Competing for Mothers in the Labor Market*

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January 8, 2024

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Abstract

A defining feature of female career paths is the "child penalty," a persistent drop in employment, hours, and earnings following childbirth. To distinguish between the extensive and intensive labor supply dimensions of the earnings penalty, I estimate a general equilibrium search model featuring more productive firms relying more on longer hours and asymmetric information over women's preferences for time at home after birth. The model rationalizes the child penalty and shows that the intensive margin is a significant determinant of the long-run wage penalty. A maternity leave policy provides a short-run retention gain for low-income workers but fails to narrow the gender wage gap because firms respond to the policy by offering lower wages.

*I extend my warmest thanks to Alberto Bisin, Guillaume Fréchette, and Kevin Thom, for their invaluable guidance and continued support throughout this project. My paper has benefited tremendously from comments and discussions with Tslil Aloni, Pierre Bodéré, Ludivca Ciasullo, Chris Flinn, Jimena Galindo, Guido Menzio, Guillaume Nevo, and Paolo Varraso.

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1 Introduction

The arrival of a child is associated with lasting changes in labor market outcomes for new mothers across the world. Fathers, however, remain largely unaffected. In the US, around one in four mothers leaves their pre-birth employer at childbirth, and those who stay employed reduce their weekly hours by around 15%. The initial drop in employment and earnings is long-lasting: even 10 years post first birth, employment is 25% lower and earnings are 30% lower. This phenomenon, referred to as the "child penalty", is the most important factor in explaining gender inequality. Kleven et al. (2019) show child penalties explain 80% of the gender earnings gap in Denmark, and Kleven (2022) establishes that they explain 90% of the employment gap and over half of the earnings gap in the US.

Periods of non-employment surrounding childbirth can significantly disrupt the career trajectories of new mothers. Moreover, by opting for jobs with reduced hours, working mothers may face a different wage progression. This paper provides a novel framework for evaluating the extensive and intensive labor supply margins of the earnings penalty. Distinguishing between the two channels is crucial for understanding why certain policies such as parental leave provision have not been very effective in reducing earnings penalties.[1] In practice, the separation of the two channels is challenging, given that the decision to temporarily leave the workforce due to childbirth is rarely random. Pre-birth income is extremely predictive for the retention of mothers around birth, as I show in Section 2.3. Further endogeneity concerns arise because employment decisions, wages, and hours worked are pinned down jointly in equilibrium. Therefore, I build a model that accommodates earnings differences stemming from both sources, periods of non-employment, and changes in working hours.

More specifically, I develop a general equilibrium search model in which a job is the combination of income, hours, and parental leave. The model features workers who differ in how they trade off income and time spent at home. Females are affected differently by birth than males. Following the birth of a child, new mothers may be unwilling or unable to work for some period of time, creating a motive for quitting their jobs and an incentive for firms to offer parental leave as a means of retaining their workforce. Additionally, new mothers place a higher weight on time at home, which leads them to accept lower wages in exchange for reduced working hours. Firms optimally choose job characteristics, resulting

[1] See Rossin-Slater (2017) for a summary of parental leave policies and their impacts.

in mothers facing a different wage ladder from non-mothers. The increased weight on time at home upon birth serves as a way to capture how the arrival of a child changes the value of time. It encompasses various factors, including within-household negotiations, child care demands, cultural norms, and other institutional influences, and does not purely reflect a shift in personal preferences.

Firms vary in their productivity level, and differ in how hours enter their production function. This allows some firms to rely more heavily on long hours to produce effectively, as suggested by Goldin (2014). For example, a manager's presence may be required throughout all hours for the firm to function smoothly, while lower-level positions may be less reliant on full-time work. The shape of the production function governs how willing a firm is to provide a lower hours contract to mothers: the more "convex" the production function, the more costly is a low hours contract. Firms also choose whether to offer parental leave as part of their job package. Naturally, a highly productive firm loses more profit if a new mother quits, creating larger returns to leave provision.

In terms of market structure, firms post their job offers, and workers randomly find these offers while searching for a job, both in unemployment and on-the-job. A female worker's weight on money versus time at home is private information. Hence, the firm does not know how a woman will value a job at the time of writing a take-it-or-leave-it job offer. To solve this asymmetric information problem, I allow firms to post multiple jobs. Upon meeting, the worker chooses the preferred job on the list. Firms thus write type-specific incentive-compatible contracts with a lower hour option for mothers. A natural way to think about this framework in real life is that firms may advertise multiple positions on their website or elsewhere, and a candidate selects which position to apply to.

Estimation follows in two steps. In the first step, I estimate "gender neutral" parameters using CPS data from the early 1990s. I estimate the search frictions, productivity distribution, and the marginal product of hours in the production function to match male transition rates, wage and hour quartiles, and the relationship between hours and wages in the data. In the second step, I estimate parameters related to changes around birth using the National Longitudinal Survey of Youth 1979 (NLSY79), complimented by moments from the Survey of Income and Program Participation (SIPP). The NLSY79 has the unique advantage of recording fringe benefits offered by employers, including parental leave.[2] This allows me to

[2]The access to leave in the NLSY79 is defined as the availability of maternity or paternity leave that would allow a worker to return to their pre-birth job or one that paid the same.

quantify access to parental leave in the data, which is very unevenly distributed: whereas over 90% of females in the top income quartile had access to parental leave, only 40%-50% of females in the bottom quartile had access. I exploit the panel structure of the data-set to show that both pre-birth income and access to parental leave are extremely predictive for whether a new mother chooses to stay with their pre-birth employer after the birth of their first child. These empirical findings highlight the importance of modeling endogenous leave provision and worker retention choices at birth. For estimation, I simulate model-implied retention and child penalties and match them to their data counterparts. I pin down the change in the value that females place on time at home post birth, and how long females are unwilling to work post birth by targeting what type of jobs are left behind, how long it takes for mothers to return to paid work, and how strongly working mothers reduce their hours post-birth.

The model is targeted to match the drop in earnings and hours in the year of birth, whereas the longer-run dynamic response emerges from the model. I successfully replicate an hours penalty that remains constant over time, and a wage penalty that opens up over time. The widening wage penalty is driven both by extensive and intensive labor supply decisions. First, the cost of job loss is larger for women who stay non-employed for an extended period of time, because they would have continued to climb the job ladder in the absence of childbirth. When those women reenter paid work, they raise the average wage penalty. Secondly, mothers place a higher weight on time at home relative to non-mothers, which results in them facing a flatter wage ladder than non-mothers. The largest wage difference is observed at top firms, so as women progress in their careers and move to more productive firms, they fall behind further.

I use the model to quantify the importance of the hours decision in generating child penalties. I isolate the role of the intensive labor supply margin by eliminating periods of non-employment due to having a child. I resolve the model assuming no excess job destruction due to childbirth, revealing that a significant portion of the child penalty can be attributed to increased weight mothers place on time spent at home. Within the model, this weight change explains 71% of the wage penalty and 76% of the hours penalty.[3] This counterfactual highlights that the introduction of extremely generous leave policies, aimed at improving job continuity at birth, cannot be the sole solution to closing the gender wage

[3]Given the absence of human capital in my model, I closely match the wage penalty observed in the data for the first three years post-birth, but undershoot the long-run penalty: the model explains 60% of the long-run drop eight years post birth, and the value change thus contributes to 40% of the total wage penalty.

gap. The arrival of a child entails a persistent change in how female hours are allocated, and this imbalance in hours allocation plays a critical role in explaining long-run gender gaps.

I further quantify the role of asymmetric information in my model. Firms cannot observe the weight a female places on time at home versus money, leading them to solve an incentive compatibility problem. Mothers place a higher value on time spent at home, and thus require larger wage increases to accept jobs with longer hours. This makes providing utility to mothers without creating profitable deviations for non-mothers, who prefer working less for similar pay, challenging. This effect is particularly pronounced at the top where production relies on long hours. To create work incentives for non-mothers, firms distort the job contracts. The perfect information benchmark reveals firms do so by lowering hours for both mothers and non-mothers, and by increasing the child penalty in wages.

Finally, I analyze the impact of the US Family and Medical Leave Act (FMLA) through the lens of my model. The FMLA was introduced in 1993 and is a federal act mandating that firms provide employees with twelve weeks of unpaid, job-protected leave for care-taking and medical reasons, functioning primarily as unpaid parental leave. I implement a parental leave policy within my model,[4] and generate results consistent with the empirical literature. The leave policy increases attachment to the pre-birth firm by 7 percentage points, but these employment gains fade out within a year. These effects are of similar magnitude as found in Waldfogel (1999*b*) studying the FMLA. The policy does not reduce the child penalty because the policy preserves jobs of mothers at the bottom of the income distribution, who in the absence of the policy would have returned to work fairly quickly. Those low-income jobs are not associated with a large wage penalty.

Additionally, firms respond to the policy by offering lower wages, especially for mothers. This finding is consistent with the findings of Blair & Posmanick (2023), and is related to Thomas (2016), who shows firms promote women less following the FMLA introduction. The model-implied increase in the longer-run wage penalty is modest, at 0.5 percentage points eight years post birth. While failing to reduce the child penalty, the policy has few overall welfare effects, with the expected lifetime utility of a female entering the labor market essentially unchanged. Nonetheless, a utility redistribution occurs toward expectant mothers working in low-income jobs. This observation highlights that despite a lack of positive effects on long-term labor market outcomes, the policy successfully insures expectant

[4] The FMLA is subject to specific conditions such as a year of tenure, and working at least 20 hours per week. I impose the hours restriction in my model, but cannot implement the tenure restriction.

mothers against adverse outcomes. This raises the question of the intended outcomes of leave policies, because they can assist vulnerable populations without necessarily addressing gender disparities.

Literature. The literature on gender gaps in the labor market is vast and spans many fields within economics. For a comprehensive summary, see Blau & Kahn (2017). I contribute to three strands within this literature.

First, and most importantly, I contribute to a literature that uses equilibrium search models to study gender gaps. Morchio & Moser (2023) use Brazilian data to show that women place relatively more weight on amenities than men. These amenity differences are found to be important for rationalizing the gender pay gap. Most closely related is Xiao (2020) who use Finnish data and write a search-and-matching model featuring human capital, amenities, and stochastic fertility. They find that shifting parental leave to men significantly lowers the wage gap. Amano-Patiño et al. (2020) allow for differences in turnover behavior between genders, human capital, and stochastic fertility, and also use NLSY79 data. Within the first two papers, amenities are considered to be a bundle of non-pay job characteristics. I explicitly model two key dimensions of amenities, namely hours and parental leave. Directly modeling hours is critical for separating the component of the earnings gap that is due to reduced labor intensity, from a reduction in hourly wage rates. I further innovate by allowing for endogenous retention of workers around birth, and endogenous leave provision.[5]

This paper is also closely related to Carry (2022), who directly models the hours margin in a search-and-matching framework and allows firms to differ in productivity and their need for long hours. The focus of their paper is to analyze the gendered effect of a minimum workweek in France, whereas I focus on the gendered effect of childbirth, additionally incorporating fertility and on-the-job search. The paper further relates to the broader literature on explicitly modeled amenities in search models, relating to work by Dey & Flinn (2005) on health insurance, Le Barbanchon et al. (2021) on commuting costs, and Jarosch (2023) on job security. Finally, I add to the literature on asymmetric information in search models (see e.g. Guerrieri et al. 2010 and Carrillo-Tudela & Kaas 2015).

Second, this paper is related to a large empirical literature on the impact of birth on labor market outcomes. For example, Kleven et al. (2019) assess child penalties in Denmark, finding that they explain the vast majority of the total gender earnings gap. Additionally,

[5] As I show in section 2.3, staying employed around birth is strongly affected by the attributes of the pre-birth job, and accounting for the selectiveness in exit out of employment is crucial for policy counterfactuals.

women are less likely to become managers and are more likely to work in a public sector job post-birth. Albrecht et al. (2018) show that among high skilled workers in Sweden, wage growth strongly declines for women but not men after first childbirth. This divergence does not stem from gender differences in mobility, but from men experience larger gains both from staying at and switching firms. Andresen & Nix (2022) study differences between adopting, heterosexual non-adopting, and same-sex couples. They rule out biological factors as the main driver of child penalties, as the long-term effect of childbirth is similar across adopting and non-adopting heterosexual couples. Among female same-sex couples, both partners are equally affected by childbirth in the long run. Ciasullo & Uccioli (2022) exploit a labor law reform in Australia that allows workers to ask for more regular, predictable schedules. Mothers that have access to this arrangement work more and experience smaller employment and hour penalties in the years following birth.

Third, this paper contributes to the literature evaluating the relationship between parental leave access and female labor outcomes. The literature is mostly empirical, with a detailed overview given by Rossin-Slater (2017). Schönberg & Ludsteck (2014) exploit maternity leave expansions in Germany, uncovering a negative short-run effect on employment but almost no longer-run effects. Kleven et al. (2020) exploit maternity leave expansions in Austria, and do not find any long-run effects on child penalties. Lassen (2022) shows that a parental leave reform in Denmark increased leave-taking of mothers while leaving fathers unaffected. They further find that the relative earnings potential within a couple does not drive child penalties, whereas gender identity plays an important role. Waldfogel et al. (1999) compares the US, UK, and Japan, concluding that parental leave coverage increases job continuity around birth in all three countries. Olivetti & Petrongolo (2017) perform a cross-country comparison illustrating that short job-protected leave entitlements are beneficial for female employment, with positive effects driven by low-skilled mothers.

As for US policies, a number of papers study the introduction of the FMLA, finding a positive effect of the FMLA on leave coverage and job continuity around birth (see e.g. Waldfogel 1999*b*, Hofferth & Curtin 2006). Blair & Posmanick (2023) evaluate the long-run effects of the FMLA concluding that it led to a slowdown of the gender wage convergence. Rossin-Slater et al. (2013), among others, study the introduction of paid leave in California in 2004, and document an increase in leave-taking. They find a positive impact on hours of working mothers in the medium run. Bana et al. (2020) also analyze the introduction of paid leave benefits in California using a regression-kink design. Higher benefits do not increase maternity leave duration nor labor force attachment among women near the kink.

Bailey et al. (2019) assess the long-term effects of the California policy change also using administrative data, revealing a negative impact on employment and income for first-time mothers in the longer-run.

Finally, I wish to highlight two papers that investigate parental leave policy reforms through the lens of a model. Thomas (2016) sets up a signaling model in which today's hours reveal information about future hours. Maternity leave weakens the signal, leading to an increase in employment and a decrease in promotions. These predictions are supported by the data, as the FMLA reduced the probability of females getting promoted. Tô (2019) also writes a signaling model in which parental leave duration reveals willingness to work in the future. The model predicts that an extension of leave duration will lead to an increase in earnings inequality as more workers reveal their type. The effect of a parental leave reform in Denmark offers support for this theory. Both models are stylized, featuring a two-period horizon that sheds insight into the impact of informational asymmetry on female outcomes. This paper offers an alternative margin through which asymmetric information may affect workers: firms may separate worker types by offering job bundles of varying hours and wage combinations. The quantitative nature of my model also allows me to explore long-run effects, assess counterfactual policies, and perform welfare analysis.

