Time Off and Trade-Offs: The Distributional Effects of Paid Parental Leave Policies on Fertility and Child Human Capital *

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Abstract

This paper studies the interplay between paid parental leave policies (PPL), fertility, and child human capital, highlighting heterogeneous effects across the income and education distribution. Using micro-level data, I show that the introduction of PPL in the U.S. is associated with an increase in fertility but a decline children's long-term outcomes. To rationalize these findings, I develop a heterogeneous-agents model that combines fertility and parental investment decisions feeding into a function of human capital that accumulates across multiple stages of childhood. Calibrated to U.S. data, the model positive fertility response, which are larger for low-educated women consistently with my empirical estimates. I then use it as a policy laboratory to study a more generous paid leave scheme and show that fertility responses vary across the income and education distribution, generating a quantity–quality trade-off among families facing binding budget constraints. Finally, I show that in the absence of fertility responses, PPL would raise child human capital, underscoring the central role of fertility in shaping policy effects.

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1 Introduction

Over the past few decades, fertility rates have dropped to historically low levels across most high-income countries[1]. At the same time, widening inequality has raised concerns about unequal opportunities for children[2], directing policymakers' attention toward pronatalist policies and early-childhood interventions. Among these policies, paid parental leave (PPL) have gained increasing popularity among policymakers as a tool to support parents in providing care during the earliest stages of a child's life.[3] PPL can increase fertility by reducing the opportunity cost parents face when spending time outside the workforce to care for a newborn (Olivetti and Petrongolo, 2017). In addition, by providing financial compensation, paid leave can ease family budget constraints, making it more affordable to raise multiple children.

While the positive effects of PPL on fertility are well established[4], the evidence on the long-term implications of PPL 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).[5] Yet empirical findings are mixed, with limited evidence of positive impacts.[6] One possible explanation, largely overlooked in the literature, is that PPL's effects on fertility may induce a quantity–quality trade-off (Becker and Lewis, 1973): as family size grows in response to the policy, parents must spread resources across more children, reducing per-child investment and potentially undermining children's human capital. The consequences of this trade-off are likely to vary across the income distribution, as families differ in both their ability to absorb the costs of additional children and their baseline levels of investment. Against the backdrop of global

[1]In the U.S., fertility has fallen to about 1.6 births per woman, a historic low and well below replacement (The Economist, 2025)

[2]Since 1980, the U.S. has seen income inequality increase by about 20% (Center, 2020). Moreover, roughly 16.3% of U.S. children under 18 live in households below the poverty threshold (America's Health Rankings, 2025).

[3]OECD, 2023 "Joining Forces for Gender Equality: What is Holding us Back?" Chapter 23.

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

[5]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).

[6]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)

fertility decline and rising inequality, understanding how family policies influence these dynamics is crucial for designing effective and equitable interventions.

This paper examines how paid parental leave influences fertility and child human capital in four steps. First, I provide new empirical evidence of the positive and heterogeneous effects of PPL on fertility, as well as negative effects on children's college enrollment. Second, I build a quantitative model that incorporates interactions between paid leave, fertility, and parental investment across multiple phases of childhood. I calibrate this model to U.S. data to study how fertility and investment vary across the income and education distribution. Third, I use the calibrated structural framework as a policy laboratory to analyze the PPL's effects on fertility decisions, parents' monetary investments, their allocation of time between work and childcare over the course of parenthood, and the implications for child development. Finally, I clarify the underlying mechanisms through a counterfactual analysis that shuts down fertility responses to the policy.

The first contribution of this paper is to empirically document the effects of PPL on fertility and child development by leveraging variation from two U.S. state-level policy reforms. First, I exploit the introduction of six weeks of paid leave in New Jersey and find 5.8-10.2% rise in the total fertility rate among women most likely to benefit from the policy (i.e., those in stable marital and employment relationships). This increase is concentrated among women with less than a college degree. Second, I empirically investigate the effects of PPL on child development. Because of data limitations, I cannot study both fertility and children's outcomes using the same reform. Instead, I turn to California's earlier policy, which also introduced six weeks of paid leave, to estimate long-term effects on children, finding a decline in college attendance of between 2.3 and 3.5 percentage points among those exposed.

Several mechanisms could explain these findings. First, increased family size can dilute per-child investment and undermine children's human capital, potentially inducing a quantity–quality trade-off. Second, PPL can alter parental investment through its impact on labor supply: delayed return to work and changes in hours influence both time and income, shaping the timing, amount and type of investment (time or money) parents devote to their children, with lasting effects on their human capital. By abstracting from these structural channels, reduced-form analyses capture only composite effects, without identifying the underlying mechanisms — whether fertility responses reduce per-child investment and whether changes in labor supply offset or amplify variations in early parental time and monetary investment.

To rationalize my empirical results, I build a structural heterogeneous-agents model with endogenous fertility, maternal labor supply (including leave-taking decisions), and parental investment in children across multiple stages of childhood. This investment feeds into a sequential process of human capital accumulation throughout childhood. In the model, households consist of couples who are heterogeneous in income, maternal education, access to paid leave, and risk of infertility, and therefore face different incentives in their fertility and investment decisions.

The model's main contribution is to incorporate the direct and indirect mechanisms through which paid leave can influence children's outcomes. First, in the technology of child human capital, investment at each stage of childhood affects future human capital through self-productivity and dynamic complementarities.[7] Second, individuals face multiple trade-offs when choosing to have children and invest in them. In fact, investing in children entails monetary expenditures on education, foregone labor income from time devoted to childcare, and slower wage growth from delayed return to work. In 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 labor supply and earnings, and reduce per-child resources when fertility rises, consistent with the mechanism of the quantity–quality trade-off.

Calibrated to data from the U.S. — the only high-income country without widespread paid leave[8]— my quantitative model replicates a set of untargeted moments. Specifically, it fits closely fertility rates across the female labor income distribution. Moreover, it matches reasonably well the share of low– and highly educated families with more than one child. By capturing these key empirical regularities, the model provides a

[7] Cunha and Heckman (2007)'s concept of self-productivity posits that human capital at each stage builds on the stock accumulated in earlier stages; dynamic complementarities refers to to the idea that early investments increase the productivity of later investments, making skills most effectively accumulated through a sequence of inputs over time.

[8] 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.

credible tool for counterfactual analysis and therefore serves as a suitable laboratory for policy experiments.

Building on this calibrated framework, the second contribution of the paper is to simulate the introduction of PPL through two experiments. The first experiment replicates New Jersey's paid leave scheme, previously analyzed through a reduced form approach, and yields a 4.45% increase in completed fertility, accounting between 40 and 80% of the empirically estimated effect.[9] A second experiment introduces a more generous policy providing 18 weeks of paid leave, which raises fertility by 11%. In both experiments, consistent with my empirical findings, fertility responses are much stronger among low-educated mothers than among highly educated mothers (7% vs. 2% under the six-week scheme; 17% vs. 3.6% under the 18-weeks scheme). In line with Golightly and Meyerhofer (2022), fertility rises only along the intensive margin, without changing the share of childless families. Further heterogeneity analysis shows that the effects are concentrated among middle-income families in the first scenario and among lower-middle-income families in the second. These latter results align with Lalive and Zweimüller (2009), who document lasting fertility effects among lower earners but only temporary effects among higher earners.

Next, I investigate the effects of the simulated policies on child human capital, which closely mirror the policy consequences for fertility. Under the 6-week PPL policy, early human capital falls by up to 2% among children from middle-income families, where fertility responses are strongest, and the effect persists into late childhood. Under the 18-weeks scenario, the largest reductions in early human capital—up to 10%—occur among children in lower-income families, again reflecting stronger fertility responses, though the negative effect is halved in later stages. At the bottom of the income distribution, where fertility remains unchanged, human capital modestly improves as a result of greater parental investment. Conversely, families at the top of the income distribution combine higher fertility with greater time investment, which enhances their children's human capital. Overall, the experiments suggest that PPL raises fertility

[9]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.

among families facing binding budget constraints at the cost of a quantity–quality trade-off: parents spread resources across more children, leading to declines in human capital accumulation, while only the richest families avoid this trade-off.

To conclude, I run an additional experiment that grants families 18 weeks of paid leave while preventing them from adjusting their fertility. In the absence of fertility responses, the policy modestly improves children's human capital—up to a 4% increase in early childhood, declining to 2% in later stages—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.

