Time to Grow Up? The Distributional Effects of Parental Leave Policies on Fertility and Child Human Capital *

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Abstract

This paper examines the distributional effects of introducing paid leave policies in the US on fertility and children's human capital. Using a life cycle model calibrated to US data, I simulate the introduction of a paid parental leave policy, and find that it raises fertility by 9%, primarily among low-income families. The policy generates a quantity-quality trade-off: while paid leave increases parental time investment in newborns, fostering early development, it reduces investments in later childhood for families with stronger fertility responses who face financial constraints, leading to losses in human capital. These findings highlight the potential for paid leave to boost fertility but also reinforcing income-related disparities in child outcomes.

*JEL classification: J1, J2, J3

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1 Introduction

Over recent decades, paid parental leave policies (PPL) have gained increasing popularity among policymakers as a tool to support parents in providing care during the earliest stages of a newborn's life.[1] While high-income countries have been at the forefront of implementing these policies, the US stands out as the only advanced economy without government-mandated PPL. Only a minority of states within the country have recently introduced the policy at the local level.[2]

Paid parental leave (PPL) policies are designed to reduce the opportunity costs of raising children, potentially leading to increased fertility rates. By providing financial compensation, PPL can ease family budget constraints, making it more affordable to care for multiple children. Additionally, the policy lowers the opportunity cost of time for parents who temporarily leave the workforce to care for their newborns. Simultaneously, PPL can promote children's human capital development during early childhood through increased parental time investment. While greater time investment during early childhood may have limited direct effects, its consequences can be significant through the mechanism of dynamic complementarity — the productivity of current investments increases with the existing stock of human capital, which is itself shaped by earlier investments (Cunha and Heckman (2007)). However, the policy's potential effects on fertility might induce a trade-off between the quantity and quality of children (Becker and Lewis (1973)), with families across the income distribution experiencing heterogeneous impacts. This highlights the complexity of PPL's role in shaping family dynamics and child development outcomes.

To date, a limited number of studies (Gahramanov et al. (2020), Yew et al. (2022)) have simulated the introduction of parental leave policies in the US accounting for

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

[2] 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.

both endogenous fertility and parental investment. The models in these studies abstract from important components, such as human capital accumulation, and thus overlook the dynamic effects of such policies on child development. Moreover, both studies present models featuring representative agents, which, while providing insights into average policy effects on the quantity-quality trade-off, fail to capture potential heterogeneous responses. As documented by Doepke et al. (2022), family policies have significantly contributed to recent changes in the relationship between fertility, female education, and income through their varying effects on fertility across the distribution[3]. The importance of heterogeneity is also highlighted by observable disparities in childbirth and investment behaviors across income and education levels, even in the absence of PPL. For instance, in the US, college graduates have, on average, 13% fewer children than their less-educated counterparts (CPS data, fertility supplement). Furthermore, when comparing families with the same number of children, highly educated and higher-earning parents invest significantly more time and money in their children (Guryan et al. (2008), Ramey and Ramey (2009)). All of this indicates that individuals with different characteristics, and thus facing different incentives, may have varied fertility and investment responses to policy interventions aimed at reducing the opportunity cost of time associated with having and raising children.

This paper advances the existing literature by estimating the distributional effects of introducing paid parental leave (PPL) on fertility and child development. It does so by building a life cycle model that incorporates agents' heterogeneity across income and education, endogenous fertility and investment choices, and a sequential accumulation of human capital across childhood[4]. The model is calibrated to the US economy and used as a policy laboratory to estimate the heterogeneous effects of scaling California's Paid Family Leave (PFL) policy to a national level.

[3]In their survey on the economics of fertility in developed countries, Doepke et al. (2022) dedicate a section to new theoretical frameworks they develop to explain the progressive flattening (or reversal) of fertility trends across the maternal education distribution.

[4]Cunha and Heckman (2007)'s concept of self-productivity states that human capital at each stage builds upon the stock accumulated in previous stages.

The results show that the introduction of this policy increases fertility by an average of 9 percent. Consistent with the empirical literature on the effects of California's PFL on fertility (Golightly and Meyerhofer (2022)), this increase occurs entirely at the intensive margin, expanding family size among individuals who already have children rather than incentivizing childless individuals to transition into parenthood. Fertility increases are concentrated among families in the bottom income tercile (up to 16 percent higher birth rates) and, to a lesser extent, in the top income tercile where birth rates increase by up to 11 percent. The policy generosity is not sufficient to impact fertility decisions among families at the very top of the distribution who face the greatest opportunity cost of time. This pattern suggests that paid leave compensation relaxes budget constraints for poorer families, providing financial incentives to have more children, while also reducing the opportunity cost of time, enabling higher-earning families to expand their family size. In contrast, families in the middle of the income distribution, who face less binding budget constraints than poorer families and lower opportunity costs of time than wealthier families, show little response to the policy.

The increase in fertility rates at the intensive margin generates a trade-off between the quantity and quality of children. Larger family sizes dilute the resources parents can invest in their children across childhood. On one hand, paid leave compensation encourages parents to invest more time in their newborns, benefiting early child development. On the other hand, despite the dynamic complementarities characterizing human capital formation (Cunha and Heckman (2007)), increased investment in early childhood is insufficient to reinforce investment in later stages. Instead, later investments decline for families with strong fertility responses, but disproportionately between low- and high-income families. Specifically, increasing birth rates among low-income families leads to a significant loss of human capital (between 3 and 10 percent), whereas high-income families show only limited reductions in parental investment, lead-

ing to a moderate decline in human capital (as much as 2.5%).

The findings of this paper suggest that introducing paid leave can effectively increase fertility rates, particularly at the opposite ends of the income distribution. However, the growth in birth rates comes at the cost of reduced child human capital among low-income families, who cannot maintain previous levels of investment when family size grows. Among higher-income families, child human capital decreases slightly, but the effect is mitigated by a more limited reduction in parental investments. Overall, the policy exacerbates disparities in parental investments and child outcomes across the income distribution.

The paper proceeds as following: section 2 provides a review on the relevant economic literature on the topic, section 3 provides details on the theoretical model. Within Section 4, 4.1 presents the data employed to compute the relevant moments and features of the model, while 4.2 and 4.3 define the parameters' calibration and the structural estimation, respectively. Section 4.4, describes the policy experiment consisting of introducing parental leave policies in a baseline model and the results of this policy introduction. The model limitations and way forwards are discussed in section 5. Finally, section 6 concludes and Section 7, the Appendix, provides further details.

