

# **Parental Leave Policies, Fertility, and Labor Supply\***

Daisoon Kim              Minchul Yum

November 2025

## **Abstract**

South Korea faces persistently low fertility rates and large gender gaps in labor supply. Under traditional women's roles, more generous parental leave makes it difficult to narrow gender gaps while increasing fertility. To examine how recent reforms operate beyond these static channels, we develop a dynamic, heterogeneous household life-cycle model in which couples jointly choose careers, labor supply, savings, childcare, and fertility. The model is calibrated to recent Korean cohorts and incorporates Korea's segmented labor markets, where career-oriented jobs are inflexible and involve high entry costs. Our quantitative results show that generous parental leave benefits can raise fertility and reduce gender gaps in labor supply and wages over the life cycle. These dynamic effects arise because parental leave job protection allows more women to remain in career-oriented jobs during childrearing years, enabling long-term career progression. Without job protection or segmented markets, this career-retention channel weakens and policy effects diminish or reverse.

**Keywords:** Parental Leave, Birth Rates, Labor Supply, Gender Gaps, Segmented Labor Markets, Job Protection, Social Norm.

**JEL codes:** E24, J22, D13, J13, J16.

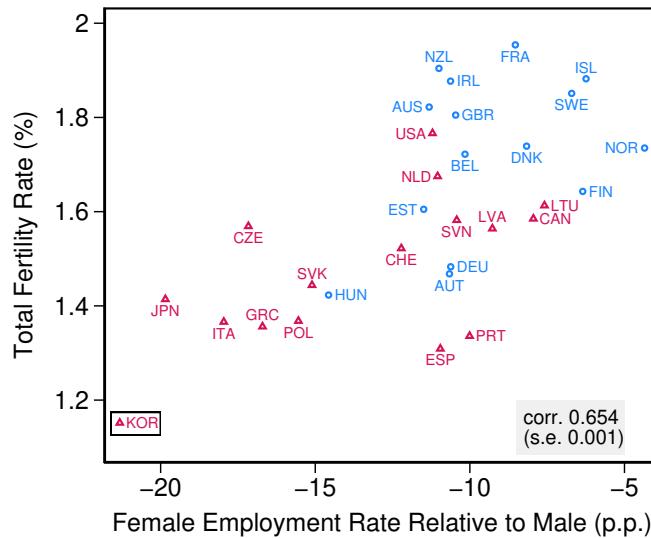
---

\*Kim: Department of Economics, North Carolina State University (dkim29@ncsu.edu); Yum: Department of Economics, Virginia Commonwealth University and CEPR (yumm@vcu.edu). We thank James Banks, Mary Ann Bronson, Diego Daruich, James Heckman, Chris Herrington, Christine Ho, Jay Hong, Shinhyc Kang, Barış Kaymak, Soojin Kim, Astrid Kunze, Eunhye Kwak, Oksana Leukhina, and Michèle Tertilt for their valuable comments. We also benefited from feedback by seminar participants at Alicante, Brown, the Cleveland Fed, CREST Paris, Doshisha, Georgetown, GRIPS, JNU, KDI, KLI, Manchester, Memphis, NHH, SMU, SNU, Southampton, USC, and VCU, as well as conference participants at Chicago Fertility Conference, Families in Macro Workshop, the GRIPS-UT Macro and Policy Workshop, the NCSU Workshop on Gender & Inequality in Economics, Midwest Macro in Richmond, the Surrey-UCL-Essex-Soton Macro Workshop, and the UN Family Policy & Population Research Forum. Daisoon Kim gratefully acknowledges support from the FRPD grant at NCSU (PINS No.132582).

# 1 Introduction

South Korea (hereafter Korea) faces two stark and interrelated challenges: low fertility and large gender gaps in labor supply. Fertility rates in Korea have remained persistently low for several decades, while Korea continues to exhibit the highest gender gap in labor supply among developed countries. Figure 1 illustrates these patterns by plotting female employment rates relative to male employment against the total fertility rate, both averaged over the past decade (2010–2019). The two variables are strongly positively correlated across countries (correlation of 0.65), with Korea standing out starkly in the bottom-left corner of the figure, highlighting the magnitude of these concerns for Korean society and policymakers.<sup>1</sup>

**Figure 1:** Gender Gaps in Labor Supply and Fertility Across Countries



Notes: The x-axis shows the employment rate gap (%) between working-age females and males within the same subgroup, while the y-axis represents the total fertility rate. Countries are categorized into two groups based on public expenditure on family benefits (as a percentage of GDP): blue circles denote high expenditure (ranks 1–15), and red triangles indicate low expenditure (ranks 16–31). Data represent country averages over the period 2010–2019. Source: OECD.

In response to these challenges, the Korean government has recognized the need to

<sup>1</sup>Although Figure 1 is inspired by Doepke et al. (2023), who highlight that the relationship between female participation rates and fertility has shifted from negative to positive, our figure offers unique value for two reasons. First, South Korea was not included in their changing relationships. Second, while they plot female labor supply, we plot gender gaps. Since countries may have distinct institutional and cultural factors that influence both male and female labor supply, the positive correlation in Figure 1 is more pronounced than when using female labor supply alone, as demonstrated in Appendix Figure A1.

expand family policies and, in particular, views parental leave (PL) as a key instrument to address them simultaneously.<sup>2</sup> In recent years, the government has implemented substantial reforms, shifting from a low, flat benefit to a generous earnings-dependent system with gradually increasing caps and incentives for couples' joint use.

How effective are these PL policies in increasing fertility and narrowing the large gap in labor supply? What mechanisms drive these policy effects, whether successful or not? While a sizable empirical literature examines PL reforms, these studies are conducted in countries with differing underlying institutions, often yielding mixed results.<sup>3</sup> Because differences in estimated effects may partly reflect these institutional features, such as labor market structures, quantitative theoretical analysis can be particularly valuable yet remains limited in the existing literature, as emphasized by [Doepke et al. \(2023\)](#). This paper provides such a theoretical and quantitative analysis of PL policies to investigate these questions.

To highlight a fundamental mechanism that can arise in models of PL, we begin with a simple static framework that captures the core time-allocation trade-offs shaping fertility and female labor supply responses to PL policies. In this setting, we show that more generous PL benefits—which effectively act as a subsidy to non-working time for parents—may be inherently unable to simultaneously increase fertility and reduce gender gaps in labor supply. While this static framework clarifies an important force relevant to many PL environments, it cannot capture how PL interacts with dynamic incentives, labor market segmentation, and long-term career progression. These considerations require a richer, dynamic life-cycle model.

Our quantitative model explicitly allows couples to make joint decisions about labor supply and PL while considering their future career prospects within an otherwise standard life-cycle framework with endogenous fertility. The fertility component of the model follows the tradition of [Becker and Tomes \(1976\)](#), where parents value both the quantity and quality of children. Additionally, the model incorporates features that link fertility choices to relevant factors, including childcare requirements for newborns and the added burden on working mothers. These factors impose both financial and time constraints on parents, influencing their fertility and labor supply decisions.

A key decision introduced in our model is the PL choice made by both mothers

---

<sup>2</sup>In line with [Olivetti and Petrongolo \(2017\)](#), the positive relationship in Figure 1 is also shaped by family policies, as evidenced by the fact that countries with higher public expenditure on family benefits (as a percentage of GDP) appear in the upper-right corner (blue circles).

<sup>3</sup>See, e.g., empirical studies on the effects of PL policies on fertility ([Dahl et al., 2016](#), [Malkova, 2018](#), [Farré and González, 2019](#), [Raute, 2019](#)) and female labor supply ([Lalive and Zweimüller, 2009](#), [Kleven et al., 2024](#)) among others.

and fathers. We incorporate the major benefits and costs of PL in a parsimonious way. On the benefit side, parents value the additional time spent with children, with social norms reinforcing an unequal gendered division of care. A central advantage of PL in a dynamic environment is job protection: PL allows parents to remain in career-oriented jobs and preserve their job quality upon returning from leave. This job-security role is a central mechanism embedded in our dynamic quantitative model. On the cost side, we model two key dynamic forces. First, because current labor supply generates future career returns in the spirit of [Imai and Keane \(2004\)](#), parents anticipate that taking PL may slow career progression. Second, we include nonpecuniary stigma costs to reflect the widely recognized discomfort—especially among men—associated with taking PL ([Kim and Lundqvist, 2023](#)).

The job-protection role of PL may be especially important in Korea's segmented labor markets.<sup>4</sup> Accordingly, we assume dual labor markets with two job types—regular and nonregular—with frictions that largely prevent transitions between them. Regular jobs offer several advantages, including higher wages, job stability, and opportunities for promotion. However, these career-oriented jobs are costly to enter and, importantly, less flexible, typically requiring long working hours and uninterrupted periods of employment to develop one's career.

We calibrate the model using longitudinal data from women born between 1970 and 1975 and their family members in the Korean Labor and Income Panel Study (KLIPS), who experienced the old regime of low, flat PL benefits during their main childbearing years. Our calibrated model successfully replicates the observed life-cycle patterns of labor supply, job types, wages, and fertility choices for both female and male household members. In particular, our calibrated model captures the marked and persistent decline in women's regular-job employment around childbirth, in contrast to the relatively stable patterns observed for men.

Using the calibrated model, we evaluate two recent versions of more generous PL policies. We find that these policies, whether implemented through a shift to a more generous earnings-dependent system or through even higher benefit caps, can persistently narrow gender gaps in labor supply over the life cycle while also raising fertility to a quantitatively meaningful extent (up to 10%). Notably, they increase women's *lifetime* labor supply, despite the short-run labor supply costs of having children. In our dynamic framework, the job-protection role of PL, combined with segmented labor markets, allows women to better balance career and family over time, with more gen-

---

<sup>4</sup>This is a key characteristic of Korea's labor markets, as documented in Section 3.

erous PL benefits inducing more women to enter and remain in regular jobs.<sup>5</sup> These sustained improvements in women's career trajectories also contributes to narrowing gender wage gaps over the life cycle.

To illustrate and quantify the importance of job protection and labor market segmentation in driving our results, we conduct two key counterfactual exercises. In the first, we shut down the job-protection role of PL; in the second, we relax labor market frictions by removing the entry costs to regular jobs.<sup>6</sup> In both cases, our benchmark quantitative findings of more generous PL benefits become substantially weaker, and in the latter case, women's lifetime labor supply even decreases. These findings highlight the critical roles played by job protection and segmented labor markets in shaping the effects of PL policies through the career-retention channel, by enabling more women to remain in career-oriented jobs during childrearing year and supporting their long-term career progression.

We also conduct several additional exercises using the model economy. To evaluate the joint-use incentive program that was part of the recent reforms, we compare its effects to two counterfactuals: a policy that mandates joint use and a scenario in which fathers' PL take-up is exogenously fixed at zero. We find that incentivizing joint PL use is only marginally effective at increasing fathers' participation, yet it performs substantially better than a mandate. Strict mandates discourage PL use by both mothers and fathers, even reducing fertility.

Finally, we also repeat the same policy experiments in economies adjusted to reflect recent developments in Korea, including rising demand for private education spending, fewer children at early ages, and more egalitarian gender norms in child-care. These adjustments shift the baseline model toward patterns consistent with the declining fertility rates and increasing female labor supply observed in recent years. Across these alternative environments, however, our benchmark quantitative results on the effects of more generous PL policies remain broadly similar.

As highlighted by [Doepeke et al. \(2023\)](#), the literature lacks quantitative theoretical analyses of PL. Notable exceptions include [Erosa et al. \(2010\)](#), who examine its welfare implications, with bargaining dynamics as the key mechanism. Our focus on couples' joint labor supply and career concerns over the life cycle ([Borella et al., 2022](#), [Guner et al., 2023](#)), along with the analysis of various PL policies—including changes in benefit schemes, caps, and joint-use incentives—is novel and distinguishes our work in the

---

<sup>5</sup>This mechanism is consistent with reduced-form evidence such as [Baker and Milligan \(2008\)](#).

<sup>6</sup>Removing entry costs alone substantially increases women's regular-job employment, narrowing gender gaps in labor supply and raising fertility, even without any PL policy reforms.

literature.<sup>7</sup> Since fertility and life-cycle labor supply are central decision variables, our paper also relates to quantitative studies using structural models of endogenous fertility and labor supply but without PL decisions.<sup>8</sup>

In terms of modeling choices, our framework also incorporates borrowing constraints and incomplete asset markets—a workhorse model framework in the literature—as young and relatively low-income households often face borrowing constraints, which may hinder fertility choices, particularly when prospective parents anticipate high monetary costs of having children.<sup>9</sup> Moreover, our model, in which both partners in a couple make their career choices endogenously, aligns with recent studies emphasizing the importance of modeling joint decision-making within couples (Bick and Fuchs-Schündeln, 2017, Borella et al., 2022, Erosa et al., 2022, Guner et al., 2023), despite the heavier computational burden it imposes, particularly in life-cycle frameworks.<sup>10</sup>

Along the path to gender gap convergence (Goldin, 2014), many developed countries have introduced family-friendly policies, including PL (Olivetti and Petrongolo, 2017). However, empirical evidence on the effects of such policies on gender gaps in labor markets and fertility remains mixed (see, e.g., Lalive and Zweimüller 2009, Dahl et al. 2016, Farré and González 2019, Kleven et al. 2024, Corekcioglu et al. 2024, Bronson and Sanin 2025). The literature examines various policy dimensions, including not only benefit generosity but also leave duration, with much of the evidence coming from European contexts.<sup>11</sup> Variation in findings may stem from differences in broader societal characteristics, such as labor market structures and gender norms. By capturing these underlying mechanisms, our theoretical framework provides a useful lens for understanding how PL policies shape fertility and labor supply outcomes.

This paper is organized as follows. Section 2 introduces a simple static model of PL and women's time-allocation trade-offs. Section 3 documents key life-cycle patterns in

---

<sup>7</sup>Adda et al. (2017) estimate a rich structural life-cycle model of female labor supply that incorporates maternity leave (but with exogenous male behavior) to quantify the career costs of children using German data. Their counterfactual analysis focuses on a policy that provides a lump-sum cash transfer at birth. Jakobsen et al. (2024) examine the complex linkages between fertility and labor supply using a rich structural model estimated for Denmark. Their analysis also considers several policy reforms, including the complete removal of maternity leave, using their model that abstracts from fathers' PL. They find that this reform reduces fertility while increasing female labor supply.

<sup>8</sup>See, e.g., Bick (2016), Greenwood et al. (2016), Daruich and Kozlowski (2020), Zhou (2022), Kitao and Nakakuni (2024), and Guner et al. (2024) for recent contributions. For broader discussions, see the literature reviews in Doepke and Tertilt (2016), Greenwood et al. (2017) and Doepke et al. (2023).

<sup>9</sup>Adda et al. (2017) and Choi (2017) also highlight the importance of assets in fertility decisions.

<sup>10</sup>As such, our quantitative theoretical approach differs from Yamaguchi (2019) and Wang (2022), who estimate discrete choice models of female labor supply and PL take-up but abstract from wealth heterogeneity through savings and joint decision-making within couples.

<sup>11</sup>For a comprehensive review of the empirical findings, see, for example, Doepke et al. (2023) and Hart et al. (2024).

labor supply, careers, and wages by gender, as well as labor market dynamics around childbirth events by gender. Section 4 develops the quantitative life-cycle model. Section 5 discusses model calibration and evaluates the model’s fit. Section 6 presents the main quantitative exercises. Finally, Section 7 concludes.

## 2 A Simple Model of PL, Gender Gaps, and Fertility

To illustrate a key obstacle to achieving both higher fertility and reduced gender labor supply gaps through PL policies, we present a simple static model of household decision-making. The model captures the traditional trade-off in women’s time allocation between labor supply and child-rearing, as well as the role of more generous PL benefits in shaping these choices within this trade-off.

**Setup of the Model** We consider a household consisting of a female  $f$  and a male  $m$  partner who maximize joint utility. Utility is derived from consumption  $c$  and the number of children  $n$ , while disutility arises from labor supply, denoted by  $h_f$  and  $h_m$  for the female and male partners, respectively.

Household income depends on wages,  $w_f$  and  $w_m$ , and each partner’s respective labor supply. Having a child incurs costs, denoted by  $x$ , which increase with the female labor supply  $h_f$ , reflecting the assumption that mothers bear the majority of child-rearing responsibilities. Additionally, these costs rise with the female’s wage, capturing the opportunity cost of outsourcing child-rearing activities, such as childcare services, which are assumed to be priced similarly to the mother’s wage rate.

We assume that PL benefits are available only to female workers, providing a replacement rate  $\theta \in [0, 1]$  of their wage per child for time spent away from work  $(1 - h_f)$ .<sup>12</sup> Normalizing total time endowment to 1, the household’s budget constraint is:

$$c + xn \leq \sum_{g=f,m} w_g h_g + \theta w_f (1 - h_f) n, \quad (1)$$

where  $x = \eta h_f w_f$  and  $\eta$  captures the degree of the education burden and childcare.

---

<sup>12</sup>This assumption is made to focus on the theoretical result we aim to highlight in this section. In the full dynamic model from Section 4 onward, we relax this assumption and allow both partners to use PL for evaluating the policy effects quantitatively.

The household maximizes the following utility function:

$$\max_{c,x,n,h_f,h_m} \log c - \sum_{g=f,m} \chi_g \frac{h_g^{1+\sigma_h}}{1+\sigma_h} + \phi \log n, \quad (2)$$

subject to equation (1). Here,  $\chi_g > 0$  represents the disutility weight on labor supply, and  $\phi > 0$  captures the utility weight of having children. We consider parameter values that ensure interior solutions, where  $c, x, n > 0$  and  $h_f, h_m \in (0, 1)$ .

**Optimality Conditions** We first present the optimality conditions that characterize household decisions. The optimal labor supply decision implies that the gender labor supply gap ( $h_m/h_f$ ) is given by:

$$\frac{h_m}{h_f} = \left( \frac{\chi_f}{\chi_m} \right)^{\frac{1}{\sigma_h}} \left( \frac{w_m}{w_f} \right)^{\frac{1}{\sigma_h}} \left[ \frac{1}{1 - (\eta + \theta)n} \right]^{\frac{1}{\sigma_h}}. \quad (3)$$

This equation shows that the labor supply gap widens with a larger gender wage gap ( $w_m/w_f$ ). It also shows that a higher childcare burden ( $\eta$ ) increases the gap for a given fertility level ( $n$ ), as mothers bear a disproportionate share of childcare responsibilities.

The gender wage gap and childcare burden also influence fertility choices. The household's optimal fertility decision is characterized by:

$$n = \left( \frac{1}{1 + 1/\phi} \right) \left( 1 + \frac{w_m}{w_f} \frac{h_m}{h_f} \right) \left[ \frac{1}{\eta - \theta \left( \frac{1}{h_f} - 1 \right)} \right]. \quad (4)$$

First, this equation highlights that the gender wage gap ( $w_m/w_f$ ) affects fertility through changes in the opportunity cost of having a child: a narrower wage gap reduces the incentive to have more children. Second, the childcare burden ( $\eta$ ) negatively impacts fertility, as higher costs make having children more expensive.

**The Trade-Off in PL Policies: Fertility vs. Gender Labor Supply Gaps** We now present the main result of this section, highlighting the trade-off in PL policies that aim to achieve two goals: boosting fertility and reducing the gender labor supply gap. Differentiating equations (3) and (4) with respect to  $\theta$ , we find that the labor supply

gap *worsens* when PL becomes more generous if and only if:

$$\underbrace{n}_{\text{Direct channel}} + \underbrace{(\eta + \theta) \frac{dn}{d\theta}}_{\text{Indirect channel via fertility}} > 0. \quad (5)$$

The first term captures the direct effect on the labor supply gap: as  $\theta$  increases, women's opportunity cost of working rises in proportion to the number of children, reducing their labor supply. The second term reflects the indirect effect of more generous PL policies on labor supply through changes in fertility choices. When fertility increases, the labor supply gap worsens in proportion to the sum of childcare burden and the existing level of PL generosity.

Note that if PL policies boost fertility ( $dn/d\theta > 0$ ), the overall effect on female labor supply relative to male labor supply is negative.<sup>13</sup> This implies that more generous PL benefits cannot simultaneously increase fertility and reduce the gender labor supply gap. This result highlights the trade-offs in using PL generosity: while generous PL benefits can encourage childbirth, they may also widen the gender labor supply gap by reducing women's labor supply, particularly with strong childcare burdens.