Related literature: This paper contributes to a growing literature on the effects of paid leave policies. Existing structural work has typically assessed the impact of PPL on fertility and female labor supply (Bronson and Sanin, 2024; Erosa et al., 2010; Kim and Yum, 2025; Wang, 2022; Yamaguchi, 2019) or on child outcomes (Youderian, 2019), but rarely both.

From a theoretical and quantitative perspective, this paper aims to complement models focusing exclusively on fertility and labor supply, by introducing a sequential accumulation of child human capital to inform policy consequences for child development. Among these models, those that completely abstract 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 result in biased predictions about the effects of paid leave, which may influence choices not only through income effects but also driving parents to substitute between children's quantity and quality.

Structural models that study the effects of paid leave on child development may also be biased if they ignore how the policy alters fertility and labor supply, thereby missing important indirect effects. For example, increased parental time investment enabled by paid leave may be offset by greater family size, diluting per-child resources. Likewise, shifts in labor supply, whether through reduced working hours or delayed re-entry, can affect both time and income, influencing future investments in children with potentially offsetting effects.

A limited number of papers incorporates both fertility and child human capital (Chan and Liu, 2018; Gahramanov et al., 2020; Yew et al., 2022), yet these frameworks restrict attention to a single stage of childhood and abstract from household heterogeneity (Gahramanov et al., 2020; Yew et al., 2022). Combining fertility and child human capital formation while assuming a single-stage investment process fails to capture the dynamic interplay between early and later childhood. In reality, parents allocate resources over the entire course of a child's development. If paid leave increases fertility at the intensive margin, the resulting dilution of per-child investment extends beyond infancy. Similarly, changes in earnings trajectories due to leave-taking affect both time and monetary investment in later periods, which can reinforce or attenuate long-run policy impacts.

This paper advances the literature by providing a heterogeneous agents model that embeds the essential features to analyze the dynamic and distributional effects of the policy. This framework allows to disentangle the direct and indirect effects of paid leave policies on children's outcomes. In particular, it captures how early parental time investment (a direct channel) interacts with changes in fertility and labor supply (indirect channels) to influence per-child investment. Moreover, by incorporating heterogeneity in family income and maternal education, the model explains the varying effects of PPL across households, providing insights into its distributional and welfare implications.

The paper proceeds as follows: Section 2 presents a motivating, reduced form analysis. 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 5, describes the policy experiments and presents their results. The model limitations are discussed in Section 6. Finally, Section 7 concludes.

2 Reduced-form Analysis

In this section, I investigate through a quasi-experimental analysis the implication of introducing PPL on fertility and children's long-term outcome.

To conduct this analysis, I employ a two-way fixed effects (TWFE) specification and exploit exogenous variation in leave eligibility from the staggered introduction of PPL in two U.S. states, New Jersey and California. In Subsection 2.1, I analyze the impact of New Jersey's paid leave reform on female fertility by evaluating how birth rates respond to the policy introduction. In Section 2.2, I proceed by assessing the long-term educational outcomes of children exposed to California's paid leave scheme by analysis how the probability of college enrollment at age 19 (proxy for human capital) is affected by the policy.[10]

The results indicate that paid parental leave policies may simultaneously encourage higher fertility while negatively affecting children's education outcome, highlighting a potential unintended consequence of such reforms. This pattern is consistent with the concept of quantity–quality trade-off, whereby increases in family size come at the expense of the level of investment each child receives, ultimately affecting long-run outcomes such as educational enrollment.

2.1 Paid leave policies and fertility

I examine the implications of the New Jersey paid leave program, implemented in 2009, on female fertility outcomes relying on a simple two-way fixed effects strategy and data from the American Community Survey (ACS). A similar analysis of impacts of this six weeks policy introduction on fertility is conducted by Golightly and Meyerhofer (2022). The authors 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 rate

[10]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. As a result, I use the New Jersey reform to study short-run fertility effects and the California reform to analyze longer-run child outcomes.

following the policy intervention.[11] While their data offers finer temporal resolution on fertility, it lacks individual-level information on employment, work history, or income, resulting in less accurate identification of policy eligibility. In contrast, by using repeated cross-sections from the ACS, I can better approximate eligibility by leveraging detailed work-related characteristics.

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.[12] 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.[13]

Data and Empirical Strategy

The analysis consists of implementing a two-way fixed effects approach comparing the yearly birth rates between New Jersey and Maryland (a comparable state in the North East USA where paid leave have not been implemented) before and after the introduction of the New Jersey's FLI.

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 40 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

[11] Golightly and Meyerhofer (2022) find very close results for the analysis of the implications of fertility of the introduction of 12 weeks of paid leave in California

[12] 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.

[13] Reated information available on this website.

employed married women who are eligible to job protection during parental leave under the Family and Medical Care Act (FMCA).[14] Observations are weighted using ACS person weights.

In the TWFE, treatment status is assigned as follows:

$$\text{Treat}_{i,c} = \begin{cases} 1 & \text{if state is NJ} \\ 0 & \text{if state is ML} \end{cases}$$

$$\text{Post}_t = \begin{cases} 1 & \text{if year } t > 2009 \\ 0 & \text{otherwise} \end{cases}$$

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.

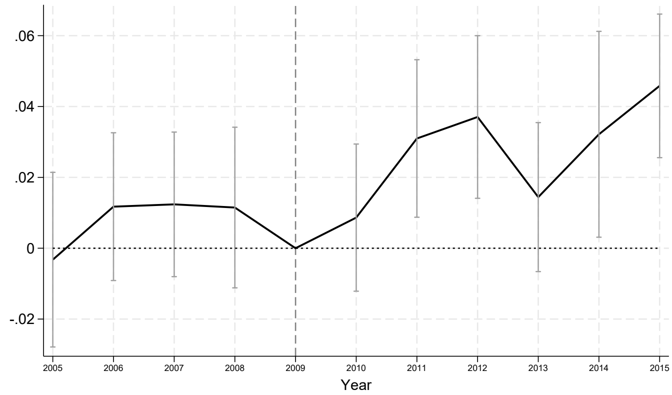
Results

Figure 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

[14] 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.

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.

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 20–44.

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 1.6 percentage points (significant at the 10% level). This corresponds to a 12% increase in birthrates compared to the baseline in 2009. While the magnitude and precision of this estimate is somewhat attenuated in the year following the reform relative to later event-time peaks due to averaging over years with weaker effects, it corroborates the overall trend. 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

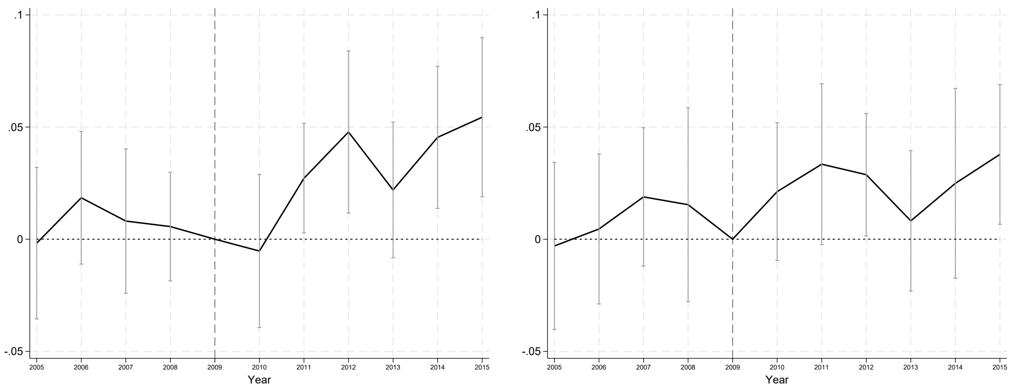
	(1) Married, Employed + JP
Treat × Post	0.0156*
	(0.0082)
Baseline birth rates (2009)	12.8
% change	12.19
Observations	51,741

Notes: This table reports the result from a Two-way fixed effect 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 educational enrollment. The left panel presents results for women with less than a college degree, while the right panel shows results for those with a college degree or higher. The reform appears to have had a more pronounced impact on the fertility of less-educated women, who experienced an average increase in birth rates of approximately 1.8 percentage points, statistically significant at the 10% level. In contrast, the estimated effect for college-educated women is smaller—around 1.35 percentage points—and not statistically significant. These findings suggest that women with lower levels of education were more responsive to the policy intervention, potentially reflecting differences in 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 (see section 5), I compute the policy-induced change in the Total Fertility Rate (TFR). The TFR aggregates age-specific fertility rates across all reproductive age groups, representing the number of children a woman would have over her lifetime if she experienced the current fertility rates at each age. 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 stable relationships, which best mirrors the population in the model, the TFR increases by 5.7% among cohabiting women and by 10.2% among married women, 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 5. A detailed description of the procedure is provided in **Appendix B**.

