analysis. Upon the policy introduction, the total fertility rate rises by 9.6% among women that are more likely to benefit from the policy (i.e., those in stable marital and employment relationships). However, these relatively large estimates may partly reflect that the identification strategy cannot disentangle whether the policy raises the total number of children or merely shifts the timing of births.

Determining the policy induced increase in completed fertility is essential to assessing its impact on child human capital, accounting for potential quantity-quality trade-offs. Moreover, PPL can influence children's long-term outcomes thorough other mechanisms. Namely, it can alter parental time and monetary investment via its impact on labor supply. In addition, the reallocation of investments from formal to parental childcare can either hinder or benefit children, depending on the relative quality of the two forms of care, which in turn may vary with parents' skills and education (Danzer and Lavy, 2018; González, 2013). By abstracting from these structural channels, reduced-form analyses capture only composite effects, without identifying the underlying mechanisms.

To shed light on the mechanisms underlying the interplay between PPL, fertility, and children's skill formation—and to address the inherent limitations of reduced-form approaches, I turn to a structural approach. In the second step of my analysis, I develop a life-cycle model with heterogeneous agents, endogenous fertility, maternal labor supply (including leave-taking decisions), and parental investment in children across multiple stages of childhood. These investments feed into a sequential process of human capital accumulation. In the model, households are formed by couples who

[4] Only a minority of states within the country have recently introduced the policy at the local level: California in 2004, New Jersey in 2014, New York in 2018, Washington in 2020, Massachusetts in 2021, Connecticut in 2022, District of Columbia in 2020, Oregon in 2023.

are heterogeneous in income, maternal education, access to paid leave, and risk of infertility, and thus face different incentives in their fertility and investment choices.

The novelty of the model lies in incorporating both the direct and indirect mechanisms through which paid parental leave can influence children's outcomes. First, in the human capital production function, investments at each stage of childhood affect future skills through self-productivity and dynamic complementarities.[5] Second, households face multiple trade-offs when deciding whether to have children and how much to invest in them. Investing in children entails monetary expenditures on education, foregone labor income from time devoted to childcare, and slower wage growth due to delayed labor market re-entry. Within this framework, longer paid leave duration can increase early-life parental time, *directly* enhancing children's human capital. *Indirectly*, it can alter later time and monetary investments through changes in family size, labor supply, and earnings.

After structurally estimating the parameters to fit data from the U.S., the model replicates a set of untargeted moments. Specifically, it fits fertility rates across the female labor income distribution and the share of low- and highly-educated families with more than one child, thereby providing a credible tool for counterfactual analysis.

Building on this structural framework, I use the model to estimate the effects of introducing PPL on fertility and children's skills. I simulate the expansion the New Jersey's paid leave scheme at a national level and find that this yields a 4.45% increase in completed fertility, accounting for 46% of the empirically estimated effect.[6] In line with Golightly and Meyerhofer (2022), fertility rises only along the intensive margin, without changing the share of childless families. Furthermore, the effects are concentrated among middle-income families and, consistent with my empirical estimates, among low-educated women. The policy effects on child human capital closely mirror the policy consequences for fertility. Early human capital falls by up to 2% among children from low- to middle-income families, where fertility responses are strongest, and the effect persists into late childhood.

As a final step, I run an additional counterfactual exercise that grants families with the same widespread 6-weeks leave scheme while preventing them from adjusting their fertility. In this scenario the policy modestly improves children's human capital. This

[5] Cunha and Heckman (2007) define self-productivity as the process by which human capital at each stage builds on the stock accumulated in earlier stages, while dynamic complementarities imply that early investments increase the productivity of later ones, making skill formation most effective through a sequence of inputs over time.

[6] The empirical estimate is based on the total fertility rate (TFR), a period measure that may reflect changes in the timing of births rather than a lasting increase in completed fertility. For instance, women may have anticipated the policy and shifted births earlier, creating a temporary spike. Since the model predicts completed fertility, which abstracts from timing, this comparison should be interpreted with caution: the model may explain a larger share of any long-run fertility effect than the range reported here suggests.

grows by up to 0.85% in early childhood, and to 0.5% in the latest stage—particularly among families in the lower half of the income distribution. These findings highlight that, while PPL can successfully raise fertility, it may unintentionally deepen inequalities in child outcomes. By contrast, if fertility remains unchanged, PPL enhances cognitive skills, especially among children from disadvantaged families. These results make a case for complementing PPL with policies such as targeted support for parental investment or income-based assistance. Moreover, they underscore the importance of accounting for heterogeneity in both policy design and evaluation.

This paper contributes to three main strands of literature. First, it complements structural studies evaluating the effects of PPL. These papers typically examine the implications of the policy for fertility and female labor supply (Bronson and Sanin, 2024; Erosa et al., 2010; Kim and Yum, 2025; Wang, 2022; Yamaguchi, 2019) but not for children's outcomes.[7] Among these models, those that abstract entirely from parental investment overlook the fact that parents value their children's long-term outcomes and make fertility and labor supply decisions accordingly. Excluding this dimension can lead to biased predictions about the effects of paid leave, which may influence fertility and labor supply decisions not only through income effects but also by inducing parents to substitute between the quantity and quality of children. By introducing a sequential process of child human capital accumulation, in a model featuring endogenous fertility and labor supply, this paper complements existing work allowing to better inform the broader impacts of this policy. By incorporating heterogeneity in family income and maternal education, the model also explains the varying effects of PPL across households, providing insights into its distributional implications.

Second, my work is closely related to the literature implementing structural models to study parental investments in children and their effects on child human capital formation. Abbott et al. (2019); Adamopoulou et al. (2025); Bolt et al. (2023); Daruich (2018); Yum (2023), develop dynamic structural frameworks to analyze how parental investments shape child development, and Caucutt and Lochner (2020); Molnar (2023) emphasize the dynamic complementarity between time and monetary investments. I complement these studies by showing how endogenizing fertility decisions amplifies differences in child investments and outcomes across the income distribution and between high- and low-educated couples, accounting for the dynamic complementarity of parental inputs. Moreover, I provide insight of the impact of PPL in this context. This study is mostly related to the work of Petit (2019); Zhou (2021), who analyze

[7] Youderian (2019), who compares the effects of different early childhood interventions in an overlapping-generations model with child human capital accumulation, represents a notable exception.

the effects of alternative policies to PPL—those targeting parental monetary investments rather than time—on fertility and children's skills, highlighting the role of the quantity–quality trade-off.

Third, this paper contributes to the empirical literature on the effects of PPL on fertility and children's skills formation. First, it provides new evidence of the pronatalist effects of PPL through a difference-in-difference analysis, in line with the results of studies using similar methodologies such as Golightly and Meyerhofer (2022); Laplante (2024); Raute (2019) who find positive effects. In contrast, regression discontinuity studies—pioneered by Lalive and Zweimüller (2009)—generally find limited effects of PPL on fertility or labor supply, as shown by Kleven et al. (2024), Dahl et al. (2016), and Cygan-Rehm (2016). As Bronson and Sanin (2024) notes, such designs often compare groups with overlapping post-reform exposure, biasing estimates toward zero. Moreover, studies findings no effects of the policy are based in contexts characterized by already generous family policies and evaluate the effects of relatively marginal reforms. By comparison, I show that similar interventions in low-support settings like the U.S. yield stronger effects. This paper also complements the empirical literature estimating PPL's effects on child development (Albagli and Rau, 2019; Baker and Milligan, 2015; Carneiro et al., 2015; Dahl et al., 2016; Danzer and Lavy, 2018; Dustmann and Schönberg, 2012; Liu and Skans, 2010; Rasmussen, 2010). By developing a structural model, I can disentangle the direct and indirect effects through which PPL affects this outcome, helping to explain the inconsistent findings in reduced-form studies. Specifically, the model captures how early parental time investment (a direct channel) interacts with fertility and labor supply responses (indirect channels) to shape per-child investment.

The paper proceeds as follows: Section 2 presents the reduced form analysis which motivates the implementation of a structural approach. Section 3 provides details on the theoretical model. Section 4 presents the data employed to compute the relevant moments and features of the model, as well as the parameters' calibration and their structural estimation. Section 6, describes the policy exercises and presents their results. The model limitations are discussed in Section 7. Finally, Section 8 concludes.

2 Reduced-form Analysis

In this section, I investigate through a quasi-exerciseal analysis the implication of introducing PPL on fertility. I employ a difference-in-differences specification and exploit exogenous variation in leave eligibility from the introduction of PPL in New Jersey. In Section C.1 of the Appendix I complement this analysis by investigating the long-term educational outcomes of children exposed to California's paid leave scheme. The results report a positive effect of the policy introduction on probability of giving birth and a negative correlation with the probability of college enrollment at age 19 (proxy for human capital).[8]

Among the other studies investigating the effects of paid leave reforms on fertility, Laplante (2024) find increases in births ranging from 17% to 46%, depending on the mother's level of education. Raute (2019) studies a reform in Germany that replaced means-tested flat maternity benefits with 12 months of earnings-related parental leave (at a 67% wage replacement rate), and finds that it led to up to a 23% increase in the probability of giving birth. Finally, Ang (2015), who analyzes the increase in the generosity of parental leave programs under the Quebec Parental Insurance Plan, estimates a 23.5% increase in the birth rate associated with the reform.

2.1 Paid leave policies and fertility

I examine the implications of New Jersey's Paid Family Leave Insurance (PLI) program, implemented in 2009, on female fertility outcomes using a difference-in-differences strategy and repeated cross-sections from the American Community Survey (ACS). A similar analysis of the effects of this six-week policy introduction is conducted by Golightly and Meyerhofer (2022), who use a difference-in-differences approach based on state-level monthly birth data from the National Vital Statistics System and estimate a 3% increase in birth rates following the policy in New Jersey.[9] While their data provides high-frequency information on fertility timing, it lacks individual-level details on employment, income, or work history—key variables for identifying potential eligibility. In contrast, the ACS allows for a more refined approximation of exposure based on detailed labor market characteristics. Replicating their broad sample approach and not restricting to women most likely to benefit from the policy, I estimate a 6% increase in the probability of giving birth—twice the magnitude they report (see B.1 in Appendix). This raises concerns about potential confounding factors other than the policy implementations driving an increase in fertility in the treated state and not the control.

[8]While ideally both empirical analyses would be based on a single policy reform, data constraints make this infeasible. The California PFL program was implemented in 2004, but data I implement from the American Community Survey only began including significantly larger samples in 2005. This prevents a credible analysis of fertility effects using pre-policy trends. Conversely, the New Jersey FLI program, introduced in 2009, is too recent to allow for an evaluation of long-term child outcomes such as college enrollment.

[9]Golightly and Meyerhofer (2022) report similar effects for California's earlier six-week paid leave policy.

Policy Context

The New Jersey Family Leave Insurance (FLI) program, implemented in July 2009, provided six weeks of partially paid leave (85% of previous wage) to bond with a newborn or newly adopted child. The policy was announced in May 2008.[10] Eligible parents needed to have worked at least 20 weeks earning at least the state minimum wage each week, or earned a cumulative total of 1,000 times the minimum wage. Payroll funding began on January 1, 2009, when mandatory employee payroll deductions for the FLI program took effect.[11]

Data and Empirical Strategy

The analysis consists of implementing a difference-in-differences approach comparing the yearly birth rates between New Jersey and Maryland before and after the introduction of the New Jersey's FLI [12]. Section A provides a detail explanation of the choice of Maryland as control.

I use a repeated cross-section from the ACS database spanning from 2005 to 2016. The ACS respondents are asked if they gave birth in the past 12 months. I select women aged 20 to 39 residing either in New Jersey (treated group) or Maryland (control group), eligible for the policy (i.e. who report to have worked at least 20 weeks in the previous 12 months exploiting a variable reporting how many weeks the respondent worked in the past 12 months). To align with the theoretical model presented in section 3, which focuses on employed women in stable relationship, I restrict the sample to employed married women who are eligible to job protection during parental leave under the Family and Medical Care Act (FMCA).[13] Observations are weighted using ACS person weights.

In the diff-in-difference, treatment status is assigned as follows:

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[10]As highlighted by Golightly and Meyerhofer (2022) in New Jersey, paid leave expanded existing benefits under the State Disability Insurance (SDI) program program, so the reform represents an extension rather than a new entitlement. This also implies that PPL effects may be larger in states without prior paid leave access.

[11]Related information available on this website: https://www.njsba.org/services/labor-relations/resources/paid-family-leave/?utm$_source = chatgpt.com$.

[12]An alternative strategy would consist of comparing eligible and ineligible women within New Jersey. The eligibility criteria require recipients of the benefits to be employed in New Jersey and to have worked at least 20 weeks earning a minimum weekly amount, or to have earned a total annual income above the threshold established for program eligibility. The ACS data only allow to approximate eligibility by reporting the number of weeks worked in the previous 12 months, but not the weekly earning or total income at the time, preventing to identify compelling treatment and control groups.

[13]To qualify for 12 weeks of job-protected leave, women must have worked at least 1,250 hours in the past year. This is proxied by self-reported typical weekly hours times number of weeks worked in the past 12 months.

$$\text{Treat}_{i,c} = \begin{cases} 1 & \text{if state is NJ} \\ 0 & \text{if state is ML} \end{cases} \qquad \text{Post}_t = \begin{cases} 1 & \text{if year } t > 2009 \\ 0 & \text{otherwise} \end{cases}$$

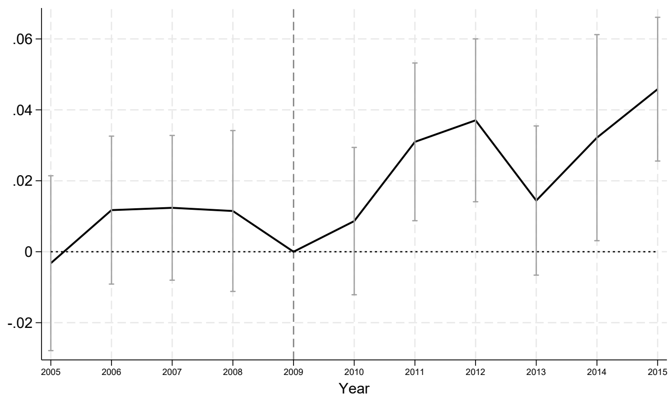
The specification assumes the following form:

$$\text{Fertility}_{ict} = \alpha + \beta(\text{Treat}_{ic} \times \text{Post}_{ct}) + \gamma X_{ict} + \lambda_c + \lambda_t + \lambda_a + \epsilon_{ict}$$

where Fertility_{ict} is an indicator for whether woman i in county c and year t reported a birth in the last 12 months; Treat_{ic} is an indicator for residing in New Jersey; Post_{ct} is an indicator for post-2010 survey years; X_{ict} includes controls for marital status, race, education, and income; λ_c, λ_t, and λ_a are county, year, and age fixed effects, respectively; and ϵ_{ict} is an error term clustered at the county level.

Results

Figure 1: Event Study: Effect of Paid Leave Reform on Fertility in New Jersey Relative to Maryland



Notes: These plots show the evolution of fertility differences between New Jersey (treatment group) and Maryland (control group) from 2005 to 2015. The left panel reports the estimates for women with less than a college degree, and the right panel presents the estimates for college graduates. The dependent variable is an indicator equal to one if a woman reported giving birth in the past 12 months. Coefficients represent year-specific differences relative to 2010, the omitted reference year. Vertical bars denote 90% confidence intervals. The vertical dashed line at 2009 marks the benchmark year after which birth rates potentially affected by the 2009 reform could be observed in the ACS. Standard errors are clustered at the county level. All regressions include fixed effects for age, county, state, and year, and control for dummies for college graduates and race (white vs non-white). The sample is restricted to married women aged 20 to 39.

Figure 2 displays event study estimates evaluating the differential evolution of fertility between New Jersey and Maryland around the 2009 implementation of New Jersey's paid leave policy. The plotted coefficients show no statistically significant differences between New Jersey and Maryland in the pre-reform period (years -4 to 0), supporting the validity of the parallel trends assumption. While effects remain modest in the immediate post-reform year (2010), a clearer upward trend emerges thereafter. From 2014 onward, treatment effects become both larger and precisely estimated, with coefficients reaching 3.1 percentage points in year 6 (significant at the 5% level), 3.7 pp in year 7 (5% level), and peaking at 4.6 pp in year 10 (1% level), suggesting a delayed but substantial fertility response to the policy. Yet these post-treatment dynamics may also reflect confounding time-varying shocks correlated with treatment rather than causal policy effects.

These dynamic patterns are consistent with the cumulative nature of childbearing decisions and the lag between policy eligibility and observable births. The regression results presented in Table 1 confirm these findings, indicating a statistically significant average treatment effect of 2.2 percentage points (significant at the 1% level). This corresponds to a 17% increase in birthrates compared to the baseline in 2009. Together, these results suggest that New Jersey's paid leave reform raised fertility among eligible women, particularly several years after implementation, when awareness and utilization of the policy likely matured.