However, the simple model in this section focuses on the women's time allocation trade-off in a static setting, abstracting from key dynamic factors such as the long-term career impacts of taking PL in an environment with segmented jobs that differ in wage growth and entry barriers to career-oriented ones. In the next section, we present stylized facts on Korea's segmented labor market, followed by a quantitative model that incorporates these dynamic aspects for a more rigorous analysis of PL policies and their macroeconomic effects.

### 3 Empirical Observations on Gender Gaps in Korea's Segmented Labor Market

This section presents descriptive facts on gender gaps across various dimensions in Korea's labor market, providing the foundation for the quantitative model introduced in the following sections. Throughout the paper, our analysis relies on data from the Korean Labor and Income Panel Study (KLIPS), a comprehensive longitudinal dataset capturing labor market dynamics in Korea. We restrict the baseline sample to house-

---

<sup>13</sup>It may well be that  $dn/d\theta \leq 0$ , but we do not consider this case because one of its two policy objectives—higher fertility—is already unattainable.

holds where the female member was born between 1970 and 1975 (*Cohort 2*), observed in the 1998–2021 waves.<sup>14</sup> Notably, this cohort experienced PL policies that were limited in generosity and had very low take-up rates<sup>15</sup>. For robustness, we also examine other cohorts, including those born between 1965–1970 (*Cohort 1*) and 1975–1980 (*Cohort 3*). To adjust for inflation, all nominal variables are converted to 2012 Korean Won (KRW) using the CPI index. Finally, to align with the two-year model periods in the following sections, we aggregate annual data into two-year intervals. More details are available in Appendix Section B.

**Labor Supply Gaps** As highlighted in the introduction, gender gaps in labor supply remain significant in Korea. We now examine these gaps in greater detail. To construct a comprehensive measure of labor supply that captures both the intensive and extensive margins, we compute the average total weekly hours worked over two-year periods including zero observations.

Panel (a) of Figure 2 depicts the average hours worked by females and males by age, starting at ages 25–26. Notably, for males, average total weekly hours are high, around 38, even when nonworking individuals are included as zeros. Male hours worked gradually decline after their 40s, mirroring a common pattern in the life-cycle profile of labor supply observed in other countries. In contrast, females' average total hours worked are considerably lower, around 15 weekly hours at ages 25–26. Somewhat surprisingly, their labor supply then gradually increases with age. By the time their children reach school age, female labor supply begins to rise, possibly due to childcare responsibilities easing.

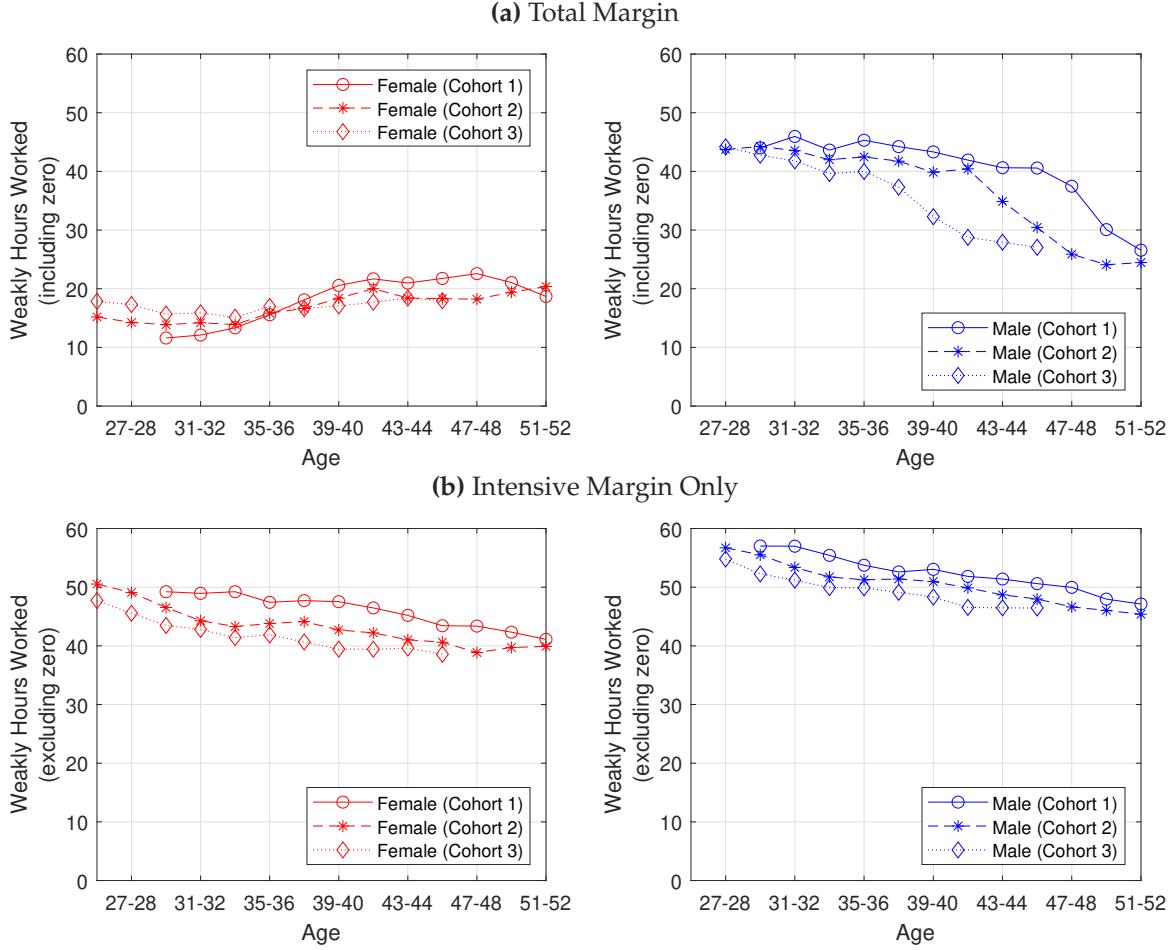
To understand how much of the variation in total hours worked is driven by the intensive vs. extensive margins, Panel (b) of Figure 2 plots hours worked excluding zero observations, capturing the intensive margin of labor supply. Average weekly hours for males is around 54, compared to 41 for females. Importantly, while a gender gap exists, it is much smaller among workers, and its decline with age is nearly parallel for both genders. This suggests that the gender gap in total hours worked is largely driven by the extensive margin, which we now examine in more detail below.

---

<sup>14</sup>Our sample focuses specifically on married couples, who are largely representative of these cohorts. Cohabitation is uncommon in Korea due to Confucianism-driven social norms, making non-marital childbearing rare as well.

<sup>15</sup>The low PL usage during the childbearing years of our baseline cohort is evident in the very low PL use share in 2010, the first year for which aggregate PL statistics are available (see Figure 6).

**Figure 2: Labor Supply Dynamics by Gender Over the Life Cycle**



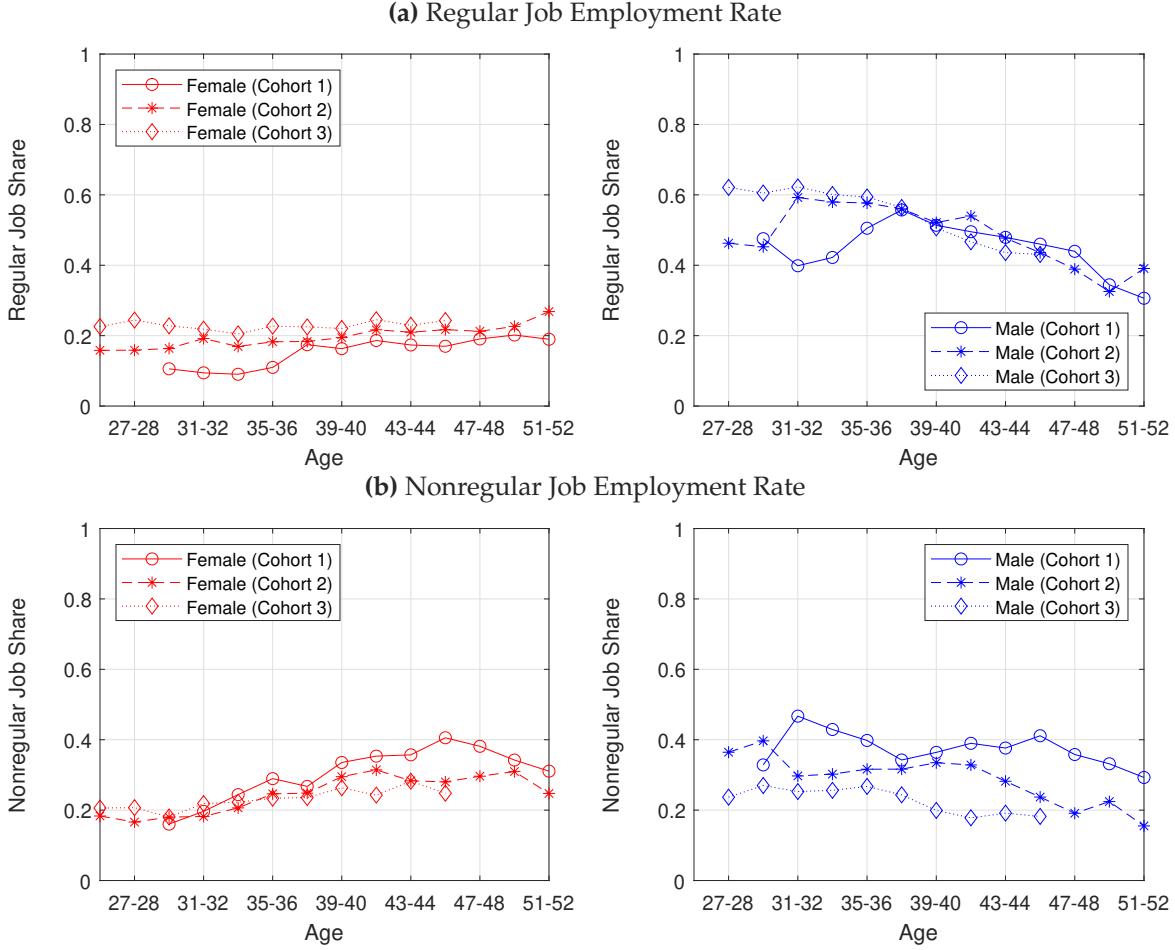
Notes: The total and intensive margins of labor supply are measured by average weekly hours worked over two years, including and excluding zeros, respectively. Cohort 1: 1965–70, Cohort 2: 1970–75, Cohort 3: 1975–80.

**Segmented Labor Markets** When it comes to employment (extensive margin), Korea's labor market is distinctly segmented, with regular jobs and nonregular jobs, the latter comprising temporary (or irregular) employment and subsistence self-employment.<sup>16</sup> In general, regular workers benefit from stable employment and higher wages through career progression but face inflexibility, as such jobs typically require long working hours. By contrast, nonregular workers experience job insecurity and lower wages, despite having more flexible working hours.

Given the sizable wage and stability premium for regular jobs, it is important to examine gender gaps in the share of workers holding these positions. Figure 3 shows

<sup>16</sup>A similar dual labor market structure has been studied in a quantitative framework, e.g., for Spain ([Guner et al., 2024](#)) and Japan ([Yamaguchi, 2019](#)).

**Figure 3:** Employment Rates by Job Type and Gender Over the Life Cycle



Notes: The regular and nonregular job employment rates are calculated as the ratio of individuals with regular jobs and regular jobs, respectively, to the total observations, averaged over a two-year period. Cohort 1: 1965–70, Cohort 2: 1970–75, Cohort 3: 1975–80.

the share of male and female workers in regular jobs (Panel (a)) and nonregular jobs (Panel (b)) over the life cycle. Clearly, male workers are significantly more likely to hold regular jobs at all ages. For females, nonregular employment rates increase after their 40s, often exceeding those of males. This shift coincides with the rise in total hours worked among females, as shown in Figure 2. The fact that many of these women enter nonregular jobs with lower wages and fewer career opportunities may reflect the challenges of re-entering regular, career-oriented jobs after career breaks. The difficulty of transitioning to regular jobs later in life suggests a possible long-term impact of childbirth on women’s career trajectories, likely contributing to persistent gender wage gaps.

**Table 1:** Labor Supply Around Childbirth

| Birth Event (2 year period)                                    | Female |    |       |       |       | Male |    |      |      |      |
|--|--------|----|-------|-------|-------|------|----|------|------|------|
|  | -2     | -1 | 0     | +1    | +2    | -2   | -1 | 0    | +1   | +2   |
| <b>Panel A. Average Weekly Hours Worked Relative to -1 (%)</b> |        |    |       |       |       |      |    |      |      |      |
| Total Margins (including zero)                                 | 3.0    | 0  | -34.0 | -31.0 | -25.3 | 3.4  | 0  | -2.2 | -0.7 | 0.4  |
| Intensive Margins (excluding zero)                             | 2.5    | 0  | -2.6  | -3.8  | -12.5 | 4.7  | 0  | -0.7 | 0.1  | -0.8 |
| <b>Panel B. Employment Rates Relative to -1 (%)</b>            |        |    |       |       |       |      |    |      |      |      |
| All Jobs   | 2.7    | 0  | -31.0 | -25.7 | -8.0  | -0.0 | 0  | -1.5 | 1.8  | 0.9  |
| Regular Job  | 1.7    | 0  | -30.1 | -33.4 | -27.5 | -5.4 | 0  | -4.3 | -1.7 | 6.2  |
| Nonregular Job   | 4.2    | 0  | -32.2 | -15.1 | 18.5  | 10.0 | 0  | 3.8  | 8.4  | -9.1 |

Notes: In Panel A, the baseline average weekly working hours in the two-year period before childbirth (period -1) are 15.2 (including zero) and 45.9 (excluding zero) for females and 45.1 (including zero) and 53.2(excluding zero) for males. In Panel B, the baseline employment rates in the two-year period before childbirth (period -1) are 37.1% (all jobs), 21.5% (regular), and 31.4% (nonregular) for females and 90.0% (all jobs), 58.6% (regular), and 15.7% (nonregular) for males. Cohort 2: 1970–75.

**Career Interruptions Around Childbirth** The previous section suggested that women's re-entry into the labor market often occurs via nonregular jobs, implying difficulties in resuming career-track employment. We now pinpoint the primary driver of these interruptions: childbirth. Table 1 presents the labor supply and employment rate changes around a birth event (period 0).<sup>17</sup>

The results reveal a profound and gender-asymmetric impact. Panel A shows a dramatic drop in the extensive margin of female labor supply. Mothers' total weekly hours (including zeros) fall by 34.0% in the birth period and remain 25.3% below the pre-birth level four years later (period +2). The intensive margin (hours for those still working) shows a more modest initial decline (-2.6%) but a penalty that grows over time, reaching -12.5% by period +2. This confirms the large drop in total hours is driven overwhelmingly by exits from the labor force.

Panel B reveals the crucial role of labor market segmentation in this process. At the birth event, regular job employment for mothers plummets by 30.1%. This decline is persistent and shows no recovery; four years later, employment in this sector remains 27.5% below the pre-birth level, demonstrating a significant "career exit." In stark contrast, while nonregular employment also drops initially (-32.2%), it rebounds sharply, rising to 18.5% above the pre-birth level by period +2. This divergent pattern strongly indicates that mothers who exit the labor force struggle to re-enter career-track posi-

<sup>17</sup>While prior literature often focuses on the first birth, we pool all birth events to ensure adequate sample size. The central finding remains robust.

tions and instead transition into nonregular employment.

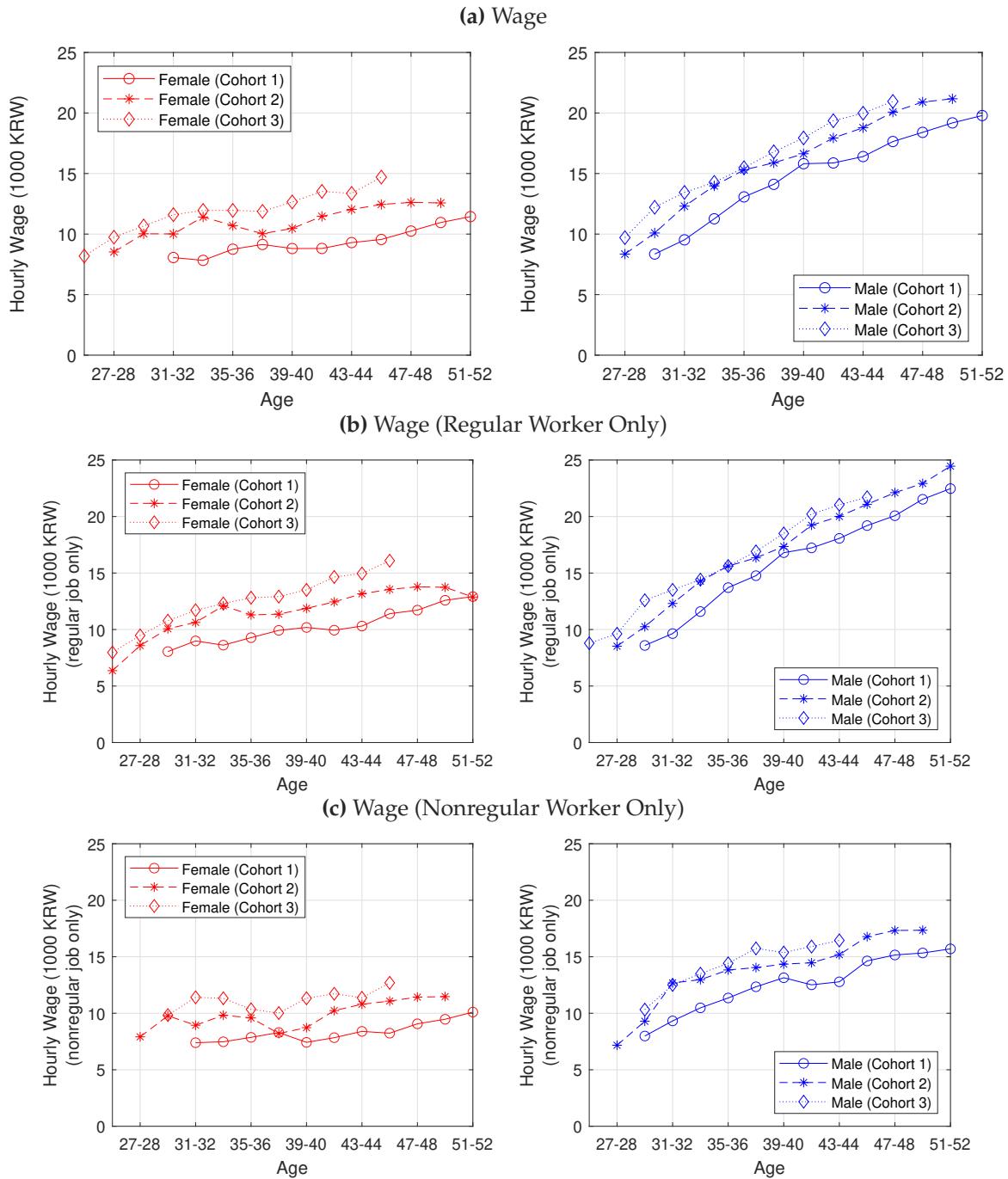
This entire negative effect of birth is borne exclusively by mothers. Fathers' labor supply and employment patterns remain remarkably stable across all measures. Their working hours (Panel A) and job employment (Panel B) are stable with negligible fluctuations. Notably, male regular job employment sees a slight dip at birth ( $-4.3\%$ ) but recovers to  $6.2\%$  above the pre-birth baseline by period +2. The childbirth-induced shift from regular to nonregular jobs is a uniquely female phenomenon and provides a clear mechanism for long-term career penalties, likely forming the root of the persistent gender wage gaps examined next.