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 11** in **Appendix A** examines how results change when these restrictions are progressively relaxed. Less restrictive samples show slightly noisier pre-trends and reduced precision, but effects remain consistent. As the sample narrows to women better positioned to benefit, the estimated fertility effect rises from about 3% in the most inclusive sample to over 12% 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 12** shows no impact on employment, supporting robustness. Finally, **Figure 13** 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 12.2%) 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.

2.2 Paid leave policies and children's outcome

To complement the earlier evidence that PPL increases fertility, 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[15] 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

[15] 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)

children born up to 12 months before the official start date could still qualify.[16]

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 two-way fixed effect:

$$CE_{ict} = \alpha + \beta(\text{Treat}_{ic} \times \text{Post}_{ct}) + \gamma X_{ict} + \lambda_t + \lambda_c + \varepsilon_{ict} \tag{1}$$

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

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 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 **Table 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 8** in the **Appendix A** 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 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 Two-way fixed effects 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.

3 Structural approach

The limitations of the empirical exercises presented in this section caution against drawing strong causal conclusions from this specific empirical setting. Moreover, even when based on richer data or more precise identification strategies, reduced-form approaches remain 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

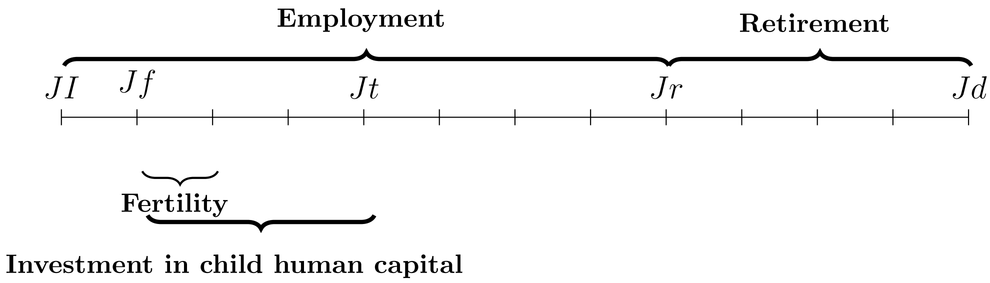
The life-cycle framework developed in this paper portrays a single generation of individuals progressing through four main stages of life, spread over 13 model periods, each corresponding to five years.

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, and their entitlement to paid leave (from employers or the state), under a scenario without federally mandated paid leave.

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. In this model, child human capital accumulates over three periods of childhood: since the period when children are born to the third and last period of childhood, J_I. Children do not make choices and after the third and last period of childhood, parents stop investing in their human capital. They value the quantity and quality of their children for one more period, J_t, without directly investing in them.

From J_t until the age of retirement, agents go back to supply labor inelastically 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



Individuals gain utility from consumption and leisure time. If the children have not yet left the household, they value their number and their human capital, while facing a fixed cost of parenthood. Agents discount the utility from the future period at the discount factor β.

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 ($g \in m, f$ for male and female individuals, respectively) as displayed in equation (3). 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 (4)), 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 (5), which is correlated with female education e. A tax rate τ_{SS} corresponding to social security coverage, applies to y.

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. This 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 C.3**.

The state variable $p \in \{0, 1\}$ captures whether the household is eligible to receive any compensation for a limited duration of parental leave, either through an employer-provided benefit or by residing in a state with an existing SDI program.[17] 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.[18]

Since the beginning of the life-cycle, agents participate in the labor force. The value function for the young workers V_j^w is the following:

$$V_j^w(e, z_m, z_f, x, p) = \max_c u(c) + u(\ell) + \beta E[V_{j+1}^f(e, z_m', z_f', x, p)] \tag{2}$$

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

$$y = w_f l_f + w_m l_m \tag{3}$$

$$\log(w_g) = \gamma_{g,j,e} + z_g, g \in m, f \tag{4}$$

$$z_g' = \rho_{z_g,e} z_g + \zeta_g, \zeta_g \sim N(0, \sigma_{\zeta_g,e}), \tag{5}$$

$$1 = l \tag{6}$$

Preferences

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

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

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 C.1**.

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

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

[18] 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.

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

Agents gain utility from consumption and disutility from labor. The preferences for leisure are governed by the weight θ and by v, the inverse of the Frish elasticity.

In this period, as 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 6 and is fully allocated to market work l, while leisure ℓ=0) and consume their entire labor income.

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).[19]

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:

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

[19]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, Todd and Wolpin (2007), Aizer and Cunha (2012), Caucutt and Lochner (2020) and Fuchs-Schündeln et al. (2022)

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.

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.[20] 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:

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

Preferences over children quantity and quality

Upon choosing to have children, altruistic 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 C**). I define child-related utility in equation (7), which parents incorporate into their own maximization prob-

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

lem. 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.

$$U(n, h_{k_i}) = \eta_n \left(\frac{n}{\sigma_n}\right)^{\sigma_n} + \eta_{h_k} n^{\kappa} \left(\frac{h_{k_i}}{\sigma_{hk}}\right)^{\sigma_{hk}} - X_e \tag{7}$$

$$\eta_n, \eta_{h_k}, X_e \in (0, 1)$$

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.[21] 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.

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)[22], with the same endowment on initial

[21] 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.

[22] 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

human capital h_{k0}.

The dynamic problem in this period can be written as follows:

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

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

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

$$1 = l_m + \alpha_m tn^{\epsilon_2}$$

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

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

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

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

$$B = \alpha_b\, w_f\, d \quad (9)$$

$$d = min(\ell n + \alpha_f t_1 n^{\epsilon}, \bar{T}_s) \quad (10)$$

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 ϵ_1 and ϵ_2.

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: $m(1 - t)n_1^{\epsilon}$.

As a result, early-childhood labor supply is elastic ($l_g < 1$) because time with children is chosen first, and labor adjusts residually. The share of this time spent by each parent on childcare, α_g, is calibrated from the data and allows for joint childcare

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.

($\alpha_m + \alpha_f \geq 1$). Further details on parental time allocation are provided in Section 4.1. Moreover, time investment presents economies of scale dictated by the parameter ϵ_2.

In this period, the primary caregiver (typically the women according the data[23]) spends some time outside the labor force upon giving birth (i.e. on maternity leave). The time on leave is split between leisure ℓ and time spent in childcare, while upon returning to work, time is spent in market labor and childcare. The decision over leisure is dictated by the disutility from work (i.e. both market work and childcare time) or, equivalently, the utility of leisure $u(\ell)$ which can be rewritten as $u(1-(1-\alpha_f)tn^{\epsilon_2}-\ell n)$ as only mothers benefit from leisure. While leisure can be exclusively taken during leave, maternal (and paternal) time investment takes place both during the time on leave and upon returning to work. As women take a separate period of leave for each child, leisure time does not present economies of scale in the number of children.

In the baseline scenario, representing the U.S. economy in the absence of federal PPL, I assume that a fraction of women p_b is entitled to paid leave benefits equal to an α_b fraction of previous earnings for up to a maximum duration of $\overline{T}_b$, as by equations (9) and (10). The time on leave comprises the entire time women spend in leisure and an unspecified portion of the time spent caring for their children in this period. Any time spent not working beyond $\overline{T}_b$ will be unpaid. In the counterfactual scenario c, presented in Section 5.1, PPL becomes more generous and universal (i.e., $\alpha_c = 1$).

To proxy skills depreciation, I assume that leave-takers (I restrict them to be women, according to the data) 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.

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. (2024) and abstract

[23] Although policy makers are moving towards a system where both parents are equally eligible to family leave, research show that in most cases parental leave are almost entirely taken by women. Future studies might build on Søgaard and Jørgensen (2023) and investigate the role of the allocation of leave between the two caregivers in this context.