Table 1: Regression output table

	(1) Married, Employed + JP
Treat × Post	0.0218***
	(0.0079)
Baseline birth rates (2009)	12.8
% change	17.03
Observations	51,741

Notes: This table reports the result from a difference-in-differences regression estimating the effect of paid leave (PL) on fertility for married women who are employed and entitled to job protection (JP). The dependent variable is a binary indicator equal to one if the respondent reported a birth in the past 12 months. The regression includes controls for age, a White race indicator, and a college graduate (CG) dummy. Fixed effects are included for state, year, and county. Standard errors clustered at the county level are reported in parentheses.
* p<0.10, ** p<0.05, *** p<0.01.

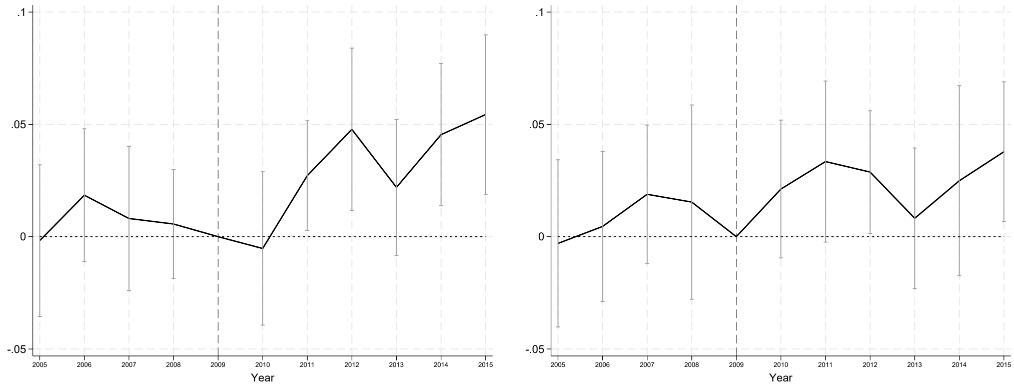
Heterogeneous effects by education

Figure 2.1 displays the estimated effect of the reform on birth rates, disaggregated by education. While the difference in average effects between less- and more-educated women is not statistically significant, the event study patterns suggest that the former were more responsive. The left panel shows results for women without a college degree, for whom the estimated effects rise more consistently and steeply after the policy introduction in 2009. Point estimates increase from 2.7 percentage points in 2011 to

4.8 pp in 2012, and reach 5.4 pp in 2015. These gains are statistically significant in each after 2010, suggesting a sustained post-reform response in fertility for this group.

Right panel presents the estimated effects for highly educated women. After a moderate increase of 2.1 pp in 2010, estimates fluctuate—3.3 pp in 2011, dropping to 0.8 pp in 2013, then recovering slightly to 2.5 pp in 2014 until reaching 3.8 in 2015. Except for the latter, none of these estimates are statistically significant, and there is no clear cumulative rise. This suggests that the policy had marginally stronger impact on low-educated women—perhaps reflecting differences in the opportunity costs of childbearing or labor market attachment.

Figure 2: Event Studies: Effect of Paid Leave Reform for High school (left panel) versus College Graduate women (right panel)



Notes: This plot shows the evolution of fertility differences between New Jersey (treatment group) and Maryland (control group) from 2005 to 2015 for women with women with less and a college degree (left panel) and college graduate women (right panel) separately. The dependent variable is an indicator equal to one if a woman reported giving birth in the past 12 months. Coefficients represent year-specific differences relative to 2010, the omitted reference year. Vertical bars denote 90% confidence intervals. The vertical dashed line at 2009 marks the benchmark year after which birth rates potentially affected by the 2009 reform could be observed in the ACS. Standard errors are clustered at the county level. All regressions include fixed effects for age, county, state, and year, and control for dummies for college graduates and race (white vs non-white). The sample is restricted to married women aged 20–44.

Changes in Total fertility rate following the policy

To transform the estimated effects into a measure more comparable with the structural model's predicted impact of the policy on completed fertility, I compute the policy-induced change in the Total Fertility Rate (TFR). The TFR aggregates age-specific fertility rates across all reproductive age groups (the estimates of the effects for each aga group separately are reported in Table C.1 in the section 6 of the Appendix), representing the number of children a woman would have over her lifetime if she experienced the age-specific fertility rates observed in a given year. While TFR is a period measure that may reflect short-term timing shifts (e.g., birth anticipation), it serves as a useful summary of how the policy affects overall fertility patterns in the data.

In the empirical specification restricted to employed women in martal relationships, which best mirrors the population in the model, the TFR increases by 9.6%, within the subsample of those eligible for job protection. Although these estimates may overstate long-run fertility effects if the policy primarily induces a shift in the timing of births, they provide a useful benchmark against which to interpret the model's predictions on the policy effects on completed fertility reported in Section 6. A detailed description of the procedure is provided in Appendix C.

Discussion of limitations

The sample is restricted to women most likely to respond to paid leave—those who are married, employed, and entitled to job protection—since they are best positioned to act on the policy's incentives. Figure B.1 in Appendix B examines how results change when these restrictions over marriage, current employment status, and eligibility to job protection during the leave are progressively relaxed. Less restrictive samples show slightly noisier pre-trends and reduced precision, but effects remain largely consistent. As the sample narrows to women better positioned to benefit, the estimated fertility effect rises from about 7.8% in the most inclusive sample to 17% in the most restrictive. An additional concern is that restricting the sample to employed women could bias results if employment itself is endogenous to the policy; however, Figure B.2 shows no impact on employment, supporting robustness. Finally, Figure B.3 confirms that women least able to use the policy (single and out of the labor force) exhibit no detectable response.

Nevertheless, several threats to identification remain. First, the analysis spans a period overlapping with the Great Recession of 2007-2008, which may confound estimates if economic conditions differentially affected fertility trends in treatment and control states. Second, the outcome measures annual birth probabilities rather than completed fertility, which could conflate permanent fertility responses with short-run timing adjustments. In fact, the policy might have incentivizes women to shift births earlier, creating a transitory spike in birth rates rather than a lasting increase in family size. This could explain the sizable estimated increase in fertility (up to 17%) among eligible women, which may partly reflect intertemporal substitution rather than a permanent change in fertility behavior. Although these concerns do not invalidate the findings, they underscore the need for cautious interpretation and motivate the structural modeling approach developed in the next section.

3 Structural approach

The limitations of the empirical exercise presented in this section caution against drawing strong causal conclusions from this specific empirical setting. Moreover, reduced-form approaches are inherently limited in their ability to uncover the mechanisms through which paid leave affects fertility and child development. To address these challenges and provide a unified framework for interpreting dynamic policy effects, I develop a structural life-cycle model that captures the joint decisions of fertility, labor supply, and parental investment across heterogeneous households.

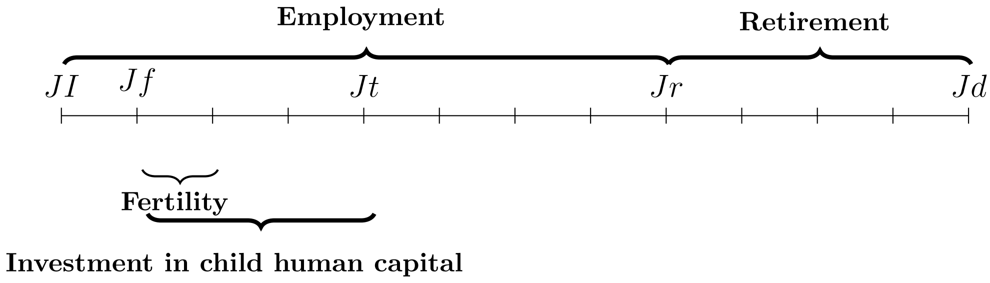
3.1 Life-cycle model

The life-cycle framework developed in this paper portrays a single generation of individuals progressing through four main stages of life, spread over 13 model periods, each corresponding to five years.

Households consist of two earners—of the same age and opposite gender—who remain together throughout their lives. Agents enter the model at age 25, already participating in the labor force, and are exogenously assigned a level of education (high school or college, reflecting female educational enrollment), fertility constraints, an initial productivity shock whose persistent component affects their labor productivity in future periods. Individuals also differ by their entitlement to paid leave. As I assume that in the baseline scenario, there are no federally mandated paid leave, only a fraction of individuals receive these from their employer or the state. For those who are not entitled, leave remain unpaid.

After entering the labor force, individuals choose whether to become parents, and in case they choose to, how many children to have and how many resources (time and money) to invest in their human capital. By choosing time investment, individuals with children also choose their labor supply. However, this only refers to the intensive margins as the model assumes full employment. Child human capital accumulates over three periods of childhood: since the period when children are born to the third and last period of childhood. In the following period, J_t, parents still value the quantity and quality of their children but stop investing in their human capital. After J_t, the children leave the household and no longer account in the household's consumption. Parents return to supply labor inelastically until the age of retirement and consume their entire labor income. Period J_r defines the beginning of the retirement, the final phase of life when agents consume their pension and ultimately die. Figure 3 summarizes the life cycle of an agent.

Figure 3: Life cycle timeline



Preferences

Individuals gain utility from consumption and leisure time according to a collective bargaining model. If the children have not yet left the household, individuals of opposite gender within the couple value their number and their human capital, while facing a fixed cost of parenthood, weighted by the parents weight μ and $1-\mu$, for wife and husband respectively. The utility of parents ($U_f + U_m$), thus, takes the following form:

$$U_f + U_m = \mu[u(c) + u(\ell) + u(n, h_k)] + (1-\mu)[u(c) + u(\ell) + u(n, h_k)]$$

Childless individuals do not gain utility from having children, and for them $u(n, h_k) = 0$. Moreover, I abstract from men's choices over leisure (as this only takes place during parental leave which they do not take as explained in **Parental leave**). Thus, for husbands, $(1-\mu)u(\ell) = 0$, and the utility of couples with children can be rewritten as follows:

$$U_f + U_m = u(c) + \mu[u(\ell)] + u(n, h_k)$$

The per-period utility over consumption is positive, increasing and concave and assumes the form of a (Constant Relative Risk Aversion) CRRA function:

$$u(c) = \frac{\frac{c}{\Psi(n)}}{1-\gamma_c}^{\frac{1}{1-\gamma_c}}$$

In absence of children $n = 0$, consumption deflation $\Psi(n) = 1$ as the household labor income is consumed entirely by the members of the couples. More details on the consumption deflation are provided in the Appendix D.1.

The disutility of labor (or utility from leisure) takes the following form:

$$u(\ell) = \frac{\theta(\ell)^{1+v}}{1+v}$$

The preferences for leisure are governed by the weight θ and by v, the inverse of the

Frish elasticity. As in the couples utility function, this is premultiplied by the Pareto weight μ, this becomes:

$$\mu u(\ell) = \frac{\mu\theta(\ell)^{1+v}}{1+v}$$

In every other period characterized by households who do not have children, agents supply labor in-elastically (time is normalized to 1 as by equation 5 and is fully allocated to market work l, while leisure ℓ=0) and consume their entire labor income.

Starting from the second period of the life-cycle, those couples who choose to become parents derive utility from both the number of children, denoted n, and their human capital, h_k. Consumption deflation increases with the number of children in the household (see Appendix D). I define child-related utility in equation (3.1), which parents incorporate into their own maximization problem. This utility function is separable in the quantity and quality of children, as in De La Croix and Doepke (2003) and Bar et al. (2018). Moreover, while children live in the household, parents gain utility from their current stock of human capital and from the discounted value of future human capital, featuring in the continuation value. The latter results from current investment and, in the middle and late stages of childhood, from the stock of human capital accumulated up to that period.

$$U(n, h_{k_i}) = \eta_n \left(\frac{n}{\sigma_n}\right)^{\sigma_n} + \eta_{h_k} n^{\kappa} \left(\frac{h_{k_i}}{\sigma_{hk}}\right)^{\sigma_{hk}} - X_e$$
$$\eta_n, \eta_{h_k}, \quad X_e \in (0,1)$$

The parameters η_n and η_{h_k} represent the weights in the utility function placed on the "quantity" and "quality" of children, respectively. As in Petit (2019), the parameter κ governs how families of different sizes value children's human capital. If $\kappa = 0$, families derive the same utility from a child's human capital regardless of how many children they have. If $\kappa > 0$, larger families value children's human capital more.[14] The parameters σ_n and σ_{h_k} capture the curvature of preferences over the number of children and their human capital, respectively. X_e is a fixed cost asociated with parenthood that varies with the individual's education level and is meant to allow for childlessness.

Working while young stage

As individuals start working in the first model period, family income y is the result of the sum of labor incomes, $w_g(e, j, z_g)$ ($g \in m, f$ for male and female individuals,

[14]The parameter κ strongly influences the importance of the quantity–quality trade-off in parental choices. With separable preferences, when $\kappa = 0$ parents treat the number and quality of children as perfect substitutes. When $\kappa > 0$, utility increases with a combination of both more children and higher human capital, reflecting a preference for balancing quantity and quality.

respectively) as displayed in equation (2). Wage w_g is given by the age profile $\gamma_{g,j,e}$ and the auto-regressive idiosyncratic shock z_g (with persistence $\rho_{z,e}$ and innovation variance $\sigma_{\zeta,e}$ as in equation (3)), vary with gender and with the level of education. During the first period of work, each individual within the couple faces an initial productivity shock z_0, corresponding to the initial value of the persistent component of the income process. This determines their level of productivity z_g, as by equation (4), which is correlated with female education e. A tax rate τ_{SS} corresponding to social security coverage, applies to labor income y (the product of individual wage and the fraction of the period spent working).

To account for the biological and circumstantial limitations on fertility, I introduce a discrete state variable $x \in \{0, 1, 2, 3\}$ that denotes the maximum number of biological children a family can have. Limiting the successful probability of having children is crucial to match realized fertility as observed in the data as it reflects real-world constraints arising from infertility, health shocks, and age-related fertility decline. The value of x is drawn at the beginning of the model, becomes known to agents in the following period when fertility choices take place. More details are provided in Appendix D.3. The state variable $p \in \{0, 1\}$ captures whether the household is eligible to receive paid leave benefits under the baseline scenario (more details are provided in **Parental leave**). Since the beginning of the life-cycle, agents participate in the labor force. Agents discount the utility from the future period at the discount factor β.

The value function for the young workers V_j^w is the following:

$$V_j^w(e, z_m, z_f, x, p) = \max_c u(c) + u(\ell) + \beta E[V_{j+1}^f(e, z'_m, z'_f, x, p)] \tag{1}$$

$$c = y(1 - \tau_{SS})$$

$$y = w_f l_f + w_m l_m \tag{2}$$

$$\log(w_g) = \gamma_{g,j,e} + z_g, \quad g \in \{m, f\} \tag{3}$$

$$z'_g = \rho_{z_g,e} z_g + \zeta_g, \zeta_g \sim N(0, \sigma_{\zeta_g,e}), \tag{4}$$

$$1 = l_g \tag{5}$$

Parenthood stages

Following the first period of work, agents choose whether to become parents. If the decide to have children, they choose their number and how to allocate their resources to benefit their human capital accumulation.

Human capital multistage formation process

Human capital accumulates across the different stages of childhood as a result of parental investment whose productivity increases with the current stock of human capital (according to the mechanism of self-productivity). Thus, besides influencing the stock of human capital developed in that period, parental investments in each period determines the development of human capital in the future (dynamic complementarity).[15]

I define human capital functional form in each stage of childhood as an adaptation of a standard technology in the literature (e.g. Fuchs-Schündeln et al. (2022); Krueger et al. (2025); Youderian (2019)). This consists of a nested constant elasticity of substitution (CES) productivity function which depicts child human capital at each phase as the combination of the stock of human capital accumulated up to that period and the investment I_i which parents' provide to their children. Because the model abstracts from heterogeneity in children's initial ability, I assume that in the first stage of childhood the technology of human capital exclusively combines parents inputs, monetary expenses m and time t, through the following function:

Technology of early human capital:

$$h_{k_1} = A_1 \left(\underbrace{\alpha(\delta_e t_1)^{\phi_1} + (1-\alpha)(m(1-t_1))^{\phi_1}}_{\text{Parental investment}} \right)^{\frac{1}{\phi_1}}$$

The multiplier A_1 captures the productivity of the technology of child human capital formation in early childhood. The parameter α refers to the weights of money and time investment, while ϕ_1 represents the elasticity of substitution between inputs. Finally, parameter δ_e allows for different productivity of time investment between families with high and low-educated mothers. The multiplier A_1 captures the productivity of the technology for child human capital formation in early childhood. The parameter α governs the relative weight of money and time investments, while ϕ_1 determines the elasticity of substitution between these inputs. The parameter δ_e allows for differential productivity of time investment across families based on the mother's education level (high vs. low). Parental inputs m and t represent the money and time invested per child, respectively. Assuming parents divide their total resources equally among children, the per-child inputs are given by total time T and money M divided by the number of children n, adjusted for scale economies in investment ($\epsilon_1, \epsilon_2 < 1$):

[15]It has been empirically documented that parental investments and existing child human capital are complements in the production of later human capital; (see, for example, Aizer and Cunha (2012); Caucutt and Lochner (2020); Fuchs-Schündeln et al. (2022); Todd and Wolpin (2007); Youderian (2019)).

$$m = \frac{M}{n^{\epsilon_1}}, \quad t = \frac{T}{n^{\epsilon_2}}$$

In the later stages of childhood, children have already accumulated a stock of human capital endogenously. This existing stock is combined with current parental investment, and the two inputs are weighted by γ and $1-\gamma$, respectively. The parameter ρ governs the elasticity of substitution between past and current inputs, capturing the degree of dynamic complementarity in human capital formation. The parameter ϕ_2 determines the elasticity of substitution between time and monetary investment in the Cobb–Douglas production function of parental investment.[16] I assume that both ρ and ϕ_2 take the same value across the human capital formation processes in both middle and late childhood. As in the earlier stage, A_i denotes the productivity of the technology of child human capital during these later phases.