Outline. The remainder of the paper is organized as follows: Section 2 describes the data and empirical analysis. Section 3 sets up the model. Section 4 discusses the estimation and model fit. Section 5 includes a decomposition of the child penalty, and a policy counterfactual. Section 6 concludes.

2 Empirical Analysis

This section serves a dual purpose. Firstly, it provides essential insights into the historical context of the late 1980s and early 1990s. These insights are paramount for guiding modeling decisions aimed at developing an appropriate framework for studying female labor market outcomes around childbirth. Secondly, it calculates key data moments that will play a pivotal role in identifying the parameters of interest in the subsequent stages of the analysis.

2.1 Data

To establish empirical patterns, I use data from the National Longitudinal Survey of Youth 1979 (NLSY79), a panel study tracking a representative cohort of US men and women born between 1957-1964. The NLSY79 provides detailed labor market histories over the life-cycle starting from the year 1979, and most importantly, contains information on fringe benefits including parental leave coverage. The purpose of this analysis is to quantify how leave coverage is distributed among workers prior and post the introduction of the 1993 federal law mandating parental leave. This section further establishes the importance of leave coverage for retention at birth. These data moments not only are crucial in informing modeling decisions, but are also used to identify model parameters, as outlined in section 4.

My sample of interest are mothers and fathers aged 22-45 at the birth of their first biological child. I focus on labor market outcomes around the child's birth date, in particular, four years prior to eight years post birth. I restrict the minimum age at first birth to 22 to observe pre-birth labor market histories. The event studies rely on estimating fixed effects off pre-event periods and comes at the expense of omitting young mothers and fathers from my sample.[6] I further exclude workers that are self-employed prior to first birth. I end up with a sample consisting of 2773 mothers and 2504 fathers who have their first birth within the sample.

Parental leave access is recorded among a wider set of fringe benefits, and is phrased as: "Does your employer make available to you maternity/paternity leave that will allow you to go back to your old job or one that pays the same as your old one?" The question was added to the survey in 1985 and until 1993 it was only recorded for the "CPS job" (most recent job) conditional on the worker working at least 20 hours per week. For the period 1985-1993, I am able to infer leave coverage during pregnancy for 83% of workers using this measure, and for the remaining 17%, I code up leave coverage as unknown.

I consider a variety of labor market outcomes which are defined as follows unless otherwise stated: monthly employment (any job held in month), weekly income (usual income conditional on working), weekly hours (usual hours conditional on working), wages (weekly income divided by weekly hours). When it comes to the employment status, I differentiate between being employed (with a job, either working or on paid leave), or non-employed

[6]The fraction of births observed in the sample with first-time parents aged less than 22 is 37%. Kleven 2022, for example, restricts the age of first birth to be 25 for the same reason in all three datasets they study (NLSY, PSID, CPS).

(a) Female Leave Access (b) Male Leave Access

Figure 1: Parental Leave Access by Income Quartile and Over Time

Notes: Sample of workers restricted to working at least 20 hours per week, as information on parental leave collected only for workers working at least 20 hrs prior to 1993 and selectively for lower hour jobs thereafter.

(without a job, either unemployed or not in the labor force).

2.2 Parental Leave Access in the US

Information on detailed fringe benefits in a panel study setting is scarce, and the NLSY79 provides a unique opportunity to evaluate access to parental leave over time, and across the income and hours distribution. As a first step, I show the extent to which high-income and high-hours jobs are more likely to provide parental leave benefits than low-income jobs. In a second step, I examine how the Family and Medical Leave Act of 1993, the first federal regulation mandating 12 weeks of unpaid leave for those covered, has impacted access.

To establish the relationship between earnings and parental leave access over time, I compute weekly income quartiles separately by age, year, and gender. A worker in the top income quartile in 1990 means that they are among the top 25% of earners of their age group and gender. I then plot average leave access for each quartile, shown in Figure 1. A large gradient between above and below median income jobs emerges. This gradient is especially pronounced for females, with those in the bottom income quartile having around $40 - 50$ percent points less access.[7] The extent of difference in access recorded here is likely a lower

[7]This positive association between pay and non-pay benefits also holds more generally, as higher-paying jobs tend to offer more generous benefits, including health insurance and paid vacation. See Appendix A

bound, as the NLSY does not record the length of parental leave that workers are entitled to. The second observation is that males are much less likely to have access to paternity leave than females do to maternal leave. Since males to this day have very low take-up of parental leave, this gender difference will not be the target of the analysis.

Access to parental leave is also unevenly distributed by hours worked, with full-time jobs offering leave at higher rates. Figure 2, shows the relationship between weekly hours and access through a local polynomial regression for the years 1985-1992, i.e. prior to the introduction of any federal leave policies. The steepest gradient is observed just below the full-time threshold of 35 hours per week: Among women usually working 30 hours per week, one in two has access to parental leave, while among those with just over 35 weekly hours, only one in four does not have access. Interestingly, females who work especially long hours are less likely to have access to parental leave than those that work typical full-time hours. The analysis so far has been descriptive, but the strong positive association between leave access, hours and income is robust to jointly controlling for hours and income, and the inclusion of relevant controls, such as age, tenure, and individual fixed effects. For further analysis, see Appendix A Table 4.

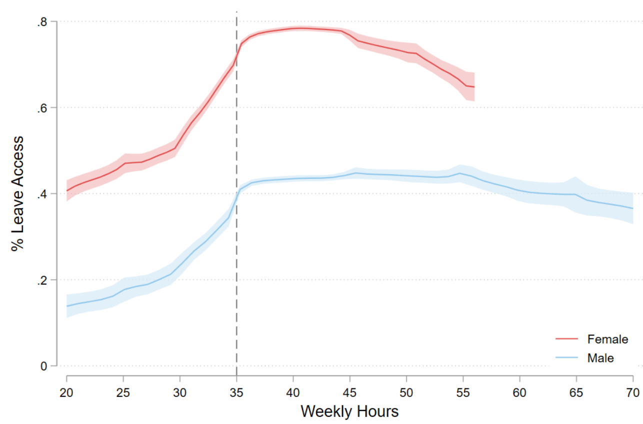


Figure 2: Relationship between Weekly Hours and Parental Leave Access

Notes: Sample years 1985-1992. Sample of workers restricted to working at least 20 hours per week. Hours top winsorized at the 2-percent level by gender.

I now turn to analyzing the Federal Medical and Family Leave Act (FMLA), enacted in February 1993.[8] The FMLA was the first federal act governing parental leave.[9] The act

Figure 14 for health coverage access by income over time.

[8]See additional information on the law by the Department of Labor here.

[9]11 states and the District of Columbia had job-protected maternity laws before 1993 of varying generosity.

granted eligible employees the right to take up to 12 weeks of unpaid, job-protected leave for specific family or medical reasons. The FMLA applied to both public and private sector employees, covering those who work for employers with 50 or more employees within a 75-mile radius and have been with their current employer for at least 12 months, having worked at least 1250 hours in the past year. This is roughly equivalent to working about 24 hours per week for 52 weeks. The act aimed to provide job security and flexibility to employees, particularly new parents, by allowing them to balance their work responsibilities with their family needs without the fear of losing their jobs.

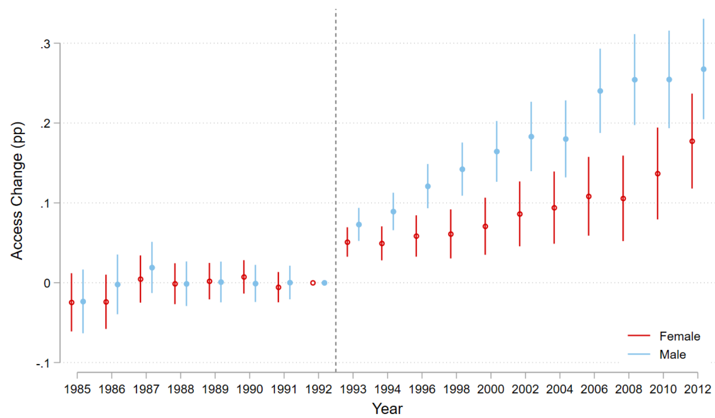


Figure 3: FMLA Event Study

Notes: Includes income, tenure, and hours controls, and education, age, and individual fixed effects. Standard errors are clustered at the person level. Sample restricted to workers with at least 20 weekly hours due to data availability.)

Perhaps surprisingly, females with top incomes were almost fully covered prior to the FMLA already. Figure 1 reveals a large increase in coverage among working males, with smaller effects for women. To investigate this more carefully, I run an event study with controls for hours worked, and individual and age fixed effects, among other controls, to determine the coverage effect net of changes in the labor market composition.[10] Figure 15 shows a modest initial increase in coverage for women of around 5 percent points. Relative to the baseline coverage rate in 1992 of 72% for females, this is a 7% increase in coverage. The rise in coverage for males is more drastic, which is natural given a baseline coverage of only

Waldfogel (1999*a*) shows that states with prior laws experienced larger increases in coverage following the introduction of the FMLA than states with no prior laws, suggesting that state laws and the FMLA may be complementary.

[10]This is particularly important in the context of the 90s, at it many welfare reforms affecting low-income workers such as the introduction of TANF and changes to the EITC were enacted during that period.

40%. Interestingly, coverage continues to increase well beyond 1993, particularly so for men, but the causes cannot be established within the NLSY. Potential explanations include firms moving from gender-specific parental leave rules to non-gendered parental leave benefits, a higher salience of the FMLA, or the additional introduction of state-wide policies.

2.3 Selective Exit at Birth

Having established the discrepancy in parental leave access across the income distribution, I now shed light on the importance of parental leave access and other pre-birth job characteristics for employment decisions around birth.

Among first-time mothers that are employed during pregnancy, one in three leaves their pre-birth employer and moves into non-employment in the months around birth. I define a first-time parent as a stayer if they are employed or associated with an employer the month prior to birth to two months post birth.[11] Conversely, a new parent is a leaver if they experience at least one month in which they are not associated with any employer. Importantly, within my definition staying mothers can take parental leave, but have to return to their pre-birth employer after this leave period. In the early 80s, the period that most in-sample births fall in, these leave periods of stayers are very short, with the median duration being 7 weeks.[12]

Whether a new mother is a stayer or leaver is highly dependent on the features of their pre-birth job. Figure 4 shows a strong positive relationship between pre-birth income and the staying decision using a local polynomial regression. The running variable is the highest weekly income recorded during the pregnancy period, expressed in 1990 US dollars. This is plotted against the probability that a worker stays employed around birth. Very few mothers with high pre-birth incomes leave employment around birth. At the top of the distribution around 90% are stayers. The graph is shown also for fathers, as a comparison. Workers with low incomes typically experience more frequent employment-to-unemployment transitions, which can explain the slight positive slope observed even for fathers.

To understand the importance of parental leave for retention at birth, I run a probit regression, controlling jointly for pre-birth income, pre-birth hours, and parental leave cov-

[11] The NLSY records within-job gaps for each employment spell. Those gaps can arise due to unpaid leave or temporary layoff, among other things. I use this measure to establish "association" with an employer.

[12] In the context of other countries with much more generous leave policies, a different definition may be more appropriate, as employment interruptions typically extend well beyond 2-3 months.

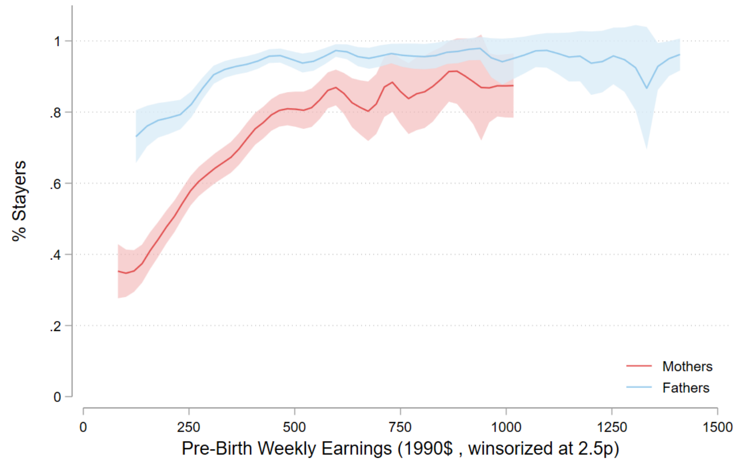


Figure 4

erage in addition to age fixed effects. The outcome variable takes value one if a worker is a stayer, zero if they are a leaver. The marginal effects are reported in 1. Both pre-birth income and access to parental leave are strongly predictive for staying employed for mothers. Having a job that offers maternity leave increases retention of mothers at birth by around 27%. This validates that the NLSY parental leave access measure is economically significant, despite being a simple yes-or-no question. In contrast, parental leave access does not predict retention at birth for fathers.

Table 1: Staying employed around birth - Marginal Effects From Probit

	Mothers		Fathers	
Access to parental leave	0.267***	(0.043)	0.013	(0.014)
2nd Income Q during preg	0.140***	(0.039)	0.086***	(0.025)
3rd Income Q during preg	0.254***	(0.039)	0.148***	(0.023)
4th Income Q during preg	0.343***	(0.039)	0.134***	(0.023)
Hours worked during preg	-0.003	(0.002)	-0.001	(0.001)
Observations	1926		2264	

Standard errors in parentheses

* $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

Notes: Sample consists of mother and fathers with a work history during the pregnancy period. Income quartiles are computed by binning the highest weekly income during pregnancy, separately for mothers and fathers. Whenever leave coverage cannot be inferred, it is coded up as missing and kept in the sample. Probit additionally includes age fixed effects, and year controls.

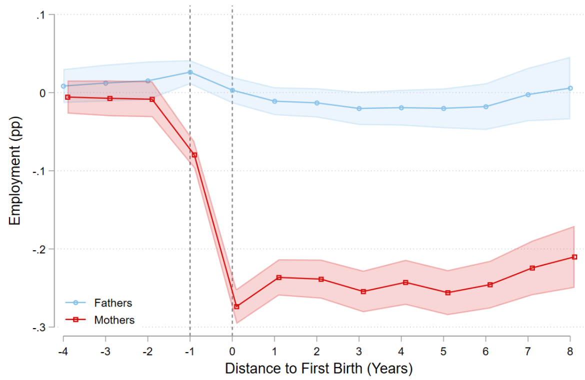
2.4 Event Studies

The extent to which pre-birth job characteristics predict mothers' retention at birth will be instrumental in identifying model parameters related to the effect of birth on labor market outcomes. Similarly, the identification depends crucially on how strongly income and hours fall past birth. I thus carefully estimate child penalties for my sample of mothers. Child penalties are typically reported for employment and total earnings, as they can be computed even if a parent is not in paid work, and if data on weekly hours are unavailable. In addition, these child penalties are easily interpretable, as they do not suffer from changes in sample composition across periods. In my case, the way that paid work measures respond is first order, and I explain below how I approach this estimation.