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:

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

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

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

$$1 = l + \alpha_g tn^{\epsilon_2}$$

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

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

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

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 (2). 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:

$$V_j^t(e, z, n, h_k) = u(c) + u(\ell) + U(n, h_{k_i}) + \beta^i U(h_{k_i}) + \beta E[V_{j+1}^w(e, z', n, h_{k_{i+1}})] \quad (12)$$

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

$$l = 1$$

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

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

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:

$$V_j^\omega(e, z) = u(c) + u(\ell) + \beta E[V_{j+1}^\omega(e, z')] \quad (13)$$

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

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:

$$V_j^r(e) = \max_c u(c) + \beta E[V_{j+1}^w(e, z', n)] \tag{14}$$

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

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 (FMLA) applied federally, but only a limited number of U.S. states[24] 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 C.2**. Moreover, I employ the PSID data to compute moments related to average fertility and childlessness by maternal 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.

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

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. In **Appendix C.4** I provide a detailed explanation of how average time investment is calculated by caregiver, education, and child's age.

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.

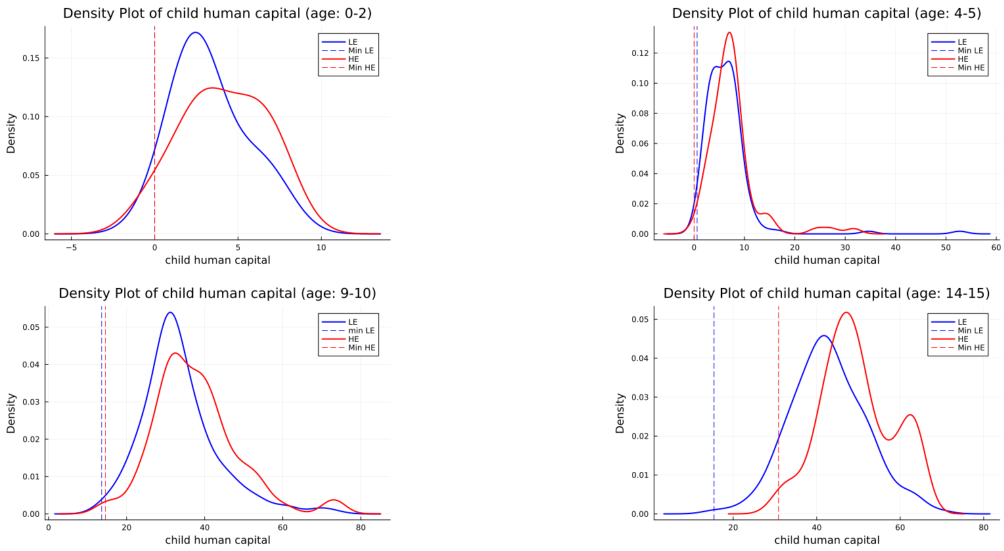
Assuming Q is the set of questions each assigning q_i points, with $q_i \in (0,1)$ and that the questions are independent between each other, then $Q = \sum(q_i)$ and $\bar{q}$ represents the test score : $\bar{q} = \frac{\sum_{i=1}^{Q} q_i^*}{Q}$

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 α_b whose calculation is described in Subsection C.4.

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 C.4)
α_{m1}	0.80	Share of mat. time, t_1	PSID-CDS (see Appendix C.4)
α_{f2}	0.40	Share of pat. time, t_2	PSID-CDS (see Appendix C.4)
α_{m2}	0.85	Share of mat. time, t_2	PSID-CDS (see Appendix C.4)
α_{f3}	0.51	Share of pat. time, t_3	PSID-CDS (see Appendix C.4)
α_{m3}	0.86	Share of mat. time, t_3	PSID-CDS (see Appendix C.4)
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			
α_b	0.4	Share of women entitled to PPL	NLSY-79 C/YA
Child human capital			
ρ	0.84	Intertemp. elasticity of substitution	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 12**. To express these raw minutes as a share of our five-year model horizon, I normalize this values by maternal education.[25] 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 $\times$ 5 days/week $\times$ 52 weeks/yr $\times$ 5 yrs. A summary the data moments and

[25]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.

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.

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).

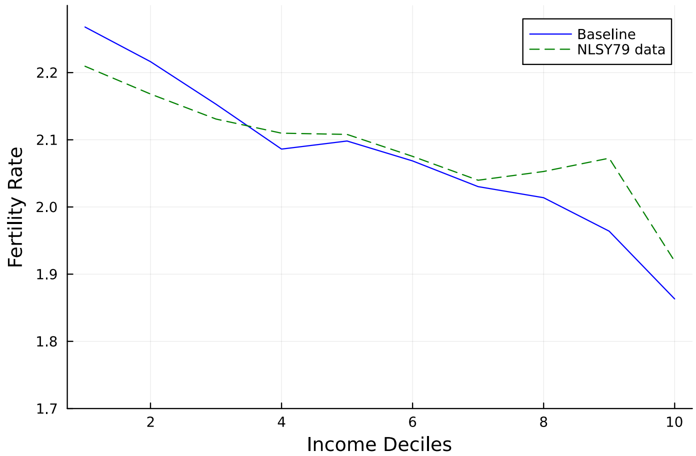
Table 5: Parameters and Data Moments for SMM

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 p. (h_{k_2}, h_{k_3})
ϕ_2	0.38	Elasticity p.
α	0.25	Relative weight of time vs money in h_{k_1}.
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})
θ	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 Policy Experiments

5.1 Introduction of widespread paid parental leave policies

After solving and structurally estimating the model, I use it to evaluate a policy that partially compensates parents for time spent with their children in early life. I run a policy experiment during the fertility and early childhood stage (J_f), providing all primary caregivers (p_c=1) with additional parental leave benefits on top of existing ones. These benefits offset earnings losses incurred while absent from work to care for newborns.

The first experiment replicates New Jersey's scheme at the national level, granting up to 6 weeks ($\bar{T} = \frac{1}{40}$ of a model period) of leave with a wage replacement rate (α_{PL}) of 85%. A second experiment extends generosity to 18 weeks. In a final counterfactual, I fix fertility to baseline levels under this policy to isolate how PPL effects on female labor supply, parental investment, and child human capital are mediated by fertility responses.

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

5.2 Results

The outcomes 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. These outcomes are compared across the income distribution under each counterfactual policy scenario, relative to the baseline. The income distribution is 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.

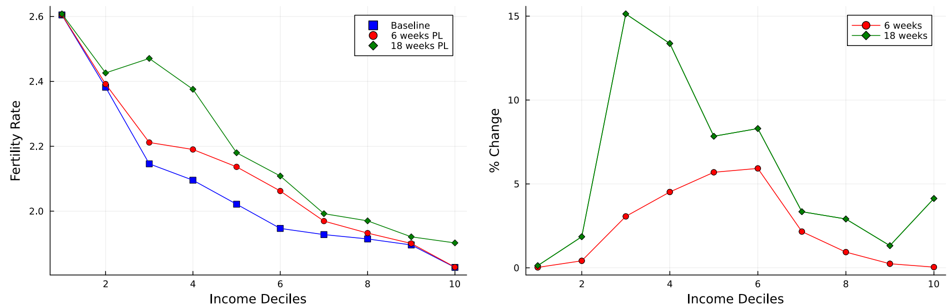
Because neither policy affects the decisions of couples without children in the baseline scenario, who remain childless in both counterfactual scenarios, the analysis focuses on the subset of families who had at least one child under the baseline. The figures distinguish between the baseline scenario (blue line, square marks), the 6-week paid leave scenario (red rile, circle marks), the 18-weeks paid leave scenario with endogenous feritlity responses (green line, diamond marks), and an alternative 18-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 experiments 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). 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 6** 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**).

A second experiment which extends the paid leave benefits to up to 18 weeks reports an average raise in completed fertility by 11%. Fertility increases by 17% among low-educated women and by 3.6% among highly educated, with stronger responses concentrates among families in the third and fourth decile of the income distribution where the increase reaches up to 15% (see **Panel B**). The policy interventions have no discernible effect on fertility at the very bottom of the income distribution, where birth rates remain the highest. In contrast, families at the top decile experience an increase in fertility under the 18-weeks scheme. Overall, these results suggest that greater PPL generosity progressively concentrates fertility responses among families at the bottom of the income distribution, encouraging additional births among families facing binding budget constraints. The sharper response under the more generous policy reinforces the idea that only sufficiently large transfers can relax the constraints faced by lower-income families. At the same time, sufficiently generous PPL also affects families at the top by reducing the opportunity cost of time associated with parenthood.