**Wage Gaps** Korea is often cited as having one of the largest gender wage gaps among developed countries. To illustrate how these gaps evolve over the life cycle, we calculate the average hourly wage by gender and age. Panel (a) of Figure 3 shows that the average male wage increases steadily with age, reflecting career progression effects. In contrast, female wage growth is slower in early career stages, likely due to promotion barriers associated with childbirth. Beyond their mid-30s, women's wages stagnate, suggesting limited career advancement opportunities. By their 50s, male workers earn nearly twice as much as female workers on an hourly basis, highlighting a significant widening of the gender wage gap with age.

The gender wage gap is even more pronounced in career-oriented jobs. Panels (b) and (c) of Figure 4 present average wages for regular and nonregular jobs by gender and age. While gender wage gaps are relatively small among younger workers, they widen significantly with age, particularly in regular jobs where career development is crucial. In nonregular jobs, the gender wage gap remains smaller but persists. These differences in wage trajectories across job types largely explain the overall widening gap seen in Panel (a).

Against the backdrop of the above empirical observations, there appears to be some potential for PL policies to influence gender disparities in labor markets and fertility dynamics beyond the static trade-off in women's time allocation described in Section 2. For example, job protection under PL can ease the burden on female workers seeking to balance work and family by allowing them to remain in regular jobs. However, as suggested earlier, the mechanisms driving these effects are complex, involving dynamic factors such as market entry frictions, future returns to current labor supply (e.g., promotions), and intertemporal substitutions. Additionally, couples may strategically adjust their labor supply in response to policy changes, making a purely reduced-form

**Figure 4:** Wage Dynamics by Gender and Job Type Over the Life Cycle



Notes: Wage is calculated as the average hourly wage in 2012 Korean Won over a two-year period.  
 Cohort 1: 1965–70, Cohort 2: 1970–75, Cohort 3: 1975–80.

analysis challenging.

Therefore, in the next section, we develop a quantitative life-cycle model in which labor supply, careers, and wages of each partner, as well as their joint fertility choices, are endogenously determined. This model allows us to assess how PL policies shape household decision-making in both the short term and over the life cycle while systematically examining the mechanisms driving these effects.

## 4 Quantitative Life-Cycle Model

### 4.1 General Model Environments

A household, or married couple, consists of two adults: a female and a male, indexed by  $g \in \{f, m\}$ . Each period corresponds to two years (see Table A3 for an overview of the age structure). Households enter the model at  $j = 1$ , when the female member is 25–26 years old. At this stage, they are ex-ante heterogeneous in education levels, denoted by  $e \equiv (e_f, e_m)$ , and in the number of children  $n$  born previously. Households make joint decisions regarding work, choosing job types  $s \equiv (s_f, s_m)$ , where each job can be either regular (permanent,  $P$ ) or nonregular (temporary,  $T$ ). Job type determines the available choice set for working hours, as detailed below. Given labor supply choices  $h \equiv (h_f, h_m)$ , households then make standard consumption-savings decisions.

At the beginning of each fertile period ( $j = 1, 2, \dots, 10$ ), households decide whether to have an additional child, subject to fecundity uncertainty. During infertile periods ( $j = 11, \dots, 14$ ), fertility is no longer a choice variable. At the end of  $j = 10, \dots, 14$ , existing children leave the household stochastically. During the old periods ( $j \geq 15$ ), households have no children and no longer make endogenous labor supply choices but receive exogenous old-age income.<sup>18</sup> Households live until  $j = 28$  (age 79–80). In all periods, they can save in assets but face standard borrowing constraints within an incomplete asset market framework.

---

<sup>18</sup>This assumption is made for practical reasons. First, the number of individuals in our baseline cohort sample declines sharply after their early 50s. Moreover, according to Statistics Korea, the average retirement age from the main job has been around 50, though many older individuals continue working in non-career-oriented jobs.

## 4.2 Children and Gender Norm

Fertility choices primarily depend on the benefits and costs of having children. We assume that children bring utility (Becker and Tomes, 1976) yet also incur costs that vary by age. A key component of our model is about the cost of having children. Due to the computational burden of tracking each child's age, we classify children into two stages: the infant period (the first two years) and the noninfant periods.

During the infant period, parents must satisfy a childcare requirement constraint:

$$\eta \leq G(t_f, t_g, x_b) \equiv \left[ \nu_t (t_f^\varphi + t_m^\varphi)^{\frac{\rho}{\varphi}} + \nu_x (x_b)^\rho \right]^{\frac{1}{\rho}} \quad (6)$$

where  $\eta$  represents the childcare burden. Childcare needs are met through the nested constant-elasticity-of-substitution (CES) technology  $G$ , which aggregates time and monetary inputs. First, parental time contributions ( $t_f$  and  $t_m$ ) are combined with a constant elasticity of substitution determined by  $\varphi < 1$  (Knowles, 2013). The aggregate time input is then combined with market goods ( $x_b$ , i.e., monetary spending on childcare) under a CES structure with the elasticity determined by  $\rho < 1$ . The share parameters are given by  $\nu_t$  and  $\nu_x$ , respectively.

A notable feature of Korean society that we incorporate into our model is the gender norm regarding childcare responsibilities (Hwang et al., 2019). First, we assume that parental time input is dictated by social norms as a function of nonworking hours:

$$t_g = (\bar{h} - h_g)\lambda_g, \quad (7)$$

where  $\lambda_g$  captures the degree of the gender norm in childcare,  $\bar{h}$  represents total time endowment, and  $h_g$  denotes hours worked by parent  $g$ . If  $\lambda_f > \lambda_m$ , this reflects a gender norm that places a greater childcare burden on mothers, aligning with societal expectations of unequal gender roles discussed in the literature.<sup>19</sup>

Children remain costly beyond the infant stage. In Korea, students attend various after-school private education programs, known as *Hagwons*, which are highly expensive and have an exceptionally high participation rate (Kim et al., 2024). At this stage, Korean parents primarily focus on enrolling their children in more and better *Hagwons*. Given this, we assume that the perceived quality of a noninfant child is an increasing function of education expenditure per noninfant child  $x_q$ :  $q = x_q^\alpha$ . Here,  $\alpha$  governs parents' demand for child quality.

---

<sup>19</sup>These gender norms, influenced in part by Confucianism (Hwang et al., 2019, Myong et al., 2021), are also prevalent in some European countries.

### 4.3 Careers: Jobs, Promotion, and Labor Supply

Fertility choices depend on their labor market implications. As illustrated in Section 3, the Korean labor market features a segmented dual structure, where career-oriented jobs are difficult to re-enter at older ages after a career break.<sup>20</sup> Our model endeavors to capture these dynamics in career choice, promotion, and labor supply.

Specifically, in each period, couples decide whether to participate in the labor market and, if so, which job type to pursue ( $s_g$ )—regular ( $P$ ) or nonregular ( $T$ ). At the end of each period, regular job workers face exogenous separation with a constant probability  $\varrho_j$ . We denote a worker's job status at the end of the period as  $\tilde{s}'_g$ .

In our model, regular jobs are attractive for several reasons. Any worker entering the labor market draws a job quality shock,  $z_g \sim \log N(0, \sigma^2 z)$ . To capture the job stability aspect of regular jobs, we assume that workers who remain in regular positions ( $\tilde{s}'_g = s_g = P$ ) retain their job quality from the previous period. In contrast, nonregular workers face uncertainty, as they receive a new job quality shock each period. Second, beyond the job stability channel, we assume that only regular workers have opportunities for career development. Assuming a discrete career status ( $\chi_g \in 1, 2, 3$ ), all new regular workers, like nonregular workers, start at the entry level, i.e.,  $\chi_g = 1$  if  $s_g = P$  and  $\tilde{s}_g = T$ . They then face a promotion probability that increases with their current labor supply. Individuals who get promoted ( $\chi'_g = \chi_g + 1$ ) earn higher wages in the subsequent period.<sup>21</sup> To account for residual factors not captured by these channels in rationalizing the higher wages of regular workers observed in the data, we assume that regular jobs offer an exogenous wage premium relative to nonregular jobs, denoted as  $\omega_{P,g}$ . Lastly, the option of PL is available only to regular job workers, as we elaborate on later.<sup>22</sup>

Despite these advantages, regular jobs are less flexible, requiring a minimum number of working hours, as in Jang and Yum (2022), denoted as  $\underline{h}_P$ , leading to a restricted choice set for hours worked:  $\mathbb{H}_P = \{\underline{h}_P, \dots, \bar{h}\}$ . Meanwhile, nonregular jobs ( $s_g = T$ ) impose no minimum working hour requirements, allowing flexibility with the choice set  $h_g \in \mathbb{H}_T = \{0, \dots, \bar{h}\}$ . Additional inflexibilities for mothers beyond this minimum-

---

<sup>20</sup>As discussed above, having children imposes significant costs on women, particularly when they are young, often requiring extended career breaks.

<sup>21</sup>Conversely, continuing regular workers who are not at the entry level ( $\tilde{s}_g = \tilde{s}'_g = P$  and  $\chi_g \geq 2$ ) face a probability of demotion ( $\chi'_g = \chi_g - 1$ ), which decreases with their current labor supply.

<sup>22</sup>In practice, temporary job workers are legally eligible for PL if their prior work period meets the minimum requirement (six months). However, PL take-up is very rare among temporary workers. Moreover, PL take-up for self-employed individuals without employees is conceptually ill-defined. Therefore, we focus on PL take-up among regular job workers.

hours requirement may arise. Infant children can impose extra burdens on mothers' labor supply that interact with the childcare requirement constraint (equation 6), and older children can likewise limit mothers' ability to work in jobs that lack flexibility. We capture these effects through two parameters,  $\iota_b$  and  $\iota_n$ , which apply to mothers with an infant and to mothers with any children in the household, respectively.

Moreover, we assume that individuals who were not in a regular job in the previous period must incur entry costs to access regular jobs. Specifically, in each period, those without a regular job history in the previous period draw entry costs  $\xi$  from an age-dependent distribution  $F_{e,g,j}(\xi; n)$ . Korea's corporate culture often favors hiring fresh graduates for new regular positions, partly due to the social importance of age, which can create tension when older employees report to younger supervisors. The distribution also depends on education, to capture the advantages associated with being college-educated, and on gender and the number of children, to reflect the additional difficulties mothers may face in entering regular jobs. Given this, we expect that average entry costs increase with age, a pattern we later confirm in the data.

#### 4.4 Parental Leave

In our model, PL take-up is one of the key decision variables. We now discuss how the advantages and costs of using PL are modeled. In our dynamic life-cycle framework, a key advantage of taking PL is job protection. Having an infant imposes time costs, pressuring parents to work less. This is particularly costly when regular jobs require a minimum number of working hours. We assume that taking PL helps workers retain their regular jobs, as it is legally counted as a working period. That is, given the PL length ( $l_g$ ) of regular workers, the labor supply set is given by:

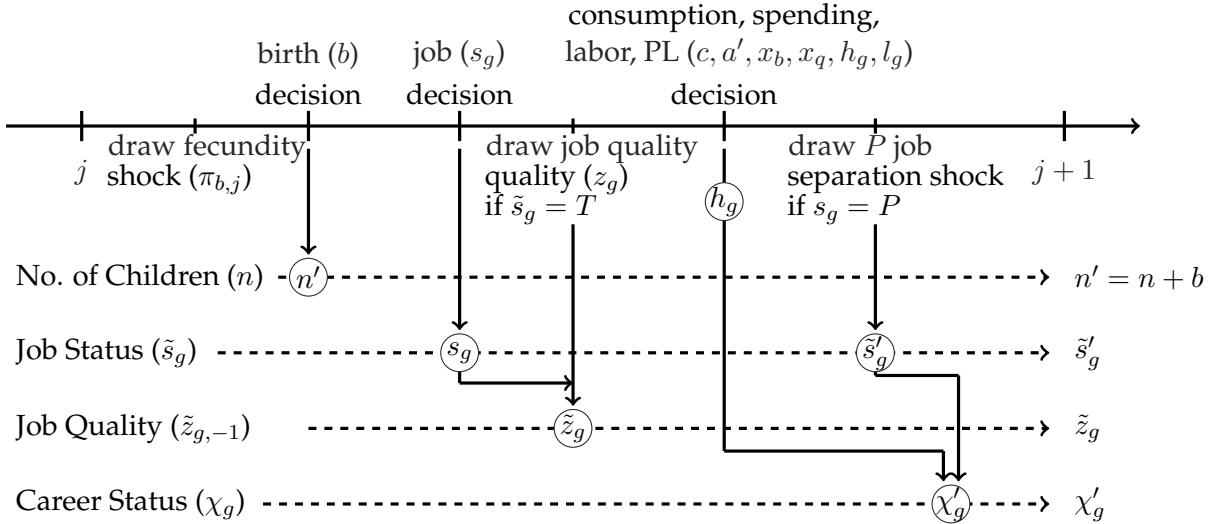
$$\mathbb{H}_P = \{h_g \geq 0 \mid \underline{h}_P \leq l_g + h_g \leq \bar{h}\}, \quad (8)$$

where PL effectively lowers the minimum required hours. This allows parents to reduce childcare burdens by working fewer hours, enabling them to keep their regular jobs and avoid entry costs when re-entering a regular job in the future.

In addition, an income effect arises from the generosity of PL monetary benefits. This effect is captured by  $\mathcal{B}(l_f, l_m, w_f, w_m)$ , which depends on PL lengths and parental wages. This function is flexible enough to capture flat benefits, wage-dependent benefits, and joint-use incentives, as explained in Section 5.2.

PL comes with costs. First, although the monetary benefit is often considered an advantage, many families choose not to take PL due to financial hardship, as the benefit

**Figure 5:** Timeline within a Fertile Period



can be far below typical earnings. Moreover, taking PL can have long-term career implications, as promotion and demotion probabilities depend on actual hours worked, excluding PL periods. Lastly, economic costs alone—whether static or dynamic—may not fully explain the low take-up rates observed in the data. As discussed next, we introduce stigma-related utility costs associated with taking PL.

## 4.5 Preferences

Households derive utility  $u(\cdot)$  from total household consumption  $c$  divided by an equivalence scale  $\Lambda(n)$  that is a function of the number of noninfant children  $n$ . Additionally, utility depends on the number  $n$  and quality  $q$  of noninfant children, captured by  $\phi(n, q)$ . Labor supply  $h_g$  incurs disutility, which also depends on the number of noninfant children to capture child-related participation costs, as discussed above. The disutility of labor supply is captured by the age-dependent function  $v$ . In addition to these standard utility components, we introduce stigma disutility associated with PL take-up  $l_g$ , captured by the function  $d(l_f, l_m)$ . This reflects the well-documented reluctance of employees, particularly men, to use PL (Kim and Lundqvist, 2023).

## 4.6 Household Optimization Problems

We first describe the household optimization problem during fertile periods ( $j \leq 10$ ). Figure 5 outlines the timeline of decisions in a fertile period.

At the beginning of each period  $j$ , households learn their fecundity realization  $\pi_{b,j}$ . If they are able to have a child, they decide whether to have a newborn. At this point, the state variables include household assets ( $a$ ), the current number of noninfant children ( $n$ ), previous job and career status ( $\tilde{s}_g, \chi_g$ ), last-period job quality ( $z_{g,-1}$ ), and education level ( $e_g \in \{1, 2\}$ , where 2 denotes college and 1 non-college). The value function at this stage is then given by:

$$W(a, n, \tilde{\mathbf{s}}, \boldsymbol{\chi}, \tilde{\mathbf{z}}_{-1}, \mathbf{e}, j) = \pi_{b,j} \max \left\{ \underbrace{\bar{N}(a, n, \tilde{\mathbf{s}}, \boldsymbol{\chi}, \tilde{\mathbf{z}}_{-1}, \mathbf{e}, j)}_{\text{value of having a new-born}}, \underbrace{\bar{V}(a, n, \tilde{\mathbf{s}}, \boldsymbol{\chi}, \tilde{\mathbf{z}}_{-1}, \mathbf{e}, j)}_{\text{value of no additional child}} \right\} + (1 - \pi_{b,j}) \bar{V}(a, n, \tilde{\mathbf{s}}, \boldsymbol{\chi}, \tilde{\mathbf{z}}_{-1}, \mathbf{e}, j), \quad (9)$$

where the value of having a newborn and having no additional child are denoted by  $\bar{N}(a, n, \tilde{\mathbf{s}}, \boldsymbol{\chi}, \tilde{\mathbf{z}}_{-1}, \mathbf{e}, j)$  and  $\bar{V}(a, n, \tilde{\mathbf{s}}, \boldsymbol{\chi}, \tilde{\mathbf{z}}_{-1}, \mathbf{e}, j)$ , respectively. Here, a bold variable represents the vector of a couple's variable:  $\mathbf{x} = (x_f, x_m)$ .

Depending on their birth choice, they then choose between regular jobs ( $P$ ) and nonregular jobs ( $T$ ). If an individual did not have a regular job history in the previous period ( $\tilde{s}_{g,-1} = T$ ) but wants to enter a regular job ( $s_g = P$ ), they must pay an entry cost  $\xi_g$  drawn from the distribution  $F_{e,g,j}(\xi; n)$ . The value of having another child ( $b = 1$ ) is thus given by

$$\bar{N}(a, n, \tilde{\mathbf{s}}, \boldsymbol{\chi}, \tilde{\mathbf{z}}_{-1}, \mathbf{e}, j) = \mathbb{E}_{\xi} \max \left\{ \begin{array}{l} \bar{N}_{PP}(a, n, \tilde{\mathbf{s}}, \boldsymbol{\chi}, \tilde{\mathbf{z}}_{-1}, \mathbf{e}, j) - \sum_g \mathcal{I}_{\tilde{s}_g=T} \xi_g, \\ \bar{N}_{PT}(a, n, \tilde{\mathbf{s}}, \boldsymbol{\chi}, \tilde{\mathbf{z}}_{-1}, \mathbf{e}, j) - \mathcal{I}_{\tilde{s}_f=T} \xi_f, \\ \bar{N}_{TP}(a, n, \tilde{\mathbf{s}}, \boldsymbol{\chi}, \tilde{\mathbf{z}}_{-1}, \mathbf{e}, j) - \mathcal{I}_{\tilde{s}_m=T} \xi_m, \\ \bar{N}_{TT}(a, n, \tilde{\mathbf{s}}, \boldsymbol{\chi}, \tilde{\mathbf{z}}_{-1}, \mathbf{e}, j). \end{array} \right\} \quad (10)$$

Note that new regular workers and temporary workers must draw a new job quality shock. The value of current job choices ( $\mathbf{s} = (s_f, s_m)$ ) before observing the job quality shock  $z_g$  is given by:

$$\bar{N}_{\mathbf{s}}(a, n, \tilde{\mathbf{s}}, \boldsymbol{\chi}, \tilde{\mathbf{z}}_{-1}, \mathbf{e}, j) = \mathbb{E}_{\mathbf{z}} N_{\mathbf{s}}(a, n, \boldsymbol{\chi}, \tilde{\mathbf{z}}, \mathbf{e}, j) \quad (11)$$

where

$$\tilde{z}_g = \tilde{z}_{g,-1} \times \mathcal{I}_{\tilde{s}_g=s_g=P} + z_g \times (1 - \mathcal{I}_{\tilde{s}_g=s_g=P}), \quad (12)$$

showing that a worker keeps their job quality  $\tilde{z}_{g,-1}$  only when they work a regular job consecutively.