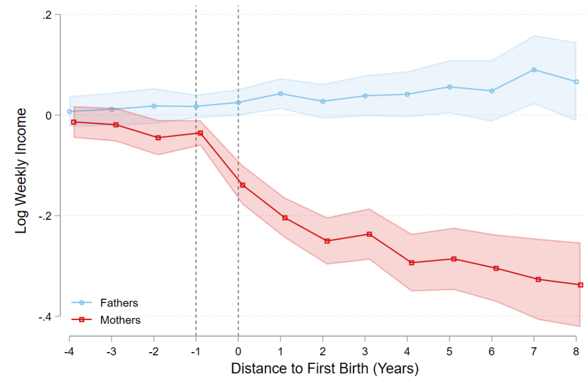
The child penalty quantification originates from the the estimation technique proposed in Kleven et al. (2019), where the dynamic impact of the first child on mothers and fathers is computed using event studies. While childbirth is not randomly assigned, there does not appear to be selection into birth based on pre-birth labor trends, as shown by the absence of pre-trends in the event studies. The event-study approach has additionally been validated using sibling-mix instruments, yielding identical results to the event-study approach (see again Kleven et al. 2019).

The typical event-study specification for child penalties includes age fixed effects to control for naturally occurring trends in labor market outcomes over the life-cycle, in addition to time fixed effects, and event-time fixed effects. These regressions are then estimated separately for mothers and fathers. Intuitively, age effects are estimated off females who have yet to become mothers. This approach is well-suited to study employment and earnings, as these outcomes are observed for all individuals regardless of labor force status. However, when considering outcomes that are only observed conditional on working, composition effects and treatment effects may get confounded, as mothers selectively move in and out of paid work. This makes it crucial to additionally control for individual fixed effects. As pointed out in Borusyak et al. (2023), this leads to an under-identification problem. To address this, I use the estimator suggested by Borusyak et al., which additionally allows for unrestricted treatment heterogeneity.[13] This unrestricted heterogeneity is a desirable property when studying the impact of birth, as exit from the labor market is very much selected on pre-birth earnings for mothers.

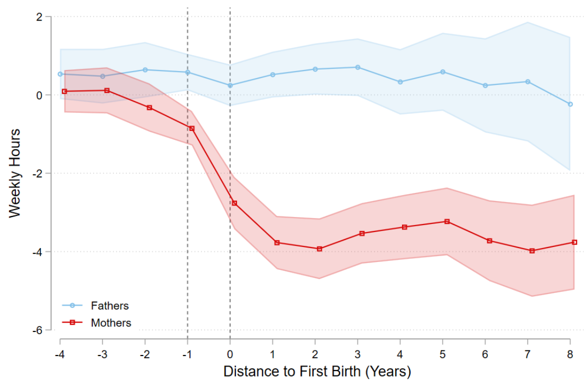
[13]An alternative method would be to include a control group of women who never become mothers, or of similar men, turning the estimation into a difference-in-differences setup.



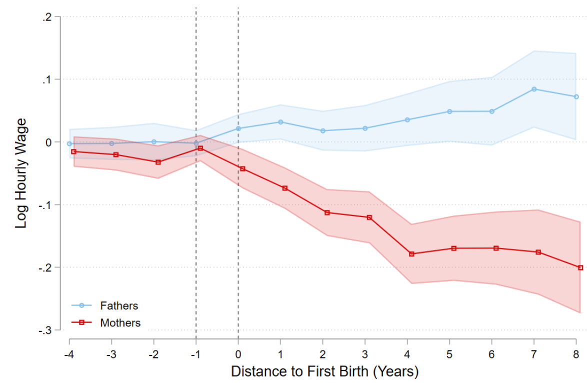
(a) Monthly Employment



(b) Weekly Log Income (cond. on working)



(c) Weekly Hours (cond. on working)



(d) Hourly Log Wages

Figure 5: Employment Outcomes around First Birth

Notes: Ages at first birth 22-45. Sample of workers restricted to at least 10 hours per week. Wages winsorized at the 5p level. Omitted period is 5 years prior to birth.

The imputation estimator has a very intuitive approach: in a first step, it estimates individual, age and year fixed effects off pre-event periods (i.e. prior to pregnancy) according to specification (1) below.

$$Y_{it} = \sum_{a} \sum_{e=HS,SC,C} \delta_{a,e} 1\{age_{it} = a\} 1\{maxeduc_i = e\} + \tau_t + \alpha_i + \epsilon_{it}, \tag{1}$$

where $\delta_{a,e}$ is the age fixed effect for an individual whose education level obtained within their life is e , τ_t is a calendar year fixed effect, and α_i is an individual fixed effect.

Since age trends differ across education levels, I allow for separate age fixed effects for individuals with a high school degree or less (HS), some college education (SC), and a college degree (C). In a second step, the estimator imputes labor market outcomes in absence of birth and computes within-person treatment effect is then computed as the difference between the realized outcome and imputed outcome. In a third step, treatment effects are aggregated to compute treatment effects for every event horizon, which are displayed in the Figures 5.

Selective exit in and out of the labor market makes event graphs for wages and hours warrant caution in interpretation, as for every event horizon, it displays average treatment effects for workers who are in paid work at that horizon. The wage penalty observed in the year of birth (event-time zero), for example, is only computed for the very selected group of mothers who are working in the NLSY survey week following their first birth.

Figure 5 showcases the child penalty estimates for the NLSY79 sample. Mothers experience a persistent drop in the extensive margin (monthly employment), and the intensive margin (weekly hours, conditional on working) upon childbirth, while fathers remain largely unaffected. The size of these penalties is consistent with other estimates for the US (see e.g. Kleven (2022)). Moreover, over time, there is a gradual widening of the income and hourly wage gap for mothers. The model at hand will enable us to explore the underlying factors contributing to this gradual increase in earnings gaps over time. The moments of interest for estimation are child penalties in the year of birth, i.e. event-year zero. These moments are chosen to identify parameters through distinct changes in labor market outcomes upon birth, without confounding factors such as depreciation of human capital, more on that in section 4.

3 Model

In this section, I build a model that can capture the empirical patterns documented above. I develop a random search model with job posting, asymmetric information about females' preferences over time at home, stochastic fertility, and heterogeneous firm productivity. Time is discrete, and workers search both in unemployment and on-the-job. The model can be seen as an extension of Burdett & Mortensen (1998).

3.1 Environment

Population. Workers can be male m or female f, and the economy is inhabited by a measure one of each type. Each period workers permanently exit the labor market with probability γ, which can be thought of as a retirement or death shock. Upon the γ-shock, workers are replaced with young workers of the same gender.

Worker preferences. Workers value money (m) and time at home (l) according to a Cobb Douglas utility function. Flow utility is given by

$$u^i(m,l) = m^{\alpha_i} l^{1-\alpha_i},$$

where α_i is the relative weight a worker places on money. This α_i differs by gender, and is further allowed to change over the life-cycle for women, triggered by the birth of their child. This feature allows me to match the reduction in hours working women experience post first birth.

Fertility. Every period, childless workers experience a child shock with probability q_b. Male workers are unaffected by the arrival of a child, while female workers may be unwilling or physically unable to work post-birth. Upon birth, they randomly draw a "birth type" which pins down whether they undergo a period of unwillingness to work post-birth, and if so, for how long.[14] This type in turn also determines how much they value parental leave. Once a mother is willing to work again, she may place a different weight on money and time at home than prior to birth. The worker problem is detailed more extensively in section 3.2.

Note that workers only have one child in this model, and after the birth of that child their flow preferences are permanently changed, both for simplicity.

Firms. Firms differ in their production technology. There is a measure one of firms with heterogeneous productivity p which is distributed according to the cumulative distribution function $H(p)$. Production is linear in the number of workers, but not necessarily linear in the work-time of a worker. There can be increasing, decreasing or constant returns to an extra unit of time input by a single worker, and these returns are allowed to vary across firms of different productivity levels, according to $\phi(p)$. The flow profit π^p of a firm p from

[14] The strict unwillingness to work assumption is for simplicity. In the next iteration of the model, I will relax this assumption of being entirely unwilling to work in the absence of leave. Workers will draw a stochastic additive flow value of non-employment, allowing workers with higher incomes to be willing to stay in absence of leave at higher rates than those with lower incomes.

filling a job $x = \{m, h, leave\}$, where m denotes income, h denotes hours, and $leave$ denotes provision of parental leave, is given by:

$$\pi^p(x) = \begin{cases} ph^{\phi(p)} - m & \text{if } leave = 0, \text{ or worker didn't experience birth shock} \\ -c & \text{if } leave = 1, \text{ and worker experienced birth shock,} \end{cases}$$

where $\phi(p)$ governs the shape of the production function.[15]. Hence, when a worker is not on leave, they work h contracted hours, and produce $ph^{\phi(p)}$ units of output. When a worker is on leave, the firm does not produce and hence misses out on output, and additionally pays a fixed cost of leave provision c.[16] Parental leave provision is a contingent benefit in this model: $leave = 1$ is the guarantee that the worker is entitled to one period of parental leave in the period of childbirth.

Contracting Environment. I assume that there are separate markets for men and women. Within a market, a firm does not observe the worker's preference type, it is assumed to be private information of the worker. Hence, a firm does not observe whether a worker has a child or not. Rather than posting a wage, the firm posts a menu of jobs $\{x^1, x^2, ..., x^n\}$, where n is chosen by the firm. Conditional on receiving the job menu, the worker picks whichever job gives the most expected lifetime utility among the posted jobs. The easiest way to relate this setting to a real world situation is by considering workers searching for jobs online. With a certain probability a worker comes across a firm's website where all their vacancies are listed, and then chooses among the listed jobs.

Moreover, the worker can change jobs within the firm freely. Hence, if a female worker in the period post birth would prefer a job different to their pre-birth job, they can switch positions within the firm immediately (conditional, of course, on being willing to work).

Consider first the case of perfect information, where the firm observes the flow preferences of any worker it meets. Moreover, allow the firm to write job offers contingent on the worker's flow preferences.[17] A childless female worker's expected lifetime utility from accepting a job

[15]This flexibility is necessary in this model in order to be able to match that high paying jobs are associated with high hours.

[16]In this type of model, production is linear in the number of employees, and there are no capacity constraints. Hence, as long as a position yields positive expected profit in the future, the firm chooses to provide leave at birth in order to preserve the match. In absence of the fixed cost c, this is true for all productivity levels.

[17]In this economy, there are as many flow preferences as there are types of workers that are willing to accept jobs. This comes from the assumption that the workers in the "birth state" reject any job offer in the

at firm p then depends on both the job bundle $\{m_1, h_1, leave_1\}$ that they get with their pre-birth flow preferences, and the job $\{m_2, h_2, leave_2\}$ they would get if they stayed with the firm post childbirth. In this case, the firm will choose to offer a contract for each worker type: (1) contract consistent of one job for male workers: $\{m_m, h_m, leave_m\}$, (2) a contract consisting of two jobs for pre-birth female workers, one for pre-birth and one for post-birth: $\{m_{1a}, h_{1a}, leave_{1a}\}, \{m_{1b}, h_{1b}, leave_{1b}\}$, (3) a contract consisting of one job for post-birth female workers: $\{m_2, h_2, leave_2\}$.

Menu length. Now consider this paper's environment where a worker's type is private information, and firms post job menus. The number of types of jobs a firm can advertise as part of the "job menu" is theoretically unrestricted. In equilibrium, it will be at most be equal to the number of distinct flow preferences in the market.[18] Workers can switch freely across all jobs within a firm. Hence, the worker's current preferred job on the menu is pinned down solely by the within-period ranking of bundles. Note that the environment does not allow for nested menus, and hence firms are not able to offer different contracts to mothers working at the firm prior to birth versus mothers that joined post birth.[19]

Timing of a period. (1) Retirement/death shocks realize. (2) New workers replace retired workers. (3) Birth shocks and associated flow preference changes realize, and transition types out of the birth state are drawn. (4) Non-employed workers contact firms with probability λ_0. (5) Employed workers contact firms with probability λ_1. (6) Workers who contact a firm choose the preferred job on the menu, given there is an acceptable offer. (7) Employed workers can choose to switch jobs within the firm. (8) Workers with access to leave who just experienced a birth shock can choose to take leave. (9) Employed workers separate exogenously with probability δ, employed workers may separate endogenously. (10) Production takes place if the worker is not on leave.

market. Hence, even though there are three different transition types post birth, allowing for type-specific contracts versus flow preference specific contracts is equivalent in this economy.

[18]It could be fewer jobs than preferences if the firm chooses to pool types.

[19]This assumption could easily be relaxed from a modelling perspective. An interesting avenue would be to explore whether firms actually offer different wage and hour combinations to those with pre-birth tenure in practice. To properly identify this, employer-employee matched data would be necessary.

3.2 Worker's Problem

Let's consider the problem of a childless female (type 1) in a firm offering two types of jobs,

$$x_1 = \{m_1, h_1, leave_1\}, x_2 = \{m_2, h_2, leave_2\}.$$

Since we allow the worker to sort into their preferred job within the firm, the worker's flow utility is given by

$$\max\Big\{u^1(m(x_1), l(x_1)), u^1(m(x_2), l(x_2))\Big\},$$

where $u^1(m,l) = m^{\alpha_1} l^{1-\alpha_2}$. Hence α_1 determines how important money is relative to time at home prior to having a child.

The value of working at this firm is then given by

$$\begin{aligned} V_1(x_1, x_2) = &\max\Big\{u^1(m(x_1), l(x_1)), u^1(m(x_2), l(x_2))\Big\} \\ &+ (1-\gamma)\beta \times \Big((1-q_b)\big[(1-\delta-\lambda_1(1-F_1(V_1(x_1,x_2))))V_1(x_1,x_2) \\ &+ \lambda_1 \int_{V_1(x_1,x_2)} \nu dF_1(\nu) + \delta V_{1,0}\big] \\ &+ q_b \sum_i \varphi_{bi} \max\{V_{bi}(x_1,x_2), V_{bi,0}\}\Big). \end{aligned} \tag{2}$$

With probability γ the worker survives in the next period, and evaluates the continuation value at discounts factor β. The continuation value can be split into two cases. In the first case, the worker does not experience a birth shock, which happens with probability $(1-q_b)$. They move to unemployment with probability δ, and get an outside offer with probability λ_1. As in the Burdett & Mortensen (1998) environment, firms cannot make counteroffers, and the worker accepts the outside firm's offer if and only if it promises a higher expected lifetime utility than the current firm. Note that the offer distribution F_1 is specified over the worker type's lifetime expected utility, because that is the object firms compete over as it determines the retention decision.