2 Literature review

This study contributes to four strands of literature. First of all, it sheds light on the joint effects of parental leave policies on fertility and child human capital formation, which cannot be disentangled in the empirical literature. Among the empirical work estimating the comprehensive effects of parental leave on fertility decisions, Golightly and Meyerhofer (2022) find that introducing 12 weeks of paid leave in California increases fertility by 2.8 percent, driven by higher order births. Cannonier (2014) identified a

positive effect of the Family and Medical Leave Act on the propensity to have children. Raute (2019) found that a reform in Germany implemented in 2007, which transitioned the benefit system from fixed benefits to wage replacement, increased fertility among higher-earning mothers. Similarly, Ang (2015) estimated positive pronatal effects of a PPL reform in Quebec. Other studies have analyze the effects of PPL reforms on fertility in reduced form reaching conflicting results (Lalive and Zweimüller (2009), Liu and Skans (2010), Dahl et al. (2016), Carneiro et al. (2015), and Farré and González (2019)). For a comprehensive survey of the literature on the effects of paid leave on fertility see Thomas et al. (2022).

Empirical investigations into the effect of Paid Parental Leave (PPL) on child development have yielded mixed results. For instance, Flores et al. (2023) find that the job protected (unpaid) leave in the US benefited education and intergenerational mobility particularly for children of less educated mothers. Conversely, Dustmann and Schönberg (2012) highlighted the policy's negative impacts on child development. While some studies find that the policy benefits particular groups (Danzer and Lavy (2018), Liu and Skans (2010)), others like Dahl et al. (2016) and Rasmussen (2010) found no significant effects on children's school performance. The varied outcomes, potentially constrained by a lack of consideration for PPL's indirect effects via changes in family size, underscore the necessity for a comprehensive quantitative model to elucidate PPL's broad impact on child outcomes. The inconsistent results across these studies may stem from unobserved heterogeneity and the limitations of quasi-experimental methodologies in capturing important indirect effects of PPL, especially its role in shaping human capital formation through the fertility channel.

Second, this paper contributes to the quantitative literature which has separately examined the heterogeneous influence of PPL on fertility decisions and child human capital formation. Erosa et al. (2010), Yamaguchi (2019), Kim and Yum (2023) and Chan and Liu (2018) develop reach life-cycle models with heterogeneous agents to esti-

mate the consequences of different parental leave policies reform on fertility decisions. By abstracting from parental investment, their models cannot inform of the consequences for children's human capital formation. The exception is Chan and Liu (2018) who investigate the effects of a range of pro-natal policies in Norway incorporating a single period technology of child human capital. However, this simplification abstract from the dynamic nature of child human capital (Cunha and Heckman (2007)) and does not allow to estimate the long term consequences of the policy on later investment through dynamic complementarity and quantity-quality effects. Other studies investigating the effects of paid leave on fertility and child development though a model relying on a simplified technology of child human capital are Gahramanov et al. (2020), Yew et al. (2022). Their framework adopt representative agents and cannot therefore speak to distributional effects which is the focus on this paper. Youderian (2019) builds an overlapping generation (OLG) model with a sequential accumulation of human capital across childhood to estimate the general equilibrium effects of early childhood policies abstracting from fertility decisions. Her results suggest that PPL are less cost-effective in improving children's human capital and intergenerational mobility compared to public spending and government subsidies to market-based childcare. The author leaves to future studies the assessment of the policy in a context of endogenous fertility choices.

Finally, this paper builds upon previous research that employs quantitative models to evaluate the distributional impacts of various family policies, other that parental leaves, including child tax credits and childcare subsidies, as explored by Kurnaz and Soytas (2019), Petit (2019), and Zhou (2021). These studies collectively find that family policies can significantly increase fertility rates, particularly among low-income families, but also draw attention to an accompanying quantity-quality trade-off that negatively affects aggregate human capital. This study complements this strand of literature by analyzing a family policy targeting parental time investment rather than the monetary investment which has been the focus of previous studies.

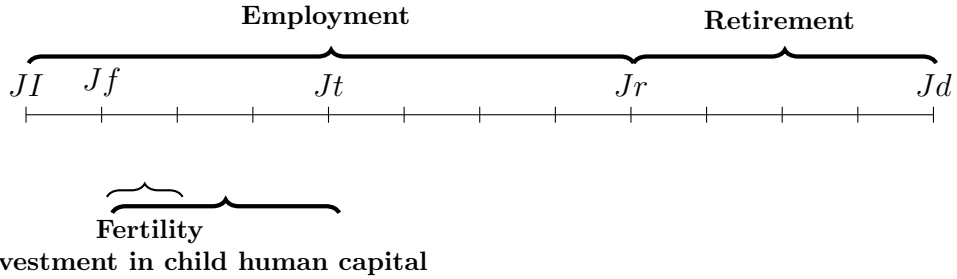
3 Model

3.1 Theoretical framework

The life-cycle framework built in this paper portrays a single generation of individuals who go through four main stages of life spread over 13 model periods, each corresponding to five years. Households are composed by two earners, who have the same age and opposite gender and stay together throughout their life. Optimizing agents enter the life cycle model at the age of 25, while they are in the labor force, and are exogenously assigned a level of education (high school or college). 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's human capital accumulates over three periods of childhood: since the period when children are born to when they become independent at age J_I (equivalent to 15). Children do not make choices and after the third and last period of childhood, parents stop investing in their human capital. The agents then enter the third stage of life where they return to supply labor inelastically and no longer provide investment to their children. In the following stage, the final one, they retire and ultimately die. **Figure 1** summarizes the life cycle of an agent.

The model adapts the work of Daruich and Kozlowski (2020), who evaluate the role of differential fertility and parental transfers in determining intergenerational mobility. Introducing endogenous parental investment in children's human capital over multiple stages of childhood, together with additional components (e.g. an endogenous labor supply during the fertility stage and parents' skill depreciation) allows me to estimate the distributional effects of parental leave policies on the quantity-quality trade-off.

Figure 1: **Life cycle timeline**



Agents are risk averse and their preferences are represented by the utility function u which is positive, increasing and concave. Agents discount the utility from the future period at the discount factor β.

During the first period of work, agents face a productivity shock z_0, corresponding to the initial value of the persistent component of the income process.

Working while young stage:

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

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

$$c = y(1 - \tau_{SS}) \tag{2}$$

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

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

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

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

The family income y is the result of the sum of labor incomes, w_g 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 (5)), vary with gender and with the level of education. Labor income w is is subject to a tax with rate τ_{SS} corresponding to social security coverage. Agents supply labor inelastically, as they do not face disutility from working. Time is normalized to one as in equation (4).

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 oh human capital (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).