For a given job choice ( $\mathbf{s}$ ) after the realization of the job quality shock, the value is

given by:

$$N_s(a, n, \chi, \tilde{\mathbf{z}}, \mathbf{e}, j) = \max_{\substack{c, a', x_b, x_q \geq 0 \\ h_g \in \mathbb{H}_{s_g}, l_g \in \mathbb{L}_g}} \left\{ \begin{array}{l} u(c/\Lambda(n)) + \phi(n, x_q^\alpha) - v(\mathbf{h}, \mathbf{e}, s_f, n, b, j) - d(\mathbf{l}) \\ + \beta \mathbb{E}_{\chi' | (\chi, \mathbf{s}, \mathbf{l}), \tilde{\mathbf{s}}} W(a', n', \tilde{\mathbf{s}}', \chi', \tilde{\mathbf{z}}, \mathbf{e}, j+1) \end{array} \right\} \quad (13)$$

subject to

$$c + x_q n + x_b + a' = \sum_g w_g h_g + (1+r)a + \mathcal{B}(\mathbf{l}, \mathbf{w}) - \mathcal{T}(\mathbf{h}, \mathbf{l}, a, \mathbf{w}) \quad (14)$$

$$w_g = \omega_{e,j} \gamma_{\chi_g} \tilde{z}_g (1 + \tilde{\omega}_{P,g} \mathcal{I}_{s_g=P}) (1 - \mathcal{I}_{g=f} \varsigma), \quad g = f, m \quad (15)$$

$$n' = n + 1 \quad (16)$$

$$\eta \leq G(\mathbf{t}, x_b), \quad (17)$$

where  $r$  denotes the return on assets, and  $\mathcal{T}(\mathbf{h}, \mathbf{l}, a, \mathbf{w})$  represents asset and labor income net of transfers. Individual wages ( $w_g$ ) depend on several factors.<sup>23</sup> First,  $\omega_{e,j}$  accounts for education premiums and age gradients in wages. Second, career status influences wages through  $\gamma_{\chi_g}$ , where promotions increase wages. Job quality  $\tilde{z}_g$  also affects individual wages. Wage premiums associated with regular jobs, to the extent not captured by career premiums, are absorbed by  $\tilde{\omega}_{P,g}$ . Finally, we introduce a wage discount for women ( $\varsigma \geq 0$ ) to account for residual factors not explicitly modeled that lower female wages relative to men, allowing the model to match the observed gender wage gap. At the end of each period, regular workers face an exogenous separation shock. If they experience this shock while holding a regular job ( $s_g = P$ ), their status in the next period changes to  $\tilde{s}_g = T$  and  $\chi'_g = 1$ .

Since this represents the value conditional on having an additional child, the number of children in the next period increases, and the childcare requirement constraint must be met, as discussed in Section 4.2. Additionally, the budget constraint accounts for monetary spending on noninfant children ( $x_q n$ ) and the infant child ( $x_b$ ) as expenses, while PL monetary benefits  $\mathcal{B}(\mathbf{l}, \mathbf{w})$  appear as income, as discussed in Section 4.4.

The value of not having an additional child ( $\bar{V}$ ) is similar to the value of having a newborn ( $\bar{N}$ ), as described above, but with  $b = 0$ , and  $x_b, l_f$ , and  $l_m$  no longer being choice variables. Moreover, the budget constraint excludes PL benefits, and the infant

---

<sup>23</sup>In the final fertile period ( $j = 10$ ), the expected future value is instead based on the first infertile-period value function and accounts for the stochastic departure of children from the household, as discussed above.

childcare constraint is not present.

The value of a household in infertile periods ( $j = 11, \dots, 14$ ) is similar to the value of not having a newborn in fertile periods, except that existing children leave households stochastically, as in Sommer (2016).<sup>24</sup> In the old periods ( $j = 15, \dots, 28$ ), there are no children ( $n = 0$ ) in the household. Instead of modeling endogenous labor supply and career choices, we assume that agents receive exogenous old-age income such as pensions and earnings. The household's value function in this stage,  $R$ , follows a conventional life-cycle model with consumption-savings decisions. See Appendix C for details on the recursive problems in the infertile and old periods.

## 5 Parameterization and Calibration

### 5.1 Calibration Strategy

For the quantitative analysis, we calibrate the model to our baseline cohort of Korean households, where females were born between 1970 and 1975. The calibration follows a two-step process, which is mostly standard, with a necessary extension in the second step, as we explain below.

First, a set of parameter values is either set or estimated externally without simulating the model. The second step involves calibrating the remaining 46 parameters. Given that male PL use is nearly zero in the calibration target period, it is not feasible to calibrate the parameter governing male PL stigma costs. Therefore, we first calibrate 45 parameters (excluding  $\mu_d$ ) to match 93 target moments, while temporarily setting  $\mu_d$  to a value that delivers zero male PL use in the baseline model. To calibrate  $\mu_d$ , we then use all the calibrated parameters to simulate a recent PL policy regime and select the value of  $\mu_d$  that matches the observed male PL use share relative to females, as described in detail below.

### 5.2 Model Parameters

The moment-matching technique we adopt relies on the informativeness of target moments for certain parameters, although the relationship is not one-to-one. We now explain these links between parameters and target moments in the second step, along with the description of externally calibrated parameters in the first step.

---

<sup>24</sup>That is, although we still capture the degree of burden caused by the number of noninfant children in the household, we do not distinguish their quality or age. This assumption facilitates computational tractability, allowing us to incorporate details related to PL and career dynamics instead.

**Children** We set the maximum number of children to three ( $n \in \{0, 1, 2, 3\}$ ). This choice is based on the observation that households with more than three children are very rare in our baseline sample. Given this, we assume that the utility from the quantity and quality of children is defined as

$$\phi(n, q) = \tilde{\phi}_n^{e_f, e_m} q = \tilde{\phi}_n^{e_f, e_m} x_q^\alpha \quad (18)$$

where the twelve parameters  $\{\tilde{\phi}_n^{e_f, e_m}\}_{n=1}^3$ , with  $e_f, e_m \in \{1, 2\}$ , are internally calibrated to match the distribution of completed fertility by corresponding education groups in the data, while  $\alpha$  is calibrated to match the observed average private education spending per child relative to income, as reported in Table 2.<sup>25</sup>

We now turn to the parameters related to the costs of children. First, we set  $\rho = 0.25$  in equation (6), according to [Hwang et al. \(2018\)](#), who estimate that parental time and market childcare are substitutable in Korea, though less so than in the United States. (e.g., [Bar et al., 2018](#)). The elasticity of substitution between mother's and father's time is governed by  $\varphi$ . We set  $\varphi = 0.4$ , implying an elasticity of substitution of 2.5, consistent with [Knowles \(2013\)](#) and [Myong et al. \(2021\)](#), who find that mother's and father's time are highly, but not perfectly, substitutable. We normalize the share parameter  $\nu_t = 1$  and calibrate  $\nu_x$  internally to match the average childcare spending relative to income. The degree of infant childcare burden is set using  $\bar{\eta} = G(0, \bar{h}/2, \bar{h}/2)$ , ensuring that childcare costs are zero ( $x_b = 0$ ) when each parent equally contributes their time allocations to newborn care. Finally,  $\lambda_f = 0.50$  and  $\lambda_m = 0.20$  are externally calibrated to the average ratio of parental time with young children to nonworking time, which is relatively stable across education groups, as reported in Table A2.

The fecundity probability for  $j = 1, 2, \dots, 10$  decreases as female age increases. To capture this age-dependent fecundity, we introduce the following functional form:

$$\pi_{b,j} = \tilde{\pi}_0 [1 - \exp(-\tilde{\pi}_1(11 - j))]. \quad (19)$$

We set  $\tilde{\pi}_0 = 0.890$  and  $\tilde{\pi}_1 = 0.246$  externally to best fit the medical literature estimates of fecundity by age ([Leridon, 2004](#)). This functional form with the parameter values generates declining fertility probabilities, as shown in Appendix Figure A5.

During the infertile periods ( $j = 11, \dots, 14$ ), children leave the household stochastically. This transition in the number of children over time follows a Binomial distribution:  $n' \sim B(n, p_n)$ . We set  $p_n = 0.955$  externally to match the ratio of the average

---

<sup>25</sup>In the data, average private education spending per child relative to income is relatively stable across education groups.

number of children in the household at  $j = 14$  to its counterpart at  $j = 11$  in the data (0.865).

**Parental Leave** In practice, PL policy design involves many dimensions and details, as noted by [Doepke et al. \(2023\)](#). This is especially true when PL benefits depend not only on an individual's choice but also on the spouse's choice and the duration of leave. Given this inherent complexity, we focus on the major aspects of PL policies, which are captured by three key variables in the PL monetary benefit function  $\mathcal{B}(l, w)$ : the wage replacement rate, the maximum PL duration, and the benefit bounds (cap and minimum). Note that in our model, PL encompasses both maternity leave and non-maternity parental leave, as implemented in practice.

Some detailed explanations for each dimension of the benefit function are in order. First, the wage replacement rate,  $\theta(l)$ , is generally modeled to depend on the PL length of each partner (i.e.,  $l \equiv (l_f, l_m)$ ). This allows us to capture the fact that mothers receive a generous 100% replacement rate for their three-month maternity leave (i.e.,  $\theta(1, \cdot) = 1$ ), whereas non-maternity PL follows different replacement rules (i.e.,  $\theta(l_f, \cdot) < 1$  for  $l_f \geq 2$ ).<sup>26</sup> Additionally, incorporating PL length for both partners enables us to account for different replacement rates introduced in recent reforms aimed at incentivizing joint PL use by allowing one partner's benefit to depend on the other's PL use.<sup>27</sup>

Next, the maximum PL length has remained one year for several decades, as discussed in Section 6.1, with recent reforms focusing on other aspects. Given this, we fix it at one year for men ( $\bar{l}_m = 4$ ) and five quarters for women, which includes an additional quarter of maternity leave ( $\bar{l}_f = 5$ ), as discussed above. Given these policy parameters, we allow eligible individuals to choose their PL length: if  $s_g = P$  and  $b = 1$ , then  $l_g \in \mathbb{L}_g = \{0, 1, \dots, \bar{l}_g\}$ ; otherwise,  $\mathbb{L}_g = \{0\}$ .

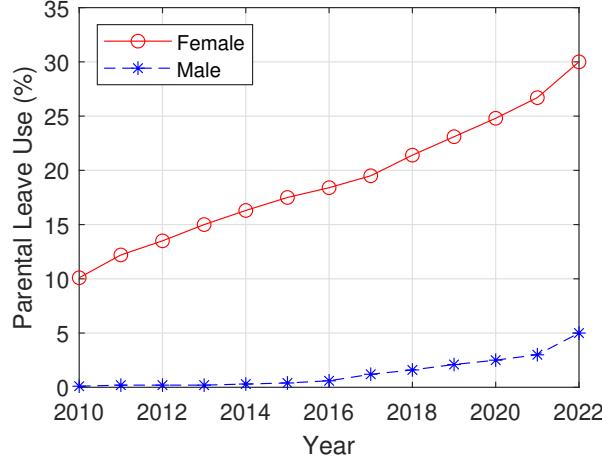
Finally, we introduce a minimum benefit ( $\underline{\Theta}$ ) and a cap ( $\bar{\Theta}(l)$ ). It is important to note that the cap has been the primary focus of recent reforms. As such, we allow the cap to primarily depend on an individual's PL length while also incorporating the partner's PL length (i.e.,  $l \equiv (l_f, l_m)$ ). For the baseline calibration prior to recent reforms, this structure enables a more generous cap on maternity leave, similar to the

---

<sup>26</sup>Paternity leave, on the other hand, has been highly limited, with a maximum duration of only a few days, as discussed in Appendix Section D. Thus, we abstract from it in the model.

<sup>27</sup>However, this feature is not included in the baseline model, which is calibrated to the period before these reforms. Details on how we model the incentive program are provided in Section 6.1.

**Figure 6:** Parental Leave Use by Gender over Time



wage replacement rate, as explained above.<sup>28</sup> Specifically, since the first two months of maternity leave are not subject to a cap, while the third month is subject to a cap, we assume that the maternity leave benefit for a quarter enters the PL benefits in the following way:

$$\mathcal{B}(\mathbf{l}, \mathbf{w}) = \sum_g b_g(\mathbf{l}, \mathbf{w}), \quad (20)$$

$$\text{where } b_f(\mathbf{l}, \mathbf{w}) = \underbrace{w_f \times \min\{l_f, 2/3\} + \min\{w_f \times \max(0, l_f - 2/3), \bar{\Theta}_f\}}_{\text{maternity}} + \underbrace{\max\{\underline{\Theta}, \min\{\tilde{\theta}w_f, \bar{\Theta}\}\} \times \max\{l_f - 1, 0\}}_{\text{non-maternity}}, \quad (21)$$

$$b_m(\mathbf{l}, \mathbf{w}) = \max\{\underline{\Theta}, \min\{\tilde{\theta}w_m, \bar{\Theta}\}\} \times l_m. \quad (22)$$

Here,  $\bar{\Theta}_f$  represents the monthly benefit cap for the final month of maternity leave, set to 0.31 (1,350K KRW).<sup>29</sup> Since the baseline calibration period features a flat benefit for non-maternity PL durations, we impose that the quarterly minimum and cap are equal in the baseline calibration:  $\underline{\Theta} = \bar{\Theta} = 0.27$ , which corresponds to approximately 300 USD per month.<sup>30</sup>

As discussed in Section 4.5, our model introduces nonpecuniary stigma costs asso-

<sup>28</sup>Additionally, this flexibility—including the interdependence of caps—allows us to incorporate a recent reform that temporarily raises the cap substantially when both spouses use PL leave. However, this program was introduced only recently and is not featured in the baseline calibration. Section 6.1 provides further details.

<sup>29</sup>Monetary values are scaled such that 1 in the model corresponds to 4,300K KRW, or approximately 3,000 USD.

<sup>30</sup>With this restriction of a constant benefit,  $\tilde{\theta}$  becomes irrelevant in the baseline economy.

ciated with using PL. This reflects the widely recognized notion that employees, particularly men, often feel uncomfortable taking PL (Kim and Lundqvist, 2023). In fact, as shown in Figure 6, the data suggest that the share of parents using any PL was very low, especially among men. Nevertheless, in our sample, mothers who take PL tend to have durations that are not particularly short.

Therefore, we specify this stigma cost as a combination of extensive margin costs ( $\tilde{d}_{0,g}$ ) and intensive margin costs ( $\tilde{d}_{1,g}$ ):

$$d(l) = \sum_g [\tilde{d}_{0,g} \mathcal{I}_{l_g > 0} + \tilde{d}_{1,g} l_g], \quad \text{where } \tilde{d}_{0,m} = \mu_d \tilde{d}_{0,f}, \quad \tilde{d}_{1,m} = \mu_d \tilde{d}_{1,f}, \quad (23)$$

where the higher intensity of this cost for men is captured by the multiplier  $\mu_d > 1$ . We first calibrate the two female parameters ( $\tilde{d}_{0,f}$  and  $\tilde{d}_{1,f}$ ) internally to match the share of mothers using PL (10.1%) and their average duration (2.7 quarters), conditional on PL use, as shown in Table 2.

Ideally, we would like to include male target moments and calibrate male parameters alongside all other parameters. However, given that the share of fathers using PL is nearly zero in the baseline calibration period, this is not feasible. Instead, we adopt an alternative strategy, as outlined in Section 5.1. We first calibrate all parameters in Table 2 using a value of  $\mu_d$  that ensures male PL use remains zero. To obtain a realistic value of  $\mu_d$ , we then apply the more generous 2022 PL policy version, as described in Section 6.1, holding the calibrated parameters fixed except for  $\mu_d$ , which is chosen to match the recent share of fathers using PL relative to mothers, shown in Figure 6. The resulting multiplier is  $\mu_d = 1.94$ , implying that male stigma costs are 94% higher than those of women.<sup>31</sup>

**Wages and Labor Markets** As shown in equation (15), individual wages depend on various components, which we parameterize as follows:

$$\omega_{e,j} = (1 + \tilde{\omega}_e \mathcal{I}_{e_g=2}) \tilde{\omega}_0 \exp(\tilde{\omega}_1(j - 1)) \quad (24)$$

$$\gamma_{\chi_g} = (1 + \tilde{\gamma})^{(\chi_g - 1)}. \quad (25)$$

The first component of the wage function is the age gradient. Specifically,  $\tilde{\omega}_0$  controls the scale, while  $\tilde{\omega}_1$  governs the age gradient of general age-wage profiles, which may reflect tenure effects or time effects. As relevant target statistics for these parame-

---

<sup>31</sup>Note that the baseline calibration remains unchanged with  $\mu_d = 1.94$  as long as male PL use remains zero in the baseline period, as noted above.

**Table 2:** Internally Calibrated Parameters

|                           | Value                 | Model                        | Data                         | Description   |
|---------------------------|-----------------------|------------------------------|------------------------------|---|
| $\tilde{\phi}^{1,1}$      | {0.124, 0.241, 0.320} | {0.062, 0.172, 0.609, 0.157} | {0.060, 0.162, 0.611, 0.166} | Pr( $n = y$ ), noncol. female                               |
| $\tilde{\phi}^{1,2}$      | {0.106, 0.206, 0.267} | {0.033, 0.167, 0.709, 0.091} | {0.030, 0.165, 0.696, 0.110} | Pr( $n = y$ ), noncol. male                                 |
| $\tilde{\phi}^{2,1}$      | {0.128, 0.246, 0.320} | {0.052, 0.239, 0.616, 0.093} | {0.049, 0.237, 0.619, 0.095} | Pr( $n = y$ ), col. female                                  |
| $\tilde{\phi}^{2,2}$      | {0.108, 0.209, 0.269} | {0.045, 0.246, 0.632, 0.076} | {0.044, 0.251, 0.614, 0.091} | Pr( $n = y$ ), col. male<br>( $y \in \{0, 1, 2, 3+\}$ )     |
| $\nu_x$                   | 0.629                 | 0.024                        | 0.024                        | Avg. childcare spending / income                            |
| $\alpha$                  | 0.280                 | 0.081                        | 0.077                        | Avg. private educ. (per child) / income                     |
| $\tilde{d}_{0,f}$         | 0.0588                | 0.063                        | 0.101                        | PL use share, female  |
| $\tilde{d}_{1,f}$         | 0.0129                | 2.38                         | 2.70                         | Avg. PL length (> 0), female                                |
| $\tilde{v}_0$             | 0.0012                | {6.16, 6.04, 5.56}           | {5.88, 5.38, 5.10}           | Hours worked (> 0), noncol. female                          |
| $\tilde{v}_1$             | 0.0204                | {6.65, 6.41, 6.37}           | {6.60, 6.18, 5.67}           | Hours worked (> 0), noncol. male                            |
|                           |                       | {5.37, 5.32, 4.83}           | {5.15, 4.85, 4.56}           | Hours worked (> 0), col. female                             |
| $\mu_v$                   | 1.511                 | {5.77, 5.57, 5.34}           | {6.06, 5.77, 5.47}           | Hours worked (> 0), col. male<br>( $j = 1-5, 6-10, 11-14$ ) |
| $\iota_f^1$               | {0.258, -0.066}       | {0.300, 0.365, 0.523}        | {0.233, 0.433, 0.506}        | Emp. rate, noncol. female                                   |
| $\iota_m^1$               | {0.190, 0.042}        | {0.790, 0.629, 0.453}        | {0.811, 0.840, 0.526}        | Emp. rate, noncol. male                                     |
| $\iota_f^2$               | {0.193, -0.042}       | {0.407, 0.411, 0.507}        | {0.419, 0.472, 0.506}        | Emp. rate, col. female                                      |
| $\iota_m^2$               | {0.162, 0.040}        | {0.836, 0.733, 0.580}        | {0.891, 0.858, 0.581}        | Emp. rate, col. male<br>( $j = 1-5, 6-10, 11-14$ )          |
| $\tilde{\varrho}_{e=1,0}$ | 0.064                 | {0.089, 0.160, 0.157}        | {0.089, 0.138, 0.235}        | Reg. emp. rate, noncol. female                              |
| $\tilde{\varrho}_{e=1,1}$ | 0.046                 | {0.478, 0.482, 0.284}        | {0.366, 0.420, 0.264}        | Reg. emp. rate, noncol. male                                |
| $\tilde{\varrho}_{e=2,0}$ | 0.038                 | {0.198, 0.243, 0.215}        | {0.224, 0.234, 0.234}        | Reg. emp. rate, col. female                                 |
| $\tilde{\varrho}_{e=2,1}$ | 0.048                 | {0.575, 0.623, 0.446}        | {0.580, 0.585, 0.418}        | Reg. emp. rate, col. male<br>( $j = 1-5, 6-10, 11-14$ )     |
| $\tilde{\xi}_0$           | 0.914                 | {0.058, 0.051}               | {0.053, 0.063}               | Reg. job entry prob., noncol. female                        |
| $\tilde{\xi}_1$           | 0.017                 | {0.227, 0.090}               | {0.261, 0.115}               | Reg. job entry prob., noncol. male                          |
| $\tilde{\xi}_n$           | 0.673                 | {0.125, 0.071}               | {0.091, 0.081}               | Reg. job entry prob., col. female                           |
| $\mu_\xi$                 | 0.498                 | {0.390, 0.170}               | {0.438, 0.243}               | Reg. job entry prob., col. male<br>( $j = 2-5, 6-10$ )      |
| $\iota_b$                 | 0.525                 | 0.666                        | 0.698                        | Reg. emp. rate at birth / -1, female                        |
| $\iota_n$                 | 0.0094                | 0.735                        | 0.675                        | Reg. emp. rate +1 / -1, female                              |
| $\tilde{\omega}_{P,f}$    | 0.156                 | {1.16, 1.67, 2.04}           | {1.30, 1.57, 1.72}           | Avg. reg. wage, female                                      |
| $\tilde{\omega}_{P,m}$    | 0.074                 | {1.51, 2.19, 2.52}           | {1.46, 2.29, 2.95}           | Avg. reg. wage, male  |
| $\tilde{\omega}_1$        | 0.024                 | {1.08, 1.20, 1.12}           | {1.04, 1.16, 1.40}           | Avg. nonreg. wage, female                                   |
|                           |                       | {1.23, 1.70, 1.88}           | {1.34, 1.79, 1.93}           | Avg. nonreg. wage, male<br>( $j = 1-5, 6-10, 11-14$ )       |
| $\tilde{\omega}_e$        | 0.259                 | {1.23, 1.66, 1.72}           | {1.38, 1.65, 1.86}           | Avg. col. wage, female                                      |
|                           |                       | {1.58, 2.33, 2.57}           | {1.57, 2.39, 2.94}           | Avg. col. wage, male  |
| $\varsigma$               | 0.298                 | {0.98, 1.19, 1.18}           | {0.80, 1.00, 1.30}           | Avg. noncol. wage, female                                   |
|                           |                       | {1.21, 1.73, 1.88}           | {1.16, 1.73, 2.19}           | Avg. noncol. wage, male<br>( $j = 1-5, 6-10, 11-14$ )       |
| $\vartheta$               | 0.982                 | 0.395                        | 0.400                        | Avg. retirement income / avg. hh earnings                   |
| $\tilde{\omega}_0$        | 0.714                 | 1.03                         | 1.00                         | Avg. male wage ( $j = 1$ ), normalization                   |
| $\sigma_z$                | 0.532                 | 0.63                         | 0.53                         | Std. dev. male wage   |

ters, we include the average male wage at  $j = 1$ , which is normalized to 1 in the model, and average nonregular worker wages by gender for the three age groups ( $j = 1\text{--}5$ ,  $6\text{--}10$ ,  $11\text{--}14$ ).