Figure 6: Changes in fertility following the introduction of paid PL



Panel A: Fertility rates across income distribution **Panel B: % change in fertility 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 experiments (circle and diamond). Panel B presents the corresponding percentage changes with respect to the baseline scenario.

Consequences for Female Labor Supply (FLS)

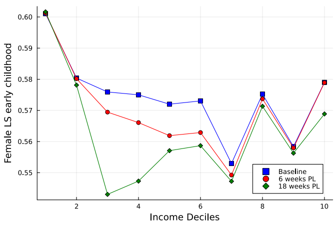
In **Figure 7**, **Panels A–C** present maternal labor supply (FLS) across the family income distribution under the three policy scenarios and at different stages of a child's development: early, middle, and late childhood. **Panels D–F** report the corresponding percentage variation from baseline FLS across policy scenarios.

During early childhood (**Panel A**), maternal labor supply is non-monotonically correlated with income. The introduction of the 6-week policy reduces maternal FLS across almost the entire income distribution, reflecting increases in fertility. The largest effects—declines of up to 2%—occur in the fifth and sixth deciles, where fertility rises the most, while changes are negligible in deciles where fertility remains unchanged (first, second, ninth, and tenth). Similarly, under the 18-weeks scheme, labor supply responses mirror fertility patterns, with reductions of nearly 6% in the third decile, 5% in the fourth, and 2% in the tenth (**Panel D**).

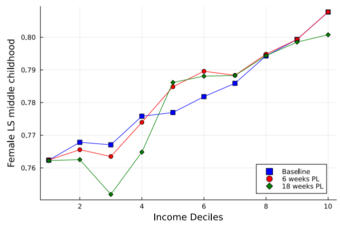
In middle childhood (**Panel B**), FLS increases monotonically with income, but policy-induced variations are not uniform across deciles (**Panel E**). The lower half of the distribution experiences declines in FLS, while changes are positive (up to 1% increase in the middle of the distribution) or negligible in the upper half, except for the top decile, where FLS decreases under the 18-weeks scheme. However, all of these changes are modest, contained within ±2%. It appears that families in the middle of the income distribution compensate for early declines in FLS by increasing it in later stages. This results in larger decreases in time investment during middle childhood for these families, compared to those in deciles 2 and 3, where fertility rises more strongly but FLS also declines (see **Panel B Figure 8**), while monetary investment remains unchanged (see **Panel E Figure 9**). In fact, higher FLS translates into greater income, which sustains per-child monetary investment despite rising fertility.

Finally, in the later stage of childhood, FLS also increases monotonically with income in the baseline scenario (**Panel C**). The policy-induced changes presented in **Panel F** are small (up to -2.6%) and concentrated among low-income families, particularly under the 18-weeks policy, and among those who exhibit stronger fertility responses to paid leave (third and fourth income deciles, followed by the 10th decile). In all stages of childhood (**Panels D-F**), under 18 weeks of leave where fertility is hold constant, FLS remains nearly unchanged across the entire income distribution. This implies that labor supply variations under PPL are mainly driven by fertility responses.

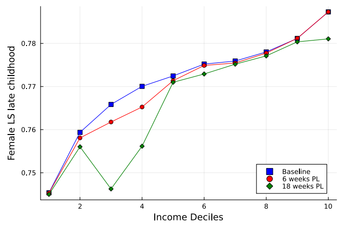
Figure 7: Female labor supply under paid leave policies



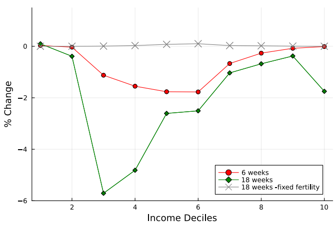
Panel A: FLS in early childhood



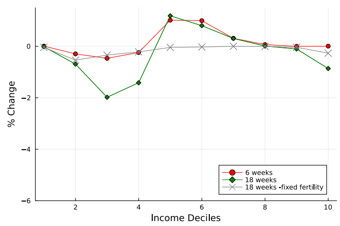
Panel B: FLS in middle childhood



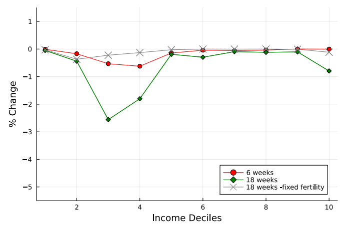
Panel C: FLS in late childhood



Panel D: % changes FLS in early childhood



Panel E: % changes FLS in middle childhood



Panel F: % changes in FLS in late childhood

Notes: Panels A, B and C show female labor supply by stage of childhood across the income distribution of families with children under different policies scenarios. Panels D, E and F show the corresponding percentage variation in each scenario compared to the baseline.

Changes in time and monetary investment across stages of childhood

Figure 8 Panel A-C shows how parental time investment families with at least one child varies compared to baseline levels in under each policy scenario. Each figure refers refers to a different stage of childhood and shows percentage change in per-child time investment across the income distribution. The figure showing parental time investment across the income distribution are presented in **Appendix D Figure 16**. In the baseline scenario, childcare time in early childhood ranges between 30% and 48% of the total time endowment available during that period. In later stages, investment is measured in minutes per day and ranges from 140 to 173 minutes in middle childhood, and from 125 to 158 minutes in late childhood.

Figure A displays how, under the 6-weeks and 18-weeks policy scenarios, increases in fertility directly translate into less time investment per child. In the first case, childcare time drops by up to 2.5%, with changes concentrated between the third and sixth income deciles, while variations are negligible at the tails. Under the more generous PPL scheme, the decline reaches 12.5% lower per-child time investment among families in the third income decile, where fertility responses are stronger, and, as in the previous scenario, changes remain large up to the sixth decile of the distribution. Interestingly, time investment grows by amost 3% among families at the top, despite their experiencing an increase in fertility. This change reflects lower FLS in this subgroup, as shown in **Figure 7 Panel D** (i.e. women in high-income families can afford to reduce their labor supply and increase their per-child time investment despite having more children). Under the counterfactual scenario where PPL is generous and fertility remains fixed at baseline levels, time investment slightly increases across the entire distribution, peaking among families in the middle (2.5% higher) and in the tenth decile (3% higher), as in the scenario with endogenous fertility.

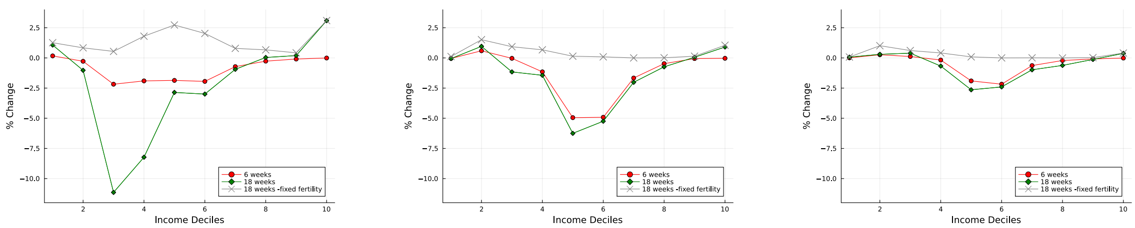
In the middle stage of childhood (**Panel B**), time investment drops by up to 5% in deciles 5 and 6 under the 6-weeks policy, and the decline reaches 6% in the middle of the distribution under the 18-weeks policy. Under the latter scenario, time investment slightly grows among families at the top of the distribution (close to a 1% increase). Holding fertility fixed, the 18-weeks of PPL slightly increase time investment across the entire distribution (up to 1.5% for families in the second decile), , though changes are generally negligible.

Notably, declines in childcare time are similar across the 6-weeks and 18-weeks policies and remain concentrated in the middle of the distribution, despite larger fertility increases under the 18-weeks scheme occurring in the third and fourth deciles.

This reflects families in these groups reducing their labor supply to limit the costs of splitting time across more children in response to strong fertility rises. By contrast, families in the fifth and sixth deciles increase FLS in middle childhood (see **Figure 7 Panel E**) in order to earn enough income to maintain the same level of monetary investment in children, and therefore limit the harm for their human capital (see **Figure 9 Panel E**). This likely reflects the elasticity of substitution between time and money inputs in the human capital production function being equal to one—consistent with a Cobb–Douglas specification—which implies that parents can readily substitute one input for the other in middle and late childhood.