As standard in the literature, I define human capital functional form in each stage of childhood as a nested constant elasticity of substitution (CES) productivity function. This function 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. Parental investment combines parents' monetary expenses m and time t which parents allocate to interact with their child. The multiplication A_I represents the productivity of investment. Parental inputs in the nested CES, m and t are weighted by the coefficient α_I and $1-\alpha_I$, respectively. Parental investment and past human capital are combined and weighted by γ and $1-\gamma$, respectively. The parameter ρ represents the coefficient of substitutability between inputs and the parameter ϕ informs on the degree of dynamic complimentarity. The parameter δ_e allows for different productivity between time investment by low and highly educated parents.

$$h_{k_i} = [\gamma h_{ki-1}^{\phi} + (1-\gamma)A_i(\alpha_i m^{\rho_i} + (1-\alpha_i)(\delta_e t)^{\rho_i})^{\frac{\phi}{\rho_i}}]^{\frac{1}{\phi}}$$

$$i \in \{1,2,3\}$$

Fertility stage:

In period $j = J_f$, besides choosing their consumption, the agents also decide the number of their children ($n \in 0,1,2,3$), and the time and money to invest in their education. This model simplifies the fertility process similarly to Daruich and Kozlowski (2020) and Zhou (2021) by assuming all children are born in the same model period (therefore within five years, agents can have up to three children) [5] J_f, with the same endowment on initial abilities h_{k0}. They grow up in the household in the consequent two periods and receive homogeneous investment.

$$V_j^w(e,z) = \max_{c,n,m,t} u(c) + \beta E[V_{j+1}^w(e,z',n,h_{k1})] + U(n,h_{k1}) \tag{7}$$

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

$$y = w_m(1-\bar{t_m}n^{\epsilon_2}) + w_f(1-t_{PL}n - t_f n^{\epsilon_2})$$

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

$$1 = l_f + t_{PL}n + t_f n^{\epsilon_2}$$

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

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

$$h_{k_1} = [\gamma h_{k0}^{\phi} + (1-\gamma)A_1(\alpha_1 m^{\rho_1} + (1-\alpha_1)(\delta_e t)^{\rho_1})^{\frac{\phi}{\rho_1}}]^{\frac{1}{\phi}}$$

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

Consumption deflation increases with the number of children in the household (see Section 4). Altruistic parents derive utility from having children and their number, n. Moreover, they value their children's human capital h_k, I define child-related utility as $U(n, h_k)$, which parents incorporate in their own maximization problem.

Children are time intensive and spending time with each newborn requires parents to be absent from work. Therefore, agents' labor supply during early childhood is elastic ($l_g < 1$) as parents choose the total amount of time spent with children, and labor constitutes a residual with respect to the time agents choose to dedicate to childcare. During this period, the first stage of child development, the amount of time spent on leave, t_{PL}, is endogenous and decided by the primary caregiver to maximize the household utility subject to the budget and time constraints as well as the technology of skills production [6]. Time spent during parental leave is individual while any other form of time investment (t_m and t_f) are collective and presents economies of scale dictated by parameter ϵ_2. Notably, the individual nature of time investment during parental leave requires the primary caregiver to make a choice over the product of leave duration and the number of children, t_{PL}. On the other hand, collective forms of time investment refer to the share of time each child in the family spends with the primary caregiver after she returns to work, and with the secondary caregiver over the entire early stage of childhood. Both measures of time investment are exogenous and their value is directly estimated from the data. Monetary investment also present some level of scalability determined by parameter ϵ_1.

Parents working and investing in their children:

In the following model periods $j = J_f + 1, J_f + 2$, agents continue consuming while

[6] Although policy makers are moving towards a system where both parents are equally eligible to family leaves, 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 leaves between the two caregivers in this context

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). The share of this time spent by each parent, α_g is calibrated from the data and allows for joint childcare ($\alpha_m+\alpha_f \geq 1$). In this period, the number of children n and the human capital each child accumulated in the previous period, h_{ki}, are fixed and appear as state variables.

$$V_j^w(e,z,n,h_{ki}) = \max_{c,m} u(c) + \beta E[V_{j+1}^w(e,z',n,h_{ki})] + U(n,h_{k_i}) \tag{8}$$

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

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

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

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

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

$$h_{k_i} = [\gamma h_{ki-1}^{\phi} + (1-\gamma) A_i (\alpha_i m^{\rho_i} + (1-\alpha_i)(\delta_e t)^{\rho_i})^{\frac{\phi}{\rho_i}}]^{\frac{1}{\phi}}$$

$$i \in \{2,3\}$$

$$a' \leq \underline{a}_{e,j}.$$

Old workers stage:

After children have passed the third stage of childhood, parents no longer gain utility from the quantity and quality of their children. They continue working for three periods and their utility maximization problem is equivalent to (1) with the difference that there is not expected innate abilities of the future child, h_{k_0} in the continuation value.

$$V_j^w(e,z) = \max_{c} u(c) + \beta E[V_7^w(e,z')] \tag{9}$$

$$c = (w_f + w_m)(1 - \tau_{SS}) - T(h, n = 0)$$

$$l = 1$$

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

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

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:

$$V_j^r(e) = \max_c u(c) + \beta E[V_{10}^w(e, z', n)] \tag{10}$$

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

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 and 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 separated by gender and education are used to build age profiles and the wage process. Details on the estimation are provided under **Income process**. Additional data sources used in this study are the National Longitudinal Survey of Youth Child -YA for maternity leave uptake, and the Fertility Supplement of the Current Population Survey (CPS) for fertility and childlessness rates by female education.

For information of households' children, I rely on the PSID's Child Development Supplement (CDS). This supplementary study starts in 1997 and collects information on at least one child between 0 and 12 per household and on their primary caregiver. The same children are eligible for follow-up of interviews in 2002 and in 2007 unless they have turned 19 by the time of the new interview. Starting from 2014, all PSID children are eligible for the interview. The survey provides time diaries filled in by the children with the help of their primary caregiver as well as a broad measure of assessment, including the Woodcock Johnson test. 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 link a total of 1452 children.

Time investment:

The CDS provides time diaries reporting the activities a child engages in over 24 hours. Starting time and end time of the activities is reported as well as who was present during the activity, distinguishing between active and passive participation. These information are collected on a representative working day and weekend day separately. By selecting activities in which either parent was actively present, I can build a measure of parents' time investment in the children. Because the model abstracts

from leisure, I restrict the analysis on working day and focus on activities children engage in while at either or both of their parents are actively participating. Following Daruich (2018) I also exclude time spent watching TV and playing videogames from the analysis 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 (in particular, Guryan et al. (2008) and Ramey and Ramey (2009)). **Table 1** 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. The Appendix, Section 7, provides a detailed description on the strategy I adopt to approximate parental time investment in early childhood accounting for the choice over parental leave take-up. In short, I calibrate time investment by a parent on leave using active time participation in children's activities on a regular workweek day by a parent outside the labor force. Because the data suggest that the women are the primary caregiver and the leave takers, I focus on the time non-working women spend with their children under the age of three and assume that would be the time amount of time that parents on leave would invest in childcare.

Time investment in the first phase of childhood is defined differently from the following pahses. On the one hand, I model the choice of time investment in early childhood as the number of weeks of leave the primary caregiver decides to take to look after a single child. On the other, time investment in middle and late childhood is the result of parents choice of aggregate investment in their children. This amount will be split between each parent according to the weight $\alpha_{g,i}$ with $g \in \{m, f\}$ and $i \in \{m, l\}$ re-

ported in **Table 1**. In Section 7, I provide further explanation on time calibration in each stage of childhood.