Technology of middle and late human capital:

$$h_{k_{i+1}} = A_i \left(\underbrace{\gamma h_{k_i}^{\rho}}_{\text{Current human capital}} + \underbrace{(1-\gamma)\left[(\delta_e t_i)^{\phi_2} m_i^{1-\phi_2}\right]^{\rho}}_{\text{Parental investment}} \right)^{\frac{1}{\rho}}, \quad i \in \{2, 3\}$$

Fertility stage

In period $j = J_f$ agents decide how many children they wish to have (over a discrete number $n \in \{0, 1, 2, 3\}$), conditional on their fertility limits x. They also decide the amount on money and the share of time to invest in their children's human capital, as well as the time the primary caregiver spends on leisure while on parental leave. The value function in this fertility period is presented in equation (8). This model simplifies the fertility process similarly to Daruich and Kozlowski (2020), Zhou (2021) and Kim (2023) by assuming all children are born in the same model period (therefore within five years, agents can have up to three children)[17], with the same endowment on initial human capital h_{k0}.

[16] Notably, the Cobb–Douglas production function is the equivalent of a CES production function with elasticity of substitution between inputs equals 1.

[17] In the literature, it is common to allow agents to choose each period whether to have a child allowing for birth spacing. However, studying the long term effects of parental investment during early childhood requires tracking children's human capital over each stage of childhood. Keeping track of a different level of human capital over multiple periods and for multiple children would dramatically increase the state-space making the solution of the model computationally infeasible.

Time allocation during fertility stage

Mothers in the the model choose how to allocate her time between market work, childcare, and leisure by weighing the marginal utility of leisure against the marginal return to labor and the marginal productivity of time in child development. If they choose to take leave time (i.e., temporarily out of the labor force), they allocate time between leisure and childcare, facing a trade-off between the utility gained from leisure and the benefit of time investment for her children' human capital. Leisure only takes place during the time on leave, but I allow for corner solutions implying that mothers spend the entire leave time looking after the child. As women take a separate period of leave for each child, leisure time does not present economies of scale in the number of children. After returning to work, leisure is no longer an option. Time is then allocated between labor and childcare, balancing the marginal return to labor with the marginal productivity of parental time.

Time investment presents economies of scale dictated by the parameter ϵ_2. Parental investments—both time and money—occur both during leave and post-leave. However, to maintain tractability, the model does not distinguish between time investment made during leave and those made afterward, as this is dictated by its marginal productivity in the technology of child human capital.[18] Time with children is endogenously chosen at the household level and the share of this time spent by each parent on childcare, α_g, is calibrated from the data and allows for joint childcare ($\alpha_m + \alpha_f \geq 1$). Further details on parental time allocation are provided in Section 4.1. I therefore abstract from intra-household bargaining over leave uptake and childcare time. Because fathers do not take leave in the model, they are also not assigned leisure time.

Parental leave

I assume that women spend a positive fraction of the first period of parenthood outside the labor force looking after the child, and thus everyone is allowed to take time off-work upon giving birth, regardless on whether they are paid for it or not. The time on leave comprises the entire time women spend on leisure and an unspecified portion of the time spent caring for their children in this period. In the baseline scenario ($s = \mathcal{B}$, with $s \in \{\mathcal{B}, \mathcal{C}\}$), representing the U.S. economy in the absence of federal PPL, I assume that only a fraction of women $p_{\mathcal{B}}$ is entitled to paid leave compensation equal to $\alpha_{\mathcal{B}}$ fraction of previous earnings for up to a maximum duration of $\overline{T}_{\mathcal{B}}$, as by equations (6) and (7). This fraction of women would receive paid leave benefits either through an

[18]This model specification is going to change in future versions of this paper to allow to clearly identify the fraction of model period spent on leave and distinguish maternal childcare during leave from the and upon returning to work.

employer-provided benefit or by residing in a state with an existing SDI program.[19] This assumption reflects the empirical fact that, even in the absence of a federal paid leave mandate, a minority of U.S. workers, primarily those in certain sectors or states, have access to some form of paid leave following childbirth.[20]

$$B = \begin{cases} \alpha_{\mathcal{B}}\, w_f\, d & \text{if } \ell > 0 \\ 0 & \text{otherwise} \end{cases} \tag{6}$$

$$d = min(\ell n + \alpha_f t_1 n^{\epsilon}, \bar{T_{\mathcal{B}}}) \tag{7}$$

Those caregivers who are not entitled to leave benefits in the baseline scenario will receive no compensation for the time spent off work. In the counterfactual scenario $\mathcal{C}$, presented in Section 6.1, PPL becomes universal (i.e., $p_{\mathcal{C}} = 1$) and everyone will receive paid leave for the time spent off work up to $\overline{T}_{\mathcal{C}}$ (see section 6.1). I abstract from risk of job-loss in the model, assuming that agents are eligible to job protection while taking leave under the Family and Medical Leave Act (FMLA).[21]

To proxy skills depreciation entailed by time on leave, I assume that leave-takers face a wage penalty, δ_p, directly proportional to the time spent off-work. This penalty has lasting effects in the following period of parenthood.

The dynamic problem in the fertility period can be written as follows:

$$V_j^f(e, z_m, z_f, x, p) = \max_{c,n,m,t} u(c) + U(n, h_k) + u(\ell) + \beta E[V_{j+1}^p(e, z', n, h_{k_{i+1}})] \tag{8}$$

$$c + mn^{\epsilon_1} = y(1 - \tau_{SS})$$

$$y = w_m(1 - \alpha_m t n^{\epsilon_2}) + w_f(1 - \delta_p(-\alpha_f t n^{\epsilon_2})) - m(1-t)n^{\epsilon_1} + \underbrace{p_{\mathcal{B}}\boldsymbol{B}n}_{\text{PL compensation}} \tag{9}$$

$$1 = l_m + \alpha_m t n^{\epsilon_2}$$

$$1 = l_f + \ell n + \alpha_f t n^{\epsilon_2}$$

$$\log(w_g) = \gamma_{g,j,e} + z_g,$$

$$z'_g = \rho_{z_g,e} z_g + \zeta_g, \zeta_g \sim N(0, \sigma_{\zeta_g,e}),$$

$$h_{k_1} = A_1 \left(\alpha(\delta_e\, t_1)\phi_1 + (1-\alpha)m(1-t_1)^{\phi_1}\right)^{\frac{1}{\phi_1}}$$

[19] U.S. states under the SDI programs provide parents with six weeks of paid leave

[20] As of March 2023, just 27% of civilian employees had access to paid family leave, as reported by the Bureau of Labor Statistics: https://www.bls.gov/ebs/factsheets/family-leave-benefits-fact-sheet.

[21] Implemented in 1993, this policy provided every employee of firms with at least 50 workers the right of up to 12 weeks of job protected, unpaid leave to look after a newborn or a fmily memeber.

$$B = \begin{cases} \alpha_{\mathcal{B}}\, w_f\, d & \text{if } \ell > 0 \\ 0 & \text{otherwise} \end{cases}$$

$$d = min(\ell n + \alpha_f t_1 n^{\epsilon}, \bar{T_{\mathcal{B}}})$$

As child human capital directly depends on parental investment, parents have incentivizes to spend time and money on their children. They jointly choose how much money and time to dedicate to each child, and both forms of investment present some economies of scale dictated by parameters $\epsilon_1, \epsilon_2 < 1$.

Because newborn and young children need to be constantly looked after, I model monetary investment as the product of the unit cost of childcare and the fraction of the mdoel period which parents are not spending with a child, $1 - t$, accounting for economies of scale in the expenditure: $m(1-t)n_1^{\epsilon}$.

Parents working and investing in their children

In the following model periods $j = J_f + i$, $i \in \{1, 2\}$, agents continue consuming while investing in their children whose human capital accumulates to form $h_{k_{i+1}}$. Agents with children choose the total amount of time to allocate to childcare (i.e. t hours for a single child and tn^{ϵ_2} collective time for all children). Beyond the first period of childhood, to keep the model tractable, I follow Adamopoulou et al. (2025) and abstract from other forms of time use, such as home production and leisure. Consequently, parents experience disutility from allocating their entire time endowment to non-leisure activities, as no time is devoted to leisure (i.e. $\ell = 0$). This period introduced two new state variables: the number of children n determined in the fertility period, and the stock of human capital h_k resulting from previous investment.

The value function of working parents is V^f:

$$V_j^p(e, z, n, h_k) = \max_{c,m,t} u(c) + u(\ell) + U(n, h_{k_i}) + \beta E[V_{j+1}^p(e, z', n, h_{k_{i+1}})] \tag{10}$$

$$c + mn^{\epsilon_1} = y(1 - \tau_{SS})$$

$$y = w_m(1 - \alpha_m t n^{\epsilon_2}) + w_f(1 - \alpha_f t n^{\epsilon_2})$$

$$1 = l + \alpha_g t n^{\epsilon_2}$$

$$\log(w_g) = \gamma_{g,j,e} + z_g,$$

$$z_g' = \rho_{z_g,e} z_g + \zeta_g, \zeta_g \sim N(0, \sigma_{\zeta_g,e}),$$

$$h_{k_{i+1}} = A_i \left(\gamma h_{k_i}^{\rho} + (1-\gamma) \left[(\delta_e t_i)^{\phi_2} m_i^{1-\phi_2} \right]^{\rho} \right)^{\frac{1}{\rho}}, \quad i \in \{1, 2\}$$

As in early childhood, parents jointly choose the total time spent with children, while the allocation of this time between mother and father is set exogenously by the data. Because children beyond infancy do not require full-time supervision, monetary investment m_i in these periods is not proportional to the time children do not spend with their parents. Instead, it consists of a monetary amount corresponding to education expenditure.

Final period of childhood

After four periods of parental investment, children's human capital formation is complete. In the fourth period of childhood, the final human capital stock of children materializes and parents continue to derive utility from both the quantity and quality of children, as in the previous three periods, but they no longer allocate resources toward their human capital. I assume that in this final period, parents value the discounted flow of human capital for three more periods (with separable utility, $\beta^i U(h_{k_i})$, $i = 3$). This simplification addresses the fact that, unlike in reality, parents in the model do not derive utility from their children's well-being. As a result, the model may under-predict investment in the final stage of childhood, especially since that investment is not rewarded with additional utility flows from the child's future outcomes. Therefore, the dynamic problem in period J_t is again given by equation (1). Children participate in household consumption. However, since parents no longer make investment decisions, they return to supplying labor inelastically and face a trivial decision problem in which they consume their entire labor income.

The value function of the retired agent is V^t:

$$V_j^t(e, z, n, h_k) = u(c) + u(\ell) + U(n, h_{k_i}) + \beta^i U(h_{k_i}) + \beta E[V_{j+1}^w(e, z', n, h_{k_{i+1}})] \tag{11}$$

$$c = (w_f + w_m)(1 - \tau_{SS})$$

$$l = 1$$

$$\log(w) + \log f^e + \gamma_{j,e} + z,$$

$$z' = \rho_{z,e} z + \zeta, \zeta \sim N(0, \sigma_{\zeta,e}),$$

Old workers stage

After children have left the household, parents no longer derive utility from either their quantity or quality. They continue to work full time for three additional periods, during which their utility maximization problem becomes trivial: with no trade-offs or choices to make, they simply supply labor inelastically and consume their entire labor income each period.

The value function of parents while empty nests V^{ω} can be written as follows:

$$V_j^{\omega}(e,z) = u(c) + u(\ell) + \beta E[V_{j+1}^{\omega}(e,z')] \tag{12}$$

$$c = (w_f + w_m)(1-\tau_{SS})$$

The agents solve the same utility maximization problem until they reach the age of retirement of 65 in period $j = 13$.

Retirement stage

At the stage of retirement, agents' source of income is the retirement benefits, π which I simply calibrate as a constant share of previous earnings vary with their education level and maintaining the value of the income shock experienced in the previous period (z_{j-1}).

The value function of the retired agent is V^r:

$$V_j^r(e) = \max_c u(c) + \beta E[V_{j+1}^w(e,z',n)] \tag{13}$$

$$c = \pi(e, e^{f_e})$$

4 Calibration

4.1 Data

The main source of data for the estimation of this model is the Panel Study of Income Dynamics (PSID), a longitudinal survey of households starting in 1968. The survey provides useful information of education, marital status, family composition and earning and work history. I select waves from 1993 to 2015, a period during which the Family and Medical Leave Act applied federally, but only a limited number of U.S. states[22] had implemented state-level paid family leave policies. I collect information on couples composed by the head (or reference person) and the spouse, regardless of whether they are legally married. I use the longitudinal data on individuals' income disaggregated by gender and education to build age profiles and the wage process. Details on the estimation are provided in Appendix D.2. Moreover, I employ the PSID data to compute moments related to average fertility and childlessness by maternal

[22] specifically California, New Jersey, and Rhode Island

education. Additional data sources used in this study are the National Longitudinal Survey of Youth (NLSY-79) for entitlement to paid leave and fertility by maternal income.

For information of households' children, I rely on the PSID's Child Development Supplement (CDS). This supplementary study starts in 1997 and collects information on at least one child between 0 and 12 per household and on their primary caregiver. The same children are eligible for follow-up of interviews in 2002 and in 2007 unless they have turned 19 by the time of the new interview. Starting from 2014, all PSID children are eligible for the interview. The survey provides time diaries filled in by the children with the help of their primary caregiver as well as a broad measure of assessment, including the Woodcock Johnson test for cognitive abilities. The identifiers of the primary caregiver (the mother in 90% of the cases) and secondary caregivers allows to link children with their parents. I collect data from the 1997 to 2019 waves of the PSID's Child Development Supplement (CDS). After restricting the sample to children who I can link to their parents and children reporting at least two consecutive observation on their test score, and selecting children younger than 17, I am left with a total of 1452 children.

Fertility heterogeneity

The Fertility Supplement of the PSID provides data on the birth history of PSID respondent. I collect these data for the pre-selected sample. To ensure consistency with the model, I restrict the sample to families with at most 3 children, and compute average completed fertility by maternal education by analyzing the number of births for women between 41 and 54. I also employ the NLSY-79 (main survey) to measure fertility rates by female income deciles. This provides a complementary source of data to the Fertility Supplement of the PSID. By taking advantage of a larger sample of 5194 working and cohabiting women between 41 and 50, reporting positive income, I compare model generated fertility rates by women income deciles to those computed from the data to validate the model (see Section 4.3).

Time investment

The CDS provides time diaries documenting the activities a child engages in over a 24-hour period. It also records the start and end times of each activity, as well as who was present, distinguishing between active and passive participation. These data are collected separately for a representative weekday and weekend day. By selecting activities in which either parent was actively present, I construct a measure of parents' time investment in their children. I use time diaries in waves from 1997, 2002 and 2007 to compute the amount of time parents spend with their children. Because the model abstracts from leisure beyond the leave period, I restrict the analysis on working day and focus on activities children engage in while either or both of their parents are actively participating. Following Daruich (2018), I also exclude time spent watching TV and playing video-games to limit the overlap between adults leisure time and active investment in children. When comparing families with two children, I find that highly educated parents report a relatively larger share of time investment compared to the lower educated counterpart, in line with the literature (Guryan et al., 2008; Ramey and Ramey, 2010). Table 2 reports the average parental time investment in a child in families with two children, distinguishing between maternal education, maternal and paternal time investment and child's age. The data do not indicate whether parents are on parental leave when completing their newborn's time diary, therefore there is no clear account on how much extra time a parent on leave would spend with her child in a regular day compared to a parent regularly working.

Time investment in each stage of childhood is split between each parent according to the weight $\alpha_{g,i}$ with $g \in \{m, f\}$ and $i \in \{m, l\}$ reported in Table 2.