In late childhood (**Panel C**), childcare time variations are contained within -2.5%, again concentrated in the middle of the distribution. Even in this stage, time investment would slightly increase in the second and tenth deciles in the absence of fertility responses.

Figure 8: Changes in Time investment under paid leave policies



Panel A: % change time inv. in early childhood

Panel B: % change time inv. in middle childhood

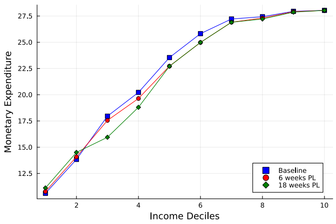
Panel C: % change time inv. in late childhood

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.

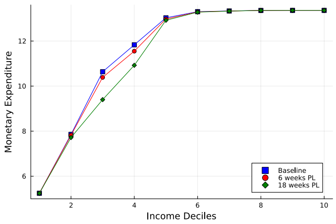
Interestingly, families in the top decile stand out as the only income group experiencing both an increase in fertility and an increase in time investment in response to PPL across all stages of childhood. Thus, the richest families do not face a quantity–quality trade-off and instead reallocate their resources to support both a larger family and more investment per child. Under generous PPL, they devote the same amount of time to children regardless of whether fertility rises. This contrasts with families in lower deciles of the distribution, who face a trade-off between having more children and maintaining the same level of per-child investment.

Figure 9 Panels A–C show parental monetary investment in children's human capital (in thousands of USD) across the income distribution, for families with at least one child. Families with higher incomes allocate increasingly more financial resources to their children's education; however, the relationship between income and investment flattens at the top of the distribution. **Panels D–F** report the corresponding percentage changes in per-child monetary investment under each policy experiment relative to the baseline scenario.

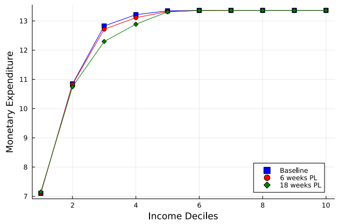
Figure 9: Monetary investment in children by stage of childhood and policy scenario



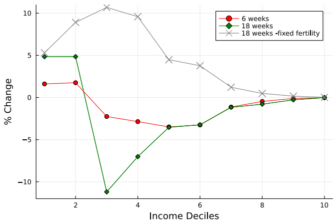
Panel A: Money inv. in early childhood



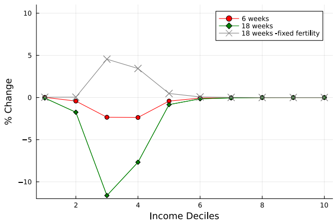
Panel B: Money inv. in middle childhood



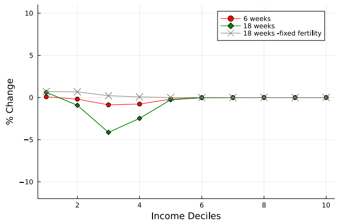
Panel C: Money inv. in late childhood



Panel D: % change money inv. in early childhood



Panel E: % change money inv. in middle childhood



Panel F: % change money inv. in late childhood

Notes: Panels A, B, and C report monetary investments in children during early, middle, and late childhood across income deciles and policy scenarios. Panels D, E and F show the corresponding percentage variation in each scenario compared to the baseline.

Following the introduction of PPL in the 6-week scenario, monetary investment in early childhood **Panel D** increases by almost 2% among households in the bottom of the distribution (deciles 1 and 2), which do not adjust their fertility in response to the policy. In contrast, changes are negative—up to 2.6%—for the middle deciles, and close to zero at the top of the distribution. Under the 18-weeks scheme, monetary investment rises by about 5% in the two lowest deciles, but falls by 11% in the third decile. The reduction becomes progressively smaller further up the distribution. When fertility is held constant, monetary investment instead increases symmetrically—by more than 10% in the third decile—with the growth rate again diminishing along the distribution.

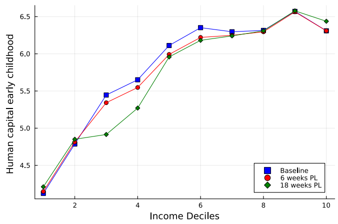
In middle and late childhood (**Panels E** and **F**, respectively), monetary investment under the 6-week policy scheme declines slightly in the third and fourth deciles, while remaining broadly unchanged elsewhere. Under the 18-weeks PPL, decreases are more pronounced and peak in the third decile, reaching -11% in middle childhood and -4.5% in late childhood. In the counterfactual 18-weeks scenario where fertility is held constant, positive changes in monetary investment mirror the declines observed when fertility is allowed to adjust. However, in middle childhood the increase in the third decile reaches only 5%—about half the magnitude of the decline under endogenous fertility. In late childhood, monetary investment changes under the fixed-fertility scenario are positive but negligible across the entire distribution.

Consequences for human capital

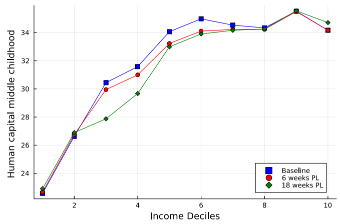
Figure 10 Panels A-C present the trend of child human capital accumulated in each stage of childhood across the income distribution and shows how it varies following the introduction of paid leave policies. The stock of child human capital is increasing in income as a result of monetary investment which presents a higher weight in the technology of human capital in early childhood ($1 - \alpha = 0.75$ as by section 4.2). However, the relationship is not monotonic since, by construction, children in some college graduate families have greater human capital than children from high school graduate families, even if the latter have higher income. This is due to the higher productivity of time investment among college-educated mothers ($\delta_{CG} > \delta_{HS}$). Because the functional form of human capital presents self-productivity (i.e. later human capital builds on the stock accumulated up to that period), the patterns of human capital across income deciles are similar across different stages of childhood.

Panels D-F 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.

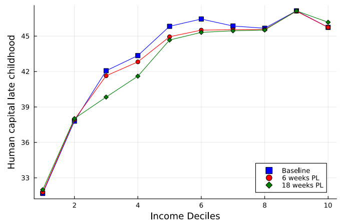
Figure 10: Child human capital by stage of childhood and policy scenario



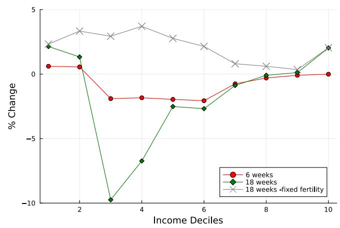
Panel A: Child human capital in early childhood



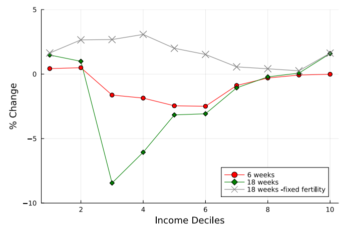
Panel B: Child human capital in middle childhood



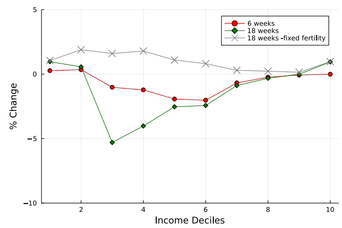
Panel C: Child human capital in late childhood



Panel D: % change child human capital in early childhood



Panel E: % change child human capital in middle childhood



Panel F: % change child human capital in late childhood

Notes: Panels A, B and C show child human capital levels by stage of childhood across the income distribution of families with children under different policies scenarios. Panels D, E and F shows percentage changes in child human capital in the corresponding stages 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.

Under the 6-week PPL scenario, child human capital drops by around 2% in deciles 3–6 at each stage of childhood. In the first stage, this reflects the reduction in per-child time investment observed in **Figure 8 Panel A** and **Figure 9 Panel D**, particularly among families experiencing increased fertility (except those at the top of the distribution). In later stages, the decline combines two forces: (i) negative changes in both time and monetary investments (**Figure 8 Panels B** and **C**, and **Figure 9 Panels E** and **F**), and (ii) the reinforcement of early-stage declines through self-productivity in the human capital production function ($\rho > 0$). Changes are modest in the rest of the distribution and even slightly positive in the first and second deciles, reflecting negligible fertility responses (**Figure 6**) and greater monetary investment (**Figure 9 Panel C**).