Table 1: Time investment by mother's education

Time	High school	College	Share
Mother, child 3-5	3 h 7 min	3 h 4 min	80%
Father, child 3-5	1 h 23 min	1 h 18 min	39%
Parents, child 3-5	3 h 46 min	3 h 39 min	
Mother, child 6-11	1 h 32 min	1 h 26 min	85%
Father, child 6-11	1 h 14 min	59 min	40%
Parents, child 6-11	2 h 23 min	2 h 8 min	
Mother, child 11-16	1 h 32 min	1 h 26 min	86%
Father, child 11-16	1 h 14 min	59 min	51%
Parents, child 11-16	2 h 23 min	2 h 8 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 time, parenteral time and total time and separating families by maternal education. The first three rows refer to early childhood, the second three rows to middle childhood and the latter 3 rows 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 (excluding watching TV and playing videogames) 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

A complementary source of data on time investment, specifically on parental leave take-up, consists of the National Longitudinal Survey of Youth Child -YA which provides information on the length of time which interviewed women spend away from work after giving birth. One question in the survey requires to indicate whether that time was covered by paid maternity leave, unpaid maternity leaves with job protection, a mix of paid and unpaid maternity leaves or no leave at all. I select women who were married or cohabiting at he time of the birth and who did not leave the labor force after having a child. In total I collect information on all women who reported to haven given birth between 2008 and 2016, and whether they were allowed to take paid,

unpaid parental leave, a combination of the two or no leave at all. I restrict the sample to women reporting these information on up to their third child (consistently with the model specification which allows agents to give birth to at most three children). The sample consists of 1023 women. On average, women with less than a college education take 7.5 weeks while college graduates take on average 9 weeks.

Child human capital

The CDS offers a wide range of measure of children cognitive skills including three of the Woodcock-Johnson Tests, reporting the scores in each test. I refer to the Applied problem test to construct a measure of child human capital [7]. The score consists of the sum of questions correctly answered, as each question is worth one point. I follow Petit (2019)'s adaptation of Del Boca et al. (2014) consisting of normalizing children test scores and setting a direct relationship between children human capital and the probability of giving a correct answer to a generic question in the AP test, $p_i(h_k) = \frac{h_k}{1+h_k}$ (this strategy implies that each question is equally challenging).

Assuming Q is the set of questions q_i and $q_i \in 0, 1$ (i.e. the outcome of the question is one point if correct and zero if incorrect) and that the questions are independent between each other, then $Q = \sum(q_i)$ and $\bar{q}$ represents the test score :

$$\bar{q} = \frac{\sum_{i=1}^{Q} q_i^*}{Q} \tag{11}$$

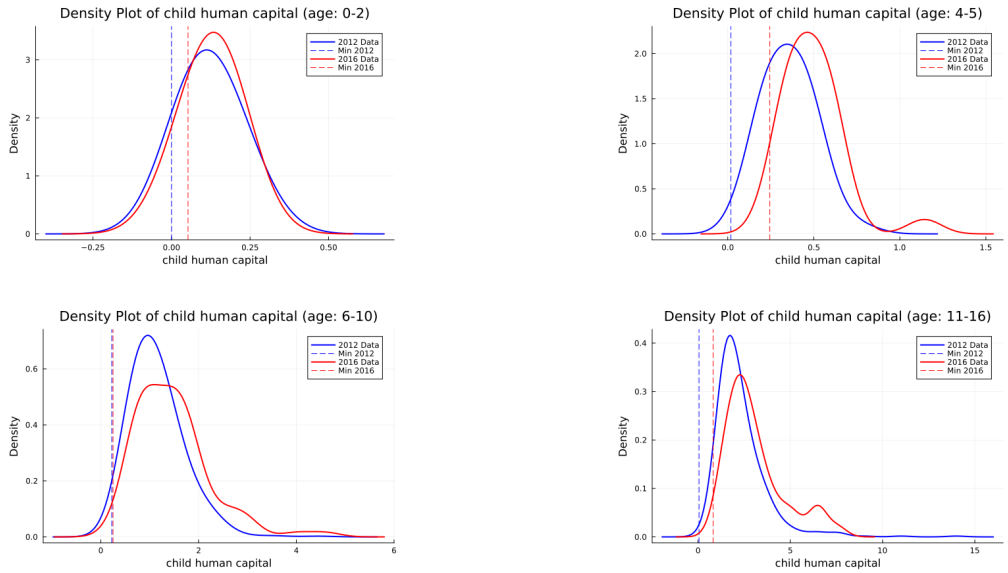
Human capital is calculated as the share of correct answers to the test:

$$h_k = \frac{\bar{q}}{1 - \bar{q}} \tag{12}$$

[7] In the literature, Del Boca et al. (2014) and Lee and Seshadri (2019)) rely on the Letter Word (LW) test scores. However, for the sample I selected, the variance of LW is significantly higher compared to the Applied Problem test scores which provides a less noisy measure of human capital.

Figure 2 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.

Figure 2: 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 five in the top right panel, children between six and 10 in the bottom left panel and children between 11 and 16 in the bottom right panel). Children's human capital is computed using a transformation of the Applied Problem test of the Woodcock-Johnson test as defined in equation (13). The data is sourced from the PSID Child Development Supplement, waves 1997, 2002, 2007, 2014, and 2019. The blue and red lines show the distribution of human capital among children with HS graduate mother, and CG mother , respectively. The dashed lines indicate which is the smallest value of human capital in each sample.

By matching CDS' individual identifies of the primary caregiver (which in the sample happens to be the mother with 0.9 probability), I can link children's information with those of their parents and compare, for example, children skills and parental time investment by maternal education [8].

[8]See Appendix for details about different in children skills and time investment by maternal education.

Preferences:

The per-period utility over consumption assumes the form of a CRRA function

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

To reflect that children's cost in non-educational consumption increases with their number and 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:

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

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

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

Table 2: Income-age profile

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

process:

$$z_{i,t,g,e} = \rho_{i,g,e} z_{i,t-1,g,e} + \zeta_{i,t,g,e} \quad \text{with} \quad \zeta_{i,t,g,e} \sim N(0, \sigma_{\zeta_{g,e}}) \tag{13}$$

$$z_{i,0,g,e} \sim N(0, \sigma_{\zeta_{0,g,e}}) \tag{14}$$

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 3**.

4.2 Parameters set exogenously

A set of model parameters are exogenously assigned a value which is either standard in the literature, provided by other papers or estimated directly from the data. Notably, parameters related to time investment, $\bar{t_m}$, $\bar{t_f}$, α_m, α_f, are computed using CDS data. The parameter determining the economies of scales in children time investment, ϵ_2 is taken from Sommer (2016) who calibrate it by matching the elasticises of parental time

Table 3: Income-age profile

	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

and monetary investment to the number of children. This parameter value is used for similar purposes by Petit (2019). The parameters referring to the financial markets and tax rates are taken from Daruich and Kozlowski (2020). Finally, I set the initial stock of human capital equivalent the average value of children at 2 years old, the youngest in the sample reporting test score.