Table 2: Time investment by maternal education

Time	High school	College	Share
Mother, child 3-5	2 h 43 min	2 h 58 min	80%
Father, child 3-5	1 h 18 min	1 h 24 min	39%
Parents, child 3-5	3 h 23 min	3 h 53 min	
Mother, child 6-11	1 h 50 min	1 h 53 min	85%
Father, child 6-11	1 h 0 min	1 h 4 min	40%
Parents, child 6-11	2 h 13 min	2 h 19 min	
Mother, child 11-16	1 h 26 min	1 h 40 min	86%
Father, child 11-16	49 min	1 h 14 min	51%
Parents, child 11-16	1 h 38 min	2 h 1 min	

Notes: The table show parental time investment (as number of minutes and as a share of total time available to the child) across different stages of childhood distinguishing between maternal, paternal and total time and separating families by maternal education. The first three rows refer to early childhood, the second three to middle childhood and the latter three to late childhood. These statistics are computed using the time diary of the PSID Child development supplement (CDS), waves 1997, 2002, 2007, and aggregating time spent by children during a working day in children in a variety of activity when at least one parent is actively participating. The data is sourced from the PSID Child Development Supplement. Refer to the main text for further details.

Access to paid leave

A complementary data source is the NLSY79 Child and Young Adult (NLSY79-CYA) survey, which records how long women spent away from work after childbirth and whether this time was covered by paid leave, unpaid leave with job protection, a mix of both, or no leave. I focus on women who were married or cohabiting at the time of birth and who remained in the labor force. The sample includes all women reporting a birth between 2008 and 2016, up to their third child (consistent with the model's limit of three births). The final sample includes 1,023 women. Among highly educated mothers, about 40% had access to paid leave, compared with 30% among the less educated.

Child human capital:
The CDS provides a wide range of measures of children's cognitive skills, including three Woodcock–Johnson Tests, with reported scores for each of them. Following Del Boca et al. (2014); Lee and Seshadri (2019); Petit (2019), I use the Letter–Word Identification Test (LW) to construct a measure of child human capital. As in Lee and Seshadri (2019), I proxy human capital with test scores based on correctly answered questions, weighting each item by the inverse of the share of respondents who answered that specific question correctly. This methodology assigns higher weight to more difficult questions (see Lee and Seshadri (2019) for more details). The resulting test scores are normalized to determine a direct relationship between a child's human capital and the probability of correctly answering a generic LW question.

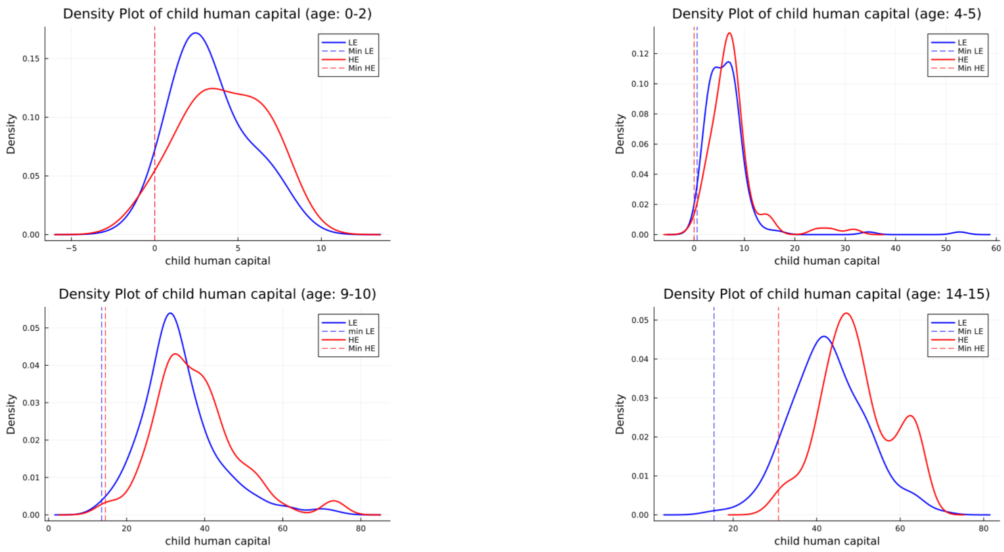
Assuming Q is the set of questions each assigning q_i points, with $q_i \in (0,1)$ and that the questions are independent between each other, then $Q = \sum(q_i)$ and $\bar{q}$ represents the test score : $\bar{q} = \frac{\sum_{i=1}^{Q} q_i^*}{Q}$

Human capital is calculated as the share of correct answers to the test: $h_k = \frac{\bar{q}}{1-\bar{q}}$.

By matching CDS' individual identifiers of the primary caregiver, I can link children's information with those of their parents and compare, for example, children skills and parental time investment by maternal education.

Figure 4 shows the distribution of human capital obtained using the transformation explained above and distinguishing between maternal education and age. Notably, the distribution of human capital of children of highly educated women is slightly shifted to the right and right-skewed in all charts, suggesting that children of highly educated parents perform better in the test scores at every age compared to children from low-educated parents.

Figure 4: Distribution of children's human capital by age and maternal education



Notes: The plots show the density distribution of children's human capital at different ages and levels of maternal education (children under 3 in the top left panel, children between 4 and 5 in the top right panel, children between 6 and 10 in the bottom left panel, and children between 11 and 16 in the bottom right panel). Human capital is computed using a transformation of the Letter–Word Identification test (LW) of the Woodcock–Johnson test, following the methodology in Lee and Seshadri (2019), as defined in equation (16). Data come from the PSID Child Development Supplement (1997, 2002, 2007, 2014, 2019). The blue and red lines show the distribution of human capital among children with high school graduate mothers and college graduate mothers, respectively. Dashed lines indicate the smallest value of human capital in each sample.

4.2 Parameters set exogenously

A set of exogenously assigned model parameters are summarized in Table 3. First, parameters referring to allocation of childcare time between parents, $\alpha_{i,m}$, $\alpha_{i,f}$, are computed using CDS data as detailed in Subsection 4.1. Second, following Petit (2019), I assign the values estimated by Sommer (2016) to the parameters determining the economies of scales in parental time and monetary investment, ϵ_1 and ϵ_2. The author calibrates these parameters by matching the elasticities of parental time and monetary investment to the number of children. Third, the parameters denoting tax rates are taken from Daruich and Kozlowski (2020). Forth, I assign to the intertemporal elasticity of substitution ρ the same values calibrated by Youderian (2019) who uses a similar technology of child human capital to the one I implemented. Finally, the penalty associated with maternal loss of experience while away from work, δ_p, is calibrated using estimates from Dechter (2014), who finds a human-capital depreciation of roughly 1% for each month (on maternity leave) off work. Since in my model, the horizon is five years (60 months), letting $f = \frac{\text{months out of work}}{60}$ denote the fraction of the period spent away, the resulting flat-rate penalty is $L(f) = 0.01 \times (60\,f) = 0.60\,f$

which calibrates δ_p. Using CDS data, I set the initial stock of human capital equivalent to the average value of children at 2 years old, the youngest in the sample reporting test score. Moreover, I report the share of women entitled to paid leave in the baseline scenario $\alpha_{\mathcal{B}}$ whose calculation is described in subsection 4.1.

Table 3: Exogenously calibrated parameters

Parameter	Value	Description	Source
Demographics			
	5	Time period	
J_s	25	Age at beginning of the lifecycle	Arbitrary assigned
J_f	30	Fertility decision	Arbitrary assigned
J_t	45	Children are independent	Arbitrary assigned
J_r	65	Retirement	Arbitrary assigned
J_d	85	Death	Arbitrary assigned
Prices			
τ_{ss}	0.125	Tax rate	Daruich and Kozlowski (2020)
Preferences			
β (annual)	0.935	Discount factor	Standard range
γ_c	0.8	Coefficient of risk aversion	Caucutt and Lochner (2020)
Scalability			
ϵ_1	0.92	EOS money investment	Sommer (2016)
ϵ_2	0.54	EOS time investment	Sommer (2016)
Time investment			
α_{f1}	0.39	Share of pat. time, t_1	PSID-CDS (see Appendix ??)
α_{m1}	0.80	Share of mat. time, t_1	PSID-CDS (see Appendix ??)
α_{f2}	0.40	Share of pat. time, t_2	PSID-CDS (see Appendix ??)
α_{m2}	0.85	Share of mat. time, t_2	PSID-CDS (see Appendix ??)
α_{f3}	0.51	Share of pat. time, t_3	PSID-CDS (see Appendix ??)
α_{m3}	0.86	Share of mat. time, t_3	PSID-CDS (see Appendix ??)
Initial abilities			
h_{k0}	0.17	Initial human capital	PSID-CDS
Motherhood penalty			
δ_p	0.6	Wage loss for time off-work	Dechter (2014)
Paid leave			
$\alpha_{\mathcal{B}}$	0.4	Share of women entitled to PPL	NLSY-79 C/YA
Child human capital			
ρ	-0.45	Intertemp. elasticity of substitution (coefficient of dynamic complementarities)	Youderian (2019)

Notes: This table reports the description and values of the parameters calibrated externally. EOS stands for 'economies of scale'.

4.3 Internally calibrated parameters through Simulated Method of Moments (SMM)

The remaining model parameters determine parents' altruism (preferences for fertility and children's human capital), and the human capital functional form for early, middle, and late childhood. These are the most relevant parameters to drive the results of the model. Therefore, I estimate this set of parameters by minimizing the distance between the relevant moments computed from the data and those generated by the model Simulated Method of Moments (SMM). Because the values of the parameters potentially affect multiple moment at the same time, I report the moments' fit and the estimated parameters values separately.

I estimate preference parameters by matching two fertility moments, completed fertility and the share of childless couples, separately for college- and high-school-educated women. For the child-human-capital parameters, I match the average human capital of children in early childhood, between 4 and 6 years old, the average human capital of children in middle childhood, between 9 and 11 years old, and the average human capital of children in middle childhood, between 14 to 16 years old. To purge any scale effects, each of those human-capital moments is computed only for families with exactly two children.

Moreover, I match moments on parental time investment, calculated as the average minutes per day a child spends with either parent (or both) in each phase of childhood, as reported in Table 2. To express these raw minutes as a share of our five-year model horizon, I normalize this values to align them with the time structure of the model.[23] Similarly, I match average parental time investments by maternal education for the middle-childhood (ages 9–10) and late-childhood (ages 14–15) phases. Finally, to capture women's labor supply in the first period of parenthood, I compute the share of time spent working for mothers with two children (at least one under age five) by dividing their annual hours worked by the total time endowment over the five-year model horizon—namely 11 hours/day × 5 days/week × 52 weeks/yr × 5 yrs. The structure of the model only allows me to estimate the produce of the pareto weight μ and the coefficient of disutility form labor θ and not the two coefficients separately. A summary the data moments and their model counterpart is reported in Table 4, while the estimated parameters values are reported in Table 5.

The simulated model moments are close to the data counterpart. This suggests that the calibrated model can successfully capture the key empirical patterns in the data and provides a reasonable framework for analyzing the effects of introducing PPL.

[23] I assume the reported daily minutes apply to 11 hours of activity per day times 5 days per week (excluding weekends), multiply by 52 weeks per year, and then by 5 years, and finally divide by the total minutes in the five-year period. Concretely, assuming m is the average daily childcare minutes, we compute $\frac{m \times 5\text{ days} \times 52\text{ weeks} \times 5\text{ years}}{60\text{ min/hr} \times 11\text{ hrs/day} \times 7\text{ days/week} \times 52\text{ weeks/yr} \times 5\text{ yrs}}$, yielding the fraction of total available time devoted to childcare.

Table 4: Moments used for SMM calibration

Moment description	Model	Data
Avg. fertility, college graduates (CG)	1.78	1.72
Avg. fertility, high-school graduates (HS)	1.88	1.90
Share childless, CG	0.13	0.15
Share childless, HS	0.10	0.11
Avg. hk_1, CG	6.64	6.71
Avg. hk_1, HS	5.60	5.82
Avg. hk_2, CG	36.20	36.61
Avg. hk_2, HS	30.53	33.22
Avg. hk_3, CG	48.00	49.20
Avg. hk_3, HS	42.00	42.80
Avg. hours worked, CG with child <5	0.61	0.55
Avg. hours worked, HS with child <5	0.62	0.55
Avg. time investment (t_2), CG	0.18	0.21
Avg. time investment (t_2), HS	0.18	0.20
Avg. time investment (t_3), CG	0.18	0.18
Avg. time investment (t_3), HS	0.18	0.14

Notes: This table reports the moments matched in the simulated–method-of-moments. Fertility and labor supply statistics come from PSID (1993–2015). Human-capital moments refer to families with exactly two children and are computed using CDS data (1997–2019).

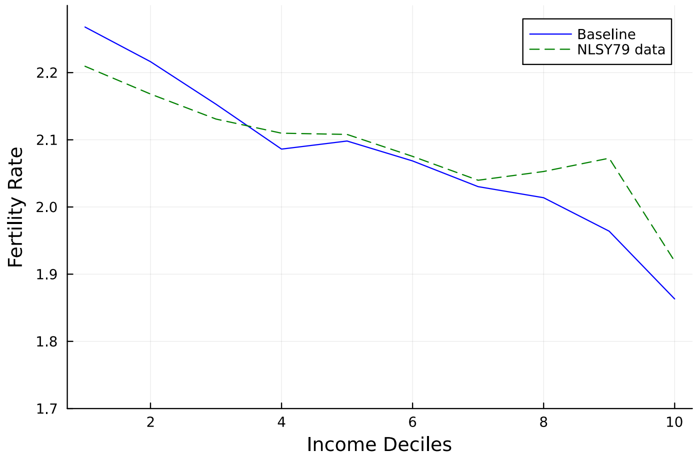
Table 5: Parameters and Data Moments for SMM

Parameter	Value	Description
η_n	1.15	Utility children's n
σ_n	0.21	Utility children's n
κ	0.13	Utility children n
X_{e1}	2.6	Fixed cost, HS
X_{e2}	2.9	Fixed cost, CG
η_k	0.2	Utility children's h_k
σ_{hk}	0.49	Utility children's h_k
ϕ_1	-0.6	Elasticity time and money, h_{k_1}
ϕ_2	0.38	Elasticity time and money, h_{k_2},h_{k_3}
α	0.25	Relative weight of time vs money in h_{k_1}.
γ	0.84	Weight of past human capital, h_{k_2},h_{k_3}
A_{I1}	2.55	Productivity inv. (h_{k_1})
A_{I2}	8.4	Productivity inv. (h_{k_2})
A_{I3}	4.0	Productivity inv. (h_{k_3})
δ_{CG}	1.16	Productivity time inv CG vs HS. (h_{k_3})
$\mu\theta$	1.66	Disutility of work

Notes: This table reports the parameters values resulting from the SMM estimation.

To further validate the model, I report in Figure 5 untargeted moments on the relationship between women's labor income and completed fertility at the intensive margins detailed in Subsection 4.1. I rank women into ten income deciles and plot the average number of children for each decile in both the baseline model and the NLSY79 data. The model reproduces the key negative earnings–fertility gradient. Although the model slightly under-predicts fertility among the top deciles, the close fit across most of the distribution confirms that the internally calibrated preference and human-capital parameters generate a realistic earnings–fertility trade-off although it was not directly targeted. Table 6 presents two additional non-targeted moments: the share of highly and less-educated families with at least two children. These moments are replicated relatively well by the model, reinforcing the credibility of its quantitative fit.

Figure 5: Untargeted moments: relationship between fertility and female income



Notes: The figure plots average completed fertility at the intensive margins by maternal income decile for the baseline model (blue) and NLSY-79 data (green). The sample refers to employed women between 40 and 50, reporting positive labor income and to be living with a partner.

Table 6: Comparison of Untargeted Moments

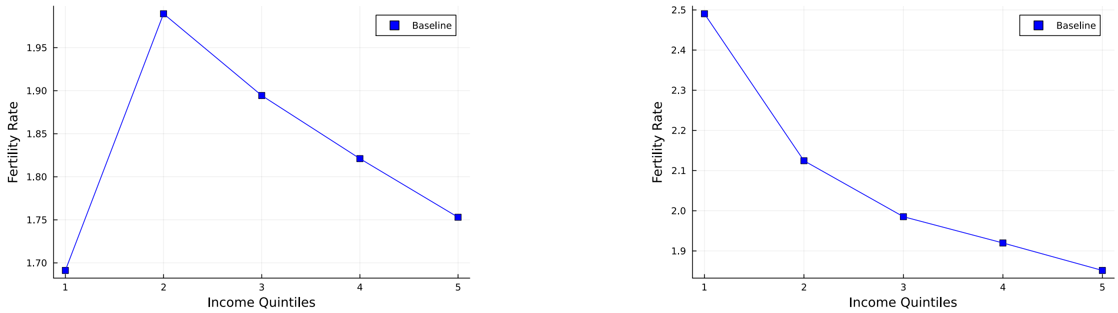
Non-targeted moment	**Model**	**Data**
Share with >1 child, CG	0.77	0.68
Share with >1 child, HS	0.80	0.72

Notes: This table compares the model-generated and data values for two untargeted moments: the share of College Graduate and High School Graduate families with more than one child.