In the model, regular jobs are attractive because they provide career benefits by enabling workers to move up the career status ( $\chi_g$ ). These promotion effects are captured by  $\tilde{\chi}$ , which is set to 0.2 in accordance with the promotion estimation, as detailed in Appendix Section B.3. Wages also depend on  $\tilde{\omega}_{P,g}$ , which applies only to regular job workers. This helps to match regular job wage premiums observed in the data. We internally calibrate these parameters to match average regular job wages by gender for the age groups ( $j = 1\text{--}5$ ,  $6\text{--}10$ ,  $11\text{--}14$ ).

Next, the college premium parameter ( $\tilde{\omega}_e$ ) together with the female-specific discount factor ( $\varsigma$ ) are internally calibrated to match mean wages by education and gender for the three age groups ( $j = 1\text{--}5$ ,  $6\text{--}10$ ,  $11\text{--}14$ ) in the data. Finally, equation (15) also depends on a job quality shock, assumed to be drawn from a log-normal distribution:  $z_g \sim \log N(0, \sigma_z^2)$ . The dispersion of the shock ( $\sigma_z$ ) is internally calibrated to match the observed standard deviation of log wages, as shown in Table 2.

We now turn to exogenous components related to labor market transitions. In the model, regular job workers are subject to an age-dependent separation shock ( $\varrho_j$ ), specified as:

$$\varrho_{e,j} = \tilde{\varrho}_{e,0} \exp(\tilde{\varrho}_{e,1}(j - 1)). \quad (26)$$

The parameters  $\tilde{\varrho}_{e,0}$  and  $\tilde{\varrho}_{e,1}$  are internally calibrated to match regular employment rates by education and gender for the age groups ( $j = 1\text{--}5$ ,  $6\text{--}10$ ,  $11\text{--}14$ ). At the same time, entry into regular jobs is not frictionless in the model and is governed by entry costs ( $\xi$ ). In the data, the probability of entering a regular job declines sharply with age, likely reflecting Korean corporate culture and potential age discrimination, as discussed in Section 4.3. There are also gender and educational differences. To replicate these patterns, we specify the distribution of entry costs to be:

$$\begin{aligned} F_{e,g,j}(\xi; n) &= U[0, \bar{\xi}_{g,j}(n)\bar{\xi}_e], \\ \bar{\xi}_{g,j}(n) &\equiv \tilde{\xi}_0 \exp(\tilde{\xi}_1(j - 1)) (1 + n\tilde{\xi}_n \mathcal{I}_{\{g=f\}}). \end{aligned}$$

and use the average regular entry probability by education and gender in the two age groups ( $j = 2\text{--}5$ ,  $6\text{--}10$ ) to internally calibrate the entry cost parameters  $\tilde{\xi}_0$ ,  $\tilde{\xi}_1$ ,  $\tilde{\xi}_n$  and  $\mu_\xi$ .<sup>32</sup>

---

<sup>32</sup>We exclude the first period because the model imposes initial conditions where all individuals begin without regular job experience.

Finally, we estimate the transition matrix  $\pi(\chi'| \chi, (P, P), \mathbf{h})$ , which governs the mapping from current labor supply to promotion probability, directly from the data. The key property of this transition matrix is that the probability of promotion increases with labor supply, while the probability of demotion decreases with labor supply. We specify this relationship as follows:

$$\pi_{P,g,j}^{motion}(h_g) = \left[ 1 + \left( \frac{1}{\Pi_{P,g,j}^{motion}} - 1 \right) \exp(-\zeta_P^{motion}(h_g - 5)) \right]^{-1}, \quad (27)$$

where *motion* represents either promotion (*u*) or demotion (*d*), and  $\Pi_{P,g,j}^{motion}$  denotes the probability of promotion or demotion, conditional on  $h_g = 5$  for each group.<sup>33</sup> We classify groups along two dimensions: gender and broad age groups (27–44 and 45–52). The parameter  $\zeta_P^{motion}$  is estimated using logistic regressions with fixed effects by household, gender, and broad age group. The estimated coefficient for promotion is 1.23, while for demotion, it is -1.37, both of which are statistically significant at the 1% level, based on clustered standard errors. Details are provided in Appendix Section B.3.

**Consumption and Labor Supply** The utility function for consumption follows the standard form in macroeconomics and life-cycle literature:

$$u(c/\Lambda(n)) = \frac{(c/\Lambda(n))^{1-\sigma_c}}{1-\sigma_c}, \quad (28)$$

where we set the inverse elasticity of intertemporal substitution to  $\sigma_c = 2$ , a commonly adopted value in the literature. We define the equivalence scale as  $\Lambda(n) = 1.5 + 0.3n$ , based on the OECD modified equivalence scale. This scale assigns a value of 1 to the adult head, 0.5 to an additional adult, and 0.3 to each child under age 14. Old-age income is assumed to depend on final career status and education level, scaled by  $\vartheta$ , as specified in Appendix Section C. This parameter is internally calibrated to match 0.4, the ratio of average old-age household income to average household earnings. Finally, we set the discount factor to  $\beta = 0.92$  and the two-year real interest rate to  $r = 0.1$  externally.

We categorize total hours worked over a two-year model period into 9 bins, where each nonzero bin could be interpreted as 9 weekly hours.<sup>34</sup> A value of 5 indicates

---

<sup>33</sup>The benchmark hours of  $h_g = 5$  correspond to the mode of the distribution for both female and male regular job working hours.

<sup>34</sup>See Appendix B.3 for exact categorization formulas. This process helps mitigate measurement errors and, more importantly, ensures consistency with the discrete labor supply choices in the quantitative model.

that average weekly hours worked is greater than 36 and less than or equal to 45, corresponding to typical full-time work conditional on employment. This is set as the minimum required labor supply for regular jobs,  $\underline{h}_P$ .

Next, we specify the disutility of working,  $v(\mathbf{h}, \mathbf{e}, s_f, n, b, j)$ , as a combination of the standard constant-Frisch-elasticity function for the intensive margin of labor supply and participation fixed costs for the extensive margin, both with age-dependent shifters:

$$v(\mathbf{h}, \mathbf{e}, s_f, n, b, j) = \sum_g \left[ v_{e_g} \tilde{v}_0 \left( 1 + \iota_b \mathcal{I}_{\{b=1, s_f=P\}} \right) \exp((j-1)\tilde{v}_1) \frac{h_g^{1+\sigma_h}}{1+\sigma_h} \right] \quad (29)$$

$$+ \iota_{0,g}^{e_g} \exp((j-1)\iota_{1,g}^{e_g}) \mathcal{I}_{\{h_g>0\}} \right] + \iota_n(b+n) \mathcal{I}_{\{h_f>0, s_f=P\}}. \quad (30)$$

The parameter  $\sigma_h$  represents the inverse of Frisch elasticity and is set to 2, as is standard in the literature. We assume that labor supply shifters for the intensive margin depend only on age, while those for the extensive margin depend on age and gender. These parametric assumptions are motivated by the labor supply patterns documented in Figure 2, which show that the intensive margin declines with age in a parallel fashion, whereas the age gradient in the extensive margin differs starkly by gender. In addition, labor supply exhibits education dependence, captured by  $v_{e_g}$ , which takes the value  $\mu_v$  if  $e_g = 2$  (college) and 1 if  $e_g = 1$  (noncollege). This reflects the empirical observation that, despite higher wages among college-educated workers, labor supply does not exhibit clear differences by education level. These labor disutility parameters for both the intensive and extensive margins are internally calibrated to match total hours worked by gender and education, as well as employment rates by gender and education for the age groups ( $j = 1-5, 6-10, 11-14$ ), as reported in Table 2.

Finally, as discussed in Section 4.3, to capture the inflexibilities of regular jobs that can arise when young children are present, mothers with a newborn experience a shift in the disutility shifter  $\iota_b$ , and mothers who choose to work in a regular job face an additional participation cost per child in the household, denoted by  $\iota_n$ . These two child-related cost parameters are internally calibrated to match (i) the ratio of mothers' regular-job employment rate at birth relative to the pre-birth period and (ii) the ratio of mothers' regular-job employment rate one period after birth relative to the pre-birth period. Together, these moments capture the magnitude of motherhood penalties in regular-job attachment.

**Tax and Transfers** The tax function net of transfers is given by:

$$\mathcal{T}(\mathbf{h}, \mathbf{l}, a, \mathbf{w}) = \sum_g [E_g - (1 - \tilde{\tau}_s) E_g^{1-\tilde{\tau}_p} \bar{E}^{\tilde{\tau}_p}] + \tilde{\tau}_k r a - T, \quad (31)$$

where  $E_g$  includes earnings and PL benefits,  $\bar{E}$  denotes average individual earnings, and  $T$  represents lump-sum transfers. The capital income tax rate is set to  $\tilde{\tau}_k = 0.14$ , and  $T$ , which captures various welfare programs, is set at 10% of average household income. The progressive labor income tax follows the functional form of [Heathcote et al. \(2017\)](#). Since the Korean National Tax Service does not allow joint filing, we apply this function separately to each partner. We set  $\tilde{\tau}_p = 0.175$  for progressivity and  $\tilde{\tau}_s = 0.169$  for scale, based on [Lim and Kim \(2023\)](#).

**Initial Distributions** We take the initial distribution of couples' education and their corresponding number of children directly from the data, as summarized in Appendix Table A1. Two patterns are worth noting. First, college-educated individuals are more likely to marry partners with similar education levels, reflecting a strong pattern of educational assortative matching, similar to what is observed in the United States ([Greenwood et al., 2014](#)). Second, more educated parents tend to have fewer children at younger ages, suggesting a negative relationship between education and early fertility. This pattern may be driven by delayed family formation among highly educated individuals, as many choose to spend more than four years completing higher education (officially a four-year college degree) in Korea.<sup>35</sup>

### 5.3 Calibration Results and Model Fit

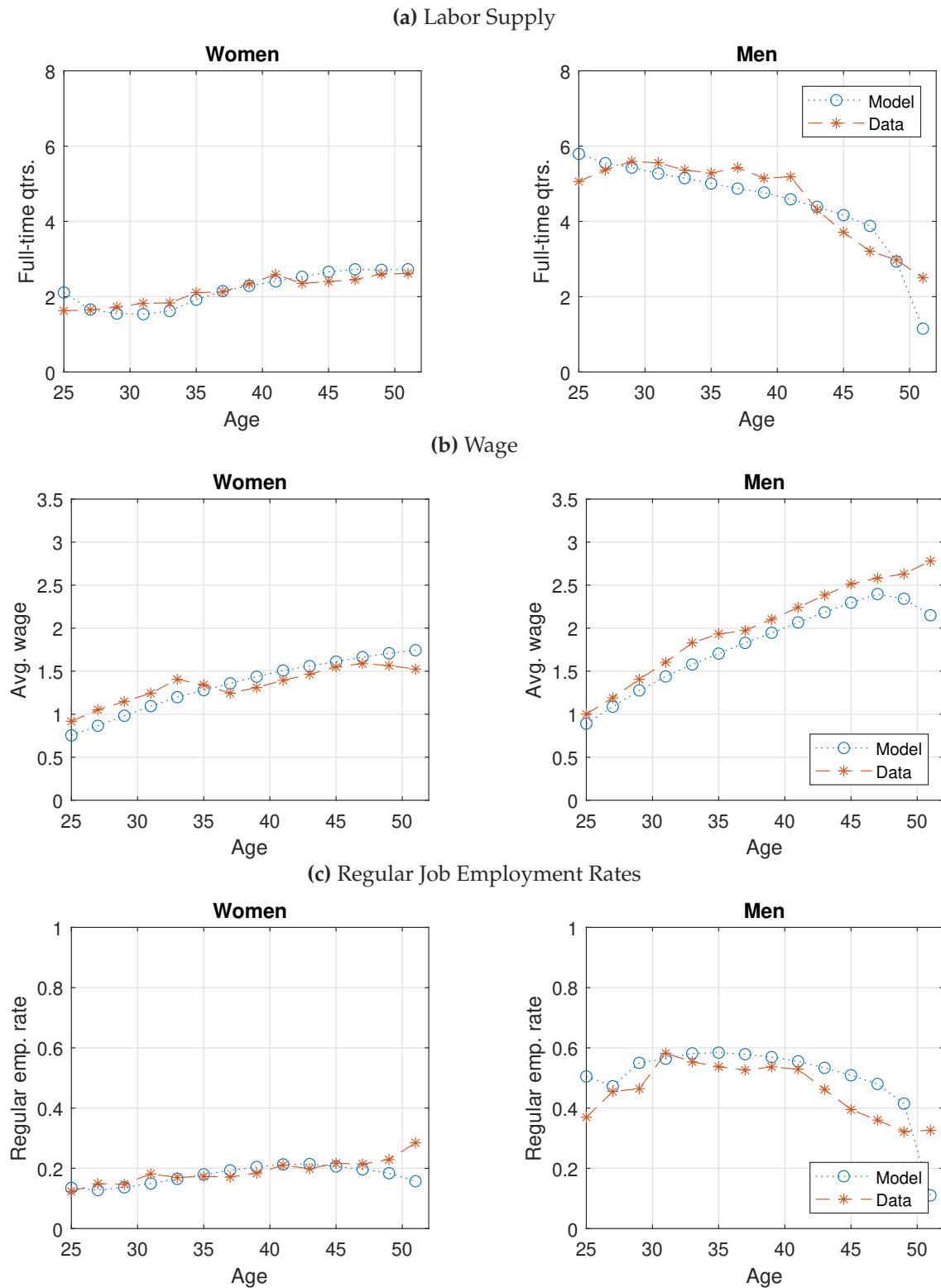
Table 2 summarizes the internally calibrated parameters, their target statistics, and the match between model-implied and empirical data moments. Given the degree of overidentification, the model performs well in matching the target statistics. We now discuss the model fit in greater detail, focusing on the key dimensions outlined in Section 3.

Panel (a) of Figure 7 presents the age profile of labor supply by gender. While we only targeted the average over the three broad age groups (as shown in Table 2), the model successfully captures more detailed two-year age patterns. In particular, as highlighted in Section 3, the model replicates the key pattern where female labor sup-

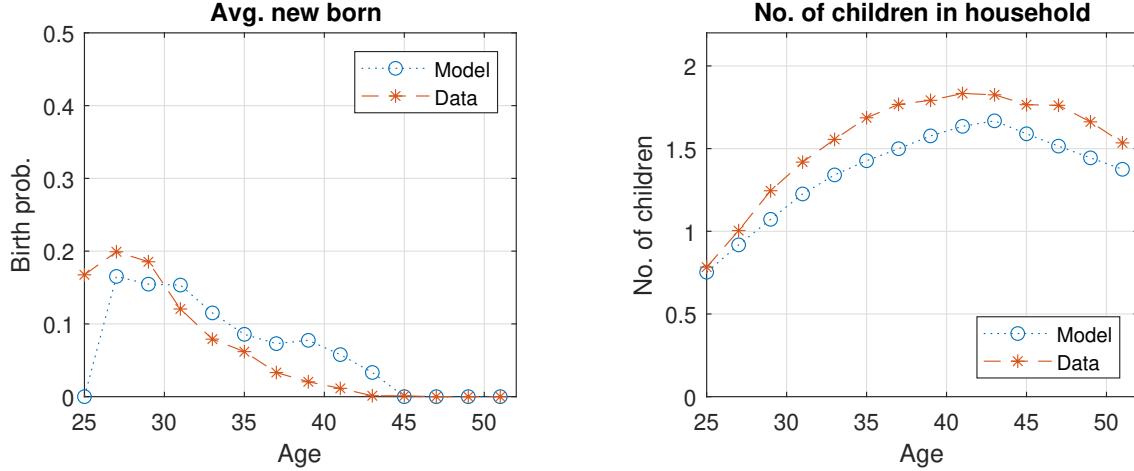
---

<sup>35</sup>Additionally, most men in Korea are required to complete mandatory military service, which lasts approximately two years (recently reduced to 1.5 years) and is typically served during their college years, further contributing to delayed marriage and family formation among the college-educated.

**Figure 7: Labor Supply, Job, and Wage by Age and Gender**



**Figure 8:** Children in Households by Age



ply increases with age as childbearing and childcare responsibilities decline, whereas male labor supply tends to decrease, particularly after their 40s. Table 2 also shows that a 2.2% higher disutility of work for the college-educated ( $\mu_v = 1.022$ ) allows the model to reproduce similar labor supply patterns across education levels, despite large wage gaps between college- and noncollege-educated workers.

The left panel displays the childbirth probability within two-year periods, capturing the timing of childbirth, while the right panel shows the average number of children per household by age. In the model, these dynamics are shaped by fecundity, externally calibrated through equation (19), as well as by endogenous fertility choices. Notably, the model's statistics align well with the data across all ages. Note that up to age 45, these moments are not directly targeted in calibration because the target moments include only the distribution of completed fertility, not the timing of births. In contrast, the declining trend after age 45 is more directly calibrated, as its slope is calibrated to match the data through the Binomial parameter ( $p_n$ ), as discussed in Section 5.2.

Panel (b) of Figure 7 plots the age profile of wages by gender, which is largely disciplined by internal calibration, subject to the parsimonious parametric assumptions in equations (15) and (24). The model successfully reproduces the widening gender wage gap over the life cycle. The gender wage gap in the model is primarily driven by direct effects, which stem from gender-related differences in career-related parameters that govern wages, such as  $\tilde{\gamma}_m = 0.181$  being larger than  $\tilde{\gamma}_f = 0.153$ , as well as the female-specific wage discount ( $\varsigma = 0.221$ ). These differences contribute to lower wage growth for women compared to men. In addition to these direct effects, indirect effects arise through their impact on endogenous labor supply and career choices,

**Table 3:** Career Interruptions Around Childbirth: Model vs. Data

| Birth Event (2-year period)         | Model |       |       | Data |       |       |
|-------------------------------------|-------|-------|-------|------|-------|-------|
|                                     | -1    | 0     | +1    | -1   | 0     | +1    |
| Regular Job Emp Rate rel. to -1 (%) |       |       |       |      |       |       |
| Female                              | 0.0   | -33.4 | -26.5 | 0.0  | -30.2 | -33.5 |
| Male                                | 0.0   | 2.8   | -0.1  | 0.0  | -4.3  | -1.7  |

further amplifying the gap with an additional premium on regular jobs ( $\tilde{\omega}_P = 0.107$ ).