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 and late childhood. These are the most relevant parameters to drive the results of the model and therefore they are estimated by minimizing the distance between the relevant moments computed from the data and those generated by the model. Although

Table 4: Exogenously calibrated parameters

Parameter	Value	Description	Source
Demographics			
	5	Time period	
J_s	25	Age at beginning of the lifecycle	
J_f	30	Fertility decision	
J_t	45	Children are independent	
J_r	65	Retirement	
J_d	85	Death	
Prices			
τ_{ss}	0.125	Tax rate	Daruich and Kozlowski (2020)
Financial Markets			
r	3%	Interest rate	Daruich and Kozlowski (2020)
ι^s	1%	College-loan wedge (annual)	Daruich and Kozlowski (2020)
Preferences			
$\beta(annual)$	0.935	Discount factor	
γ_c	0.8	Coefficient of risk aversion	Caucutt and Lochner (2020)
Scalability			
ϵ_1	0.92	Economies of scales mon. investment	Sommer (2016)
ϵ_2	0.54	Economies of scales time investment	Sommer (2016)
Time investment			
α_{f1}	0.39	Share of paternal time early childhood	
α_{m1}	0.80	Share of maternal time early childhood	
α_{f2}	0.40	Share of paternal time mid childhood	
α_{m2}	0.85	Share of maternal time mid childhood	
α_{f3}	0.51	Share of paternal time late childhood	
α_{m3}	0.86	Share of maternal time late childhood	
Initial abilities			
h_{k0}	0.17	Initial human capital	

Note: This table reports the description and values assigned to the parameters calibrated externally.

the values of of the parameters are potentially affected by more than one moment at the same time, I identify one moment per parameter which plays the most crucial role in determining the value of such parameter.

Preferences over children quantity and quality:

I employ separable preferences among quantity and quality of children as standard in the literature (De La Croix and Doepke (2003), Bar et al. (2018)). These take the following form:

$$U(n, h_{kj-6}) = \eta_n \frac{n}{\sigma_n}^{\sigma_n} + \eta_{h_k} n^{\kappa} \frac{h_{kj-6}}{\sigma_{hk}}^{\sigma_{hk}} - X_e \tag{15}$$

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

The parameters η_n, η_{h_k} measure the wights in the utility function of the "quantity" and "quality" of children, respectively. As in Petit (2019), the parameter κ controls how families of different size value children's human capital. If $\kappa = 0$, families derive the same utility from child's human capital, regardless of the number of children, and if $\kappa > 0$, larger families value more child's human capital. The parameters σ_n, σ_{h_k}, measure the curvature of the preferences for the number of children, their human capital , respectively. X_e is a fixed cost, varying with individuals' education, that allows for preferences for childlessness by capturing utility costs such as the quality of sleep. The moments I use to estimate these parameters are the average completed fertility of high school graduate women, the share of families with two children for high school and college graduate women separately, the difference between average fertility of high school graduates to college graduates, and the share of childless families where the mother is highly and low educated, the average human capital at the end of childhood for children with HS graduates mothers and the difference in human capital at the end of childhood between children of high school and college graduates mothers, respectively. I compare children human capital in families with two children to filter out possible family size effects on children skills.

Child human capital formation:

$$h_{k_i} = [\gamma h_{ki-1}^{\phi} + (1-\gamma) A_i (\alpha_i m^{\rho_i} + (1-\alpha_i)(\delta_e t)^{\rho_i})^{\frac{\phi}{\rho_i}}]^{\frac{1}{\phi}} \tag{16}$$

$$i \in \{1, 2, 3\}$$

The data moments are computed from the PSID data and CPS fertility supplement using waves form 2001 to 2018. I compared them to the model simulated moments to estimates simultaneously the parameters defining the utility from having children and their human capital, and those determining the human capital functional form.

Among the parameters determining children's human capital functional form, γ is the weight of human capital in the previous stage of childhood featuring in the technology of human capital formation. The most informative moments for the calibration of this parameter is the coefficient of the regression of human capital in period i on human capital in period $i-1$, which in the data corresponds to five years earlier. I select families with two children to compute this moment. The sample size of children reporting information on human capital in at least two consecutive periods consists of 841 children.

Among the moments chosen for the calibration, the one affecting the value of intertemporal elasticity parameters, ϕ is the coefficients of the regression of human capital in each period on the logarithm of family income in that period. Parameter α_1 represents the weight of monetary investment in the CES investment function, and ρ_1 the intra-temporal elasticity of substitution in early childhood, while α_2 and ρ_2 play the equivalent role in the functional form in the middle and late childhood. On the one hand, α_1 is calibrated to match the average parental leave take up by low educated women with two children from the NLSY79-C/YA, and ρ_1 the average lave take up

by highly educated women with two children. On the other hand, the values of ρ_2 and ρ_2 are set to match the average time children in the middle and late childhood which children of low and high educated women spend with their parents, respectively. Even these moments are calculated selecting families in which two children are present. A_1, A_2 and A_2 are the parameters determining the productivity of investment in the first and later stage of childhood, respectively. I estimate these parameters using the moments computed from the CDS and in particular the Applied Problems scores of the and Woodcock-Johnson test. These correspond to the average human capital of children in early childhood, between 4 and 6 years old, the average human capital of children in middle childhood, when they are between 9 and 11 years old, and the average human capital of children in middle childhood, at 14 to 16 years old. A summary of the parameters, their calibrated values and the moments which most inform their calibration is reported in **Table 5**.

The simulated model moments are close to the data counterpart with a few notable exception. In particular, the model overestimates the coefficient of log earnings in the regression of human capital on family income.

4.4 Policy Experiment

After solving and structurally estimating the model, I use it as a policy laboratory to estimate the effect of a policy introduction partially compensating parents for the time spent with their children at the beginning of their life. With this purpose, I run a policy experiment during the stage of fertility and early childhood (J_f). The experiment consists of providing primary caregivers with parental leave benefits to partially offset the earning losses they face while they are absent from work to look after their newborn children.