Under the 18-weeks PPL scenario, the declines in child human capital are larger, particularly in deciles 3–6, due to stronger fertility responses that generate a quantity–quality trade-off. Children in these deciles face substantial losses—up to 10% in early childhood, 8.4% in middle childhood, and more than 5% in late childhood. Conversely, children in the first, second, and tenth deciles experience small gains (up to 2%

in early childhood, tapering to about 1% in late childhood). Among high-income families, child skills increase despite positive fertility responses. This pattern is driven by higher time investments at every stage of childhood (**Figure 8 Panels A–C**) and by the reinforcement of early investments through self-productivity in the human capital production function.

Under the final counterfactual scenario, fertility is held constant, and individuals can only use the benefits of the 18-weeks policy scheme to increase consumption and investment in their children. In this case, child human capital rises slightly at every stage of childhood and across the entire income distribution, though at different rates. The largest gains are concentrated below the sixth decile, peaking in the fourth decile with increases of 4%, 3%, and 1.8% in early, middle, and late childhood, respectively. Children from families at the top of the distribution also experience positive effects, driven by higher time investments under this scenario (**Figure 8**).

6 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.

7 Conclusions

In this paper, I investigate the interplay between paid parental leave (PPL), 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—mostly among low-educated women—and a decline in the probability of college enrollment for children whose parents were exposed to the policy.

To rationalize these findings, 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, leave-taking, 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 as a policy laboratory to investigate the distributional effects of PPL on several outcomes. As a first experiment, I replicate the 6-week reform which I analyzed through a reduced-form approach. The model predicts a 4.45% increase in completed fertility, whereas the empirical estimates rely on changes in the total fertility rate (TFR), a period measure that may partly reflect short-term timing shifts, such as birth anticipation. As such, the model cannot capture shifts in time of births but predicts structural fertility response. . It reproduces between 40–80% of the observed increase in TFR, 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. 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.

As a second experiment, I extend the policy to 18 weeks of leave. Fertility responses are stronger and concentrated in the third to sixth deciles, while families at the very bottom remain unaffected. These increases trigger a quantity–quality trade-off: parents spread resources across more children, reducing per-child investment and lowering human capital whenever fertility rises. An exception occurs for families in the top decile. For them, PPL reduces the opportunity cost of time, encouraging additional births, but their resources are sufficient to sustain higher per-child investment, avoiding the trade-off. Female labor supply is also negatively affected by the presence of additional children, especially in the earliest stages of parenthood. As for monetary investment, the most pronounced declines in FLS happen among income groups where fertility increases the most.

Finally, to test whether the negative effects of PPL on children's human capital are indeed driven by fertility, I run a counterfactual experiment in which fertility is fixed at baseline levels. In this scenario, families increase both time and monetary investment per child across nearly the entire distribution and at each stage of childhood, generating positive and lasting effects on children's human capital.

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

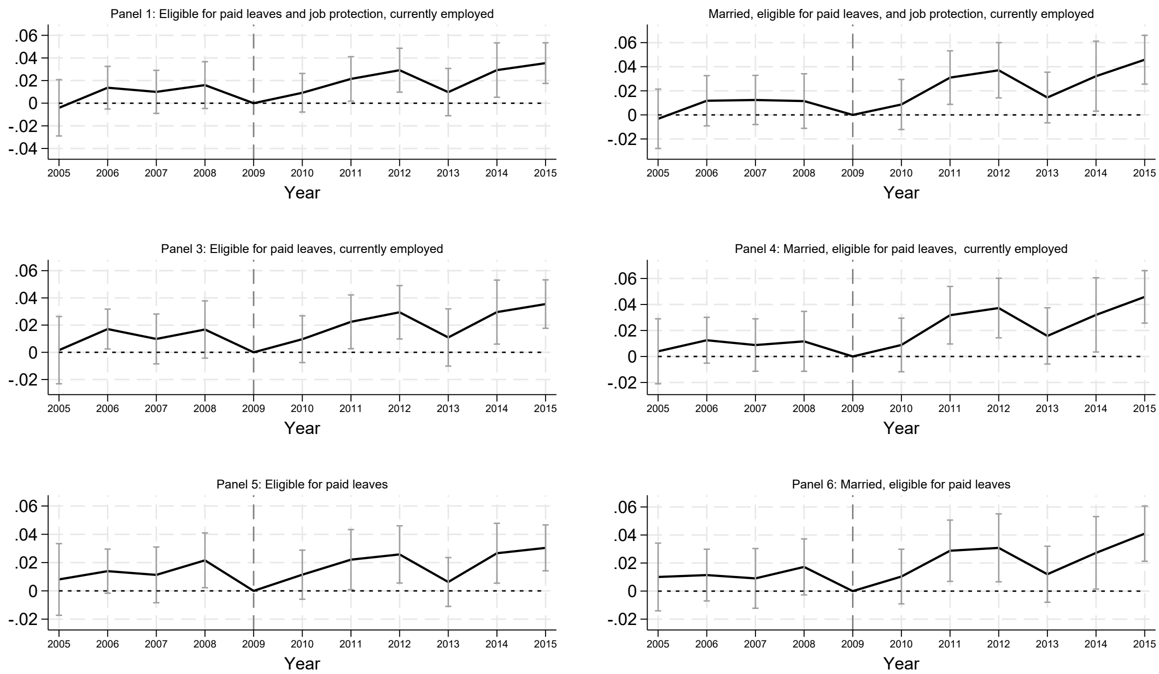
A Additional Results of Empirical Analysis

The output of the analysis of PPL on fertility relaxing the sample restrictions are presented in Figure 11. 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 11 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 11 are complemented by the regression estimates in Table 7, 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 11: Event Study: Effect of Paid Leave Reform on Fertility in New Jersey Relative to Maryland



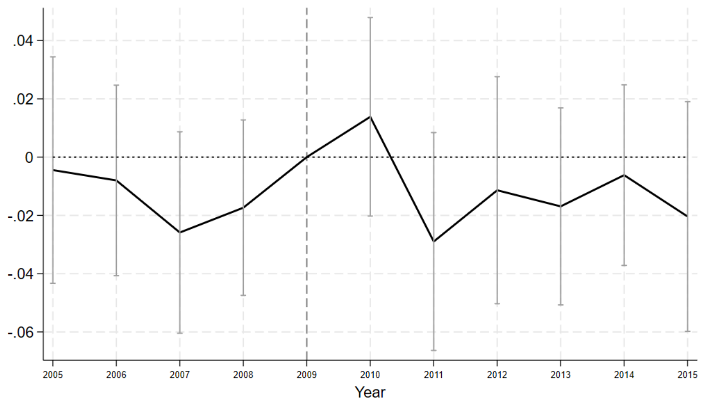
Notes: This set of event study plots shows the evolution of fertility differences between New Jersey (treatment group) and Maryland (control group) from 2005 to 2015. The dependent variable is an indicator equal to one if a woman reported giving birth in the past 12 months. Coefficients represent year-specific 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 20–44.

Table 7: TWFE Estimates by age group (different sub-samples by Restrictiveness)

	Cohabiting			**Married**		
	(1) Empl. + JP	**(2)** Employed	**(3)** Eligible to PPL	**(4)** Empl. + JP	**(5)** Employed	**(6)** Eligible to PPL
Treat × Post	0.0094	0.0079	0.0034	0.0156*	0.0148**	0.0090
	(0.0074)	(0.0067)	(0.0070)	(0.0082)	(0.0072)	(0.0074)
Eligibility	Yes	Yes	Yes	Yes	Yes	Yes
Employment	Yes	Yes	No	Yes	Yes	No
Job Protection	Yes	No	No	Yes	No	No
Baseline birth rates (2009)	11.4	11.4	11.8	12.8	12.8	13.2
% change	8.25	6.93	2.88	12.19	11.56	6.82
Observations	63,205	66,075	71,568	51,741	54,363	58,906

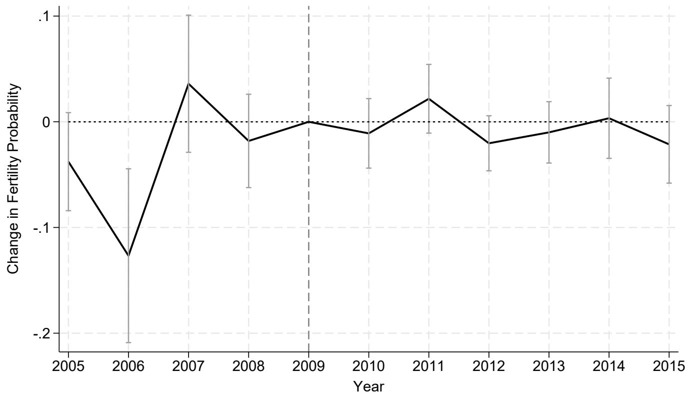
Notes: This table reports results from Two-way fixed effects regressions estimating the effect of paid leave (PL) on fertility. Samples are progressively relaxed from the most restrictive—employed women entitled to job protection—to broader eligibility groups. Columns 1–3 show results for cohabiting 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 12: 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 13: Event Study: Effect of paid leave reform on fertility for single unemployed women



Notes: This figure reports results from Two-way fixed effects 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 8: 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 Two-way fixed effects 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.