In the second case, the worker experiences a birth shock. At this point they start trading off money and time at home according to the utility function $u^2(m,l) = m^{\alpha_2} l^{1-\alpha_2}$, where α_2 can differ from the previous weight on money, α_1. New mothers all share the same α_2

conditional on being willing to work, but differ in their willingness to work immediately following birth. I model this "unwillingness" as a shift in the level of the non-employment value.[20] Prior to birth, they are unsure about their demand for time off work, but upon the birth shock this uncertainty realizes. They draw a birth type b_i, associated with a birth value V_{bi}, equation (3).[21]

$$\begin{aligned} V_{bi}(x_1, x_2) =& leave(x_1) \max\Big\{u^2(m(x_1), l(x_1)), u^2(m(x_2), l(x_2)), u^2(m_{res}, 1) + \theta_{bi})\Big\} \\ &+ (1 - leave(x_1)) \max\Big\{u^2(m(x_1), l(x_1)), u^2(m(x_2), l(x_2))\Big\} \\ &+ (1-\gamma)\beta\Big(q_{bi}\max\{V_2(x_2), V_{2,0}\} + (1-q_{bi})\max\{V_{bi}(0, x_2), V_{bi,0}\}\Big) \end{aligned} \tag{3}$$

$$V_{bi,0} = u^2(m_{res}, 1) + \theta_{bi} + (1-\gamma)\beta\Big(q_{bi}V_{2,0} + (1-q_{bi})V_{bi,0}\Big) \tag{4}$$

The birth type b_i is informative about how unwilling women are to work for pay post birth. It determines the size of θ_{bi}, which shows up as a boost to the flow value of non-employment in $V_{bi,0}$, equation (4). It also shows up in type b_i's value of employment in equation (3): if a worker chooses to go on parental leave following birth (conditional on it being offered), they get to consume the flow value of non-employment, $u^2(m_{res}, 1) + \theta_{bi}$. Additionally, b_i governs how quickly a worker returns to "regular" willingness to work post birth, i.e. $\theta = 0$: with probability q_{bi}, the worker transitions to worker type 2, whose value of employment $V_2(x_1, x_2)$ is given by equation (5). Note also that while a worker is a birth type, they do not search in the labor market.

$$\begin{aligned} V_2(x_1, x_2) =& \max\{u^2(m(x_1), l(x_1)), u^2(m(x_2), l(x_2))\} \\ &+ (1-\gamma)\beta \times \Big((1 - \delta_2 - \lambda_1(1 - F_2(V_2(x_1, x_2))))V_2(x_1, x_2) \\ &+ \lambda_1 \int_{V_2(x_1,x_2)} \nu dF_2(\nu) + \delta_2 V_{2,0}\Big) \end{aligned} \tag{5}$$

The full set of value functions is given in Appendix B.1.

[20]Initially, I tried modeling this "unwillingness to work" as a nested case of the utility function by simply allowing *alpha* to change twice. Quantitatively, this didn't generate enough quitting upon birth.

[21]Complete uncertainty over birth types is assumed for simplicity and can be relaxed to where workers have partial or full knowledge over how they will react to birth. Arguably, biological births pose uncertain health risks which can affect the ability of a woman's physical ability to work.

3.3 Firm's Problem

A firm with productivity p maximizes the expected profit obtained from their job menu, subject to incentive compatibility. This expected profit is equal to the sum of profits obtained from each type of worker (pre-child female type 1, post-child female type 2, and male type m), weighted by the probability of each type seeing the post and accepting to work at the firm. Note that a firm's probability of hiring a worker out of unemployment or poaching a worker from another firm depends solely on the expected lifetime utility those outside options give. Firms are competing over utilities, and hence the set of job offer distributions $\{F_1, F_2, F_m\}$, and equilibrium job distributions $\{G_1, G_2, G_m\}$ in the firm's problem can be defined over utilities rather than bundles.

Denote by V_i a worker i's value function in employment, and $V_{i,0}$ the corresponding value of unemployment. Denote by J_i^p the expected value of a worker of type i working at firm p, and let Π_i^p be the expected profit the firm makes off type i. Let the measures of workers of each type be $\{n_1, n_{bi}, n_2, n_m\}$ set of unemployment rates be $\{u_1, u_{bi}, u_2, u_m\}$. The firm's objective function is thus given by:

$$\max_{x_1,x_2,x_m} \left\{ \Pi_1^p(x_1, x_2) + \Pi_2^p(x_2) + \Pi_m^p(x_m) \right\} \tag{6}$$

$$\textit{s.t. ICs:} \quad \max(V_2(x_2), V_{2,0}) \geq V_2(x_1) \tag{7}$$

$$\max(V_1(x_1, x_2), V_{1,0}) \geq V_1(x_2, x_2), \tag{8}$$

where constraint (7) ensures that mothers prefer their job (x_2) or non-employment to the job of non-mothers (x_1), and constraint (8) ensures that non-mothers never choose the job intended for mothers.

The expected profits Π_i^p from each type $i \in \{1, 2, m\}$ are defined as the product of the expected profit of hiring a worker of type i, J_i^p and the expected measure of workers the firm expects to meet who would accept a job at firm p:

$$\Pi_1^p(x_1, x_2) = J_1^p(x_1, x_2)\Big[\lambda_0 u_1 1_{\{V_1(x_1,x_2) \geq V_{1,0}\}} + \lambda_1(n_1 - u_1)G_1(V_1(x_1, x_2))\Big], \tag{9}$$

$$\Pi_2^p(x_2) = J_2^p(x_2)\Big[\lambda_0 u_2 1_{\{V_2(x_2) \geq V_{2,0}\}} + \lambda_1(n_2 - u_2)G_2(V_2(x_2))\Big], \tag{10}$$

$$\Pi_m^p(x_m) = J_m^p(x_m)\Big[\lambda_0 u_m 1_{\{V_m(x_m) \geq V_{m,0}\}} + \lambda_1(n_m - u_m)G_m(V_m(x_m))\Big]. \tag{11}$$

Workers that would accept a job at firm p are composed of (1) the unemployed who prefer working for firm p to non-employment ($V_i(x_i) \geq V_{i,0}$), and (2) workers currently working at a firm offering less expected lifetime utility than firm p, the mass of which is given by $G_i(V_i(x_i))$.

The expected profit from a type i worker, J_i^p, is given by:

$$
\begin{aligned}
J_1^p(x_1, x_2) &= \Big(\pi^p(x_1) + (1-\gamma)\beta q_b \sum_i \varphi_{bi} J_{bi}^p(x_1, x_2) 1_{\{V_{bi}(x_1,x_2) \geq V_{bi,0}\}}\Big) \\
&\quad \times \frac{1}{1-(1-\gamma)\beta(1-q_b)(1-\delta-\lambda_1(1-F(V_1(x_1,x_2)))}, \\
J_{bi}^p(x_1, x_2) &= (1-leave(x_1))\pi^p(x_2) + leave(x_1)(1_{\{u^2(m(x_2),l(x_2)) \geq u^2(m_{res},1)+\theta\}}\pi^p(x_2) \\
&\quad - 1_{\{u^2(m(x_2),l(x_2)) \leq u^2(m_{res},1)+\theta\}} c) + q_{bi}(1-\gamma)\beta J_2^p(x_2), \\
J_2^p(x_2) &= \pi^p(x_2) \frac{1}{1-(1-\gamma)\beta(1-\delta-\lambda_1(1-F(V_2(x_2)))}, \\
J_m^p(x_m) &= \pi^p(x_m) \frac{1}{1-(1-\gamma)\beta(1-\delta-\lambda_1(1-F(V_m(x_m)))}.
\end{aligned}
$$

The expected profit from hiring a male worker, J_m^p, is standard. For female workers, the firm accounts for the fact that (a) the worker may leave the firm upon childbirth, (b) leave provision aids with retention but comes at a cost, and (c) the profit made from a female worker differs post birth.

3.4 Solving for the Equilibrium

Def: Equilibrium. The steady-state equilibrium of this economy is given by: a set of worker value functions $\{V_1(x_1,x_2), V_{bi}(x_1,x_2), V_2(x_2), V_m(x_m), V_{1,0}, V_{bi,0}, V_{2,0}, V_{m,0}\}$, a set of firm policy functions $\{x_1^*(p), x_2^*(p), x_m^*(p)\}$, a set of stationary worker measures $\{n_1, n_{bi}, n_2, n_m\}$, a set of stationary unemployment rates $\{u_1, u_{bi}, u_2, u_m\}$, a set of offer distributions $\{F_1, F_2, F_m\}$, and a set of stationary equilibrium utility distributions $\{G_1, G_2, G_m\}$, such that

1. $\{n_1, n_{bi}, n_2, n_m\}$, $\{u_1, u_{bi}, u_2, u_m\}$, and $\{G_1, G_2, G_m\}$ satisfy the equations in Appendix B.2,

2. the worker value functions solve the worker's problem in Appendix B.1,

3. the firm policy functions $\{x_1^*(p), x_2^*(p), x_m^*(p)\}$ give the solution to the firm's problem

(6) for every productivity level p,

4. the firm policy functions give rise to the offer distributions $\{F_1, F_2, F_m\}$.

Solution Method. I solve for the worker value functions with standard value function iteration, taking as given firm's policy function. I solve the firm's problem in two steps.

First step. The first step is akin to a cost minimization problem, the firm finds the profit maximizing way to deliver given expected lifetime utilities subject to incentive compatibility. Denote by $\{\nu_1, \nu_2, \nu_m\}$ the lifetime utilities that need to be delivered to pre-birth females, post-birth females, and males, respectively. The Step-1 problem is hence given by

$$\begin{aligned}
&\max_{x_1,x_2,x_m} \left\{ \Pi_1^p(x_1, x_2) + \Pi_2^p(x_2) + \Pi_m^p(x_m) \right\} && (12)\\
&s.t. \; V_1(x_1, x_2) \geq \nu_1 \\
&\quad V_2(x_2) \geq \nu_2 \\
&\quad V_m(x_m) \geq \nu_m \\
&\textit{ICs:} \quad \max(V_2(x_2), V_{2,0}) \geq V_2(x_1) \\
&\quad \max(V_1(x_1, x_2), V_{1,0}) \geq V_1(x_2, x_2)
\end{aligned}$$

Denote the solution to this problem as $\{x_1(\nu, p), x_2(\nu, p), x_m(\nu, p)\}$. Define the indirect flow profit that the firm makes from type i as $\pi_i^p(\nu) := p(1 - l_i(\nu, p))^{\phi(p)}) - w_i(\nu, p)$.

Second Step. In the second step, I rewrite the firm's problem as a choice over lifetime utilities:

$$\max_{\nu_1,\nu_2,\nu_m} \left\{ \Pi_1^p(x_1(\nu, p), x_2(\nu, p)) + \Pi_2^p(x_2(\nu, p)) + \Pi_m^p(x_m(\nu, p)) \right\} \qquad (13)$$

I then guess and verify that in equilibrium the lifetime utility a firm provides is increasing in the firm's productivity: $\nu_i'(p) \geq 0$, for $i \in \{1, 2, m\}$.[22] Consequently, in this equilibrium

[22]In the standard Burdett & Mortensen (1998) framework with heterogeneous firms, the authors show that a solution to the problem exists and is unique. Existence is less obvious in my environment because as productivity changes, so does the shape of the production function. Hence, it could be possible for this equilibrium to break down if the convexity of the production function increases "too quickly" relative to the increase in productivity. In that situation, firms produce very little unless workers have close to zero leisure, but since worker's marginal utility of leisure is infinity at zero leisure, it becomes very expensive to provide

there is a one to one mapping between the offer distribution and the firm productivity distribution, $F_i(\nu_i(p)) = J(p)$, which further implies

$$F_i'(\nu_i) = J(p)/\nu_i'(p). \tag{14}$$

I use equation (14) to rewrite the set of first order conditions of (13) as a $3x3$ system of ordinary differential equations:

$$M_p \begin{pmatrix} \nu_1'(p) \\ \nu_2'(p) \\ \nu_m'(p) \end{pmatrix} + \Pi_p = 0, \tag{15}$$

where M_p is a 3x1 vector, and each entry governs how flow profit responds to increases in ν ($\frac{\partial \pi_i(\nu,p)}{\partial \nu_j}$), and Π_p is a 3x1 vector containing the positive retention effect on profit as ν increases.

I then solve for the equilibrium of the economy using numerical methods outlined in Achdou et al. (2022). Details of the solution method are listed in Appendix B.3.

4 Estimation

I first define functional forms and make assumptions on the heterogeneity of females. I then outline the estimation of parameters which follows in two main steps.

Functional Forms. On the firm side, I assume that productivity follows a gamma distribution, with mean μ and variance σ.[23] The time input h of a worker ranges from 0 (no work) to 1 (maximum work input, associated with zero leisure). The firm's production function is given by $ph^{\phi(p)}$. Depending on the size of $\phi(p)$, the return to a single worker's time input is increasing ($\phi > 1$), decreasing ($\phi < 1$), or constant ($\phi = 1$). Firms differ in their production technologies according to $\phi(p) = \phi_0 + \phi_1 \tilde{p}(p)^{\phi_2}$,[24] which of course nests the case of equal production functions across the productivity distribution. This flexible form

utility to workers. I solve my problem numerically, and also verify the candidate equilibrium numerically. For reasonable ranges of convexity, the solution converges and satisfies second order conditions.

[23]Choosing the mean and variance of a gamma distribution is equivalent to choosing location and scale parameters.

[24]I rescale p to lie between zero and one, giving $\tilde{p}$.

allows more productive jobs (e.g. managerial) to require more time input in order to produce effectively, than a lower level job.

On the worker side, I allow for three types of reactions to a child shock which I refer to as "birth types". These types, $\{b_1, b_2, b_E\}$, are each randomly drawn with probabilities $\{\varphi_{b1}, \varphi_{b2}, \varphi_{bE}\}$, respectively. The first type is unwilling to work for exactly one period of leave. Recall that the willingness to work upon birth is pinned down by the size of θ_{bi}, the boost in the flow value of unemployment in equation (4). Hence, for type b_1 any size of θ_{b1} will do - so long as type b_1 would quit any job in absence of leave. After that one period, θ_{b1} deterministically reverts back to zero. An intuitive way to think of this type is as those for whom the typical leave duration period firms offer is sufficient to be able to work again. At that point, a female whose pre-birth job offered leave will return to work at their firm - given that their post-birth job is acceptable now that they have a child, while a female without a job to come back to will start looking for a new job.