Table 5: Parameters and Data Moments for SMM

Parameter	Value	Description	Moment	Data	Model
η_n	1.06	Utility children's n	avg fertility HS	1.85	1.87
σ_n	0.55	Utility children's n	share of HS fam. with 2+ kids	0.44	0.56
κ	0.06	Utility children n	diff. fertility CG and HS	-0.08	-0.14
X_{e1}	3.41	fixed cost, HS	share childless HS	0.11	0.10
X_{e2}	4.18	fixed cost, CG	share childless CG	0.13	0.114
η_k	1.75	Utility children's hk	avg hk_3 HS	2.86	2.84
σ_{hk}	0.4	Utility children's hk	diff. hk_3 CG and HS	0.58	0.41
γ	0.5	weight hk_{t-1}	coef. $\delta hk_t = \alpha + \beta hk_{t-1} + \epsilon$	1.59	1.47
ϕ	-1.9	elasticity p. (hk_2, hk_3)	coef. $\delta hk_t = \alpha + \beta y_t + \epsilon$	0.40	1.20
α_1	0.65	weight of money	avg PPL HS	7.5 weeks	7.4 weeks
α_2	0.6	weight of money	avg share time HS	0.20	0.26
ρ_1	-0.8	elasticity p.	avg PPL CG	9 weeks	10.6 weeks
ρ_2	-0.8	elasticity p.	avg share time CG	0.23	0.26
A_{I1}	2.1	Productivity inv. (hk_1)	avg. hk_1	0.42	0.35
A_{I2}	3.8	Productivity inv. (hk_2)	avg. hk_2	1.62	1.55
A_{I3}	6.3	Productivity inv. (hk_3)	avg. hk_3	3.11	3.04
δ_{CG}	1.33	Productivity time inv CG vs HS. (hk_3)	diff. hk_1	0.22	0.31

Note: This table summarizes the moments used to internally estimate model parameters. The statistics are computed using the CDS data waves 1997 to 2019 and the Fertility Supplement of CPS 2011 to 2018. The moments on fertility refer to families with up to three children. Moments referring to child human capital refer to families with 2 children.

I model parental leave benefits by first replicating scheme applied in California and simulating such introduction at national level. This consists of providing primary caregivers with eligibility for up to 12 weeks $d = min(t, \bar{t})$ (with $\bar{t}$ equivalent to $\frac{1}{20}$ of model period) of leave with a wage compensation ranging from 60 to 70% of previous earnings, $B = \alpha_{PL}\, w_f$.

The introduction of parental leave policies transforms the budget constraint for households in J_f which becomes:

$$y = w_m(1 - \bar{t_m} n^{\epsilon_2}) + w_f(1 - t_{PL} n - t_f n^{\epsilon_2})$$

$$\text{c} + \text{a'} = (\text{w}_m(1 - \bar{t_m} n^{\epsilon_2}) + w_f(1 - t_{PL} n - t_f n^{\epsilon_2}))(1 - \tau) + (1 + r)a - m n^{\epsilon} + \underbrace{Bdn}_{\text{PL compensation}}$$

$$1 = l_f + t_{PL}n + t_f n^{\epsilon_2}$$

$$1 = l_m + \bar{t_m} n^{\epsilon_2}$$

The benefits provide parents with extra income that they can use to increase the household consumption, the monetary investment in their children during that period or to increase their family size by choosing to have more children to support.

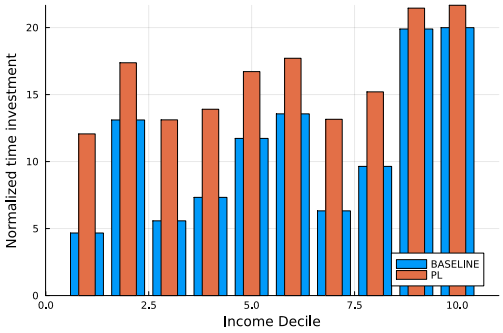
4.5 Results:

Upon the introduction of PPL currently in place in California (consisting of 70% wage replacement for 12 weeks), leave take-up increases across the entire income distribution. The rise in leave duration is particularly notable among subgroups where leave take-up was initially low (less than 10 weeks) in the baseline scenario, as shown in **Figure 3 Panel A**.

Consequences for fertility:

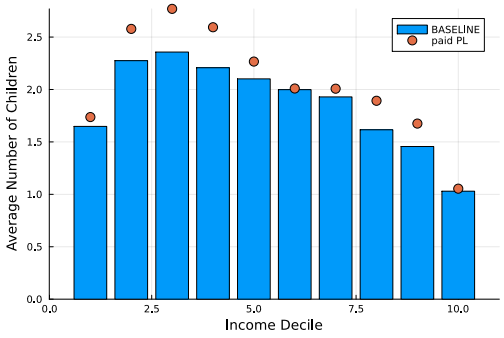
Compensated time off work incentivizes higher fertility across almost the entire income distribution (**Panel C** of Figure 4), with an average growth of 8.9 percent, shifting the average birth rate from 1.8 to 1.97. Notably, the growth is driven by higher-order births rather than a reduction in childlessness. **Figure 4 Panel D** shows the trend in fertility for households with at least one child. The figure illustrates that the increase in family size is concentrated at the opposite ends of the income distribu-