5 Outcomes baseline scenario

This subsection illustrates through a series of graphs households' choices regarding fertility, time, and monetary investments in children and how these translate into child human capital across different stages of childhood. These values are compared across the income distribution consisting of income quintiles. Except for fertility, whose patterns I show both including intensive and extensive margins (Figure 10 Panel A) and only the intensive margins (Figure 10 Panel B). These are computed by ranking families based on average lifetime income, measured as the mean of parents' labor income (net of taxes and skill depreciation) from the first model period up to the last period in which children are present in the household.

Figure 6: Fertility across the income distribution



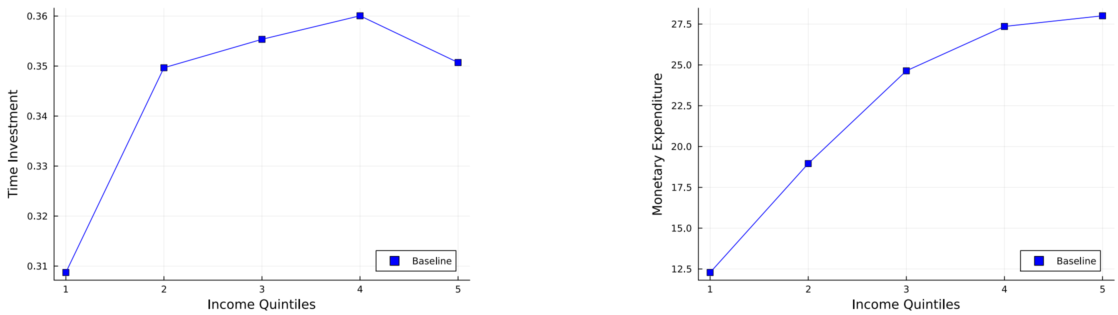
Panel A: Fertility rates across income distribution

Panel B: Fertility rates (intensive margins) across income distribution

Notes: Panel A shows completed fertility rates across the family income distribution. Panel B focuses on the intensive margin of fertility (excluding childless couples).

Figure 6, Panel A, shows fertility rates across families' income quintiles. Completed fertility ranges from 1.7 among families in the lowest quintile—where a larger share of couples remain childless due to financial constraints—to a peak of 2.0 children on average among families in the second quintile, before gradually declining along the income distribution. Panel B reports fertility rates conditional on having at least one child (i.e., the intensive margin of fertility). Within this group, fertility peaks among the lowest-income families, reaching an average of 2.5 children, and steadily decreases across the income distribution, reaching about 1.8 among families in the highest quintile.

Figure 7: Parental investment during early childhood, across families' income distribution



Panel A: Time inv. in early childhood

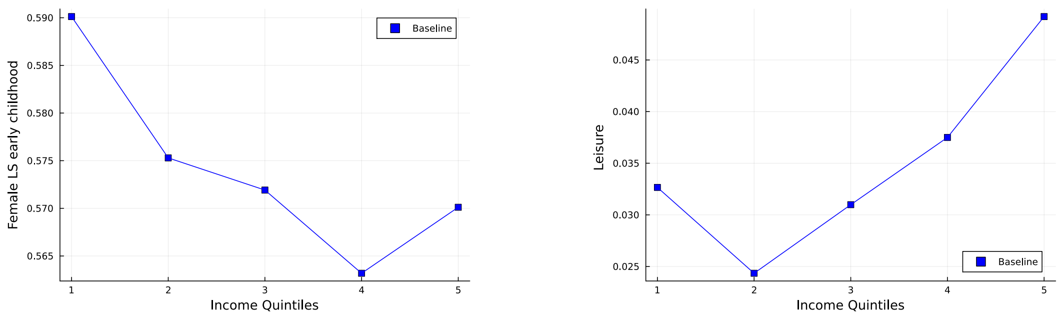
Panel B: Monetary inv. in early childhood

Notes: Panels A and B show per-child parental time and monetary investment, respectively, in the earliest stage of childhood by income decile and policy scenario compared to the baseline.

Figure 7, Panel A, shows the share of the first stage of parenthood that parents with children allocate to childcare time across the income distribution. This share rises from about 31% among families in the first quintile to 36% among those in the fourth quintile, before slightly declining to 35% for families in the top quintile, who face higher opportunity costs of time. Higher-income families can also afford greater spending on childcare, which is indirectly correlated with time investment.

The non-monotonic pattern in time investment reflects the trade-off faced by parents during early childhood: children require constant supervision, and any reduction in parental time must be compensated by purchasing external childcare. Thus, as income rises, parents substitute away from time toward monetary expenditure, which is relatively more productive in the early-childhood human capital technology ($\alpha = 0.25$). Panel B confirms that monetary expenditure increases monotonically with income in the first stage of parenthood, and the same pattern holds in later stages (see Figures E.4 in the Appendix). However, the relationship between income and investment flattens at the top of the distribution.

Figure 8: Labor supply and leisure during first period of parenthood, across income distribution



Panel A: Maternal labor supply during first period of parenthood (fraction of model period)

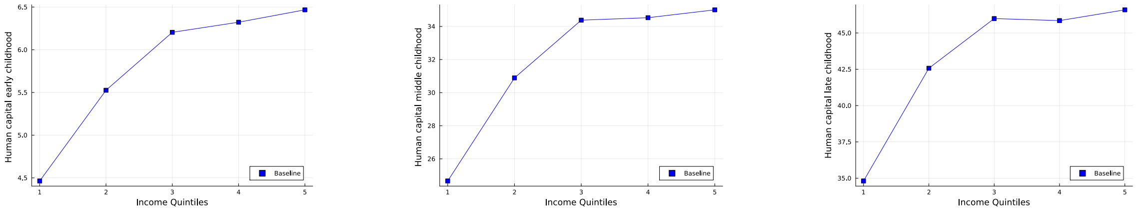
Panel B: Fraction of first period of parenthood spent in leisure

Notes: Panels A, B show maternal labor supply during the first period of parenthood and the fraction of the period spent on leisure in the baseline scenario.

Figure 8 reports the share of time that mothers in the model allocate to work and leisure during the first stage of parenthood. The pattern of maternal labor supply (Panel A) closely mirrors that of parental time investment shown in Figure **??**, Panel A. The fraction of time spent working declines from 59% among families in the first income quintile to 56.5% among those in the fourth. Mothers in the top quintile work about 57% of the period—slightly more than those in the fourth quintile—as they face stronger incentives to sustain higher monetary investments in children.

The share of time devoted to leisure, shown in Panel B, is also non-monotonic across the income distribution, ranging from roughly 2.5% to nearly 5% of the period. Women in the lowest quintile spend slightly more time in leisure than those in the second and third quintiles, reflecting a larger share of low-educated mothers in this group, who derive higher marginal utility from leisure.

Figure 9: Child human capital across stages of childhood and families' income distribution



Panel A: Child human capital in early childhood

Panel B: Child human capital in middle childhood

Panel C: Child human capital in late childhood

Notes: Panels A, B and C show child human capital in early, middle, and late childhood, by income quintile in the baseline scenario.

Figure 9, Panels A–C, show the evolution of children's human capital across the income distribution at each stage of childhood and illustrate how it changes following the introduction of paid leave policies. The stock of human capital increases with family income, reflecting higher parental time investment (though non-monotonically) and greater monetary investment, which carries a higher weight in the human capital technology during early childhood ($1 - \alpha = 0.75$, as defined in Section 4.2).

However, the relationship between income and human capital is not strictly monotonic. By construction, children in some college-graduate families attain higher human capital than children from high-school-graduate families with comparable or even higher income. This occurs when the latter experience larger transitory productivity shocks (z_g) despite lower educational attainment, given the higher productivity of time investment among college-educated mothers ($\delta_{CG} > \delta_{HS}$).

Because the human capital accumulation function features self-productivity—meaning that later human capital builds on the stock accumulated in earlier stages—the pattern of human capital across income deciles remains broadly consistent across stages of childhood.

6 Policy exercises

6.1 Introduction of widespread PPL

After solving and structurally estimating the model, I use it to evaluate a policy that partially compensates parents for the time they spend with their children in the earliest stage of life. I run a counterfactual exercise by simulating a scenario $\mathcal{C}$ during the fertility stage J_f (i.e. the first stage of childhood), providing all primary caregivers

($p_{\mathcal{C}}$=1) 6 extra weeks of parental leave benefits. These benefits offset earnings losses incurred while absent from work to care for newborns.

The first exercise replicates New Jersey's scheme at the national level, granting up to 6 weeks (on top of previous eligibility; thus, $\bar{T_{\mathcal{C}}} = \bar{T_{\mathcal{B}}} + \frac{1}{40}$ of a model period) of leave with a wage replacement rate $\alpha_{PL} = 0.85$. This alters the budget constraint in the fertility stage (equation 9) through changes in equations 6 and 7, reported below.

$$y = w_m(1 - \alpha_m t n^{\epsilon_2}) + w_f(1 - \delta_p(-\alpha_f t n^{\epsilon_2})) - m(1-t)n^{\epsilon_1} + \underbrace{p_{\mathcal{C}}\boldsymbol{B}n}_{\text{PL compensation}}$$

$$B = \begin{cases} \alpha_{\mathcal{C}}\, w_f\, d & \text{if } \ell > 0 \\ 0 & \text{otherwise} \end{cases}$$

$$d = min(\ell n + \alpha_f t_1 n^{\epsilon}, \bar{T_{\mathcal{C}}})$$

The benefits provide parents with extra income, which can be used to increase consumption, raise monetary investment, reduce work hours, or expand family size. These income shocks have dynamic effects beyond the implementation period. Early investment can substitute for or reinforce later investment, while larger family size dilutes per-child resources over time. In addition, reduced labor supply can have persistent effects through the dynamic penalty of work interruptions, influencing future labor supply and investment decisions.

In a second counterfactual $\mathcal{C}'$, I provide parents with the same benefits but fix fertility to baseline levels. By preventing fertility responses the leave, I isolate how PPL effects on female labor supply, parental investment, and child human capital are mediated by fertility responses.

6.2 Results

Aggregate effects

Upon the introduction of the policy, fertility grows on average by 4.5% and this is almost entirely happening at the intensive margin. This is re the result of the 4.56% increasing their size (5.14% if considering only those who already had children). On average, families with children also experience marginal changes in labor supply, time and monetary investment throughout childhood. Average child human capital, drops by 1% in early childhood, 1.32% in middle and 0.5% in late childhood.

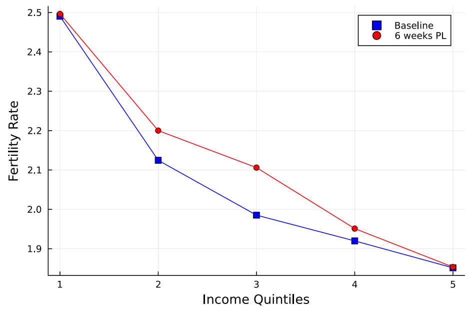
The effects of the policy intervention are illustrated through a series of graphs that show how household choices regarding fertility, time, and monetary investments in children translate into the development of child human capital across different stages of childhood. Except for fertility, these outcomes are compared across the income distribution under each counterfactual policy scenario, relative to the baseline.

Because neither policy affects the decisions of couples without children in the baseline scenario, who remain childless in both counterfactual scenarios, the analysis focuses on the subset of families who had at least one child under the baseline. The figures present the changes as percentage variation of the outcomes respect to the baseline scenario distinguish between the 6-week paid leave scenario (red line, circle marks), and the alternative 6-weeks paid leave scenario where fertility is hold constant to the levels of the baseline scenario (gray line, cross marks).

Consequences for fertility

The policy exercises reveal that introducing PPL positively affects fertility. Notably, the rising fertility rates in the model are driven by higher-order births rather than a reduction in childlessness. This result is consistent with the empirical literature Golightly and Meyerhofer (2022) who estimates the effects of introducing PPL in two U.S. states. Other studies find that PPL reforms affected fertility both at the intensive and extensive margins (Laplante, 2024; Raute, 2019). Moreover, in line with my empirical findings, the results suggest that PPL affects mostly low-educated and low-income families (results which also align with Lalive and Zweimüller (2009)). Figure 10 reports fertility rates across the income distribution (**Panel A**) and the changes compared to the baseline scenario (**Panel B**) for families that had at least one child in absence of widespread leave. Upon introducing 6 weeks of paid leave at 85% wage compensation, fertility increases on average by 4.5%, shifting the mean completed fertility rate from 1.83 to 1.91. This rise is driven by low-educated women (7%), while highly educated only respond by increasing fertility by 2%. The policy appears to affect mostly families in the middle deciles of the income distribution, where the increase picks in decile five and six (reaching 6% higher rates, as by **Panel B**).

Figure 10: Changes in fertility following the introduction of paid PL

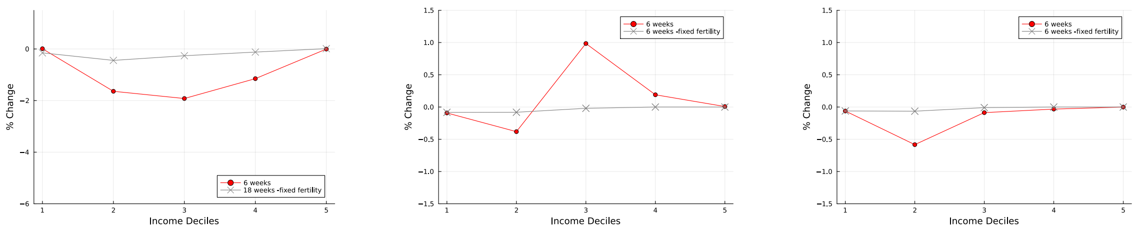


Panel A: Fertility rates across income distribution

Notes: In this figure, Panel A shows fertility levels at the intensive margins across the family income distribution, comparing rates in the baseline scenario (square marks) to the same metrics in the counterfactual scenarios featuring the two policy exercises (circles).

Consequences for Female Labor Supply (FLS)

Figure 11: Female labor supply across policy scenarios



Panel A: % changes FLS during the first stage of motherhood

Panel B: % changes FLS during the second stage of motherhood

Panel C: % changes FLS during the third stage of motherhood

Notes: Panels A, B, and C show the percentage variation in each scenario compared to the baseline of female labor supply by stage of motherhood across the income distribution of families with children.

In Figure 11, Panels A–C report the corresponding percentage variation from the baseline scenario of maternal labor supply (FLS) across the family income distribution and at different stages of parenthood (corresponding to different phases of child's development).

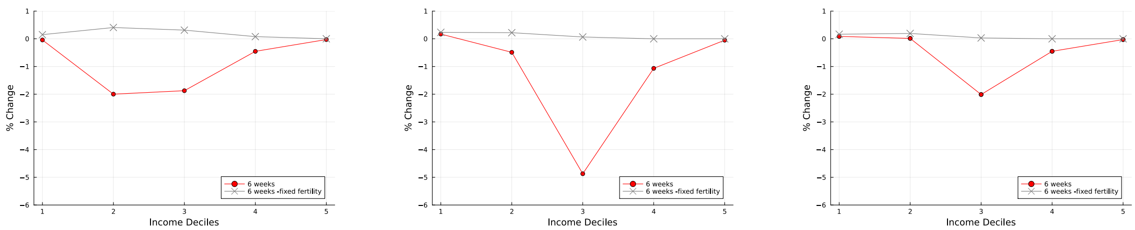
The introduction of 6 weeks of universal PPL reduces maternal FLS in the first stage of parenthood for families who respond to the policy by increasing their fertility, as a larger number of children requires them to spend more time off-work. The largest effects—declines of up to 2%—occur in the third quintile, where fertility rises the most. The changes are negligible in quintiles where fertility remains unchanged (first, second, ninth, and tenth). Under the counterfactual scenario preventing fertility responses, FLS slightly in all but the top quintile, allowing for a marginal increase in parental time investment (see Figure 12).

In middle childhood (Panel B) policy-induced variations in FLS are not uniform across deciles. The lower half of the distribution experiences declines in FLS, while changes are positive (up to 1% increase in the third quintile of the distribution), marginal but positive for women in families in the fourth quintile and negligible for those in the fifth.

Finally, in the later stage of childhood, FLS also decreases upon the introduction of the leave. These changes are small and limited to up to -0.6% for families in the second quinte. Even if this period, changes in FLS are close to null under the 6 weeks scenario with fixed fertility.

Changes in time investment across stages of childhood

Figure 12: Changes in Time investment under paid leave policies



Panel A: % change time inv. in early childhood **Panel B: % change time inv. in middle childhood** **Panel C: % change time inv. in late childhood**

Notes: Panels A, B and C show percentage change in per-child parental time investment in early, middle, and late childhood, by income decile and policy scenario compared to the baseline.