Relatedly, panel (c) of Figure 7 presents regular job employment rates by gender over the life cycle, comparing model predictions with the data. The model successfully replicates the key pattern that regular job employment rates remain consistently low for women throughout the life cycle, whereas men exhibit significantly higher rates, particularly at younger ages. In the model, these patterns arise due to structural barriers such as entry costs for regular jobs that increase with age ( $\xi_0 = 0.914$ ,  $\xi_1 = 0.017$ ) and career interruptions from childrearing, which disproportionately limit women's access to career-oriented jobs.

Table 3 compares model-generated and empirical patterns of regular-job employment around childbirth. The table reports employment rates relative to the pre-birth period (period -1) for mothers and fathers in the birth period (0) and the subsequent period (+1). In both the model and the data, women experience a sharp and persistent decline in regular-job employment at childbirth, with drops of roughly 30 percent. By contrast, men show only minor changes around birth, with regular-job employment remaining close to pre-birth levels, consistent with the data. We also examine motherhood penalty estimates along wages, hours, and earnings, and find that earnings penalties are largely driven by the extensive margin of labor supply—consistent with (Stansbury et al., 2024), who show that child penalties in Korea arise predominantly along the extensive margin.

## 6 Quantitative Results

In this section, we use our calibrated model to investigate the impact of PL policy reforms on labor supply, gender gaps, and fertility, presenting the main quantitative exercises.

## 6.1 PL Policy Reforms and Computational Experiment Design

As discussed in Section 5, Given the timing of childbearing for the baseline cohort (women born in 1970–75), the baseline model sets PL benefits at approximately 400K KRW (300 USD) per month. As detailed in Appendix D, monetary PL benefits were first introduced in 2001 and gradually increased over time. While the benefit amount was adjusted incrementally, the overall structure remained flat, with no major reforms to the replacement rate or maximum duration.

In recent years, the Korean government has expanded PL policy benefits along various dimensions, as described in Appendix D. Accordingly, our quantitative experiments in this section focus on two major policy shifts, referred to as the 2022 Reform and the 2025 Reform.

**2022 Reform** Our first reform counterfactual considers a version implemented in 2022, characterized by the following key features.

Since 2011, PL benefits have undergone a crucial transition from a flat-rate to an earnings-dependent system (Kim et al., 2023), similar to the 2007 maternity leave reform in Germany (Raute, 2019), with replacement rates improving several times over the following years. The first feature of the 2022 Reform is that, unlike the flat, limited benefits, workers receive PL benefits with a replacement rate of 80% ( $\tilde{\theta} = 0.8$ ), subject to a minimum and a cap. As detailed in Appendix D, the minimum was raised to approximately 1.5 times the baseline flat benefit (inflation-adjusted), while the maximum was increased to about 3.1 times the baseline flat benefit:  $\underline{\Theta}' = 1.5 \times \underline{\Theta}$  and  $\bar{\Theta}' = 3.1 \times \bar{\Theta}$ . Additionally, the maternity leave cap for the third month was increased by 20% in real terms, approximately 1.2 times the baseline:  $\bar{\Theta}'_f = 1.2 \times \bar{\Theta}_f$ .

Secondly, we also consider the *3+3 program*, introduced in 2022 to encourage joint PL usage in response to low take-up rates among male parents. Under this program, when both parents take PL—three months per parent (hence the name, *3+3 program*)—the replacement rate increases to 100%, and the benefit cap is significantly raised to approximately 6.3 times the baseline flat benefit:  $\bar{\Theta}' = 6.3 \times \bar{\Theta}$ .

**2025 Reform** There are ongoing policy debates suggesting that the benefit cap remains insufficient. In the next reform counterfactual, the 2025 Reform, we consider more generous caps set for implementation in 2025. Specifically, the new caps are higher but gradually decrease over time: the first and second quarter caps are 5.2 and 4.2 times the baseline flat benefit ( $\bar{\Theta}'_1 = 5.2 \times \bar{\Theta}$  and  $\bar{\Theta}'_2 = 4.2 \times \bar{\Theta}$ ), while the cap for the third quarter and beyond is 3.3 times the baseline ( $\bar{\Theta}'_3 = 3.3 \times \bar{\Theta}$ ).

**Table 4:** Effects of PL Policy Reforms in the Benchmark Economy

|                 | Labor Supply     |      |       |                |      |       | Fertility<br>Rate | Parental Leave |             |      |     |  |
|-----------------|------------------|------|-------|----------------|------|-------|-------------------|----------------|-------------|------|-----|--|
|                 | Female (by $j$ ) |      |       | Male (by $j$ ) |      |       |                   | Users (%)      | Length(> 0) |      |     |  |
|                 | 1-5              | 6-10 | 11-14 | 1-5            | 6-10 | 11-14 |                   |                | Female      | Male |     |  |
| <b>Baseline</b> | 2.01             | 2.19 | 2.67  | 5.01           | 4.06 | 3.02  | 1.80              | 6.3            | 0.0         | 2.4  | n/a |  |

### Experiments

|             | % change relative to the baseline |     |     |      |      |      | 6.6  | 24.4 | 1.9 | 4.6 | 4.0 |  |
|-------------|-----------------------------------|-----|-----|------|------|------|------|------|-----|-----|-----|--|
|             | 2022 reform                       | 0.4 | 1.2 | 0.1  | -1.4 | -0.5 | -0.3 |      |     |     |     |  |
| 2025 reform | 0.8                               | 1.1 | 0.2 | -1.5 | -0.8 | -0.3 | 8.6  | 28.0 | 4.8 | 4.5 | 4.0 |  |

Notes: Italicized numbers indicate the effects of PL reforms, expressed as percentage changes relative to the baseline economy. The last four columns report levels for each economy.

## 6.2 Benchmark Effects of PL Reforms on Labor Markets and Fertility

**Effects on Gender Gaps in Labor Supply and Fertility** We now evaluate the two versions of PL policy reforms, described in Section 6.1, using the calibrated baseline economy. Table 4 presents the key results on labor supply effects by gender for three age groups ( $j = 1-5, 6-10, 11-14$ ), as well as fertility and PL usage by gender.

A key finding is that the gender gap in labor supply shrinks, mostly driven by increases in female labor supply, while fertility also increases following the PL reforms. The increase in female labor supply is particularly pronounced during early career stages and diminishes with age. Although the fertility effects are not large, they are quite meaningful, with an increase of 6.6% (2022 reform) and 8.6% (2025 reform). Note that this result contrasts with the predictions of the static model in Section 2, where generous PL benefits are constrained by a time-allocation trade-off that prevents achieving both goals. In our life-cycle framework, however, career dynamics introduce long-term benefits from PL, allowing *lifetime* female labor supply to rise alongside higher fertility.

It is also worth noting that the effects of the 2022 Reform on labor supply and fertility arise together with the increased use of PL by mothers (24.4%), which accounts for a substantial share of the observed rise in 2022 (30%) (see Figure 6). Reflecting the higher yet still modest engagement in fathers' PL following both policy reforms, young male labor supply declines especially at younger ages. These negative effects diminish in later years ( $j = 11-14$ ).

**Table 5:** Heterogeneous Policy Effects

|                 | Lifetime Labor Supply (max: 1) |      |      |      |      |      |      |      | Completed Fertility |      |      |      |
|-----------------|--------------------------------|------|------|------|------|------|------|------|---------------------|------|------|------|
|                 | Female                         |      |      |      | Male |      |      |      |                     |      |      |      |
|                 | $e_f = 1$                      | 1    | 2    | 2    | 1    | 1    | 2    | 2    | 1                   | 1    | 2    | 2    |
| $e_m = 1$       | 1                              | 2    | 1    | 2    | 1    | 2    | 1    | 2    | 1                   | 2    | 1    | 2    |
| <b>Baseline</b> | 0.33                           | 0.18 | 0.44 | 0.26 | 0.55 | 0.59 | 0.37 | 0.48 | 1.86                | 1.86 | 1.75 | 1.74 |

### Experiments

|  | 2022 Reform | 2025 reform | % change relative to baseline |      |      |     |      |      |      |      |     |     |      |      |
|--|-------------|-------------|-------------------------------|------|------|-----|------|------|------|------|-----|-----|------|------|
|  |             |             | 0.9                           | -0.1 | -0.7 | 0.8 | -1.1 | -0.5 | 0.7  | -1.0 | 3.6 | 1.7 | 14.9 | 9.7  |
|  |             |             | 1.2                           | 0.9  | 0.5  | 0.1 | -1.6 | -0.9 | -3.9 | -0.1 | 6.5 | 1.8 | 24.3 | 10.5 |

Notes: Lifetime labor supply is calculated as the sum of total labor supply over the lifetime, divided by the maximum possible labor supply.  $e_g = 1$  denotes noncollege-educated, and  $e_g = 2$  denotes college-educated. Italicized numbers indicate the effects of PL reforms, expressed as percentage changes relative to the baseline economy.

**Heterogeneous Effects of PL Reforms** The impact of policy reforms may vary across education groups. We examine how the effects on labor supply and fertility differ in Table 5. The labor supply measure we focus on here is *lifetime labor supply*, calculated as the sum of total labor supply over the lifetime, divided by the maximum possible labor supply.

Table 5 shows that across education groups, the reforms reduce gender gaps in lifetime labor supply, with particularly pronounced convergence under the 2025 reform. Fertility responses are also considerably stronger among college-educated women, especially those married to non-college-educated men. This pattern aligns with Raute (2019), who studies Germany’s shift from a flat benefit to an earnings-dependent system and finds larger fertility responses among highly educated women. Because having more children increases job inflexibility pressures, female lifetime labor supply gains are smaller among highly educated women, illustrating that the conventional trade-off reemerges at a disaggregated level.

**Career Dynamics Channel** We now illustrate the main channel through which female labor supply increases significantly, particularly in the long term, while fertility also rises. To this end, Table 6 provides key information on the policy effects on life-cycle career dynamics, including job choices and wages over the life cycle.

Panel A of Table 6 shows a notable and persistent increase in women’s regular-job employment, indicating that more women are pursuing career-oriented positions. This rise reflects both transitions from nonregular to regular jobs, seen in the corresponding

**Table 6:** Effects of PL Reforms on Career Dynamics

**Panel A. Job Dynamics by Gender**

|                 | Reg. Emp Rate    |      |       |                |      |       | Nonreg. Emp Rate |      |       |                |      |       |
|-----------------|------------------|------|-------|----------------|------|-------|------------------|------|-------|----------------|------|-------|
|                 | Female (by $j$ ) |      |       | Male (by $j$ ) |      |       | Female (by $j$ ) |      |       | Male (by $j$ ) |      |       |
|                 | 1-5              | 6-10 | 11-14 | 1-5            | 6-10 | 11-14 | 1-5              | 6-10 | 11-14 | 1-5            | 6-10 | 11-14 |
| <b>Baseline</b> | 0.14             | 0.20 | 0.19  | 0.53           | 0.56 | 0.38  | 0.21             | 0.19 | 0.33  | 0.28           | 0.13 | 0.15  |

**Experiments**

|             | % change relative to the baseline |      |     |      |      |      |      |      |      |      |      |     |
|-------------|-----------------------------------|------|-----|------|------|------|------|------|------|------|------|-----|
|             | 2022 reform                       | 14.5 | 4.5 | 0.4  | -1.8 | -0.9 | -0.5 | -3.1 | -1.0 | 0.0  | -0.5 | 0.8 |
| 2025 reform | 17.2                              | 6.5  | 1.5 | -1.6 | -1.0 | -0.2 | -4.1 | -2.0 | -2.5 | -0.8 | 1.1  | 0.4 |

**Panel B. Wage Dynamics by Gender**

|                 | Avg. Wage        |      |       |                |      |       | Avg. Reg. Wage   |      |       |                |      |       |
|-----------------|------------------|------|-------|----------------|------|-------|------------------|------|-------|----------------|------|-------|
|                 | Female (by $j$ ) |      |       | Male (by $j$ ) |      |       | Female (by $j$ ) |      |       | Male (by $j$ ) |      |       |
|                 | 1-5              | 6-10 | 11-14 | 1-5            | 6-10 | 11-14 | 1-5              | 6-10 | 11-14 | 1-5            | 6-10 | 11-14 |
| <b>Baseline</b> | 1.12             | 1.44 | 1.45  | 1.43           | 2.10 | 2.33  | 1.16             | 1.67 | 2.04  | 1.51           | 2.19 | 2.52  |

**Experiments**

|             | % change relative to the baseline |      |     |     |     |     |      |      |     |     |     |     |
|-------------|-----------------------------------|------|-----|-----|-----|-----|------|------|-----|-----|-----|-----|
|             | 2022 reform                       | -0.6 | 0.6 | 0.9 | 0.3 | 0.1 | 0.1  | -1.6 | 0.4 | 1.5 | 0.1 | 0.1 |
| 2025 reform | -0.3                              | 0.8  | 1.1 | 0.3 | 0.3 | 0.4 | -1.1 | 0.4  | 1.5 | 0.2 | 0.3 | 0.6 |

Notes: Panel A reports the effects on employment rates, while Panel B reports the effect on wages. Wages are normalized such that the male wage in  $j = 1$  is set to one. Italicized numbers indicate the effects of PL reforms, expressed as percentage changes relative to the baseline economy.

decline in nonregular employment, and new entries into regular jobs from individuals previously out of the labor force. Generous PL policies support these shifts primarily because more parents benefit from the regular-job-protection role of PL, which helps female workers overcome the minimum-hours requirements associated with regular jobs. These inflexibilities often act as indirect barriers for mothers, who bear a larger childcare burden than fathers. When mothers exit the labor force around childbirth, the higher entry costs into regular jobs, especially for older workers, make it difficult to return to such positions later, pushing many toward nonregular work. A further mechanism is that the attractiveness of regular jobs increases with more generous PL benefits, since eligibility for PL requires employment in regular positions.

These career-oriented shifts also contribute to narrowing gender wage gaps, as shown in Panel B of Table 6. In the short term, however, PL reforms lead to a decline in the

average wages of young female workers. This negative effect reflects the short-run career costs of taking PL, which are especially pronounced in regular jobs. As discussed in Sections 4.3 and 4.4, using PL reduces *actual* labor supply, slowing career advancement and increasing the likelihood of demotions, thereby lowering average wages at younger ages. Over time ( $j = 6\text{--}14$ ), female wages begin to rise, particularly for regular-job workers, because PL allows them to avoid career breaks during earlier periods, remain attached to high-paying regular jobs, and maintain career progression. Consequently, their lifetime earnings improve and gender wage gaps narrow.

### 6.3 The Role of Job Protection and Labor Market Segmentation

The policy experiments in the previous section demonstrate that generous PL policies can simultaneously increase fertility and narrow life-cycle gender gaps in labor supply and wages. These positive outcomes operate through a dynamic career-retention channel: job-protected leave enables women to maintain attachment to career-oriented *regular* jobs even during their childrearing years. In a segmented labor market with high re-entry costs, this protection is essential for sustaining long-term career progression. To illustrate the importance of these elements for shaping the labor supply and fertility effects of PL reforms, we consider two counterfactual economies: (i) one in which PL does not provide job protection (“w/o protection”) and (ii) one without labor market segmentation (“w/o segment”).

**The Role of Job Protection** First, we illustrate the importance of the job-protection mechanism by conducting the 2025 PL reform in an economy where PL does not help with career retention (“w/o protection”). In this scenario, taking leave provides the same benefit payments but no longer offers an effective waiver of the minimum-hours requirement. The leave duration  $l_g$  no longer counts toward the minimum work period  $\underline{h}_P$  needed to retain a regular job (i.e., the condition becomes  $\underline{h}_P \leq h_g$  rather than  $\underline{h}_P \leq h_g + l_g$ ). As a result, taking leave exposes women to the risk of losing their regular-job status.

Table 7 shows that when job protection is removed, far fewer women choose to use PL in the baseline: the share of women using PL falls from 6.3% (Benchmark) to 4.7% (“w/o protection”). The 2025 reform still increases PL use, but to a much smaller extent—reaching 21.5%, compared with 28.0% in the benchmark. Without this strong career-retention incentive, the policy’s positive effect on fertility is sharply reduced. The reform raises fertility by just 1.7%, in contrast to an 8.6% increase in the benchmark.

**Table 7:** Parental Leave Job Protection and Labor Market Segmentation

| <b>Panel A. Parental Leave Effects</b>                       |  |      |       |                |      |       |                |                |                     |             |      |      |  |
|--|--|------|-------|----------------|------|-------|----------------|----------------|---------------------|-------------|------|------|--|
|  | Labor Supply   |      |       |                |      |       | Fertility Rate | Parental Leave |                     |             |      |      |  |
|  | Female (by $j$ )                                       |      |       | Male (by $j$ ) |      |       |                | Users (%)      |                     | Length(> 0) |      |      |  |
|  | 1-5  | 6-10 | 11-14 | 1-5            | 6-10 | 11-14 |                | Female         | Male                | Female      | Male |      |  |
| <b>Baseline</b>  |  |      |       |                |      |       |                |                |                     |             |      |      |  |
| Benchmark  | 2.01   | 2.19 | 2.67  | 5.01           | 4.06 | 3.02  | 1.80           | 6.3            | 0.0                 | 2.4         | n/a  |      |  |
| Alternative PL structure / labor market                      |  |      |       |                |      |       |                |                |                     |             |      |      |  |
| w/o protection   | 2.01   | 2.19 | 2.67  | 5.00           | 4.05 | 3.01  | 1.78           | 4.7            | 0.0                 | 1.4         | n/a  |      |  |
| w/o segment  | 2.56   | 2.86 | 3.01  | 4.89           | 3.75 | 2.66  | 2.16           | 3.6            | 0.5                 | 2.0         | 3.9  |      |  |
| <b>Experiments: 2025 reform</b>                              |  |      |       |                |      |       |                |                |                     |             |      |      |  |
|  | <i>% change relative to the baseline</i>               |      |       |                |      |       |                |                |                     |             |      |      |  |
| Benchmark  | 0.8  | 1.1  | 0.2   | -1.5           | -0.8 | -0.3  | 8.6            | 28.0           | 4.8                 | 4.5         | 4.0  |      |  |
| Alternative PL structure / labor market                      |  |      |       |                |      |       |                |                |                     |             |      |      |  |
| w/o protection   | 4.4  | 2.8  | 0.9   | -2.0           | -3.5 | -4.3  | 1.7            | 21.5           | 0.2                 | 3.0         | 3.0  |      |  |
| w/o segment  | -9.0   | 1.1  | 0.6   | -4.1           | -0.9 | -0.9  | 3.9            | 45.5           | 9.8                 | 4.8         | 4.0  |      |  |
| <b>Panel B. Heterogeneous Effect across Education Groups</b> |  |      |       |                |      |       |                |                |                     |             |      |      |  |
|  | Lifetime Labor Supply (max: 1)                         |      |       |                |      |       |                |                | Completed Fertility |             |      |      |  |
|  | Female   |      |       |                | Male |       |                |                | 1                   | 1           | 2    | 2    |  |
| $e_f =$  | 1  | 1    | 2     | 2              | 1    | 1     | 2              | 2              | 1                   | 1           | 2    | 2    |  |
| $e_m =$  | 1  | 2    | 1     | 2              | 1    | 2     | 1              | 2              | 1                   | 2           | 1    | 2    |  |
| <b>Baseline</b>  |  |      |       |                |      |       |                |                |                     |             |      |      |  |
| Benchmark  | 0.33   | 0.18 | 0.44  | 0.26           | 0.55 | 0.59  | 0.37           | 0.48           | 1.86                | 1.86        | 1.75 | 1.74 |  |
| Alternative PL structure / labor market                      |  |      |       |                |      |       |                |                |                     |             |      |      |  |
| w/o protection   | 0.33   | 0.18 | 0.44  | 0.26           | 0.54 | 0.59  | 0.37           | 0.48           | 1.85                | 1.86        | 1.70 | 1.72 |  |
| w/o segment.   | 0.40   | 0.27 | 0.44  | 0.32           | 0.51 | 0.53  | 0.42           | 0.45           | 2.41                | 2.03        | 2.25 | 2.00 |  |
| <b>Experiments: 2025 reform</b>                              |  |      |       |                |      |       |                |                |                     |             |      |      |  |
|  | <i>% change relative to the corresponding baseline</i> |      |       |                |      |       |                |                |                     |             |      |      |  |
| Benchmark  | 1.2  | 0.9  | 0.5   | 0.1            | -1.6 | -0.9  | -3.9           | -0.1           | 6.5                 | 1.8         | 24.3 | 10.5 |  |
| Alternative PL structure / labor market                      |  |      |       |                |      |       |                |                |                     |             |      |      |  |
| w/o protection   | 1.2  | 0.4  | 1.9   | 4.9            | -1.6 | -0.9  | -4.3           | -5.1           | 3.6                 | 0.4         | 12.9 | -1.0 |  |
| w/o segment.   | -1.6   | -2.2 | -2.0  | -3.3           | -1.6 | -1.0  | -8.8           | -2.7           | 6.1                 | 2.3         | 11.5 | 1.1  |  |

Notes: "w/o protection" indicates that PL use is not counted as working period and therefore does not reduce the minimum required working period for regular jobs ( $h_P \leq h_g$ , not  $\underline{h}_P \leq h_g + l_g$ ). "w/o segment." refers to the absence of entry barriers for regular jobs, i.e., zero entry cost for regular job positions ( $\xi_g = 0$ ). Italicized numbers indicate the effects of PL reforms, expressed as percentage changes relative to the corresponding baseline economy.