Figure 3: Changes in PL take-up following the introduction of paid PL

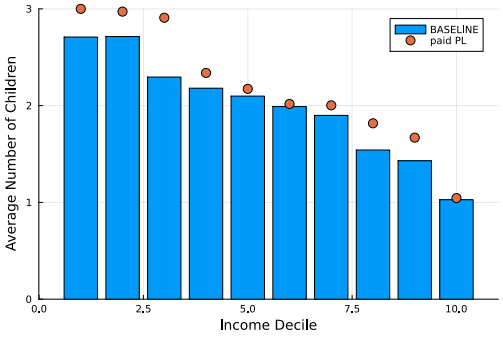


Panel A: Parental leave take-up by parents' income

Figure 4: Changes in fertility following the introduction of paid PL

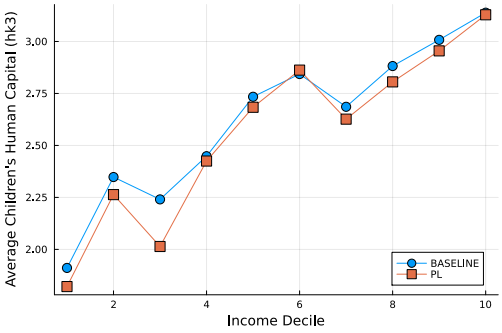


Panel C: Fertility rates by parents' income

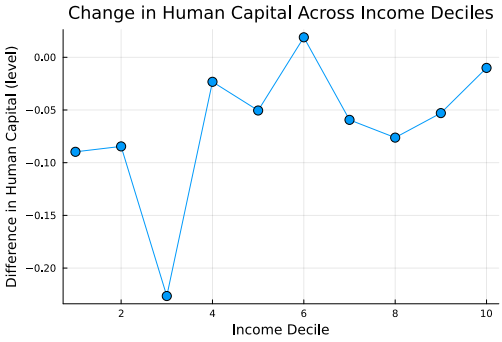


Panel D: Fertility rates by parents' income - intensive margins

Figure 5: Changes in time investment following the introduction of paid PL

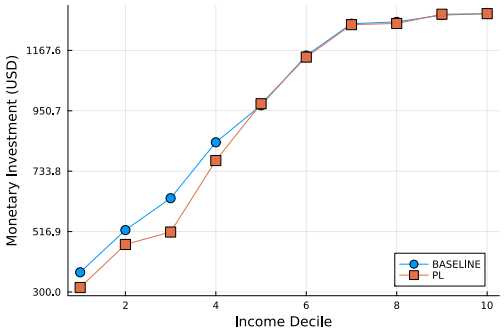


Panel E: Time investment in middle childhood

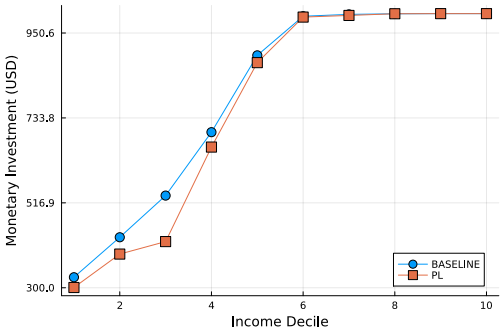


Panel F: Time investment in late childhood

Figure 6: Changes in monetary investment following introduction of paid PL

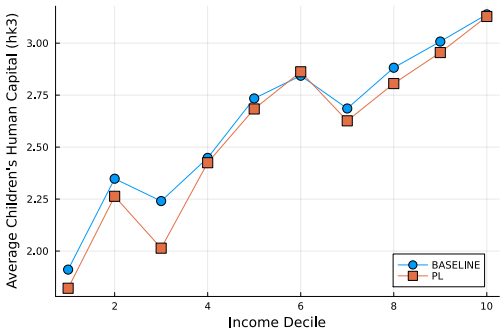


Panel G: Monetary investment in early childhood

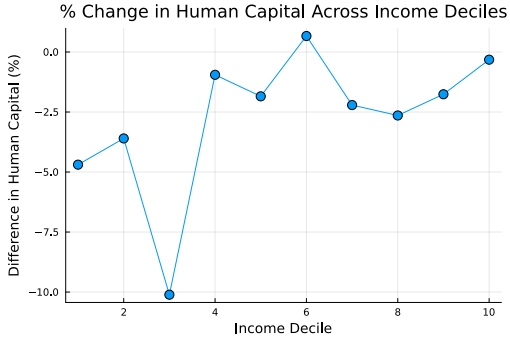


Panel H: Monetary investment in middle childhood

Figure 7: Changes in human late human capital following introduction of paid PL



Panel I: Child human capital in late childhood



Panel J: Changes in late child human capital due to PPL

tion, reinforcing the already high rates among low-income families and flattening the negative income-fertility relationship at the top. Interestingly, the generosity of the policy is not sufficient to impact fertility decisions of individuals at the very top of the distribution, who continue to exhibit the lowest birth rates. In the bottom tercile, fertility increases on average by 16 percent (from 2.4 to 2.8). Simultaneously, it grows by 11 percent in the top income tercile (from 1.3 to 1.45) among highly educated families. Families in the middle of the distribution experience negligible changes in fertility, which remains around 1.9 per household.

Changes in time investment in middle and late childhood:

Figure 5 shows the trend in parental time investment across the distribution for families with at least one child. In the baseline scenario, time investment is discontinuous, ranging between 140 and 173 minutes per day in the middle stage of childhood and between 125 and 158 minutes per day in the later stage of childhood. The investment pattern is similar across different stages of childhood due to the presence of dynamic complementarity between early and later investment (**Figure 3**, **Figure 5 Panel E**, and **Panel F**).

The policy experiment leads to an increase in investment in early childhood by compensating parents for temporarily leaving the workforce to look after their child. However, this temporary increase in investment is insufficient to reinforce investment in later stages, which is more affected by the increase in family size. In particular, families where fertility increases the most are those in which parents reduce the time spent with their children the most, as shown in **Figure 5 Panel E** for middle childhood and **Panel F** for later childhood.

Changes in monetary investment in early and middle childhood:

Figure 6 shows the trend in parental monetary investment in children's human capital (in thousands of USD) across the 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 income distribution. The introduction of paid leave decreases investment for families in the lower half of the distribution, both in early and late childhood, while it does not affect investment among higher-earning households. Families at the bottom of the distribution experience a significant increase in fertility, which generates a quantity-quality trade-off. Moreover, they face financial constraints and cannot afford to maintain the same per-child investment after having more children.

Consequences for human capital:

Figure 7 Panel A presents the trend of child human capital accumulated up to the latest stage of childhood across the income distribution and how it varies following the introduction of paid leave policies. The stock of child human capital is increasing in income although not monotically because, by construction children of higher educated parents tend to have higher human capital than children from less educated families even if the latter have higher income ($\delta_{CG} > \delta_{HS}$). 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 7 Panel A** present the magnitude of such loss in human capital reporting the percentage change compared to the baseline scenario in absence of paid leave. The main loss of human capital for children across distribution occurs for the first tercile, particularly the third decile where greater fertility translates into a 10 percent reduction in child human capital through lower parental investment. In contrast, the human capital of children in the top income tercile drops by less than 2.5 percent, although the fertility response for this group is also significant.

5 Discussion

This paper examines the role of paid parental leave policies in influencing fertility and child human capital, highlighting how these effects vary across different income levels. The findings suggest that a policy experiment expanding California's Paid Family Leave (PFL) to a national level results in increased higher-order births, concentrated at the bottom and top of the income distribution. Notably, adults in the lowest income tercile experience the largest increase (16 percent), followed by those in the top tercile, where birth rates grow by 11 percent. These results suggest that paid parental leave policies boost fertility rates by effectively relaxing financial constraints for low-income individuals and time constraints for higher-earning parents. In line with the empirical literature, the effects occur entirely at the intensive margin of fertility (Golightly and Meyerhofer (2022), Bassford and Fisher (2016)). This suggests that paid leave does not encourage otherwise childless women to transition into motherhood but rather induces mothers to have additional children. The results indicate that fertility overall increases by 9 percent. This effect is large and may be inflated by the fact that the model does not capture a child penalty mechanism through experience accumulation during work and experience depreciation while off work, which might constitute a disincentive to have multiple children even in the presence of paid leave (Kleven et al. (2019)). Future directions of this study should incorporate such mechanism.

The model indicates that the policy's impact on fertility generates a quantity-quality trade-off that negatively affects children's human capital, which accumulates across childhood. Although family size increases at both ends of the distribution, parental investment drops significantly more among lower-income parents, as they lack the financial resources to maintain the same level of per-child investment after their family size increases. As a result, the loss of human capital for children in the bottom tercile of the income distribution ranges between 3 and 10 percent. In contrast, higher-earning parents who experience growing fertility rates as a result of the policy

implementation respond to larger family size with a more moderate reduction in per-child investment. Consequently, the human capital of children in the top income tercile drops by less than 2.5 percent. Overall, this reinforces existing disparities between income groups.

This model has several limitations that I plan to address in future iterations. Here, I present the two main shortcomings and plans for improving the model.