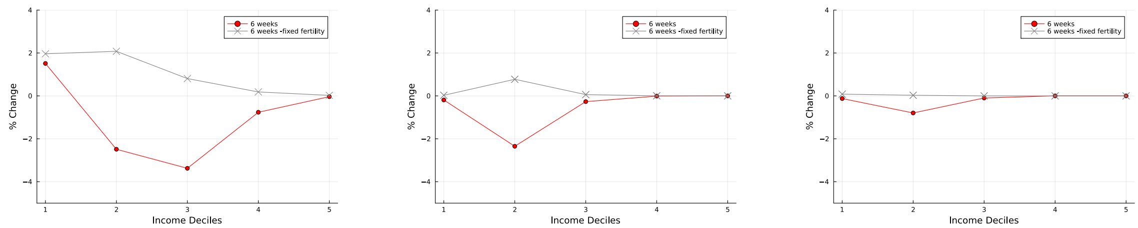
Figure 12 Panels A-C show how per-child parental time investment across stages of childhood varies compared to baseline levels under the two policies scenario. The figure showing the level changes in parental time investment across the income distribution and the different scenarios is presented in Appendix E Figure E.3.

Panel A displays how, under the 6-weeks, increases in fertility directly translates into less time investment per child. In the first case, childcare time drops by up to 2%, with changes concentrated between the second and the third income quintiles, reflecting a larger increase in family size, while variations are negligible at the tails. Under the counterfactual scenario where fertility remains fixed at baseline levels, time investment slightly increases across the entire distribution, also peaking among families in the second and third deciles (growing by 0.4%). Assuming that the entire extra time is spent with a child during leave this could correspond to spend on leave 4.35

extra weeks (1.5% higher fraction of the model period). Families at the top of the distribution appear to be unresponsive to the leave policy. In later stages of childhood, per-child time investment keeps decreasing among families who responded to the reform by growing their fertility. The change is most pronounced at the middle of the distribution (where it reached -5% and -2% in late childhood), while it attenuates in the other deciles compared to the previous period. Under the scenario with omitted fertility responses, time investment marginally grown but changes are negligible.

Changes in monetary investment across stages of childhood

Figure 13: Changes in monetary investment across childhood stages



Panel A: % change in money inv. in early childhood

Panel B: % change in money inv. in middle childhood

Panel C: % change in money inv. in late childhood

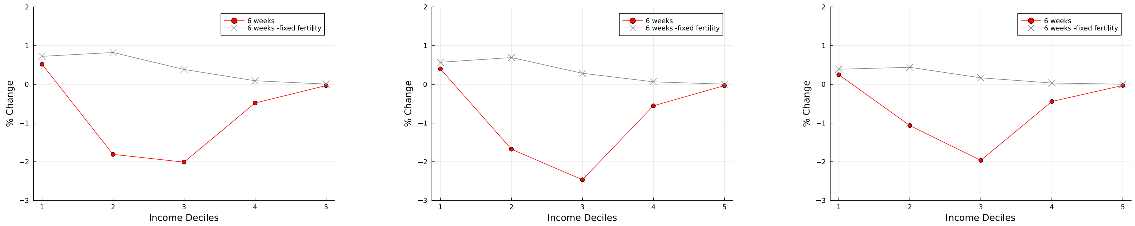
Notes: Panels A, B, and C present the percentage variation relative to the baseline in parental monetary investment during early, middle, and late childhood across income quintiles under different policy scenarios.

Figure 13 Panels A–C show percentage changes in per-child monetary investment (in thousands of USD) under each policy scenario relative to the baseline across the income distribution, for families with at least one child. Following the introduction of PPL in the 6-week scenario, monetary investment in early childhood (Panel A) increases by almost 2% among households in first quintile of the distribution, which do not adjust their fertility in response to the policy. In contrast, changes are negative—up to 3.7%—for the thrid quintile, and close to zero at the top of the distribution. Under the 6 weeks scenario with fixed fertility, monetary investment rises by about 2% in the two lowest quintiles, but the positive effects are smaller moving along the distribution.

In middle and late childhood (Panels B and C), monetary investment under the 6-week policy scheme declines by over 2% and 0.9%, respectively, among families in the second income quintile. The changes are negligible in the rest of the distribution. Under the fixed-fertility scenario the changes mirror the effects in the previous scenario, with families in the second quintile increasing monetary investment during the middle stage of childhood by 0.8%.

Consequences for human capital

Figure 14: Child human capital by stage of childhood and policy scenario



Panel A: % change in child human capital in early childhood | **Panel B: % change in child human capital in middle childhood** | **Panel C: % change in child human capital in late childhood**

Notes: Panels A, B, and C show percentage changes in child human capital during early, middle, and late childhood across the income distribution of families with children under different policy scenarios. Results are reported for three counterfactuals: 6 weeks of PPL, and 6 weeks of PPL with fertility held fixed, each relative to the baseline.

Panels A-C 14 show the percentage changes in child human capital in response to PPL compared to the baseline scenario in absence of paid leave. Upon the introduction of PPL, human capital declines mostly across income groups where the fertility response was stronger as a result of the quantity-quality trade-off which induced parents to dilute their investment among multiple children. The exception are families in the lowest income quintile who did not adjust their fertility in response to the policy. Instead, by increasing their monetary expenditure (as shown in Figure 13), these families led to a growth in child human capital by 0.85% in early childhood. The increase is slightly smaller but still positive for children in the latest stages of childhood. The human capital of children in families in the highest income quintile, who experiences negligible changes in fertility and in parental investment, remains unaltered.

The changes in child human capital for families in the second to fourth quintiles follow as similar pattern across stages of childhood. Child human capital in the third quintile is most affected by the policy (-2% in early childhood, -2.5% in middle childhood and -2% late childhood), followed by families in the second quintile (-1.85 % in early childhood, -1.6% in middle childhood and -1% late childhood) and the fourth quintile (at most -0.5% decrease in each stage).

In absence of fertility responses, child human capital would have been positively affected by the introduction on PPL as a result of greater per-child monetary and time investment. Under the 6-weeks scenario with fixed fertility, changes are concentrated in the two lowest quintiles of the distribution. For this families, child human capital grows on average by up to 0.85% in early childhood and up to 0.7% and 0.5% in later stages. This results from greater time investment, and especially monetary investment, in early childhood resulting from PPL benefits. The coefficient of dynamic complementarity (ρ

= -0.6) and the high weight of past human capital (γ = 0.84) in the functional form makes so that changes in early childhood skills have lasting effects in later stages oof of development.

7 Discussion of the structural model

The structural model developed in this paper has several limitations that suggest directions for future research. First, for tractability I assume that multiple children are born within a five-year period and that birth decisions occur simultaneously. This affects parental time and resource allocation, since siblings directly compete for equal investments. A more realistic model would allow for child spacing and distinguish between lifetime income constraints (affecting siblings of different ages) and temporary budget constraints (when children of similar ages require simultaneous investments). Incorporating endogenous fertility over multiple periods would increase complexity but better capture these dynamics.

Second, the model does not allow to identify leave duration. Agents endogenously choose how much time to allocate to leisure, which in the model is assumed to occur only during parental leave. The remaining time within each model period (which spans five years) is allocated between childcare and paid work. However, since the model does not track when childcare occurs, whether during leave or after returning to work, it cannot disentangle changes in leave duration from shifts in within-period time allocation. This limitation arises from the necessary simplification of modeling each period as a five-year span, which combines infancy and early childhood to allow for tractable modeling of human capital accumulation across multiple stages.

Third, only the primary caregiver is entitled to parental leave, and childcare time is split exogenously. In reality, policies have evolved to include both parents. Future extensions could introduce an endogenous allocation of leave between mother and father while keeping state space manageable—for example, by adding limited choice variables for paternal leave and childcare without re-estimating the full model.

Finally, the model includes only cohabiting couples, excluding single women, who represent about 40% of U.S. women (ACS). Although my estimates show little fertility response among single women, their relevance remains: single-earner households may be more sensitive to policy incentives. A future extension could incorporate them by assigning a stochastic probability that one partner leaves the household.

8 Conclusions

In this paper, I investigate the interplay between paid parental leave, fertility, and child outcomes. Using micro-level data, I contribute to the empirical literature by showing that the introduction of 6 weeks of paid leave in the U.S. is associated with an increase in fertility between up to 17% among women better positioned to respond tot he policy— with marginally larger effects among low-educated women. The empirical estimates may reflect both an actual increase in children ever born and short-term timing shifts, such as birth anticipation.

To overcome this limitation and investigate the broader implications of policy induced effects on fertility, I build a partial-equilibrium heterogeneous-agents model in which individuals differ by gender, age, education, labor productivity, access to paid leave, and infertility risk. The model features endogenous fertility decisions, and parental time and monetary investment across different stages of childhood which feed into a sequential process of human capital accumulation. Calibrated to U.S. data, the model replicates fertility rates across the female income distribution as well as the share of large families among both low- and high-educated households.

I then use the model to investigate the distributional effects of PPL on several outcomes. As a first exercise, I replicate the 6-week reform which I analyzed through a reduced-form approach. Upon providing parents with a partial wage compensation for the time they spend off work to the equivalent of 6 weeks, the model predicts a 4.45% increase in completed fertility. As such, the model cannot capture shifts in time of births but predicts structural fertility response. . It reproduces between 35–75% of the observed increase in Total fertility rate, a share that may overstate the true policy effect if large part of the empirical response reflects a temporary reallocation of births rather than a lasting increase in fertility. The simulated response is concentrated among low-educated individuals, in line with the data, and driven primarily by increases in higher-order births —a pattern consistent with the findings of Golightly and Meyerhofer (2022). Fertility increases are most pronounced in the middle of the income distribution and lead to declines in per-child investment at every stage of childhood, reducing human capital accumulation by up to 2%. Families at the bottom of the distribution, who do not increase their fertility, instead use the benefits to raise their early monetary investment in children. Thanks to self-productivity in the technology of child human capital, these early increases translate into lasting improvements in child outcomes by 0.5% in late childhood.

As a second exercise, to test whether the negative effects of PPL on children's human capital are indeed driven by fertility, I run a counterfactual exercise in which fertility is fixed at baseline levels. In this scenario, families slightly increase both per-child time and monetary investment across nearly the entire distribution and mostly in the earliest stage of childhood, generating positive and lasting effects on children's human capital, although small (up to 0.5% increase in late childhood skills).

Taken together, these results show that while PPL can effectively boost fertility, it may also exacerbate disparities in child outcomes, particularly among families facing binding budget constraints. A strategy to raise fertility without compromising child development could involve complementing PPL with measures such as targeted childcare subsidies for low-income families. In the model, children's human capital in these households declines under PPL primarily because of reduced monetary investment across all stages of childhood and reduced time investment in early childhood. Providing additional financial resources would help offset these declines, mitigating the adverse effects of the quantity–quality trade-off. Moreover, thanks to self-productivity and dynamic complementarities in human capital accumulation, early investments reinforce later ones, creating positive spillovers for children's skill formation.

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Appendix

A Selection of Control State

This section lays out the rationale for selecting Maryland as the control state for New Jersey. I begin by presenting summary statistics for candidate states in the North East USA, as New Jersey, where paid leave have not been implemented. Table A reports weighted means for New Jersey and each candidate control state, along with the control–treatment differences and their statistical significance, for variables plausibly correlated with the probability of giving birth. I Focus on nearby counties to minimize cross-regional heterogeneity in labor markets and demographics between New Jersey and the potential controls, motivating the choice of Maryland. Table A summarizes New Jersey and Maryland on the same covariates, reporting weighted means and standard errors. Finally, Figure A.1 shows the raw trend in birth rates across the two states and over time.

Based on the pre-policy summary statistics, Maryland is the closest match to New Jersey across the covariates most plausibly related to baseline fertility and policy exposure. Maryland differs from New Jersey by essentially zero (and statistically insignificant) amounts on education ($\Delta = 0.017$), number of children ($\Delta = -0.009$), employment ($\Delta = 0.005$), weeks worked ($\Delta = 0.090$), family size ($\Delta = -0.021$), and the age of the youngest child ($\Delta = 0.322$). Where differences are statistically significant, their magnitudes are modest relative to other candidate controls: average age is only about 0.6 years lower (vs. $\sim$ 0.8–1.2 in Pennsylvania, Ohio, Illinois, Virginia), racial composition differs by -0.042 (vs. $+0.079$ to $+0.197$ elsewhere), and the gaps in total and wage income (about \$7k and \$1.5k) are far smaller than those observed for Pennsylvania, Ohio, Illinois, Virginia, Delaware, or Connecticut (often \$6k–\$36k and accompanied by significant imbalances in parity or family size). New York is also relatively close on several labor-market and demographic margins, but is still a worse control than Maryland because it shows a large, significant difference in the age of the youngest child ($\Delta = +2.916^{***}$), a significant gap in parity ($\Delta = -0.047^{***}$), and larger income gaps (e.g., wages $\Delta \approx -\$2{,}756^{***}$). Overall, Maryland minimizes both the number and the magnitude of imbalances on the variables most relevant to birth rates, making it the most credible single-state control for the analysis.

Figure A.1 further support the choice of Maryland as a suitable control to New Jersey in this setting: over the pre-policy period (through 2009) the New Jersey and Maryland series track one another closely and exhibit no systematic differences in trend.

Table A.1: Differences in weighted means (Control State − New Jersey)

Variable	Maryland	Pennsylvania	Virginia	Ohio	Illinois	Delaware	Connecticut	New York
Age	−0.595***	−0.798***	−0.983***	−1.162***	−0.956***	−0.844***	−0.254***	−0.523***
Dummy for white ethnic group	−0.042***	0.186***	0.052***	0.197***	0.079***	0.059***	0.102***	0.017
Education (years)	0.017	−0.220***	−0.157***	−0.421***	−0.205***	−0.369***	0.002	0.035***
Dummy for married	−0.027***	−0.036***	0.005	−0.033***	−0.020***	−0.046***	−0.041***	−8418.160***
Family income	−7,036.743***	−29,000***	−16,900***	−35,600***	−20,900***	−23,000***	−5,301.951***	−0.042***
Number of children	−0.009	0.027**	−0.050***	0.128***	0.078***	0.046	−0.051***	−0.047***
Employed	0.005	−0.003	−0.005	−0.009***	−0.008***	0.005	0.003	−0.000
Wage income	−1,505***	−10,100***	−5,883***	−12,400***	−8,014***	−6,464***	−2,109***	−2756.821***
Weeks worked	0.090	−0.044	0.070	0.006	−0.118	0.188	0.212	0.058
Family size	−0.021	−0.069***	−0.108***	0.023	0.044***	−0.028	−0.102***	−0.014
Age youngest child	0.322	−0.415	1.812***	−2.828***	−0.918*	−0.080	1.698**	2.916***
Dummy for US citizen	0.050***	0.123***	0.074***	0.139***	0.055***	0.088***	0.047***	0.027***

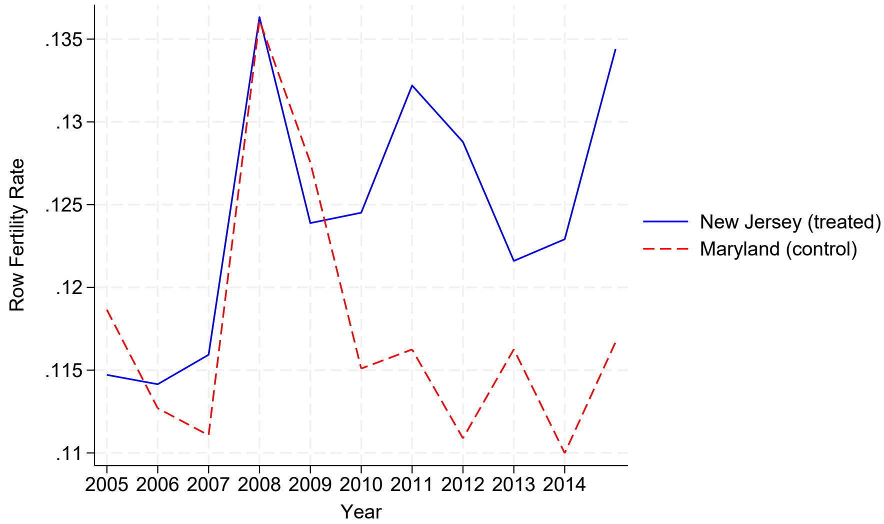
Notes: Entries are mean differences (Control − Treatment), where the treatment state is New Jersey, captured until 2009. Asterisks denote significance levels: $^{*}p < 0.10$, $^{**}p < 0.05$, $^{***}p < 0.01$. Variables match the original specification. Monetary differences are in dollars.