B 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 9: Two-way Fixed Effects Estimates – Married (Employed + Job Protection)

Age Group	(1) Married, Emp + JP	(2) Cohabiting, Emp + JP
15–19	-0.0224	-0.0211
20–24	0.0393	0.0285
25–29	0.0116	-0.0005
30–34	0.0233	0.0147
35–39	0.0086	0.0027
40–44	0.0013	0.0016
45–49	-0.0012	0.0015
Baseline TFR (NJ in 2009)	2.95	2.41
% Change in TFR	10.25	5.68

Notes: This table reports coefficients from two-way fixed effects 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 Parametrization

C.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:

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

C.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 10** reports the estimates of *age* and age^2 for each regression.

Table 10: Age profiles

	High school	College
	Men	
Age	0.085	0.0559
$\text{Age}^2 \cdot 1000$	-8.325	-5.327
	Women	
Age	0.0681	0.0287
$\text{Age}^2 \cdot 1000$	-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 11**.

Table 11: 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

C.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.

C.4 Time investment in children

I use CDS 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.

[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.

Following Daruich (2018), I also exclude time spent watching TV and playing videogames 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, 2009). **Table 12** 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 12**.

Table 12: 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	

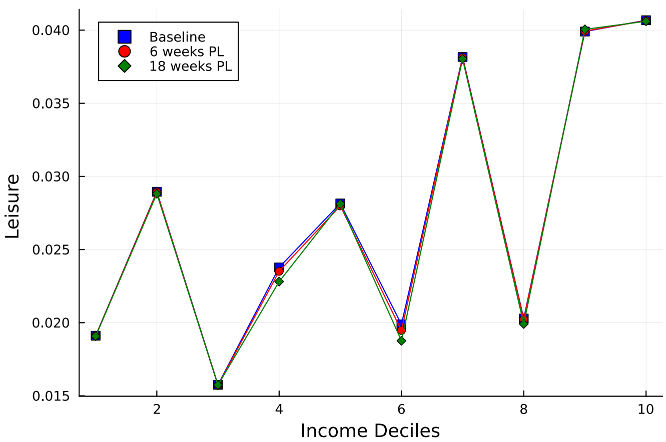
Notes: The table show parental time investment (as number of minutes and as a share of total time available to the child) across different stages of childhood distinguishing between maternal, paternal and total time and separating families by maternal education. The first three rows refer to early childhood, 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

D Other results: consequences for leisure during leave duration

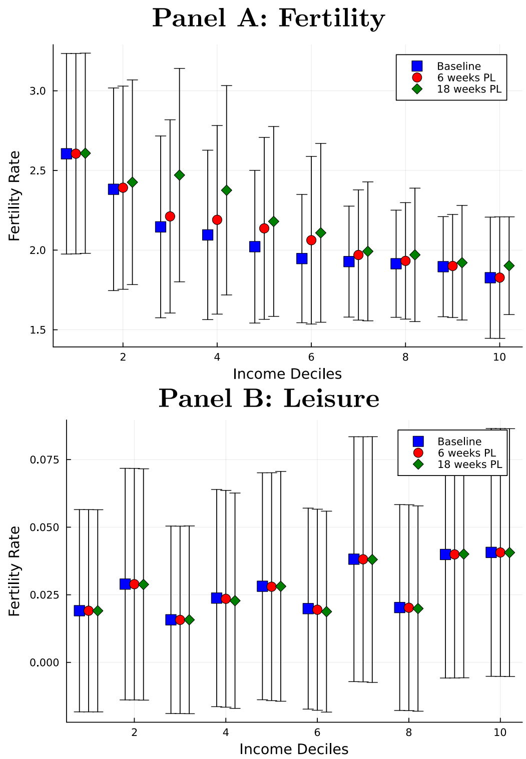
Figure 14 presents trends in leisure time taken by women during leave across households' income distribution under the different policy scenarios. The share of leisure does not display a consistent trend across the income distribution because parental leave is taken only by mothers, whereas family income 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.

Figure 14: Changes in leisure following the introduction of paid PL



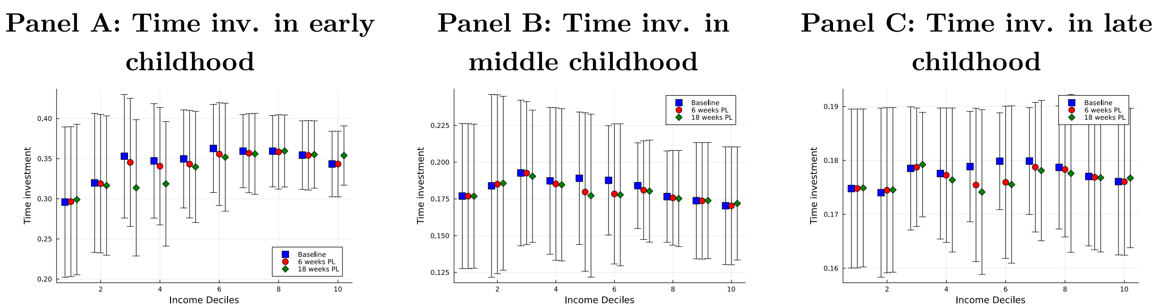
Notes: The figure shows trends in the share of time in the first period of childhood which the primary care-giver allocates to leisure (which in the model can only be taken during parental leave) across the income distribution of families with children and scenarios.

Figure 15: 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.

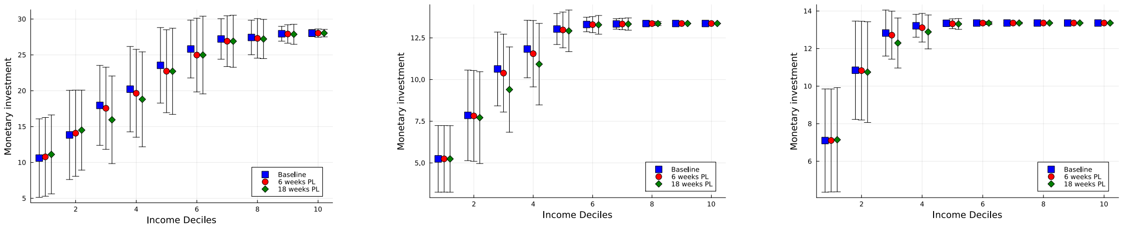
Figure 16: Time investment in children by stage of childhood and policy scenario



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.

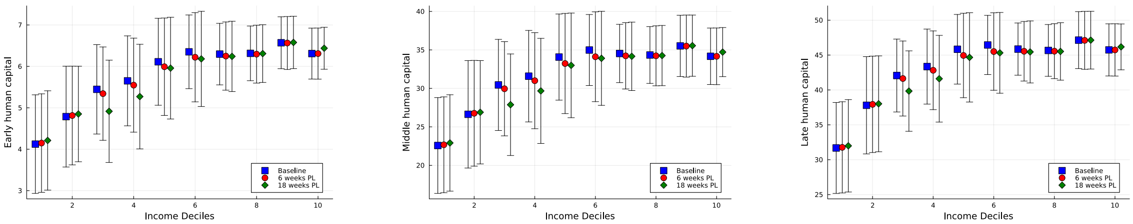
Figure 17: Monetary investment in children by stage of childhood and policy scenario

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 18: 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.

E Solution Method

E.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,

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