First, to increase model tractability, I have simplified the birth process by assuming that multiple children are born within a five-year period and that birth decisions occur simultaneously. This assumption affects parents' decisions regarding time and monetary investments in each child, as multiple children directly compete for parental resources and each child receives the same amount of attention. A more realistic model would allow for child spacing and distinguish between the quantity-quality trade-off caused by lifetime income constraints (affecting siblings with different ages) and that caused by temporary budget constraints (arising from having multiple children of similar ages requiring similar investments at the same time). Although incorporating endogenous fertility decisions over multiple periods would significantly increase the model's complexity, it would better capture the dynamics of parental decision-making regarding fertility and resource allocation.

Second, the current model implies that only the primary caregiver is entitled to either paid or unpaid parental leave. While traditionally this policy was reserved for mothers (i.e., maternity leave), the format has progressively evolved into a more inclusive model where both parents are eligible for parental leave allowances. To account for the endogenous division of leave take-up between caregivers without dramatically increasing the state space, I plan to integrate an endogenous allocation of leave between mother and father in the policy experiments. This will involve maintaining a vector of limited dimensions for parental leave take-up decisions in the baseline sce-

nario, assuming only the primary caregiver is entitled to job-protected parental leave. After calibrating the parameters and validating the model, I will modify the vector of time investment decisions in the counterfactual scenario with mandated parental leave policies to account for combinations of maternal and paternal leave take-up.

6 Conclusions

This study develops a life cycle model, calibrated to the US economy, to examine the impacts of paid parental leave (PPL) policies on fertility and child human capital. By incorporating heterogeneous agents and a detailed demographic structure, the model evaluates the policy's distributional effects on fertility and child development.

The findings highlight the crucial role that heterogeneity plays in shaping PPL's effects. While fertility rates rise by an average of 9% across income groups, the increases are most pronounced among lower-income families, who already exhibit higher baseline birth rates, and higher-income families, who initially have the lowest fertility rates. These results suggest that PPL policies alleviate financial constraints for less wealthy parents, encouraging additional births, while also reducing the opportunity cost of time for higher-income parents, incentivizing family expansion.

However, because the increase in fertility happens at the intensive margins, the policy introduces a trade-off between quantity and quality. Larger family sizes dilute the resources available for investment in each child. Although paid leave supports greater parental time investment in newborns, benefiting early child development, the compensation is insufficient to maintain pre-policy levels of per-child investment throughout childhood. This effect disproportionately impacts low-income families, leading to greater declines in child human capital (up to a 10% loss), while higher-income families experience only moderate reductions (around 2.5%).

These findings underscore the need to consider heterogeneity when designing family policies. While PPL policies can effectively boost fertility, they may also exacerbate disparities in child outcomes unless complemented by measures such as targeted parental investment support or income-based assistance. Future research should build on this framework by exploring alternative paid leave policy designs that simultaneously promote fertility and preserve investments in child development.

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7 Appendix

7.1 Appendix A

Time investment calibration

To approximate the time that a parent would invest in her child human capital while on parental leave, I refer to the average time non-worming women spend with their children on a week day. **Table 1** distinguishes between the time working and non-working women spend with their newborn (child under 2) and **Table 1** reports the average time fathers spend with the new born (under 2 year old) and the amount of time mothers and father spend with their children between three and 5 years old. It implies that women not working spend with their children 1.61 the mount of time spent by women working full time. I use this measure to approximate the time a child receives as time investment from a parent on leave.

In the model, the choice of time investments is defined differently in early childhood compared to the middle and late stage of childhood. In early childhood (ranging from the birth to the child to the fifth year), the primary caregiver chooses how long before returning to work. Time investment in the newborn during the leave is calibrated using the data average of time investment in children under two by women non-working [9] (the data suggest it to be 5 h 27 minutes, see **Table 1**) weighed by the number of weeks of leave. For the remaining time between the end of the leave and the second year of birth of the child, I calibrate time investment as the average time a full-time working mothers report to spend with their children (i.e. 3 hours and 23 minutes). Fathers' time investment in the new born/toddler is fixed and calibrated according to the average in the data of 2 hours in a day. After the first two year and before a child will schools at age 6, parental time investment is exogenously calibrated using the data

[9] I identify women not working as those reporting less than 300 hours of work when their child is under 3 years old.

averages reported in **Table 1**). To clarify the calibration of time investment in early childhood, let PL being the number of weeks the primary caregiver takes off work to look after the new born, and τ_{PL} the number of hours spent with the child during the leave. Being a model period equivalent to five years, the first two years of childhood correspond to $\frac{2}{5}$ of model period. Maternal time investment after the leave is calibrated as the time a full time working mother spends with a child under three years old, τ_W. Maternal time investment in the first two years of childhood is given by:

$$t_{m_{0-2}} = PL \cdot \tau_{PL} + (\frac{2}{5} - PL) \cdot \tau_W \tag{17}$$

Father's time investment in the first two years is fixed as the average in the data $\tau_{f_{0-2}}$. Therefore, the total time investment a child receives in the first two years of life is the sum of maternal and paternal time investment.

$$t_{0-2} = t_{m_{0-2}} + \tau_{f_{0-2}} \tag{18}$$

In the remaining 3 years, $\frac{3}{5}$ of period, time investment in children is equal to the average parental time in the data. Time is split between mother and father using the shares α_m and α_f computed in the data for early childhood investment and reported in **Table 1**. These shares are reported in **Table 1**). Let us call τ_{p_e} the total amount of time a child spends in a regular day with either or both parents, then maternal time $\tau_{m_{3-5}}$ and paternal time $\tau_{f_{3-5}}$ are respectively:

$$\tau_{m_{3-5}} = \alpha_m \cdot \tau_{p_e} \cdot \frac{3}{5} \tag{19}$$

$$\tau_{f_{3-5}} = \alpha_f \cdot \tau_{p_e} \cdot \frac{3}{5} \tag{20}$$

Time investment for a child at kindergarten age (three to five years old), t_{3-5} , is equal to:

$$t_{3-5} = \tau_{m_{3-5}} + \tau_{f_{3-5}} \tag{21}$$

And the total time investment in early childhood t_e is defined by equation

$$t_e = t_{0-2} + t_{3-5} \tag{22}$$

Time investments in the second and third stage of childhood, t_m and t_l respectively, are calibrated similarly to time t_{3-5}. In these periods, time investment corresponds to the the total amount of time τ_{p_e} either or both parents spend with their child and this amount is allocated among the two parents using the data-calibrated shares:

$$t_i = \alpha_{f_i} \cdot \tau_{p_i} + \alpha_{m_i} \cdot \tau_{p_i} \quad \text{with} \quad i \in \{m, l\} \tag{23}$$

The values of α_{g_i} are also reported in **Table 1**.

7.2 Appendix B

7.3 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,

$$P^* = \arg\min_P \left(M(P) - \hat{M}\right)^T W^T W \left(M(P) - \hat{M}\right) \tag{24}$$

This minimization task is conducted numerically using the Limited-memory Broyden, Fletcher, Goldfarb, and Shanno (L-BFGS) optimization method. This is a second-order optimization algorithm and belongs to a class of Quasi-Newton methods. It approximates the second derivative for the problems where it cannot be directly calculated.