Table A.2: Weighted Means by Treatment Status (Maryland vs. New Jersey) and Differences

Variable	Control (Maryland)	Treatment (New Jersey)
Age	31.698	32.293
	(0.054)	(0.043)
Dummy for white ethnic group	0.654	
	(0.005)	(0.004)
Education (years)	8.256	8.239
	(0.023)	(0.020)
Dummy for married	0.801	0.828
	(0.004)	(0.004)
Family income	103,000	110,000
	(662.906)	(659.023)
Number of children	1.243	1.252
	(0.012)	(0.010)
Employed	0.928	0.922
	(0.003)	(0.002)
Wage income	39,246	40,751
	(302.512)	(293.107)
Weeks worked	48.141	48.050
	(0.097)	(0.081)
Family size	3.425	3.446
	(0.014)	(0.012)
Age youngest child	36.704	36.383
	(0.451)	(0.392)
Dummy for US citizen	0.885	0.835
	(0.003)	(0.003)

Notes: Entries are weighted means with robust standard errors in parentheses. Differences are Control minus Treatment (Maryland − New Jersey). Asterisks denote significance levels: $^{*}p < 0.10$, $^{**}p < 0.05$, $^{***}p < 0.01$. Sample sizes: Maryland N = 14,088 (Weeks worked N = 8,277); New Jersey N = 19,388 (Weeks worked N = 11,337).

Figure A.1: Raw fertility rates in New Jersey Relative and Maryland



Notes: This plot shows raw fertility rates (i.e. average number of births given in teh previous 12 months) in New Jersey (treatment group) and Maryland (control group) from 2005 to 2015. The sample is restricted to women aged 20–40 that are most likely to meet the eligibility criteria to the New Jersey FLI (having worked for up to 20 weeks in the previous year).

Argument against Pennsylvania as Control state to New Jersey in the setting

I select Maryland as the primary control state for New Jersey in the difference-in-differences analysis because it is geographically proximate and demographically similar, yet it did not implement a paid-leave reform or other major family-policy changes around the same time. In contrast, Pennsylvania experienced several concurrent developments in 2009 that could independently affect fertility — including the early activation of Extended Unemployment Benefits during the Great Recession (U.S. Department of Labor, 2009, UIPL No. 12-09), administrative adjustments to Medicaid and CHIP pregnancy coverage following the Children's Health Insurance Program Reauthorization Act (CMS SHO 10-006, 2010), and reductions in state family-planning funding during the 2009–2010 budget crisis (Guttmacher Institute, State Family Planning Funding Restrictions, 2011). These overlapping policy shocks could have influenced fertility behavior in Pennsylvania independently of paid leave. Maryland, by contrast, underwent no major state-specific fertility-related reforms in 2009; Title X and Medicaid pregnancy programs remained stable (Maryland Department of Health, Annual Report 2009), and the state did not adopt any paid-family-leave legislation until 2022 (National Partnership for Women Families, 2019). This relative policy stability makes Maryland a cleaner benchmark for identifying the causal impact of New Jersey's 2009 paid-leave policy on birth rates.

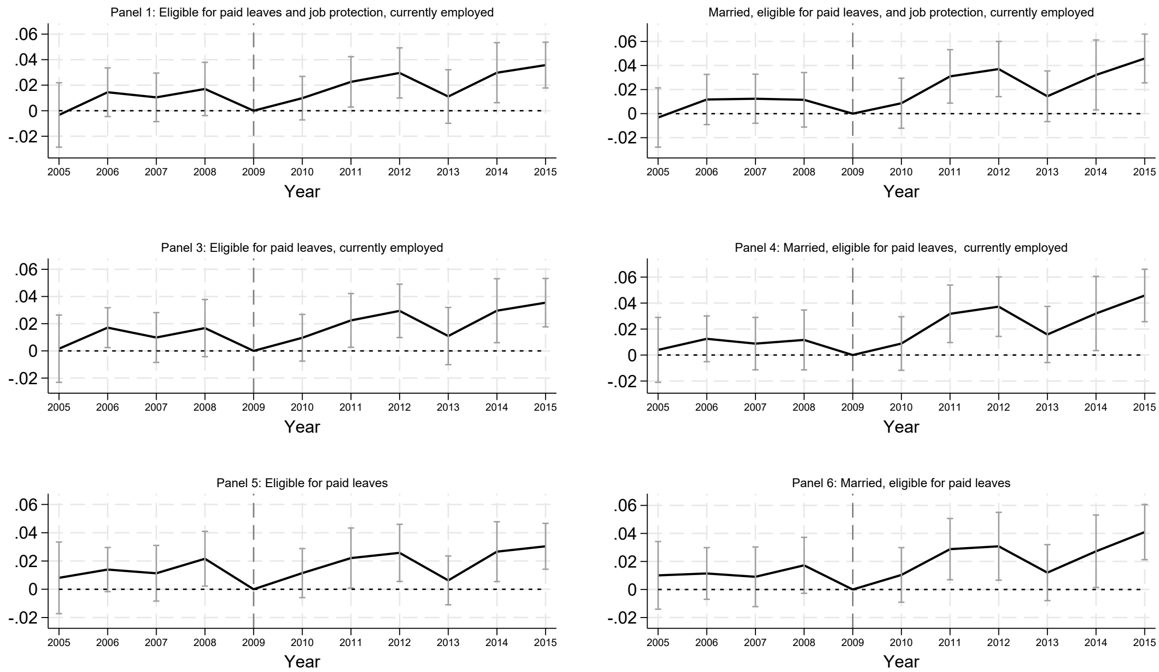
B Additional Results of Empirical Analysis

The output of the analysis of PPL on fertility relaxing the sample restrictions are presented in Figure B.1. The Figure reports six different empirical estimations of the effects of the introduction of New Jersey FLI on birth rates, progressively relaxing the sample restrictions to individuals less likely to respond to the policy.

Figure B.1 presents event study estimates of fertility differences between New Jersey and Maryland surrounding the 2009 paid leave reform, beginning from the most restrictive sample and progressively relaxing restrictions. **Panel 1** and **Panel 2** (top row) depict the most selective groups—cohabiting and married women, respectively, who are employed and likely entitled to job protection. These groups exhibit the largest policy responses, with fertility gains peaking around 3.6 percentage points (pp) for Panel 1 and nearly 5 pp for Panel 2 by 2015. Pre-trends in both cases are flat, lending credibility to the identification. **Panel 3** and **Panel 4** relax the job protection criterion, showing patterns for all employed women, cohabiting and married, respectively. Though the responses remain positive and sizable, pre-trends begin to show some mild drift, especially among the cohabiting. In **Panels 5** and **6**, the sample is further expanded to include all eligible women regardless of employment status. These less restricted samples display noisier pre-trends and attenuated post-treatment effects, which is expected as the population becomes more heterogeneous and includes women less likely to benefit directly from the policy.

The patterns from Figure B.1 are complemented by the regression estimates in Table B.1, which correspond to the same samples. While the treatment effects lose statistical significance in the least restrictive specifications—partly due to reduced power from broader heterogeneity and the temporal lag between policy implementation and observed fertility—the point estimates mirror the dynamic trends seen in the event study plots. In the most restrictive groups (Columns 1 and 2 of the table), corresponding to Panels 1 and 2, the estimated effects are 1.5 and 1.6 pp, statistically significant at the 5% and 10% levels, respectively. These results reinforce the notion that employed women entitled to job protection, particularly if married, are best positioned to act on the incentives provided by paid leave—likely due to greater financial security and institutional stability.

Figure B.1: Event Study: Effect of Paid Leave Reform on Fertility in New Jersey Relative to Maryland



Notes: This set of event study plots shows the evolution of fertility differences between New Jersey (treatment group) and Maryland (control group) from 2005 to 2015. The dependent variable is an indicator equal to one if a woman reported giving birth in the past 12 months. Coefficients represent year-specific differences relative to 2010, the omitted reference year. Vertical bars denote 90% confidence intervals. The vertical dashed line at 2009 marks the benchmark year after which birth rates potentially affected by the 2009 reform could be observed in the ACS. Standard errors are clustered at the county level. All regressions include fixed effects for age, county, state, and year, and control for dummies for college graduates and race (white vs non-white). The sample is restricted to married women aged 20–39.

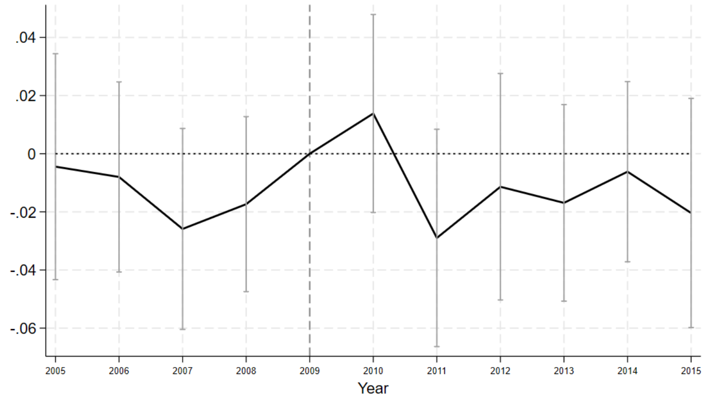
Table B.1: TWFE Estimates by age group (different sub-samples by Restrictiveness)

	Full Sample	Cohabiting			Married		
	(1)	(2) Empl. + JP	(3) Employed	(4) Eligible to PPL	(5) Empl. + JP	(6) Employed	(7) Eligible to PPL
Treat × Post	0.0053	0.0151**	0.0111*	0.0093	0.0218***	0.0168**	0.0152**
	(0.0042)	(0.0067)	(0.0063)	(0.0062)	(0.0079)	(0.0077)	(0.0074)
Eligibility	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Employment	Yes	Yes	Yes	No	Yes	Yes	No
Job Protection	Yes	Yes	No	No	Yes	No	No
Baseline birth rates (2009)	6.0	11.4	11.8	11.8	12.8	13.2	13.2
% Change	13.25	13.25	9.42	7.88	17.03	12.73	11.52
Observations	187,286	63,205	68,071	71,568	51,741	55,733	58,906

Notes: This table reports results from difference-in-differences regressions estimating the effect of paid leave (PL) on fertility. Samples are progressively relaxed from the most restrictive—employed women entitled to job protection—to broader eligibility groups. Columns 1–3 show results for cohabiting women (married and unmarried), and Columns 4–6 for married women. The dependent variable is a binary indicator equal to one if the respondent reported a birth in the past 12 months. All regressions include controls for age, a White race indicator, and a college graduate (CG) dummy. Fixed effects are included for state, year, county, and age. Standard errors clustered at the county level are reported in parentheses.

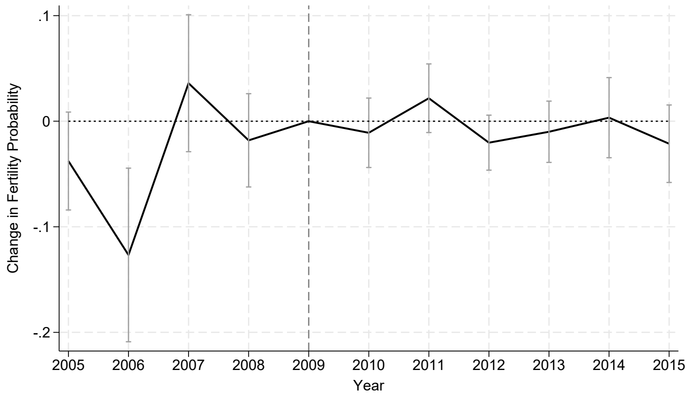
* p<0.10, ** p<0.05, *** p<0.01.

Figure B.2: Event Study: Effect of paid leave reform on women's employment in New Jersey Relative to Maryland



Notes: This event study plot shows the evolution of probability of employment between New Jersey (treatment group) and Maryland (control group) from 2005 to 2015. The dependent variable is an indicator equal to one if a woman is employed at the time of the survey. Coefficients represent year-specific differences relative to 2009, the omitted reference year. Vertical bars denote 90% confidence intervals. The vertical dashed line at 2009 marks the benchmark year after which birth rates potentially affected by the 2009 reform could be observed in the ACS. Standard errors are clustered at the county level. All regressions include fixed effects for age, county, state, and year, and control for dummies for college graduates and race (white vs non-white).

Figure B.3: Event Study: Effect of paid leave reform on fertility for single unemployed women



Notes: This figure reports results from difference-in-differences regressions estimating the effect of paid leave (PL) on fertility for women who are single and were outside the labor force in the year preceding the birth. The dependent variable is an indicator equal to one if a woman gave birth in the past 12 months. Coefficients represent year-specific differences relative to 2009, the omitted reference year. Vertical bars denote 90% confidence intervals. The vertical dashed line at 2009 marks the benchmark year after which birth rates potentially affected by the 2009 reform could be observed in the ACS. Standard errors are clustered at the county level. All regressions include fixed effects for age, county, state, and year, and control for dummies for college graduates and race (white vs non-white).

Table B.2: Placebo test: Effect of being birth after 1999 on on probability of college enrollment at Age 19

	(1) Probability of College Enrollment
Treat × Post	0.000
	(0.00105)
Constant	0.326***
	(0.00647)
Observations	72,029
R-squared	0.0387

Notes: This table reports the result of placebo test using a difference-in-differences regression estimating the effect being born after 1999 on the probability of being enrolled in college at age 19. The sample includes individuals born in California (treated) and Arizona (control). Model (1) identifies as treated individuals are those born in 1999 and therefore from parents who would not be eligible to the California Paid family Leave scheme. The dependent variable is a binary indicator equal to one if the respondent is enrolled in college at age 19. The regression includes controls for sex and race. Fixed effects are included for state, year, and county. Standard errors clustered at the county level are reported in parentheses.
* p<0.10, ** p<0.05, *** p<0.01.

C Conversion of estimates changes in probability of giving birth to changes in Total Fertility Rate

I compute Total Fertility Rate (TFR), the sum of age-specific fertility rates of age-specific fertility rates (ASFRs). In short, I divide the sample in different age groups spanning 5 years and I estimate a version of the DiD model for each age group a. TFR is computed as:

$$TFR = Int \sum_a ASFR_a$$

Where ASF_a is the average birth probability for age group a, and Int represents the width of the age interval, in this case 5 years.

The policy-induced change in TFR is:

$$\Delta TFR = 5 \sum_a \delta_a$$

Where $_a$ are the DiD coefficients of the regression for each age group.

The percentage change in total fertility in response to the policy is therefore:

$$\%Change = \Delta TFR / TFR_{baseline}$$

With $TFR_{baseline}$ being the total fertility rate before the policy introduction (i.e. before 2010). The following table report, estimates for each subsample and age group as well as the corresponding baselines TFR and $\%Change$ of TFR.

Table C.1: Difference-in-differences Estimates by subsample and age group

	Cohabiting			Married		
Age Group	**(1)** Empl. + JP	**(2)** Employed	**(3)** Eligible to PPL	**(4)** Empl. + JP	**(5)** Employed	**(6)** Eligible to PPL
20–24	0.0333	0.0410	0.0410	0.0368	0.0506	0.0449
25–29	-0.0030	0.0016	-0.0069	0.0013	0.0066	0.0128
30–34	0.0164	0.0189	0.0247	0.0250	0.0287	0.0352
35–39	0.0023	0.0078	0.0044	0.0073	0.0140	0.0098
40–44	-0.0053	-0.0050	-0.0042	-0.0047	-0.0377	-0.0033
45–49	-0.0038	-0.0027	-0.0030	-0.0039	-0.0028	-0.0031
Baseline TFR (NJ in 2009)	2.67	2.42	2.98	2.41	2.95	2.95
% Change in TFR	7.5	12.7	14.4	10	10	9.6

Notes: This table reports coefficients from difference-in-differences regressions estimating the effect of paid leave (PL) on fertility across age groups. Columns correspond to separate samples of married and cohabiting employed women entitled to job protection. The dependent variable is a binary indicator equal to one if the respondent reported a birth in the past 12 months. All regressions control for a White race indicator and a college graduate (CG) dummy. Fixed effects are included for state, year, county, and age. Standard errors clustered at the county level are reported in parentheses. The table also reports TFR int he treated state and in the pre-treatment year for both subgroups and the corresponding policy-induced change in fertility.

C.1 Paid leave policies and children's outcome

This section explores long-term educational outcomes of children whose parents are exposed to paid leave policies. Because of lack of data on children's skills, I focus on college enrollment as a proxy for human capital.