These results clearly demonstrate that job protection is a central mechanism behind the effectiveness of PL reforms in our benchmark model.

**The Role of Labor Market Segmentation** We now examine how Korea’s segmented labor market—characterized by high entry costs into regular jobs—shapes the impact of PL policy. To do so, we consider a counterfactual economy in which regular-job entry costs are removed (“w/o segment”), allowing workers to move into regular jobs without frictions.

Table 7 shows an interesting result: in the baseline economy without labor market segmentation, entry into regular jobs becomes much easier, women’s labor supply is substantially higher over the life cycle, and fertility is markedly higher (2.16).<sup>36</sup> This pattern indicates that labor market segmentation itself is a major constraint on both female labor supply and fertility in Korea.

Equally importantly, we find that the effects of the 2025 PL reform are fundamentally altered. The fertility increase from the reform is dampened, rising by only 3.9% (compared with 8.6% in the benchmark). Even more strikingly, the policy’s impact on female labor supply reverses. Although the reform dramatically increases women’s PL use (from 3.6% to 45.5%), this comes at a significant cost. Early-career female labor supply declines by 9.0% (Panel A), and Panel B shows that lifetime female labor supply falls across all education groups. This reveals a trade-off that arises in the absence of segmentation: when regular jobs are easy to re-enter, generous PL encourages women to take leave but no longer secures the long-term career benefits that regular-job retention provides, resulting in a net reduction in labor supply.<sup>37</sup>

## 6.4 Inducing Father’s PL Use

In this subsection, we examine a component of policy reforms designed to promote joint PL usage: the *3+3 program*. To assess whether this program effectively fosters more egalitarian PL use, we compare this incentive-based approach with a counterfactual policy that mandates joint PL use. Our model, which endogenizes both partners’ decisions, is well suited for conducting this experiment. Specifically, we evaluate the marginal contribution of the *3+3 program* within the 2025 Reform by comparing the

---

<sup>36</sup>With regular jobs no longer hard to regain, the value of job-protected leave collapses, and the share of women using PL in the baseline falls to 3.6% (vs. 6.3% in the benchmark).

<sup>37</sup>Interestingly, in the economy without segmentation, fathers are more likely to use PL both in the baseline (0.5%) and after the reform (9.8%) than in the segmented benchmark. This suggests that labor market segmentation and the high value of preserving a male regular job also discourages fathers’ PL use.

**Table 8:** Father's Parental Leave Use

|                 | Labor Supply     |      |       |                |      |       | Fertility Rate | Parental Leave |             |      |     |  |
|-----------------|------------------|------|-------|----------------|------|-------|----------------|----------------|-------------|------|-----|--|
|                 | Female (by $j$ ) |      |       | Male (by $j$ ) |      |       |                | Users (%)      | Length(> 0) |      |     |  |
|                 | 1-5              | 6-10 | 11-14 | 1-5            | 6-10 | 11-14 |                |                | Female      | Male |     |  |
| <b>Baseline</b> | 2.01             | 2.19 | 2.67  | 5.01           | 4.06 | 3.02  | 1.80           | 6.3            | 0.0         | 2.4  | n/a |  |

### Experiments: 2025 reform

|                       | % change relative to the baseline |     |     |     |      |      |      | 8.6  | 28.0 | 4.8 | 4.5 | 4.0 |  |
|-----------------------|-----------------------------------|-----|-----|-----|------|------|------|------|------|-----|-----|-----|--|
|                       | Benchmark                         | 0.8 | 1.1 | 0.2 | -1.5 | -0.8 | -0.3 |      |      |     |     |     |  |
| Alternative PL policy | w/o male PL                       | 3.0 | 2.5 | 0.9 | -2.2 | -2.0 | -1.3 | 7.5  | 29.0 | 0.0 | 4.5 | n/a |  |
|                       | w/o 3+3                           | 0.8 | 1.1 | 0.2 | -1.5 | -0.8 | -0.3 | 8.5  | 27.9 | 4.4 | 4.5 | 4.0 |  |
|                       | Joint mandate                     | 0.3 | 0.3 | 0.4 | 0.1  | 0.1  | 0.5  | -0.8 | 7.4  | 0.7 | 1.4 | 3.5 |  |

Notes: In "w/o male PL", male workers cannot use PL. "3+3" refers to the *3+3 program*, which incentivizes joint PL use by temporarily increasing the cap and replacement rate. "Joint mandate" requires both spouses to take PL for at least one quarter if either spouse wishes to use it. Italicized numbers indicate the effects of PL reforms, expressed as percentage changes relative to the corresponding baseline economy.

policy effects of the full reform to a modified version that removes only the *3+3 program*. In the joint-use mandate scenario, we replace the *3+3 program* with a requirement that PL can be used only if both spouses take at least one quarter of leave.<sup>38</sup> This counterfactual reflects a more rigid, prescriptive approach to promoting gender-equal PL participation and fertility. We also consider a case in which fathers are exogenously assumed not to use any PL.

Table 8 summarizes the results. It first highlights the importance of endogenizing fathers' PL choices in our benchmark model. In the "w/o male PL" scenario, fathers' PL use is fixed at the pre-reform level (0%). In this case, the 2025 reform's positive fertility effect is dampened, rising by 7.5% instead of 8.6% in the benchmark. This 1.1 percentage point difference is attributable to fathers' use of PL. Moreover, the model without male PL overstates the reform's impact on narrowing the gender labor supply gap: female labor supply in the early childrearing years increases by 3.0% in the "w/o male PL" case, compared with only 0.8% in the benchmark.

Next, the "Benchmark" and "w/o 3+3" scenarios show the marginal effect of the joint-use incentive program. We find that the *3+3 program* is modestly effective: it nudges slightly more fathers to take leave, increasing the share of male users from 4.4% to 4.8%. This is accompanied by a very small additional fertility gain—a rise of

<sup>38</sup>We assume that one quarter of maternity leave is exempt from this mandate.

8.6% compared with 8.5% without the incentive.

In sharp contrast, the “Joint mandate” policy produces markedly different outcomes. This rigid requirement, which replaces the incentive with a condition for eligibility, substantially weakens the policy’s intended effects. The mandate is restrictive enough that it overturns the fertility gains, leading to a 0.8% decline relative to the baseline. Although PL use (7.4% for women and 0.7% for men) is slightly higher than in the original baseline, it remains far below the levels generated by the 2025 “Benchmark” reform (28.0% for women and 4.8% for men).<sup>39</sup> These results highlight why a mandated joint-use policy is ineffective: rather than increasing co-participation, the mandate substantially reduces overall PL use by imposing a stringent coordination requirement.

## 6.5 Gauging Parental Leave Effects for Recent Cohorts

Our benchmark model is calibrated to the most recent cohorts who have completed their working years (based on women born between 1970 and 1975), and the policy effects we have found thus far are based on these cohorts. However, more recent cohorts in Korea have experienced notable changes in fertility behavior, childcare patterns, and family-related preferences. To assess how these developments may alter our baseline findings, we consider alternative model economies that capture several prominent trends.

**The Role of Higher Demands for Private Education** Korea is a prominent example of a society with an intense emphasis on education, often described as “education fever” (Kim et al., 2024). Unlike most European countries, Korea exhibits exceptionally high levels of private education spending, which have continued to rise in recent years. Figure A6 illustrates this trend: although average private education spending per child has been substantial for several decades, it has increased by nearly 50% in real terms over the past ten years. To capture this heightened demand for private education, we consider an alternative economy with elevated private education expenditures. Specifically, we increase  $\alpha$  by 30% relative to its calibrated value in the baseline model, which raises the ratio of private education spending ( $x_q$ ) to household income by 36%.

As Table 9 shows, this modification brings the model in line with Korea’s recent trends: baseline fertility drops markedly from 1.80 to 1.42, and female labor supply increases. In this low-fertility, high-child-cost environment, the effects of the 2025 PL

---

<sup>39</sup>Note that one quarter of maternity leave is exempt from the mandate, which explains why the share of female PL users remains higher than that of fathers under the joint mandate.

**Table 9:** Parental Leave Effects in Alternative Economies

|                                 | Labor Supply   |      |       |                |      |       | Fertility Rate | Parental Leave |      |             |      |  |
|---------------------------------|--|------|-------|----------------|------|-------|----------------|----------------|------|-------------|------|--|
|                                 | Female (by $j$ )                                       |      |       | Male (by $j$ ) |      |       |                | Users (%)      |      | Length(> 0) |      |  |
|                                 | 1-5  | 6-10 | 11-14 | 1-5            | 6-10 | 11-14 |                | Female         | Male | Female      | Male |  |
| <b>Baseline</b>                 |  |      |       |                |      |       |                |                |      |             |      |  |
| Benchmark                       | 2.01   | 2.19 | 2.67  | 5.01           | 4.06 | 3.02  | 1.80           | 6.3            | 0.0  | 2.4         | n/a  |  |
| Alternative economy             |  |      |       |                |      |       |                |                |      |             |      |  |
| with high $\alpha$              | 2.13   | 2.30 | 2.74  | 4.93           | 3.86 | 2.85  | 1.42           | 10.9           | 0.0  | 1.5         | n/a  |  |
| with $n_{j=1} = 0$              | 2.00   | 2.27 | 2.72  | 4.64           | 3.75 | 2.77  | 1.62           | 6.3            | 0.0  | 2.6         | n/a  |  |
| with $\lambda_f = \lambda_m$    | 2.05   | 2.24 | 2.71  | 4.98           | 4.09 | 3.12  | 1.79           | 6.5            | 0.0  | 2.3         | n/a  |  |
| <b>Experiments: 2025 reform</b> |  |      |       |                |      |       |                |                |      |             |      |  |
|                                 | <i>% change relative to the corresponding baseline</i> |      |       |                |      |       |                |                |      |             |      |  |
| Benchmark                       | 0.8  | 1.1  | 0.2   | -1.5           | -0.8 | -0.3  | 8.6            | 28.0           | 4.8  | 4.5         | 4.0  |  |
| Alternative economy             |  |      |       |                |      |       |                |                |      |             |      |  |
| with high $\alpha$              | 2.1  | 1.8  | 0.7   | -1.1           | -1.3 | -1.3  | 10.8           | 36.4           | 0.8  | 4.3         | 4.0  |  |
| with $n_{j=1} = 0$              | 1.7  | 2.0  | 0.2   | -2.9           | -1.5 | -1.1  | 13.2           | 29.2           | 5.0  | 4.5         | 4.0  |  |
| with $\lambda_f = \lambda_m$    | 0.7  | 1.1  | 0.1   | -1.4           | -0.8 | -0.4  | 8.9            | 28.7           | 5.0  | 4.5         | 4.0  |  |

Notes: Italicized numbers indicate the effects of PL reforms, expressed as percentage changes relative to the corresponding baseline economy.

reform on fertility and gender gaps remain broadly similar to the benchmark. The fertility increase is 10.8% (vs. 8.6% in the benchmark), and the reform generates even stronger female labor supply responses.

**The Role of Lower Initial Number of Children** A well-documented feature of Korea's recent fertility decline is the substantial delay in childbearing. Unlike the 1970–75 benchmark cohort, more recent cohorts increasingly enter early adulthood without children. To capture this shift, we simulate an alternative economy in which all households begin with zero children at age 25 ( $n_{j=1} = 0$ ).

As Table 9 shows, this modification lowers the baseline fertility rate to 1.62, consistent with recent trends. More importantly, it amplifies the impact of the 2025 reform. The fertility increase reaches 13.2%, compared with 8.6% in the benchmark. The reform also narrows the gender gap more effectively, inducing stronger behavioral responses from both parents: female labor supply at young ages ( $j = 1-5$ ) rises by 1.7% (vs. 0.8% in the benchmark), while male labor supply at those ages declines by 2.9% (vs. 1.5%)..

**The Role of Equal Gender Norm** While Korean society has traditionally held unequal social norms regarding childcare, these norms have been weakening in recent years (Kim et al., 2024). To examine the implications of this shift, we consider an alternative economy in which gender norms are equalized by setting  $\lambda_f = \lambda_m = 0.35$ , the average of the two benchmark calibrated parameters.

As Table 9 shows, this change has relatively small effects on the baseline economy. The baseline fertility rate falls only slightly (1.79 vs. 1.80), and gender gaps in labor supply shrink modestly—patterns that are again consistent with recent trends. The effects of the PL policy reform on fertility and labor supply also remain very similar to the benchmark. These results align with the empirical finding of Moon and Shin (2018), who shows that shifts in social norms have only modest effects on gender roles in childcare unless the issue of overwork is addressed.

## 7 Conclusion

Motivated by South Korea’s dual challenges of low fertility and large gender disparities, this paper first documents the key dimensions of these gaps over the life cycle. We then develop a structural life-cycle model of couples with endogenous fertility and career dynamics, calibrated to cohorts who experienced the earlier regime of low, flat PL benefits. The model replicates key labor market behaviors and family decisions observed in the data. Through a series of policy experiments, we assess the effects of expanding PL benefits on fertility and labor market outcomes. Our central finding is that more generous PL benefits can raise fertility while simultaneously narrowing gender gaps in labor supply over the life cycle and, in the long run, gender wage disparities as well.

In our dynamic framework, these positive effects arise from a career-retention channel: job-protected leave, interacting with Korea’s segmented labor market, enables more women to remain in career-oriented regular jobs during their childrearing years. We show that if either the job-protection role of PL or labor market segmentation is removed, the ability of PL reforms to raise fertility and reduce gender gaps is substantially weakened or even reversed. Our results may help explain the mixed empirical evidence on PL reforms across countries: when labor market frictions differ, the strength of the career-retention channel—and therefore the policy’s effects on fertility and labor market outcomes—can vary substantially. We also find that increases in fathers’ PL use, though still modest, contribute to higher fertility, and that incentive-based policies promoting joint PL use are more effective than mandates, as rigid joint-

use requirements discourage PL participation and can even reduce fertility.

Our analysis focuses on the supply side, capturing the benefits and costs of PL from the household's perspective, while incorporating demand-side factors only in a reduced-form manner. This focus is appropriate given our interest in evaluating statutory policy reforms in a setting where PL use has historically been low. However, as PL use rises to levels observed in countries such as those in Scandinavia, demand-side mechanisms are likely to become increasingly important.<sup>40</sup> As existing demand-side frameworks often rely on simplified representations of family decisions, combining richer supply-side dynamics—such as those modeled here—with endogenous detailed demand-side responses would be a challenging yet valuable direction for future research.

## References

- Adda, Jérôme, Christian Dustmann, and Katrien Stevens, "The Career Costs of Children," *Journal of Political Economy*, 2017, 125 (2), 293–337.
- Baker, Michael and Kevin Milligan, "How Does Job-Protected Maternity Leave Affect Mothers' Employment?," *Journal of Labor Economics*, 2008, 26 (4), 655–691.
- Bar, Michael, Moshe Hazan, Oksana Leukhina, David Weiss, and Hosny Zoabi, "Why did rich families increase their fertility? Inequality and marketization of child care," *Journal of Economic Growth*, 2018, 23 (4), 427–463.
- Becker, Gary S and Nigel Tomes, "Child Endowments and the Quantity and Quality of Children," *Journal of Political Economy*, 1976, 84 (4), S143–62.
- Bick, Alexander, "The quantitative role of child care for female labor force participation and fertility," *Journal of the European Economic Association*, 2016, 14 (3), 639–668.
- and Nicola Fuchs-Schündeln, "Taxation and Labour Supply of Married Couples across Countries: A Macroeconomic Analysis," *The Review of Economic Studies*, 10 2017, 85 (3), 1543–1576.
- Borella, Margherita, Mariacristina De Nardi, and Fang Yang, "Are Marriage-Related Taxes and Social Security Benefits Holding Back Female Labour Supply?," *The Review of Economic Studies*, 03 2022, 90 (1), 102–131.
- Bover, Olympia, Nezih Guner, Yuliya Kulikova, Alessandro Ruggieri, and Carlos Sanz, "Family-friendly policies and fertility: what firms got to do with it?," 2025. Unpublished Manuscript.

---

<sup>40</sup>Recent work such as [Bover et al. \(2025\)](#) shows that firms' hiring and promotion decisions can play an important role in shaping the effects of PL policies.

- Bronson, Mary Ann and Deniz Sanin, "The Power of Policy Incentives: Female Labor Supply, Fertility and Parental Leave Policy Design," 2025. Unpublished Manuscript.
- Choi, Sekyu, "Fertility risk in the life cycle," *International Economic Review*, 2017, 58 (1), 237–259.
- Corekcioglu, Gozde, Marco Francesconi, and Astrid Kunze, "Expansions in paid parental leave and mothers' economic progress," *European Economic Review*, 2024, 169, 104845.
- Dahl, Gordon B, Katrine V Løken, Magne Mogstad, and Kari Vea Salvanes, "What is the case for paid maternity leave?," *Review of Economics and Statistics*, 2016, 98 (4), 655–670.
- Daruich, Diego and Julian Kozlowski, "Explaining Intergenerational Mobility: The Role of Fertility and Family Transfers," *Review of Economic Dynamics*, 2020, 36, 220–245.
- Doepke, M. and M. Tertilt, "Chapter 23 - Families in Macroeconomics," in John B. Taylor and Harald Uhlig, eds., , Vol. 2 of *Handbook of Macroeconomics*, Elsevier, 2016, pp. 1789–1891.
- Doepke, Matthias, Anne Hannusch, Fabian Kindermann, and Michèle Tertilt, "The Economics of Fertility: a New Era," in "Handbook of the Economics of the Family, Vol. 1," Elsevier, 2023, chapter 4.
- Erosa, Andrés, Luisa Fuster, and Diego Restuccia, "A general equilibrium analysis of parental leave policies," *Review of Economic Dynamics*, 2010, 13 (4), 742–758.
- , —, Gueorgui Kambourov, and Richard Rogerson, "Hours, Occupations, and Gender Differences in Labor Market Outcomes," *American Economic Journal: Macroeconomics*, 2022, 14 (3), 543–90.
- Farré, Lídia and Libertad González, "Does paternity leave reduce fertility?," *Journal of Public Economics*, 2019, 172, 52–66.
- Goldin, Claudia, "A Grand Gender Convergence: Its Last Chapter," *American Economic Review*, April 2014, 104 (4), 1091–1119.
- Greenwood, Jeremy, Nezih Guner, and Guillaume Vandenbroucke, "Family Economics Writ Large," *Journal of Economic Literature*, 2017, 55 (4), 1346–1434.
- , —, Georgi Kocharkov, and Cezar Santos, "Marry Your Like: Assortative Mating and Income Inequality," *American Economic Review*, May 2014, 104 (5), 348–53.
- , —, —, and —, "Technology and the Changing Family: A Unified Model of Marriage, Divorce, Educational Attainment and Married Female Labor-Force Participation," *American Economic Journal: Macroeconomics*, 2016, 8 (1), 1–41.