The second birth type, b_2, is also assumed to have a sufficiently large θ_{b2} that makes them entirely unwilling to work following birth. In contrast to type b_1, one period of leave may not be enough: θ_{b2} reverts back to zero at rate q_{b2}. Recall that firms get to choose between offering one period of leave or no leave at all. Hence, the only way that type b_2 keeps their pre-birth job is if their firm offers leave, and they get "lucky" that their θ_{b2} reverts back to zero after one period.

The third type, b_E, never enters the "birth state" in the first place, i.e. $\theta_{bE} = 0$. This type stays with the pre-birth firm even in absence of parental leave, conditional on the firm offering an acceptable post-birth job.[25] This type can be thought of as needing less than the typically provided leave duration in order to be able to work post-birth, and is necessary to reconcile that there exist workers who stay employed in the absence of official parental leave.[26]

Step 0. In an initial step, I fix a number of parameters outside of the model, namely $\{\beta, \gamma, q_b\}$. One model period equals one month. The discount rate $\beta = 0.9967$ is set to match a yearly interest rate of 3%. The retirement/death rate $\gamma = 0.00185$ is set to match an average retirement age of 65 years. For the fertility rate (birth shock) $q_b = 0.00833$, I target the cumulative distribution function of age at first birth among women born in

[25] Firms may not want to offer jobs that are acceptable to mothers because they need more leisure or income in order to accept a job.

[26] Those workers likely use other forms of leave, such as vacation and sick days, as shown in the report Laughlin (2011).

the 1960s with at least one child. I estimate q_b using the Generalized Method of Moments (GMM).

Step 1. My model assumes away any gender differences stemming from sorting into different industries or occupations, or from differences in job finding rates. Both males and females have access to the same market and search technology. I first estimate all the parameters related to the market and search technology using CPS data from the early 1990s on prime-aged men, as I am calibrating my model to the period just prior to the introduction of the FMLA in 1993. The CPS has a much larger sample size and hence gives better estimates of transition rates which are crucial for estimating the contact rates. The parameters of interest are the search parameters $\{\lambda_0, \lambda_1, \delta\}$, the firm productivity and production function parameters $\{\mu, \sigma, \phi_0, \phi_1, \phi_2\}$, and the worker preference parameter α_m.

I target job transition rates, means, variances and quartiles of the income and hours distribution, and the relationship between income and hours. This gives me 9 parameters to fit 18 moments, which I calibrate internally. Note that since model hours lie between zero and one, I fix the maximum availability of working hours to convert model hours to "real" hours. I assume that the upper bound is 48 hours per week, which translates to a six-day work week. This is roughly at the 90th percentile of the hours distribution for men. The shape of $\phi(p)$ is identified by the relationship between hours and income in the data. In this type of model, a more productive firm offers a higher lifetime utility, with the question being of how to deliver this extra utility optimally. The firm unambiguously offers higher income, but the extent to which a more productive firm wants to increase or decrease worker hours depends on the marginal product of time-input, which is exactly governed by $\phi(p)$. The parameter estimates are given in Table 2, and the data and model-implied moments are displayed in Appendix Table 5.

As shown in Appendix Table 5 I undershoot both the variance in income and hours, as the only source of differences in my model comes from productivity and production function differences. For instance, all males are assumed to have the same skill level, and the same value for time at home, α_m. Adding additional sources of heterogeneity would aid in achieving sufficient dispersion in hours and income. The model replicates the positive relationship between hours and income. In terms of untargeted moments, it predicts a wage schedule that is increasing the number of weekly hours, which is consistent with the data. In this model, the best jobs are those with long hours but disproportionately high pay.

Step 2. In a second step, I estimate parameters related to changes around birth by

Table 2: Parameter Set 1

Parameter	Value	Description	Identifying Moments
Gender Neutral Parameters			
β	0.9967	Discount factor	Yearly interest rate
λ_0	0.25	Unemployment offer rate	Male u, UE rate
λ_1	0.1	On-job offer rate	Male EE rate
δ	0.012	Exogenous destruction	Male EU rate
Demographic Rates			
γ	0.00185	Exit shock	Average retirement age
q_b	0.00833	Fertility shock	CDF age at first birth
Worker Preferences			
α_m	0.8	Type m preference for money	Male hours and wages
Firm Production Technology			
μ	90	Parameter of H	Male hours and wages
σ	75	Parameter of H	Dispersion hours and wages
ϕ_0, ϕ_1, ϕ_2	0.7, 1.7, 3.2	Convexity of production function	R/s hours and wages

Notes: R/s is an abbreviation for the term relationship.

exploiting the panel structure of the NLSY79. There are three sets of parameters left to estimate. The first set, $\{\alpha_1, \alpha_2\}$, gives the within-period trade-off of time at home and income for mothers and non-mothers, respectively. The second set pins down the prevalence of paid work immediately post birth: $\{\varphi_{1b}, \varphi_{2b}, q_{2b}, c\}$ denote the share of each of the three birth types, the transition rate back to normal willingness to work, and the cost of leave provision for firms, respectively. The final two parameters are $\{\delta_2, cc\_cost\}$, the exogenous match destruction rate for mothers, and the cost of child care. The child care cost acts as a minimum acceptable wage threshold, it is incurred only if a mother is at work.

The last set of parameters, $\{\delta_2, cc\_cost\}$, are calibrated outside the model: I set δ_2 to match the increase in employment-to-non-employment transitions observed post birth. This is the only search technology parameter allowed to differ post birth, as it is the most important margin of difference observed in the data. Some of the excess movement out of employment in the data is likely due to additional births, but the rate also remains heightened for those with only one child. Child-care costs are calibrated using SIPP data from the year 1990, and are set to equal the average incurred cost for children less than six years old.

The remaining parameters are internally calibrated by matching model-simulated moments to their data counterparts. As outlined in Table 3, the parameters are identified by stark changes in labor market outcomes around birth. In particular, I target pre-birth hours, the initial reduction in hours and income[27], pre-birth leave coverage, average retention at birth, the relationship between pre-birth income and retention, and the speed of return to paid work. The hours decline upon birth is particularly informative about the weight mothers place on time at home. The relationship between pre-birth income and staying with the pre-birth employer, and the duration of time spent non-employed post birth help identify the "birth type" parameters. In total, I match 9 moments to jointly estimate the 6 remaining parameters, with details given in Appendix Table 6.

Table 3: Parameter Set 2

Parameter	**Value**	**Description**	**Identifying Moments**
Demographic Rates			
φ_{b1}	0.62	One period leave needed	R/s retention & pre-birth income, speed of reentry
φ_{b2}	0.14	Long leave needed	R/s retention & pre-birth income, speed of reentry
q_{b2}	0.018	Fade out, φ_{b2}-type	Avg retention at birth, speed of reentry
Worker Preferences			
α_1	0.73	Type 2 preference for money	Pre-birth hours
α_2	0.58	Type 2 preference for money	Initial income and hours drop post birth
Other parameters			
c	1200	Cost of leave provision	Pre-birth leave coverage
cc_cost	82	Cost of childcare	Avg weekly child care cost (SIPP, 1990)
δ_2	0.018	Exogenous destruction	Inrease in EN transitions post birth

Notes: R/s is an abbreviation for the term relationship.

I compute model-implied child penalties analogously to the estimation strategy of data penalties in section 2.4. I first simulate worker trajectories with random childbirth. In then simulate the counterfactual path that would have realized if the worker hadn't had experienced a fertility shock. The within-person child penalty for every event-period prior to birth is defined as the difference between realized and counterfactual simulated outcomes. Note that the hours and income penalty can only be computed whenever the worker is in paid work.[28] The overall child penalty at event time t is the average child penalty incurred by individuals that are in paid work at event time t.

[27]The data moments of interest are within-person event study estimates in the year of birth.

[28]I keep the randomness of the search technology the same for both simulations, so that whenever the worker is in paid work post birth, they are also observed in paid work in the counterfactual simulation.

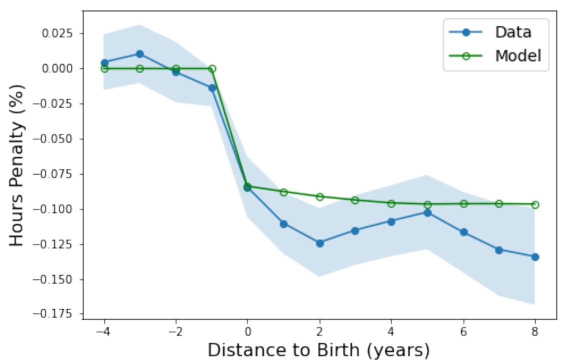
4.1 Model Fit

The model fit is shown in Figures 6 and 8. The model is targeted to match the initial drop in earnings and hours in the year following birth, whereas the longer-run dynamic response emerges from the model. I successfully replicate an hours penalty that does not recover, and a wage penalty that opens up over time. I undershoot the extent of the wage penalty in the long run, potentially because human capital becomes a relevant channel for mothers who stayed out of the labor force for a long time. The widening wage penalty is driven by two main sources within my model. First, the cost of job loss is larger for women who stay non-employed for an extended period, as they would have continued to climb the job ladder in the absence of childbirth. When those women reenter paid work, they raise the average wage penalty. Secondly, mothers face a flatter wage ladder compared to non-mothers, as displayed in Figure 7. The largest wage penalty is observed at top firms, and as women progress in their careers and move to better firms, they fall behind further.

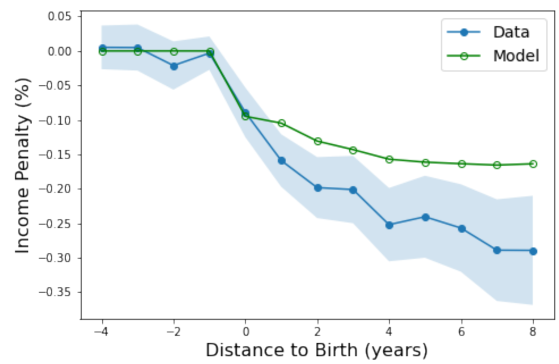
Note that the difference in the wage ladder for mothers and non-mothers depends crucially on the model parameters. The ability of the model to generate a flattened ladder for mothers without directly targeting the wage penalty across the income distribution is reassuring. In my framework, firms anticipate that mothers place a higher weight on time at home, and hence compete for mothers with lower hour and lower income contracts. While mothers unambiguously work fewer hours, the size of the wage penalty could go either way and crucially depends on the production function parameters. Recall that under my estimates, more productive firms rely more on longer hours to produce; their production function is scaled up but also more convex. This means that offering reduced hours is more costly, the more productive the firm is, leading to larger compensating differentials. This gives intuition as to why wages for mothers and non-mothers are similar at the bottom of the productivity distribution, but largely different at the top.

In terms of monthly employment, my estimates target that one in three females leave employment in the months around birth, conditional on having worked at some point during pregnancy. As can be seen in Figure 6c, employment in the data (the blue line) drops already during pregnancy, while these anticipatory effects are absent in my model. In terms of the dynamics, employment in my model partially recovers, while the penalty is more persistent in the data. This is primarily due to the fact that in the data, females may have more than one child, while my model is restricted to a single birth for simplicity.[29]

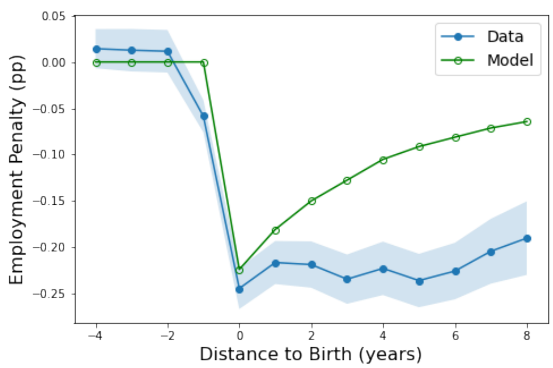
[29] The employment dynamics match well the behavior of mothers who only have one child. There are few



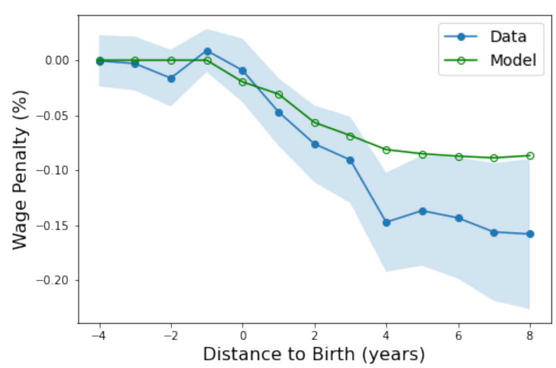
(a) Hours



(b) Income



(c) Employment



(d) Wages

Figure 6: Model Fit - Child Penalties

Notes: Hours, income, and wage penalties are estimated on a weekly level. Employment is measured monthly (whether a worker was employed at any point of the month).

5 Penalty Decomposition and Counterfactuals

My model contains two primary sources of long-term child penalties: the cost of job loss and changes in the trade-off of money and time spent at home. While the scarring effect of losing a job is well-studied in the literature, the second source is not typically present when decomposing child penalties in search models, as hours are not typically modeled. In section 5.1, I quantify how much this weight on time contributes to child penalties by turning off the first source, i.e. eliminating the cost of job loss within my model.

A second non-standard ingredient in my model is the asymmetric information, the fact

such mothers in the already small NLSY79 data-set, which is why I use all mothers in my estimation.