Data and Policy Context

Because New Jersey's paid leave reform is too recent to observe long-run child outcomes, I turn to California, which implemented its Paid Family Leave (PFL) program in 2004. Similarly to the New Jersey's FLI, which was modeled on the California policy, the California's PFL provided parents with six weeks of partial wage replacement (approximately 70% of previous earnings) to bond with a newborn or newly adopted child. Due to its relatively broad eligibility criteria[24] the policy offers virtually universal coverage to working Californians. Notably, although the program was implemented on July 1, 2004, it allowed eligible parents to file claims for bonding leave as long as the child had entered the family within the previous 12 months, meaning that parents of children born up to 12 months before the official start date could still qualify.[25]

[24]The California's PFL eligibility criteria required earnings of at least 300 US dollars in an SDI-covered job during any quarter within the five to seventeen months prior to filing a claim (Golightly and Meyerhofer, 2022)

[25]As by PFL Fact Sheet: https://onlabor.org/wp-content/uploads/2014/09/de8714cf.pdf

I use data from the ACS spanning from 2012 to 2023, focusing on individuals aged 19 born in California, the treated state, and Arizona (a neighboring and demographically comparable state where no similar policy has been introduced). At this age, most U.S. students have completed high school and are either enrolled in college or not, making college enrollment at age 19 a relevant proxy for human capital investment. However, because the ACS does not report the respondent's month of birth, it is not possible to precisely identify which respondents were born withing the 12 months preceding the policy implementation (on July 1, 2004) or later, and thus whose parents would have been eligible for paid leave. Consequently, I conduct two separate analyses to account for this limitation. First, I adopt a conservative approach and treat only individuals born in 2004 (i.e. those who turned 19 in 2023) as exposed to the policy. Second, I expand the treated group to include those born in 2003, acknowledging that only parents of children born in the second half of that year would have been eligible.

Empirical Strategy

To estimate the effect of PFL exposure on college enrollment, I assigned the treatment status based on the following equation:

$$\text{Treat}_{ic} = \begin{cases} 1 & \text{if state is CA} \\ 0 & \text{if state is AZ} \end{cases}$$

$$\text{Post}_t = \begin{cases} 1 & \text{if year } t > T \\ 0 & \text{otherwise} \end{cases}$$

$$T \in \{2022, 2023\}$$

Next, I implement the following difference-in-differences:

$$CE_{ict} = \alpha + \beta(\text{Treat}_{ic} \times \text{Post}_{ct}) + \gamma X_{ict} + \lambda_t + \lambda_c + \varepsilon_{ict} \tag{14}$$

where CE_{isct} is an indicator for whether individual i in state s, county c, and year t is enrolled in college; $\text{Treat}_s \times \text{Post}_t$ is the interaction term identifying individuals born in California (treated state) after 2003/2004; and X_{isct} includes individual-level controls for sex and race. The model includes fixed effects for state (λ_s), year (λ_t), and county (λ_c). Standard errors are clustered at the county level. The regression is weighted using ACS person weights.

Results

The results of the analysis are reported in Table C.2. Column (1) present the regression estimates of Model (1) in which only respondents born in California and in 2004 are considered treated. This specification ensures that all treated individuals were born within 12 months following policy implementation in July 2004 and are therefore eligible for the policy. The results show that these individuals are 3.5 percentage points less likely to be enrolled in college at age 19, and this effect is statistically significant at the 5% level.

In Model (2), whose output are reported in Columns (2) of C.2, the treated group is expanded to include individuals born in 2003, under the assumption that some of them may also have been exposed to the policy. While the estimated effect remains negative and statistically significant, the magnitude decreases to -2.3 percentage points and is significant at the 5% level. This attenuation is consistent with the inclusion of individuals born before July 1st, 2003, who were not actually eligible for the policy, introducing misclassifications in treatment status. To further assess the validity of the identification strategy, Table B.2 in the Appendix B reports the results of a placebo test in which the policy implementation year is falsely assigned to 2018. The absence of significant effects in this placebo analysis aligns with the main findings.

Table C.2: Effect of Paid Leave Exposure on College Enrollment at Age 19

	(1) College Enrollment, 2023	(2) College Enrollment, 2022
Treat × Post	-0.035**	-0.023**
	(0.0105)	(0.0161)
Constant	0.318***	0.318***
	(0.0032)	(0.0032)
Observations	105,654	105,654
R-squared	0.05	0.05

Notes: This table reports the result from a difference-in-differences regression estimating the effect of paid leave (PL) exposure on the probability of being enrolled in college at age 19. The sample includes individuals born in California (treated) and Arizona (control). Model (1) identifies as treated individuals those born in 2004 and therefore from parents who would be eligible to the California Paid Family Leave conditional on being employed (only working parents of those children born before July 1st 2003 would be eligible to the reform). Model (2) identifies as treated individuals are those born in 2003. The dependent variable is a binary indicator equal to one if the respondent is enrolled in college at age 19. The regression includes controls for sex and race. Fixed effects are included for state, year, and county. Standard errors clustered at the county level are reported in parentheses.
* p<0.10, ** p<0.05, *** p<0.01.

Overall, the negative effects on college enrollment resulting from this analysis point to an adverse impact of the policy on child human capital. Taken together with the previously documented positive fertility response, this pattern supports the interpretation that increased family size may have diluted parental resources, consistent with a quantity–quality trade-off mechanism.

Limitations

Several limitations to the identification strategy in this analysis must be acknowledged. First, due to data constraints and the relatively recent implementation of the reform, the analysis relies on a single post-treatment cohort—or at most two—namely, individuals aged 19 in 2023 (Model 1) and those aged 19 in 2022 and 2023 (Model 2). This limits the ability to assess pre-existing trends or implement an event study design. Second, college enrollment at age 19 is an imperfect proxy for longer-term outcomes such as educational enrollment, as it does not account for children who delay university entry beyond age 19 or for those who may be enrolled at that age but later drop out. Finally, as previously discussed, the lack of information on respondents' month of birth prevents precise identification of a sharp cutoff between those exposed to the policy and those not. The exposure definition in this analysis assumes that all individuals born in 2004 or later were affected by the policy, which may not fully reflect actual eligibility or take-up, especially for children born to non-working parents.

D Parametrization

D.1 Consumption deflation

To reflect that the number of children deflates household consumption $\Psi(n)$, and that this cost increases with their age, I use the OECD equivalence scale to estimate per-capita consumption in the household. A value of 1 to the household head, 0.7 to each other adult, including teenagers, and 0.5 to each child:

$$\Psi(n) = \begin{cases} 1.7 + 0.7n & \text{if } j = J_f, \\ 1.7 + 0.5n & \text{if } J_f < j \leq J_f + 2. \end{cases}$$

D.2 Income process

To construct age profiles, I use PSID data on couples from the SRC sample and build a panel dataset with information on couples age, women's education, annual earnings and yearly hours worked. I select full time workers (individuals reporting at least 1600 hours of work per year) and compute hourly wages by diving individuals earnings by yearly hours worked and deflate the values using 2017 prices. I select individuals older than 22. The age profiles are computed by regressing individuals' log-earnings fitting a second polynomial on age. For men and women by separately also distinguishing by education for women and by partner's education for men. Table D.1 reports the estimates of age and age^2 for each regression.

Table D.1: Age profiles

	High school	College
Men		
Age	0.085	0.0559
Age^2 ·1000	-8.325	-5.327
Women		
Age	0.0681	0.0287
Age^2 ·1000	-7.433	-2.688

As standard in the literature, I assume that the income process follows and AR(1) process:

$$z_{i,t,g,e} = \rho_{i,g,e} z_{i,t-1,g,e} + \zeta_{i,t,g,e} \quad \text{with} \quad \zeta_{i,t,g,e} \sim N(0, \sigma_{\zeta_{g,e}}) \tag{15}$$

$$z_{i,0,g,e} \sim N(0, \sigma_{\zeta_{0,g,e}}) \tag{16}$$

I use residuals of the second order polynomial in age by gender and education to calibrate the persistent component of labor productivity $\rho_{g,e}$, with g and e referring to gender and education. This is estimated by regressing the residuals by their lagged observations (referring to two years prior as PSID in the years period analysed collects information biannually). Following Petit (2019), I use the fourth lag of the residuals as an instrument in the first lag to control for measurement error. The variance of the residuals of this regression informs on $\sigma_{\zeta_{g,e}}$. To calibrate $\sigma_{z_0,g,e}$ I use the variance of the residual obtained by fitting a second order polynomial in age to log wages of young workers between 20 and 24. The estimated values are presented in Table D.2.

Table D.2: Income process

	High school	College
Men		
Persistence, ρ	0.731	0.766
Variance income shocks, σ_ζ	0.127	0.145
Initial dispersion σ_{z_0}	0.217	0.106
Women		
Persistence, ρ	0.740	0.794
Variance income shocks, σ_ζ	0.092	0.103
Initial dispersion σ_{z_0}	0.210	0.116

D.3 Probability of infertility

The distribution of x is exogenously assigned, informed by demographic data and medical studies on infertility[26] and failed pregnancies. Specifically, I calibrate the probabilities as follows:

$$\Pr(x = 0) = 0.05, \quad \Pr(x = 1) = 0.10, \quad \Pr(x = 2) = 0.25, \quad \Pr(\{ = 3) = 0.60.$$

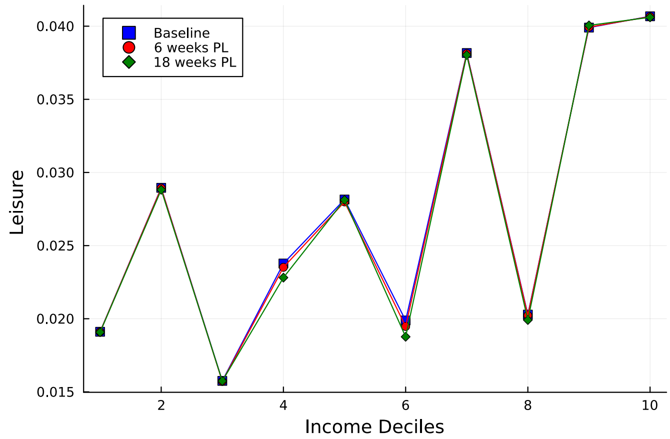
This structure reflects observed fertility patterns, where not all women are able to achieve their intended fertility due to biological limitations. In the model, this constraint tempers the fertility response to positive income shocks such as paid parental leave.

E Other results: consequences for leisure during leave duration

Figure E.1 presents trends in leisure time taken by women during leave across households' income distribution under the different policy scenarios. The share of leisure does not display a consistent trend across the income distribution because parental leave is taken only by mothers, whereas family income reflects the combined earnings of both parents. Since maternal and paternal productivity shocks are uncorrelated, maternal and family income distributions differ, potentially obscuring a clearer relationship between income and leisure that might emerge if income were measured based solely on mothers' earnings. Nevertheless, the top income decile—comprising families where both parents are high earners—exhibits the highest share of leisure (over 4% of the total time availability in that model period). PPL leave leisure time almost unchanged.

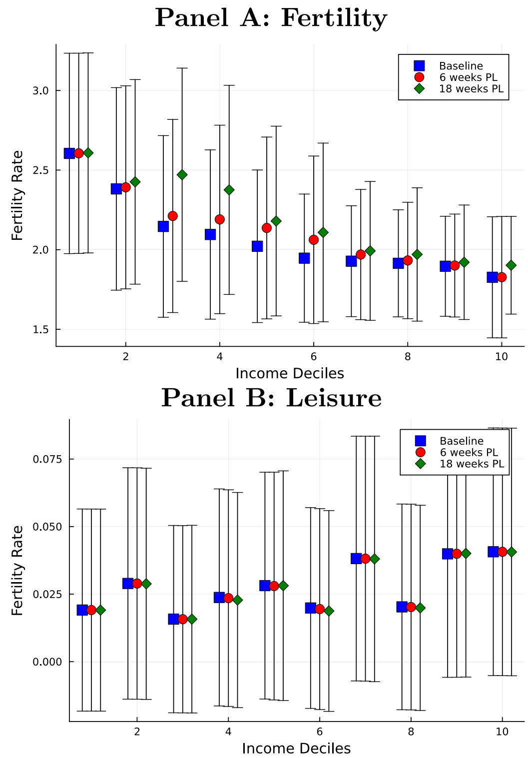
[26] Empirical estimates suggest that 5–7% of women in high-income countries are biologically infertile Mascarenhas et al. (2012). Fertility potential declines significantly with age even between 25 and 35 **?**. In addition, many women fail to reach their intended number of children due to miscarriages, delayed childbearing, or other health-related limitations Berrington (2004). These findings justify imposing exogenous upper bounds on completed fertility in a simplified lifecycle model.

Figure E.1: Changes in leisure following the introduction of paid PL



Notes: The figure shows trends in the share of time in the first period of childhood which the primary care-giver allocates to leisure (which in the model can only be taken during parental leave) across the income distribution of families with children and scenarios.

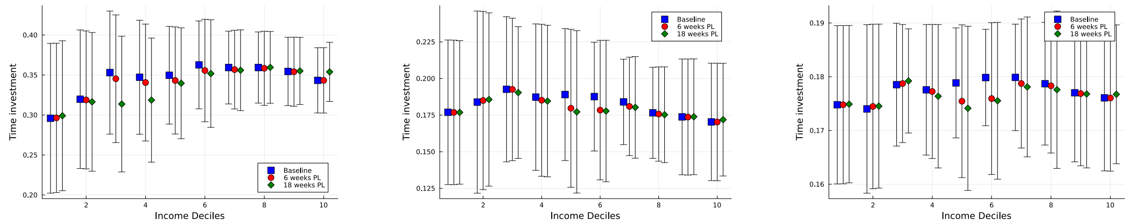
Figure E.2: Fertility and leisure by policy scenario



Note: Panels A and B show fertility and leisure time, respectively, across the income distribution of families with children under three counterfactual scenarios—6 weeks of PPL, 18 weeks of PPL with endogenous fertility, and 18 weeks of PPL with exogenous fertility—relative to the baseline. Shaded areas represent confidence intervals.

Figure E.3: Time investment in children by stage of childhood and policy scenario

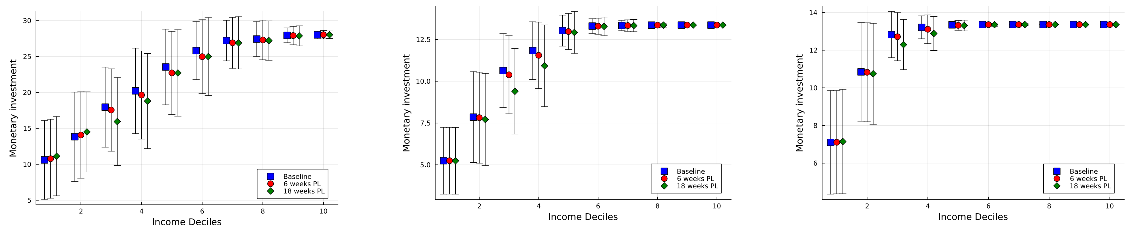
Panel A: Time inv. in early childhood	**Panel B: Time inv. in middle childhood**	**Panel C: Time inv. in late childhood**



Note: Panels A, B and C show average time investment in children across early, middle, and late childhood, by income decile and policy scenario, including confidence intervals.

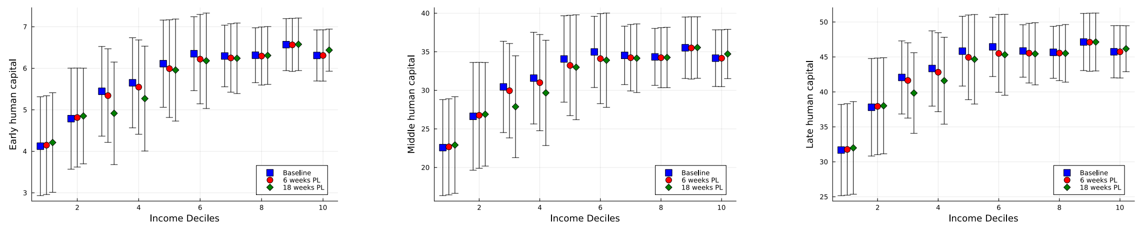
Figure E.4: Monetary investment in children by stage of childhood and policy scenario

Panel A: Money inv. in early childhood	**Panel B: Money inv. in middle childhood**	**Panel C: Money inv. in late childhood**



Note: Panels A, B, and C report monetary investments in children during early, middle, and late childhood across income deciles and policy scenarios, including confidence intervals.

Figure E.5: Child human capital across PPL scenarios, with Confidence Intervals (CI)



Panel A: Child human capital in early childhood	**Panel B: Child human capital in middle childhood**	**Panel C: Child human capital in late childhood**

Note: Panels A, B and C show presents child human capital in each stage of childhood across the income distribution of families with children in the counterfactual scenarios (6, 18 weeks of PPL with endogenous fertility and 18 weeks with exogenous fertility) relative to the baseline, including confidence intervals.

F Solution Method

F.1 Simulated Method of moments (SMM)

In order to set the parameters calibrated internally, I perform a structural estimation through the Simulated Method of Moments (SMM). Within this framework, let P denote the array of parameters, and M(P) represent the moments generated by the model based on these parameters. The goal is to find the parameter set P^* that minimizes the discrepancy between M(P) and the empirical data moments,

$$P^* = \arg\min_P \left(M(P) - \hat{M}\right)^T W^T W \left(M(P) - \hat{M}\right) \tag{17}$$