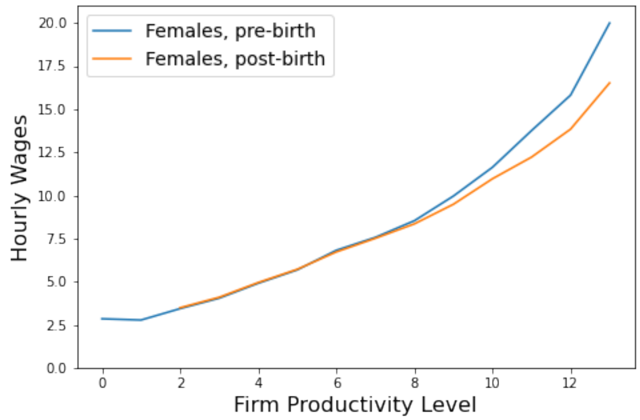
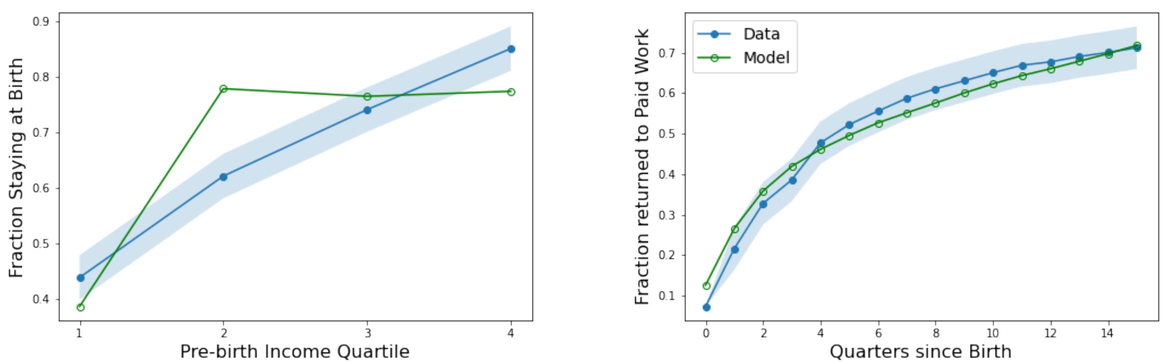


Figure 7: Wage Ladder for Non-Mothers and Mothers

Notes: Hourly Wage Policy Functions (to be interpreted as 1990 USD). Note that very low productivity firms do not offer a job to mothers that they prefer over non-employment, and hence no wage is displayed for those firms.



(a) Selective Retention

(b) Speed of Return to Paid Work

Figure 8: Model Fit

Notes: The pre-birth income quartile is computed across all first-time mothers, not controlling for age at birth in model or data. The CDF of speed of return gives the fraction of mothers that left employment around birth and returned to paid work by a certain event time, e.g. within 4 quarters since birth, 40% of leaving mothers have held a paid job at some point post birth.

that firms are unable to write contracts dependent on motherhood status. In section 5.2, I show that this information friction amplifies the second source, interacting with the change in value on time at home has on wages post birth, and making the effect larger. Finally, I consider the impact of the introduction of a federal parental leave mandate through the lens of my model in section 5.3.

5.1 Child Penalty Decomposition

In this section, I evaluate how important the intensive labor supply margin is for child penalties. This margin is not typically modeled, and this paper argues that doing so is crucial for understanding the source of earnings disparities and potential solutions. I evaluate the importance of the hours margin by eliminating excess job loss due to birth within my model.

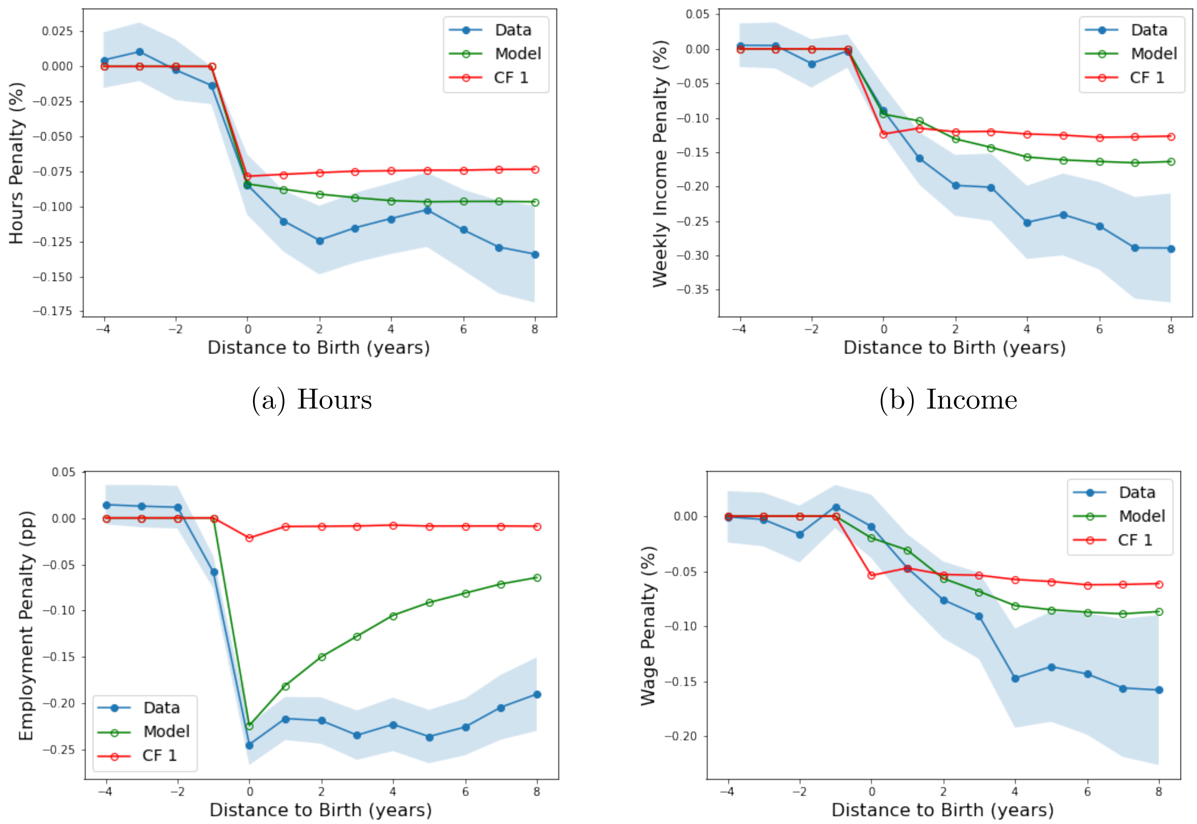
A substantial body of literature has examined the enduring effects of job loss on future earnings, with seminal work by Jacobson et al. (1993) showing that it leads to a persistent earnings scar. The cost of job loss is typically thought of as the triple of: (a) the loss of search capital - the setback in the job ladder and restarting at the bottom, (b) involuntary unemployment due to search frictions, and (c) human capital losses. Long-term, human capital losses are the most significant factor, whereas the first two dominate in the short term (see Burdett et al. 2020). Since I abstract away from human capital, my model speaks to the first two components of job loss, but not the human capital channel.[30] More specifically, when mothers leave behind their pre-birth jobs, they cannot return to their pre-birth employers, and have to start searching for a high value job again from zero. Further, they cannot move back into paid work as soon as they wish to do so - they have to wait to see a job posting due to search frictions.

I "turn off" excess job loss due to the arrival of a child by making two modelling changes. First, I assume that all mothers are willing to work immediately upon birth, meaning that they do not require leave to stay with their pre-birth employer. Secondly, the rate at which mothers move from employment to non-employment (match destruction rate) is unaffected by birth within this counterfactual. I then resolve the model under the new assumptions, keeping all other parameters at their estimated levels. Resolving the model under the new assumptions rather than just re-simulating worker paths means that firms now optimally set job offers internalizing that workers will not quit their jobs around birth. The factor driving differences in labor market outcomes stems from the lower weight placed on money.

Figure 9 shows the incurred child penalties under this counterfactual, plotted in red and labeled "CF 1". The long-run child penalties in hours, income and wages are very substantial

[30] For careful analysis of this channel, Xiao (2020) and Amano-Patiño et al. (2020).

and explain the vast majority of the total model-implied penalties, namely 71% of the wage penalty and 76% of the hours penalty. As discussed in section 4.1, the long-run penalties generated by the model are smaller than those observed in the data due to the absence of human capital. Nonetheless, the intensive margin rationalizes around 40% of the total wage penalty observed in the data eight years post birth.



(a) Hours (b) Income

(c) Employment (d) Wages

Figure 9: Child Penalty in Absence of Job Loss Channel

Notes: The red line denotes the counterfactual paths in a world without excess job loss due to birth. Hours, income, and wage penalties are estimated on a weekly level. Employment is measured monthly (whether a worker was employed at any point of the month).

Short-run income and wage penalties are larger in the counterfactual than in the baseline model. This is largely due to the fact that the majority of job loss around birth comes from new mothers leaving low-income jobs in the baseline model. Female workers at the very bottom of the income distribution that quit but return quickly to paid work actually have a wage penalty that is positive. This means that on average they are earning more post birth than they would have in absence of birth.[31] This is slightly counter-intuitive and comes from the fact that for mothers that return to paid work fairly quickly, expected wages out of non-employment are higher than those obtained if they had stayed on the job. To understand this, note that search frictions are larger on the job than in unemployment, and hence these mothers would have been "stuck" at low-income jobs in absence of birth. Those jobs pay less than the average job offer - which is what a quitting and reentering mother expects to earn at their first post-birth job. Additionally, the bottom 10% of firms do not employ any mothers because it is too costly for them to offer a job that they prefer to non-employment. This further pushes up the unconditional mean wage offer a non-employed mother faces.

The fact that the bottom 10% of firms do not employ any mothers in the model explains the slight dip in employment post birth observed in Figure 9c under the counterfactual. Around 3.6% of females that are in paid work prior to birth are employed by the bottom 10% of firms. Those females quit their job upon birth regardless of their preferences for leave.[32]

This counterfactual highlights that even in a world in which job continuity around birth can be guaranteed, child penalties will be substantial. Female workers switch to lower hour jobs post birth, and lower working hours are associated with sizably lower wages. The move toward gender equality requires an equalization in how time at home is valued between genders. This means not only splitting the burden of taking care of a child around birth, but persistently allocating hours similarly.

5.2 The Role of Asymmetric Information

Next, I quantify the role of asymmetric information in the model. Recall that firms cannot write contracts contingent on how females trade-off time at home and money. Instead each firm posts a list of two jobs, one for females with a high weight on time at home (mothers), and one for females with a lower weight on time at home (non-mothers). This involves solving an incentive compatibility problem. As mothers place a higher value on time spent at home, they are willing to take larger income cuts in exchange for lower weekly hours, and

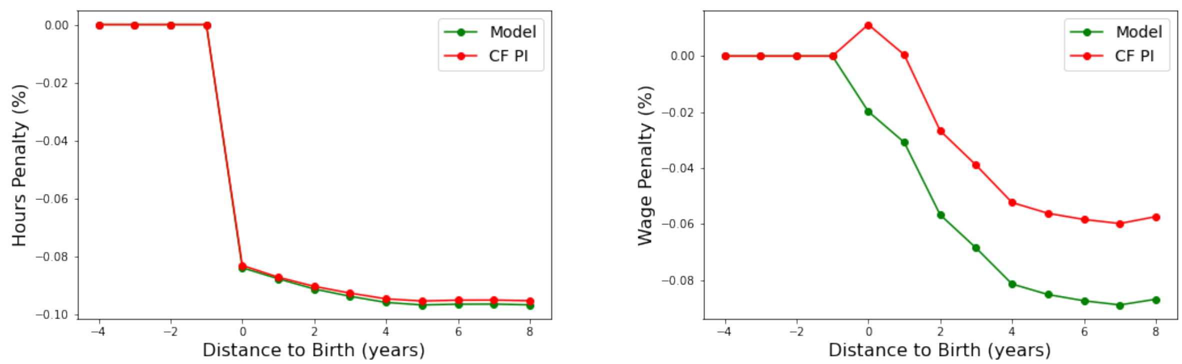
[31] Note that this is only true if they return to paid work pretty quickly. If they stay away for long periods of time, they would have made sufficient career progress in absence of birth to earn a higher wage than their expected reentry wage post birth.

[32] Referring to this counterfactual as turning off the job-loss channel is not entirely correct. The precise phrasing is that all sources of job loss are eliminated beyond those that arise due to a persistent change in how time and money are traded-off.

require larger wage increases to accept jobs with longer hours. To outline this more clearly, consider an average pre-birth job of 40 weekly hours at an hourly wage of around \$8 (1990 USD). At the estimated weights, a mother would accept 10% wage cut to switch to a 35 hour job. In contrast, a non-mother would require a 1% wage increase to accept a job with 35 weekly hours.

The example above illustrates how different the preferences across the two worker types are. This may raise the question of whether incentive constraints have any bite at all. Under the estimated parameters, they bind (for non-mothers) over the majority of the income distribution, with only a range of upper middle productivity firms having slack constraints (around 2/3 of firms have binding constraints). At the top, the intuition is as follows: a more productive firm p relies more on longer hours to produce, the production function is increasingly convex. Hence, to poach a mother, they have to find a way to both provide higher utility and induce longer hours. Since non-mothers value time at home, they prefer working less for similar pay. Firms at the top thus struggle to provide utility to mothers without creating an incentive for a non-mother to pretend to be mothers. To understand how asymmetric information interacts with the wage penalty, I solve a counterfactual assuming perfect information. The exercise reveals that top firms distort job contracts by paying non-mothers more and by lowering mother's wages (hours are slightly reduced, but pay is reduced by more). The presence of asymmetric information amplifies the wage penalty at the top, where it is already largest.

At the bottom of the productivity distribution, the main tension comes from the fact that mothers get less surplus from employment. Not only do they value time at home more which increases their flow-value of nonemployment, they also incur a childcare cost of \$82 (1990 USD) per week if they work. They thus require a sufficiently high income to make working worthwhile. For that reason, the least productive 10% of firms do not offer jobs that are acceptable to mothers in the first place. At the point where firms are sufficiently productive an choose to hire mothers, non-mothers are not compensated very well. Firms thus need to provide additional utility to non-mothers to separate them. The perfect information benchmark shows that they do so by reducing non-mothers' hours, and paying non-mothers more while paying non-mothers less. Hence, asymmetric information amplifies the wage penalty not only at the top but also in the middle. Overall, the presence of asymmetric information accounts for a third of the long-run wage penalty, as displayed in Figure 10b. Since firms distort hours of both mothers and non-mothers downward to satisfy incentive-compatibility, the hours penalty is not very affected.



(a) Hours (b) Wages

Figure 10: Child Penalty with and without Asymmetric Information

Notes: The red line (CF PI) denotes the counterfactual paths in a world with perfect information. The green line denotes the baseline model with asymmetric information. Hours and wages are conditional on employment.

5.3 Parental Leave Reform

Prior to 1993, the US had no federal law regulating parental leave provision. The NLSY79 thus provides an opportune setting to study the prevalence and distribution of firms' privately provided maternity leave. My model is estimated to the early 1990s, prior to the passing of the Family and Medical Leave Act (FMLA). It features endogenous leave provision by firms, and targets pre-FMLA coverage levels. Both these decisions were made actively, to create an environment to credibly study the effect of a parental leave policy through the lens of my model.

I evaluate the parental leave counterfactual in two steps. First, I analyze the partial equilibrium response, where workers adjust their behavior to the policy but firms do not alter contracts. Second, I resolve the model to study the general equilibrium response, and the associated welfare effect. When implementing the parental leave policy within my model, I try to replicate the conditions of the actual FMLA. The FMLA is subject to firm size restrictions, one year of tenure, and working at least 20 hours per week. I impose the hours restriction in my model, but cannot implement the tenure and firm size restrictions. Overall, the results generate by the model are consistent with the empirical literature that studies the FMLA.

Partial Equilibrium. The leave policy achieves universal coverage within the model, since no firm offers a contract with fewer than 20 hours in absence of the policy.[33] While this is a high upper-bound for the coverage effects the actual FMLA could have had, the retention impact is consistent with the data. The fraction of new mothers staying with their pre-birth employer increases by 7.2 percentage points (10%) in the parental leave counterfactual. This increase stems from low-income women that would have returned to paid work quickly even in absence of the policy. Within the model, women with top pre-birth incomes only quit if they have a persistent unwillingness to work, as their firms already provide leave. Hence, the policy only improves retention of women at low productivity firms that previously did not have access, and for whom the typically provided leave period is sufficient time off. Figure 11a shows that employment gains fade out a year post birth.

Figures 11c and 11d shows the counterfactual paths of hours and wages around birth relative to the benchmark economy with private leave provision. While hours are not affected, the wage penalty is surprisingly more pronounced in the years following birth. These negative effects fade out entirely within eight years post birth. The intuition of this stronger initial wage penalty is analogous to the explanation for the penalty decomposition exercise in section 5.1. Birth acts as a destruction of the least productive jobs. The parental leave policy preserves some of these low-income jobs, with new mothers now "stuck" at these jobs. If they had quit their jobs, they would have experienced a period of no earnings, but would have reentered paid employment at a higher expected wage. Note that total earnings (including zeros if a women is not working) are unaffected in the partial equilibrium response, as the positive effect on participation balances out lower wages (see Figure 11b).

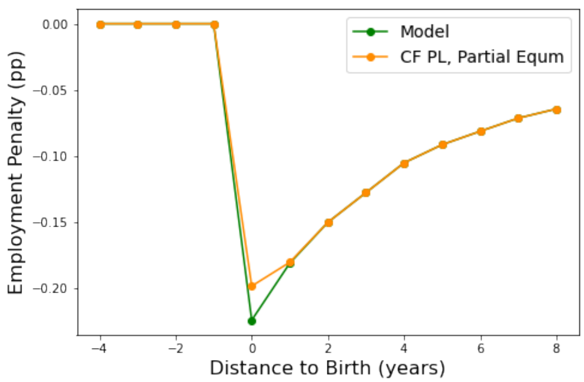
General Equilibrium. Firms' reactions to the policy can theoretically affect both the intensive and extensive margin. Firms may change how much utility to provide (intensive margin). In the extreme case, they may choose to only offer contracts that are unacceptable to mothers to indirectly avoid leave provision costs (extensive margin).[34] While the cost of leave provision is high for low productivity firms, the profit cost from distorting contracts to ensure that mothers do not want to work at their firm is even higher. Hence, employment trajectories are equivalent to the partial equilibrium response, given by Figure 11a.[35]

Firms respond to the policy by increasing hours and decreasing salary. This leads to lower

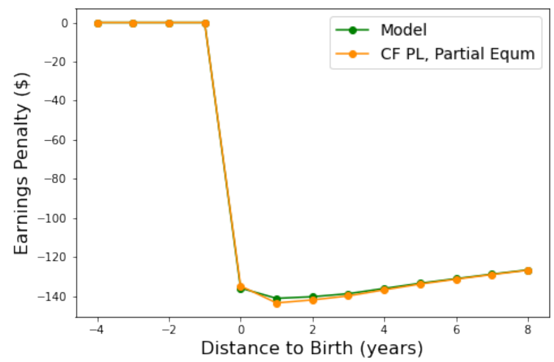
[33] If the hours threshold were higher, around full-time work, my model predicts the bunching of firms just below the threshold to evade the policy, with a large adverse effects on hours.

[34] If no job is acceptable to a new mother, they will quit at birth without taking up leave.

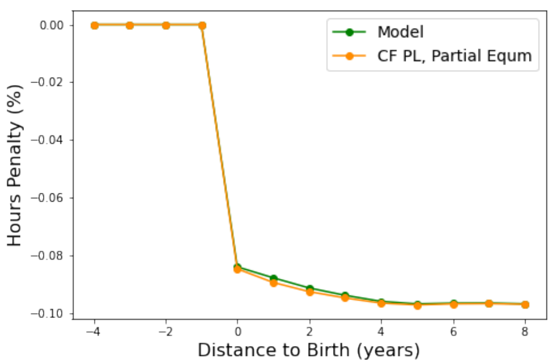
[35] Note that if my model had a hiring margin, we might see an impact on female employment, but I'd expect it to be small: a worker is more likely to move to be poached or move to unemployment for unrelated reasons than to have a baby.



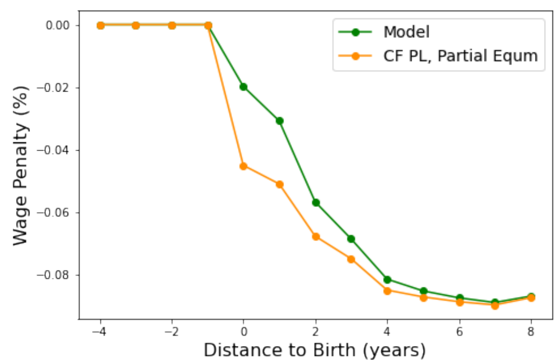
(a) Employment



(b) Total Earnings (with zeros)



(c) Hours



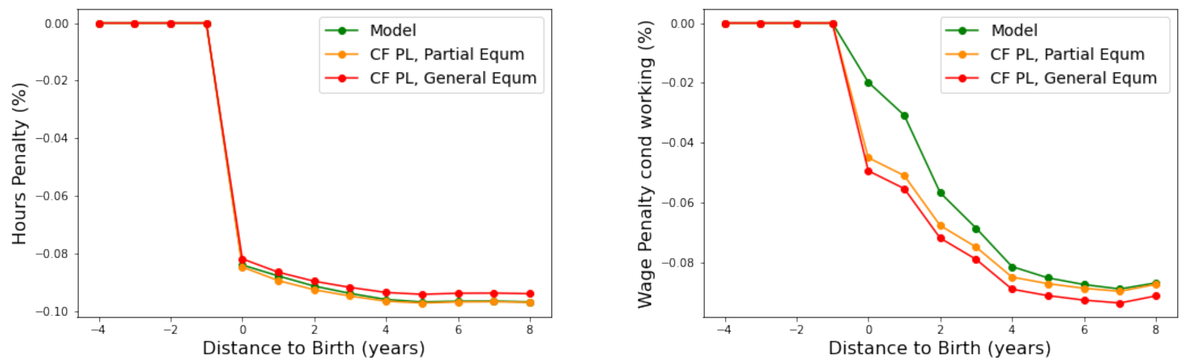
(d) Wages

Figure 11: Partial Equilibrium Effect of Parental Leave Policy

Notes: The orange line (CF PL, Partial Equm) denotes the parental leave counterfactual where workers adjust their behaviors but firms do not. The green line denotes the baseline model. Hours and wages are conditional on employment.

wages for both non-mothers and mothers, with a larger effect for mothers. The intuition is the following: low productivity firms who previously did not offer leave reshuffle the way the provide utility. They lower overall utility, and extract higher profits on the non-amenity margin by reducing wages. Because low productivity firms offer less utility, higher productivity firms have an easier time poaching workers, and offer less utility themselves despite already providing leave pre-policy.

Figure 12 shows the general equilibrium impact on the hours and wage penalty. The hours penalty is largely unaffected because hours increase similarly for mothers and non-mothers. The model-implied increase in the short-run penalty is driven by the change in composition in the labor market that we saw in partial equilibrium. The increase in the long-run wage penalty is modest at 0.5 percentage points eight years post birth. This translates into an hourly wage reduction of $0.06 in 1990 dollars, which is equivalent to 14 cents today.



(a) Hours (b) Wages

Figure 12: General Equilibrium Effect of Parental Leave Policy

Notes: The red line (CF PL, General Equm) denotes the parental leave counterfactual where firms adjust, whereas the orange line (CF PL, Partial Equm) denotes the counterfactual where firms do not adjust. The green line denotes the baseline model. Hours and wages are conditional on employment.

Welfare Impact.

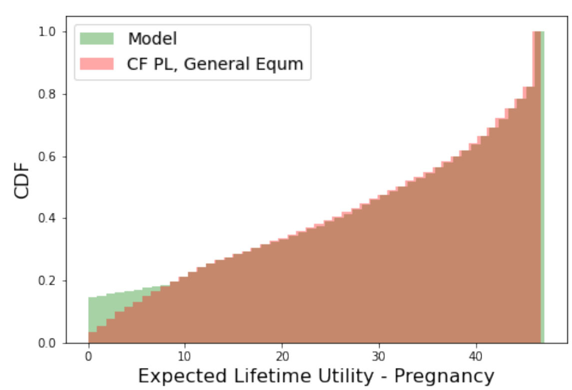


Figure 13: Distribution of Expected Lifetime Utility of Expectant Mothers

The benefit of a structural model, besides shedding light on the mechanisms through which a policy affects the economy, is the ability to perform welfare analysis. While failing to reduce the child penalty, the policy has little overall welfare effects. The expected lifetime utility of a female entering the labor market essentially unchanged; it decreases by less than 1%. Nonetheless, there is a utility redistribution toward expectant mothers working in low-income jobs, by retaining their jobs and hence smoothing out their consumption. Instead of facing a period of no labor income with uncertain duration, they now stay at their pre-birth jobs. The distribution of expected lifetime utility at the moment where a mother experiences a birth shock is shown in Figure 13. The red cumulative distribution function has less mass at extremely low utility outcomes. This highlights that despite a lack of positive effects on long-term labor market outcomes, the policy successfully insures expectant mothers against adverse outcomes. This raises the question of the intended outcomes of leave policies, as they can assist populations without necessarily addressing gender disparities.

6 Conclusion

This paper delves into the dynamics of labor market outcomes for new mothers, shedding light on the persistent impacts of childbirth on their careers. The analysis presented in this paper demonstrates that the child penalty is a complex interplay of extensive and intensive labor supply decisions. New mothers face a delicate balancing act, often opting for periods of non-employment and reduced working hours. These choices are not arbitrary, and accounting for selective exit out of the labor market is crucial for assessing the sources of the child penalty, and for evaluating policy counterfactuals.

The intensive margin generates a substantial amount of the wage penalty incurred by new mothers, capturing roughly 70% within my model. This outcome is a result of firms offering lower wage, lower hours contracts to mothers due to the increased weight placed on time at home. Mothers face a flatter wage ladder, with differences most pronounced at the highest productivity jobs. Asymmetric information over women's preferences amplifies these wage differences, as firms provide work incentives to non-mothers as a means of separating worker types. These findings suggest that the path to gender equality has to involve a persistent change in the way hours are allocated within a household, sharing responsibilities equally not just at the time of birth, but for many years thereafter.

Lastly, the paper examines the impact of the Family and Medical Leave Act through the lens of the model, rationalizing both short-run retention gains, and small but negative wage effects. The adverse impact on the child penalty is a combination of a compositional change in the labor market, as the policy preserves the jobs of low-income women, and a general equilibrium effect of firms lowering wages throughout the productivity distribution. Nonetheless, the policy redistributes utility to low-income pregnant mothers while leaving overall expected lifetime utility essentially unchanged.

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A Data

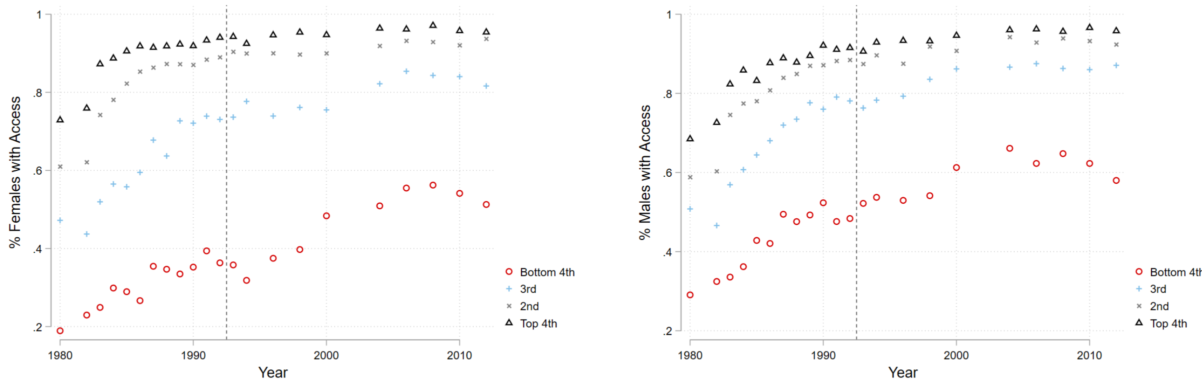
Table 4: Access to Parental Leave

	Females		Males	
Income Quartiles (relative to Bottom)				
3rd	0.096***	(0.015)	0.064***	(0.012)
2nd	0.167***	(0.017)	0.101***	(0.015)
1st (Top)	0.204***	(0.019)	0.106***	(0.017)
Hours Worked/Week				
Weekly Hours	0.008***	(0.002)	0.009**	(0.003)
Full-time (35+ Hours)	0.343***	(0.094)	0.376***	(0.093)
Full-time (35+ Hours) $\times$ Weekly Hours	-0.008**	(0.003)	-0.009**	(0.003)
Long Hours (50+ Hours)	-0.039	(0.023)	-0.001	(0.017)
Tenure (relative to less than 1 Year)				
1-5 Years	0.084***	(0.008)	0.059***	(0.008)
Over 5 Years	0.088***	(0.012)	0.072***	(0.014)
Type of Job				
Government	0.034*	(0.017)	0.089***	(0.020)
Techincal	0.009	(0.017)	0.034	(0.022)
Sales	0.007	(0.015)	-0.020	(0.019)
Admin	0.006	(0.011)	0.002	(0.019)
Service	-0.041**	(0.016)	-0.012	(0.019)
Farming	-0.116*	(0.058)	-0.090**	(0.029)
Production	0.032	(0.024)	-0.063***	(0.017)
Operators	0.026	(0.020)	-0.048**	(0.016)
Firm Size (relative to 1-5 Employees)				
6-20 Employees	0.087***	(0.017)	0.039**	(0.013)
21-50 Employees	0.158***	(0.018)	0.071***	(0.015)
51-200 Employees	0.196***	(0.018)	0.132***	(0.016)
Over 200 Employees	0.216***	(0.018)	0.182***	(0.017)
Observations	22382		26223	

Standard errors in parentheses

* $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

Notes: Sample years 1985-1992. Sample of workers restricted to ages 20-50, and working at least 20 hours per week. Hours top-winsorized at the 2p-level by gender. Regression additionally includes age, individual, year, and region fixed effects. It also controls for college enrollment. Standard errors are clustered at individual-level.



(a) Female Leave Access

(b) Male Leave Access

Figure 14: Health Insurance Access by Income Quartile and Over Time

Notes: Sample of workers restricted to working at least 20 hours per week, as information on fringe benefits leave only collected for workers working at least 20 hours prior to 1993.

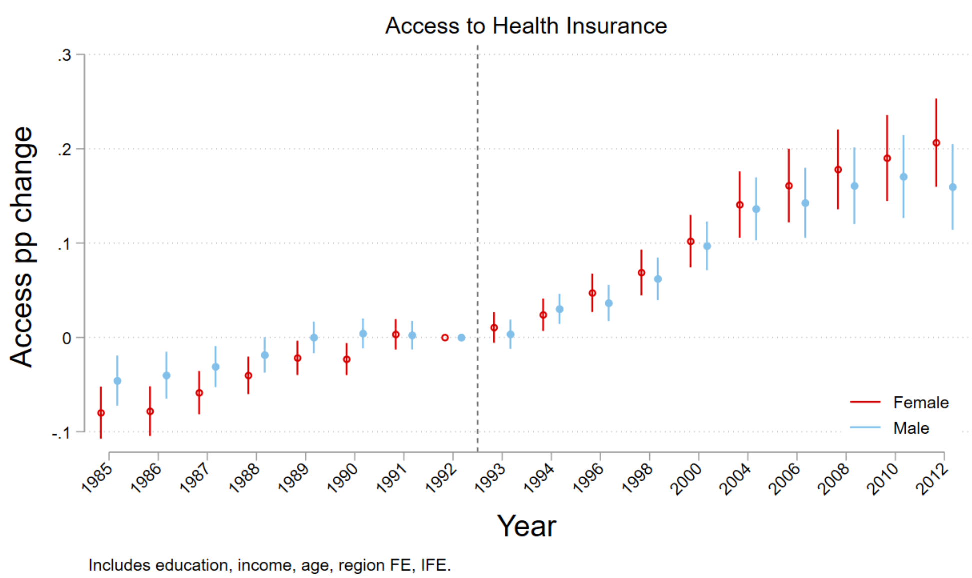


Figure 15: Placebo Event Study: Access to Health Insurance

Notes: Includes income and hours controls, and education, age, and individual fixed effects. Standard errors are clustered at the person level. Sample restricted to workers with at least 20 weekly hours due to data availability.

B Model

B.1 Worker Value Functions

Value of employment: types 1, b_i, 2, and m

$$
\begin{aligned}
V_1(x_1,x_2) =& \max\Big\{u^1(m(x_1),l(x_1)),u^1(m(x_2),l(x_2))\Big\} \\
&+(1-\gamma)\beta\times\Big((1-q_b)\big[(1-\delta-\lambda_1(1-F_1(V_1(x_1,x_2))))V_1(x_1,x_2) \\
&+\lambda_1\int_{V_1(x_1,x_2)}\nu dF_1(\nu)+\delta V_{1,0}\big] \\
&+q_b\sum_{i\in E,1,2}\varphi_{bi}\max\{V_{bi}(x_1,x_2),V_{bi,0}\}\Big) \\
V_{bi}(x_1,x_2) =& leave(x_1)\max\Big\{u^2(m(x_1),l(x_1)),u^2(m(x_2),l(x_2)),u^2(m_{res},1)+\theta_{bi})\Big\} \\
&+(1-leave(x_1))\max\Big\{u^2(m(x_1),l(x_1)),u^2(m(x_2),l(x_2))\Big\} \\
&+(1-\gamma)\beta\Big(q_{bi}\max\{V_2(x_2),V_{2,0}\}+(1-q_{bi})\max\{V_{bi}(0,x_2),V_{bi,0}\}\Big) \\
V_2(x_1,x_2) =& \max\{u^2(m(x_1),l(x_1)),u^2(m(x_2),l(x_2))\}+(1-\gamma)\beta \\
&\times\Big((1-\delta_2-\lambda_1(1-F_2(V_2(x_1,x_2))))V_2(x_1,x_2)+\lambda_1\int_{V_2(x_1,x_2)}\nu dF_2(\nu)+\delta_2V_{2,0}\Big) \\
V_m(x_m) =& u^m(m(x_m),l(x_m))+(1-\gamma)\beta \\
&\times\Big((1-\delta-\lambda_1(1-F_m(V_m(x_m))))V_m(x_m)+\lambda_1\int_{V_m(x_m)}\nu dF_m(\nu)+\delta V_{2,0}\Big)
\end{aligned}
$$

Value of unemployment: types 1, b_i, 2, m

$$
\begin{aligned}
V_{1,0} =& u^1(m_{res},1)+(1-\gamma)\beta\Big((1-q_b)(\lambda_0\int_{V_{1,0}}\nu dF_1(\nu)+(1-\lambda_0(1-F_1(V_{1,0})))V_{1,0}) \\
&+q_b\sum_i\varphi_iV_{bi,0} \\
V_{bi,0} =& u^2(m_{res},1)+\theta_{bi}+(1-\gamma)\beta\Big(q_{bi}V_{2,0}+(1-q_bi)V_{bi,0}\Big) \\
V_{2,0} =& u^2(m_{res},1)+(1-\gamma)\beta\Big(\lambda_0\int_{V_{2,0}}\nu dF_2(\nu)+(1-\lambda_0(1-F_2(V_{2,0})))V_{2,0})\Big) \\
V_{m,0} =& u^m(m_{res},1)+(1-\gamma)\beta\Big(\lambda_0\int_{V_{m,0}}\nu dF_m(\nu)+(1-\lambda_0(1-F_m(V_{m,0})))V_{m,0})\Big)
\end{aligned}
$$

Note that type m's expected lifetime utility is only a function of the bundle intended for male workers. This is because I assume that gender is observable to the firm, and I allow them to condition the offer on gender. Type 2's preferences don't change over time. If type 2 prefers bundle x_2 to x_1 today, it will prefer it also in any future period. Hence, type 2's value function can be rewritten as

$$
\begin{aligned}
V_2(x) = &\max u^2(m(x), l(x)) + (1-\gamma)\beta \\
&\times \Big((1-\delta-\lambda_1(1-F_2(V_2(x))))V_2(x) + \lambda_1 \int_{V_2(x)} \nu dF_2(\nu) + \delta V_{2,0}\Big),
\end{aligned}
$$

where $x \in \arg\max_{x_1,x_2}\{u^1(m(x_i), l(x_i))\}$ Given that incentive compatibility is satisfied, it is sufficient to write V_2 as a function of just one bundle, which is what I do when writing the firm's problem.

B.2 Stationary Objects

Worker Measures:

$$
\begin{aligned}
n_1 &= \frac{\gamma}{\gamma + (1-\gamma)q_b}, \\
n_{bi} &= \frac{\varphi_{bi} q_b n_1}{q_{bi} + \gamma/(1-\gamma)}, \\
n_2 &= 1 - (\sum_i n_{bi} + n_1), \\
n_m &= 1.
\end{aligned}
$$

Measures of unemployed workers:

$$
\begin{aligned}
u_1 &= \frac{\delta + n_1 + \gamma/(1-\gamma)/(1-q_b)}{\delta + \lambda_0 + q_b/(1-q_b) + \gamma/(1-\gamma)/(1-q_b)}, \\
u_{bi} &= \frac{\varphi_{bi} q_b (n_1 - u_1)(G_1(\tilde{V}_1(V_{bi,0})) + (1-\gamma)(1-q_{bi})(1-G_1(\tilde{V}_1(V_{bi,0}))) + \varphi_{bi} q_b u_1}{q_{bi} + \gamma/(1-\gamma)}, \\
u_2 &= \frac{\delta_2 n_2 + \sum_i q_{bi} u_{bi}}{\delta_2 + \lambda_0(1-F(V_{2,0})) + \gamma/(1-\gamma)}, \\
u_m &= \frac{\delta + \gamma/(1-\gamma)}{\delta + \lambda_0 + \gamma/(1-\gamma)}.
\end{aligned} \tag{16}
$$

Equilibrium utility distributions:

$$
\begin{aligned}
G_1(\nu) &= \frac{u_1/(n_1-u_1)\lambda_0 F_1(\nu)}{\lambda_1(1-F_1(\nu))+\delta+q_b/(1-q_b)+\gamma/(1-\gamma)/(1-q_b)},\\
G_2(\nu) &= \frac{u_2\lambda_0(F_2(\nu)-F_2(V_{2,0}))+A_2(\nu)}{(n_2-u_2)(\lambda_1(1-F_2(\nu))+\delta_2+\gamma/(1-\gamma))},\\
G_m(\nu) &= \frac{u_m\lambda_0 F_m(\nu)}{(n_m-u_m)(\lambda_1(1-F_m(\nu))+\delta+\gamma/(1-\gamma))},
\end{aligned} \tag{17}
$$

where $A_2(\nu)$ denotes the inflow of workers that experienced a birth shock and kept their jobs. More specifically, it's given by

$$
A_2(\nu) = (n_1-u_1)q_b\sum_i \varphi_i q_{bi}(G_1(\tilde{V}_1(\nu)) - G_1(\tilde{V}_1(V_{bi,0}))1_{\{\nu\geq V_{bi,0}\}}.
$$

Note that $\tilde{V}_1(\nu)$ is a function that converts type 2 expected lifetime utility to type 1 utility.

B.3 Numerical Solution Method for Firm's Problem

The solution to the firm problem is given by a vector of utilities $\nu(p) = [\nu_1(p), \nu_2(p), \nu_m(p)]$ that solves the following system of first order ordinary differential equations:

$$
M_p\frac{\partial\nu(p)}{\partial p} + \Pi_p = 0, \tag{18}
$$

where M_p is a 3x1 vector, and each entry governs how flow profit responds to increases in ν ($\frac{\partial\pi_i(\nu,p)}{\partial\nu_j}$), and Π_p is a 3x1 vector containing the positive retention effect on profit as ν increases. Recall that $\nu_i(p)$ denotes the expected lifetime utility a firm of productivity p offers to a worker type i.

In a standard job posting model, the stationary unemployment rate u can be pinned down independently of the equilibrium utility offer distribution F, as one typically assumes that the lowest productivity firm offers the reservation utility, and because there is no endogenous separation. Moreover, the stationary equilibrium utility distribution, G, can be rewritten as a function of the productivity level p, as the fraction of workers that work at or below firm p in equilibrium can be inferred from the guess that utility is increasing in productivity: the ranking of firms pins down who poaches whom, allowing one to express the fraction of workers working at a given firm in dependently of the exact policy function.

In my case, this is no longer true. Because of endogenous separation, and the fact that some firms may not want to offer bundles that are acceptable to mothers, u and G, given by equations (16) and (17), depend on the utilities provided by firms in equilibrium, i.e. they are themselves a function of the solution of the problem, $\nu(p)$, requiring me to solve for an additional fixed point. In practice, this means that M_p and Π_p in equation (18) are themselves a function of $\nu(p)$ rather than depending only on p.

To this end, I follow the explicit method outlined in the numerical appendix of Achdou et al. (2022). I convert the system of ordinary differential equations given by equation (15), to a system of partial differential equations:

$$\frac{\partial \nu_{p,t}}{\partial t} = M_{p,t}\frac{\partial \nu_{p,t}}{\partial p} + \Pi_{p,t}. \tag{19}$$

The introduction of the time dimension will aid in finding the stationary equilibrium of the economy. Notice that when $\frac{\partial \nu_{p,t}}{\partial t} = 0$, we revert back to the original system (15).

I then approximate the solution to (19) using a finite difference method. Discretizing the productivity grid, and the time dimension gives:

$$\frac{\nu_{p,t+1} - \nu_{p,t}}{\Delta t} = M_{p,t}\frac{\Delta \nu_{p,t}}{\Delta p} + \Pi_{p,t} \text{ for } p \in \{p_1, ...p_I\}.$$

This can be rearranged to the following equation

$$\nu_{p,t+1} = \nu_{p,t} + \Delta\Big\{M_{p,t}\frac{\Delta \nu_{p,t}}{\Delta p} + \Pi_{p,t}\Big\} \text{ for } p \in \{p_1, ...p_I\},$$

which gives a way to update $\nu_{p,t}$ at all productivity grid points. Given $\nu_{p,t}$, I compute $\frac{\Delta \nu_{p,t}}{\Delta p}$ using the upwind scheme. I choose a small Δ to ensure stability of the algorithm, and iterate until convergence.

C Estimation

Table 5: "Male" Moments - Data vs Model

Moment	**Data**	**Model**
Unemployment rate	0.051	0.049
EU rate	0.012	0.012
UE rate	0.29	0.25
EE rate	0.022	0.019
Weekly Income		
Mean 1990 income	553	520
Sd 1990 income	337	234
25th percentile income	0.58	0.65
50th percentile income	0.87	1.01
75th percentile income	1.27	1.33
Weekly Hours		
Mean 1990 hours	42.6	41.6
Sd 1990 hours	8.6	4.2
25th percentile hours	0.94	0.95
50th percentile hours	0.94	1.02
75th percentile hours	1.05	1.07
R/s Income and Hours		
Mean hours: Income Q1	38.7	36.3
Mean hours: Income Q2	42.7	42.3
Mean hours: Income Q3	43.7	45.25
Mean hours: Income Q4	46.1	46.5

Notes: The quartile income and hour values are rescaled by the mean, both for the model and the data to allow for easier comparison.

Table 6: “Female” Moments - Data vs Model

Moment	**Data**	**Model**
Access to leave, 1y prior	81.7%	83.2%
Retention at birth	66.1%	67.4%
Retention at birth, below med income	53.0%	56.5%
Retention at birth, above med income	79.6%	76.9%
Average Weekly Hours, 1yr prior	38.6	38.9
Wages Penalty, 1yr post	-8.9 %	-9.5%
Hours Penalty, 1yr post	-8.4%	-8.4%
Fraction returned, 1yr post	40%	42%
Fraction returned, 2yrs post	60%	55%

Notes: Prior and post is defined relative to the month of birth. Pre-birth median income is computed among all females that were working during pregnancy: above median should be interpreted as above median among other expectant mothers, no age adjustment. Fraction returned is defined on the sample of women that left their pre-birth employers. It counts the fraction of “leavers” that have been in paid work by a certain time horizon (one year post-birth, two years post-birth. For example, in the data, 40% of leaving mothers were in paid employment at some point between the month of birth and a year post-birth.