- Guner, Nezih, Ezgi Kaya, and Virginia Sánchez-Marcos, "Labor Market Institutions and Fertility," *International Economic Review*, 2024, 65 (3), 1551–1587.
- , Remzi Kaygusuz, and Gustavo Ventura, "Rethinking the welfare state," *Econometrica*, 2023, 91 (6), 2261–2294.
- Hart, Rannveig Kaldager, Janna Bergsvik, Agnes Fauske, and Wookun Kim, "Causal Analysis of Policy Effects on Fertility," *Handbook of Labor, Human Resources and Population Economics*, 2024, pp. 1–25.
- Heathcote, Jonathan, Kjetil Storesletten, and Giovanni L. Violante, "Optimal Tax Progressivity: An Analytical Framework\*", *The Quarterly Journal of Economics*, 06 2017, 132 (4), 1693–1754.
- Hwang, Jisoo, Chulhee Lee, and Esther Lee, "Gender norms and housework time allocation among dual-earner couples," *Labour Economics*, 2019, 57, 102–116.
- , Seonyoung Park, and Donggyun Shin, "Two birds with one stone: Female labor supply, fertility, and market childcare," *Journal of Economic Dynamics and Control*, 2018, 90, 171–193.
- Imai, Susumu and Michael P. Keane, "Intertemporal Labor Supply and Human Capital Accumulation," *International Economic Review*, 2004, 45 (2), 601–641.
- Jakobsen, Katrine Marie, Thomas Høgholm Jørgensen, and Hamish Low, "Fertility and Family Labor Supply," 2024. Unpublished Manuscript.
- Jang, Youngsoo and Minchul Yum, "Nonlinear occupations and female labor supply over time," *Review of Economic Dynamics*, 2022, 46, 51–73.
- Kim, Kyeongkuk, Sang-Hyop Lee, and Timothy J Halliday, "Paid childcare leave, fertility, and female labor supply in South Korea," *Review of Economics of the Household*, 2023, 21 (4), 1433–1451.
- Kim, Seongeun, Michèle Tertilt, and Minchul Yum, "Status Externalities in Education and Low Birth Rates in Korea," *American Economic Review*, June 2024, 114 (6), 1576–1611.
- Kim, Yeonjin and Åsa Lundqvist, "Parental Leave Reforms in South Korea, 1995–2021: Policy Translation and Institutional Legacies," *Social Politics: International Studies in Gender, State & Society*, 2023.
- Kitao, Sagiri and Kanato Nakakuni, "On the Trends of Technology, Family Formation, and Women's Time Allocations," 2024. Unpublished Manuscript.
- Kleven, Henrik, Camille Landais, Johanna Posch, Andreas Steinhauer, and Josef Zweimüller, "Do Family Policies Reduce Gender Inequality? Evidence from 60 Years of Policy Experimentation," *American Economic Journal: Economic Policy*, 2024, 16 (2), 110–149.

Knowles, John A, "Why are married men working so much? An aggregate analysis of intra-household bargaining and labour supply," *Review of Economic Studies*, 2013, 80 (3), 1055–1085.

Lalive, Rafael and Josef Zweimüller, "How does parental leave affect fertility and return to work? Evidence from two natural experiments," *The Quarterly Journal of Economics*, 2009, 124 (3), 1363–1402.

Leridon, Henri, "Can assisted reproduction technology compensate for the natural decline in fertility with age? A model assessment," *Human Reproduction*, 2004, 19 (7), 1548–1553.

Lim, Taejun and Aram Kim, "How Progressive Is the Most Popular Tax Scheme? The Case of South Korea," *Hitotsubashi Journal of Economics*, 2023, 64 (1), 1–17.

Malkova, Olga, "Can maternity benefits have long-term effects on childbearing? Evidence from Soviet Russia," *Review of Economics and Statistics*, 2018, 100 (4), 691–703.

Moon, Sue H and Jongtae Shin, "The Return of Superman? Individual and Organizational Predictors of Men's Housework in South Korea," *Journal of Family Issues*, 2018, 39 (1), 180–208.

Myong, Sunha, JungJae Park, and Junjian Yi, "Social norms and fertility," *Journal of the European Economic Association*, 2021, 19 (5), 2429–2466.

Olivetti, Claudia and Barbara Petrongolo, "The Economic Consequences of Family Policies: Lessons from a Century of Legislation in High-Income Countries," *Journal of Economic Perspectives*, February 2017, 31 (1), 205–30.

Raute, Anna, "Can financial incentives reduce the baby gap? Evidence from a reform in maternity leave benefits," *Journal of Public Economics*, 2019, 169, 203–222.

Sommer, Kamila, "Fertility choice in a life cycle model with idiosyncratic uninsurable earnings risk," *Journal of Monetary Economics*, 2016, 83, 27–38.

Stansbury, Anna, Jacob Funk Kirkegaard, and Karen Dynan, "Gender gaps in South Korea's labour market: children explain most of the gender employment gap, but little of the gender wage gap," *Applied Economics Letters*, 2024, 31 (17), 1726–1731.

Wang, Hanna, "Fertility and Family Leave Policies in Germany: Optimal Policy Design in a Dynamic Framework," 2022. Unpublished Manuscript.

Yamaguchi, Shintaro, "Effects of parental leave policies on female career and fertility choices," *Quantitative Economics*, 2019, 10 (3), 1195–1232.

Zhou, Anson, "The Macroeconomic Consequences of Family Policies," 2022. Unpublished Manuscript.

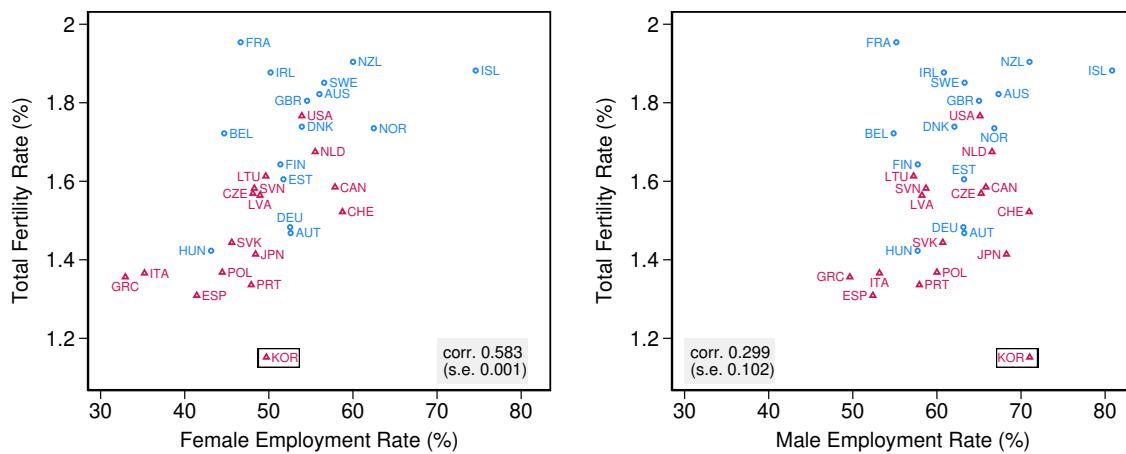
# ONLINE APPENDIX

## A Details on Evidence based on Aggregate Data

Work culture affects labor supply patterns for both men and women. Korea exhibits relatively high work pressure and long working hours, as documented in Section 3. Figure A1 plots the relationship between fertility and female vs. male employment rates separately. The left panel closely resembles the positive relationship between fertility and female labor force participation documented in Doepke et al. (2023), with the key difference being that Korea is included. As shown, female employment rates are positively associated with fertility, with a correlation coefficient of 0.58, reaffirming the findings of Doepke et al. (2023). While the correlation for male employment rates is lower (0.30) than for females, it remains positive and statistically significant.

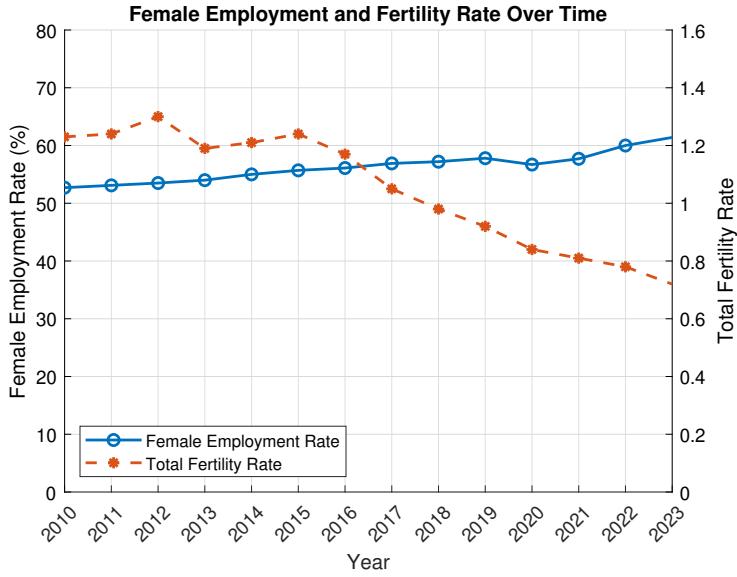
As noted in the introduction, Figure 1 plots fertility against the female employment rate relative to the male employment rate to isolate gender gap aspects while controlling for country fixed effects related to labor supply. Fertility exhibits a stronger positive correlation with the gap between female and male employment rates, yielding a correlation coefficient of 0.65—higher than that observed for female employment alone (0.58).

**Figure A1:** The Cross-Country Relationship Between Fertility and Female vs. Male Employment Rates



Notes: The x-axis displays the employment rate (%) of working-age females and males employed within the same subgroup. The y-axis represents the total fertility rate. Countries are categorized by public expenditure on family benefits (as a percentage of GDP): blue circles for high expenditure (ranks 1–15) and red triangles for low expenditure (ranks 16–31). Data are country averages over the period 2010–2019. Source: OECD.

**Figure A2:** Female Employment Rate and Fertility Over Time in Korea



One might wonder whether Korea is a puzzling case that challenges the traditional trade-off between women's work and fertility, which underlies the simple static model presented in Section 2. In Figure A2, we plot the evolution of these two variables at the aggregate level within Korea. We find that they generally move in opposite directions: since 2010, women's hours worked have been on an upward trend, while the total fertility rate has steadily declined. Note that, as we do not observe the counterfactual absence of PL benefit expansions, these time trends alone do not reflect the effects of PL policies.

## B Details on Micro Data

### B.1 Data and Variable Construction

We use data from the Korean Labor and Income Panel Study (KLIPS) to provide empirical evidence in this paper. KLIPS is a longitudinal survey of representative Korean households and individuals, conducted annually since 1998. The survey tracks 5,000 households and their members, offering detailed information on household demographics, education, labor supply, income, expenditure, and fertility. All monetary variables are originally in 2015 KRW, are adjusted for inflation using the Consumer Price Index (2015=100). We first match the individual and household survey data. Household observations are excluded if (1) no matched female member survey exists or (2) one member is an unpaid worker or a business owner with employees. The second condition ensures a focus on subsistence self-employment.

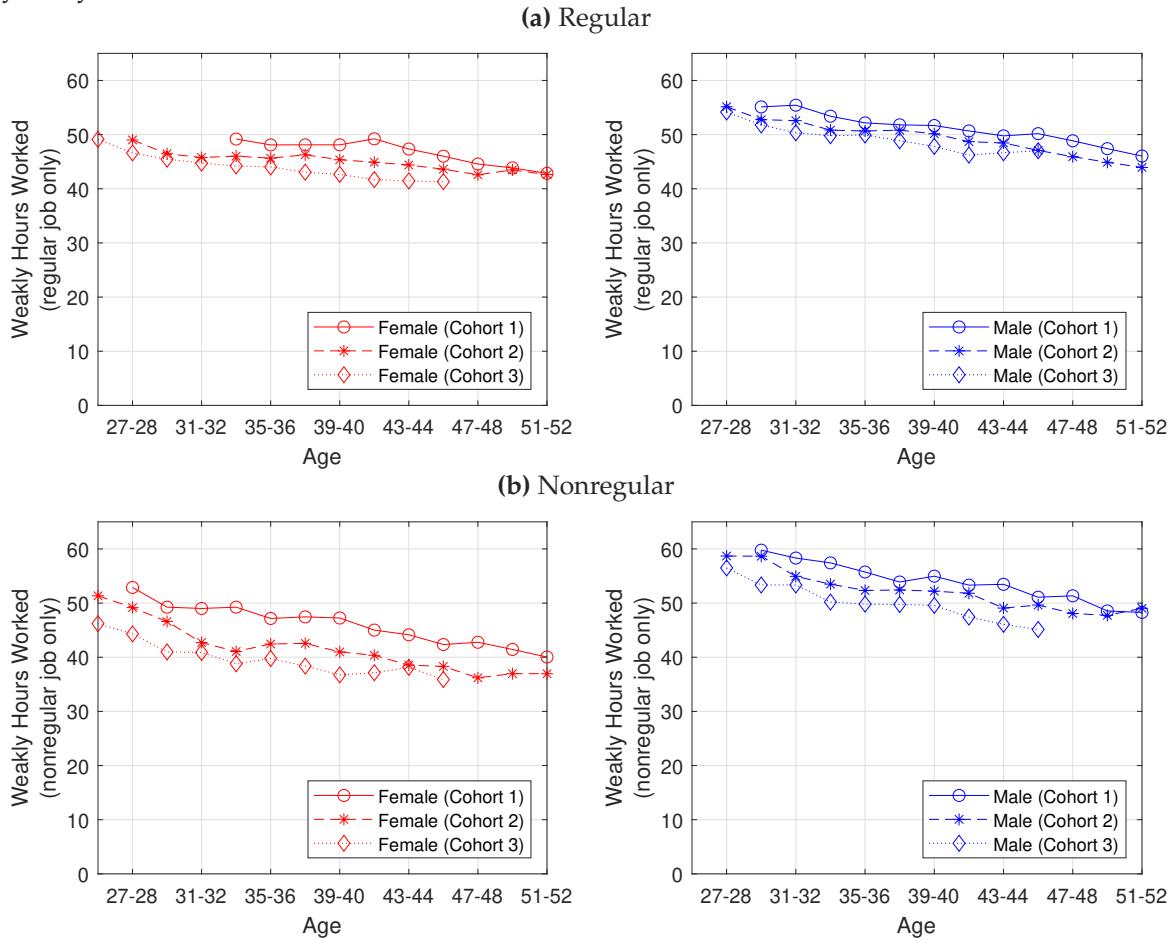
We extract the following variables from KLIPS. From the household-level survey data, we obtain household ID, year, number of (surviving) children, child age, household labor income (annual), financial income (annual), real estate income (annual), and education spending (monthly). From the individual-level survey data, we collect individual ID, year, age (computed from birth year), education status (dropout, enrolled, graduate) across educational levels (elementary, middle, high school, 2-year college, 4-year college, master's, doctorate), weekly hours worked (regular and extra hours), labor income (monthly wage and non-wage compensation), work status (wage worker, business owner, or unpaid family business worker), regular job status, and employer status.

Using the extracted variables, we define household income as the sum of household labor income, financial income, and real estate income. Childcare spending is constructed based on education spending for children aged one or younger, while non-infant education-related spending is based on education spending for children older than one. At the individual level, total hours worked are defined as the sum of regular and extra working hours, and hourly wages are calculated as labor income divided by 4.3 times working hours. Job status is categorized as regular if an individual has a regular job and positive working hours, and nonregular if they do not have a regular job but have positive working hours.

## B.2 Empirical Evidence in Section 3

After applying the sample restrictions to the 1998–2021 waves, our final sample includes 1,485 households (female and male parents) in Cohort 1, 1,537 households in Cohort 2, and 1,369 households in Cohort 3. This corresponds to 14,239 total observations for Cohort 1, 14,116 observations for Cohort 2, and 10,773 observations for Cohort 3. To maintain consistency with the two-year model periods, we first average individual variables over two-year intervals before computing cross-sectional averages for the figures in Section 3.

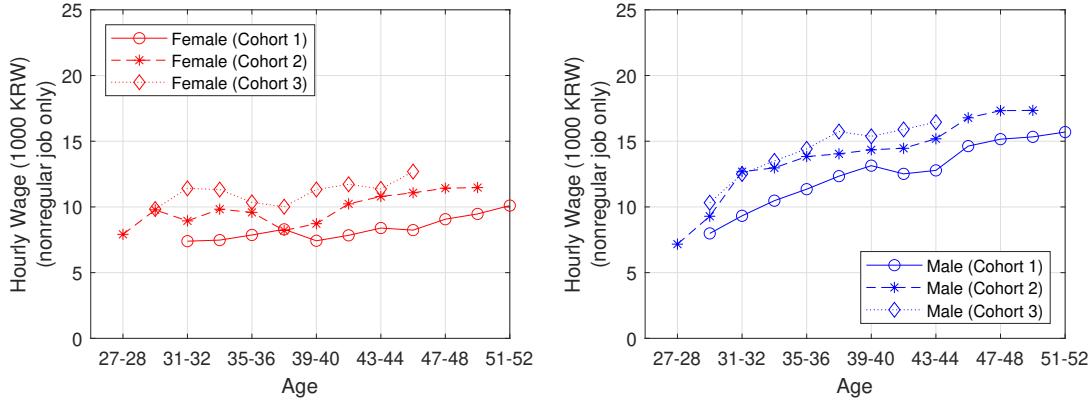
**Figure A3:** Regular vs Nonregular Labor Supply (Intensive Margin) Dynamics over the Life Cycle by Gender



Notes: Labor supply of regular workers or nonregular workers is measured by the average weekly hours worked over two years. Cohort 1: 1965–70, Cohort 2: 1970–75, Cohort 3: 1975–80.

In addition to the figures presented in Section 3, Figure A3 plots labor supply separately for regular and nonregular workers by gender, while Figure A4 shows wages for nonregular workers by gender.

**Figure A4:** Nonregular Worker Wage over the Life Cycle by Gender



Notes: Wage is calculated as the average hourly wage in 2012 Korean Won over a two-year period. Cohort 1: 1965–70, Cohort 2: 1970–75, Cohort 3: 1975–80.

### B.3 Details on Calibration

The calibration sample consists of households in which the female member was born between 1970 and 1975 (Cohort 2), as defined above. To facilitate consistency with model statistics, we define household (married couple) age solely based on the female's age, unlike in Section 3. For example, when referring to a man's wage at age 30, we mean the wage of a man whose spouse is 30, not necessarily his own age. In line with the two-year model periods, we average individual variables over two-year intervals.<sup>41</sup> The final calibration sample consists of: 1,614 households and 8,616 observations, with biannual observations ranging from 203 to 896 households.

For the consistency with the quantitative model, labor supply moments are computed after constructing average weekly hours worked over two-year periods, categorized into eight non-zero bins to capture variations in work intensity, capturing both intensive and extensive margins. Specifically,  $h_g \in \{0, 1, \dots, 8 = \bar{h}\}$  corresponds to

$$\begin{aligned}
 \text{avg. weekly hours worked} &= 0 && \text{if } h_g = 0 \\
 9 \times (h_g - 1) < \text{avg. weekly hours worked} &\leq 9 \times h_g && \text{if } 1 \leq h_g \leq 7 \\
 63 < \text{avg. weekly hours worked} &&& \text{if } h_g = 8
 \end{aligned}$$

**Initial Distribution** Table A1 reports the distribution of education sorting and fertility patterns, measured among families whose women's age is 25–26. Panel A reports the share of families by education pairing. Panel B shows the distribution of the num-

<sup>41</sup>Also, we winsorize the number of children at a maximum of three.

ber of children for each combination of the education groups.

**Table A1:** Initial Distribution

| <b>Panel A. Share</b> |       |       |      |       |
|-----------------------|-------|-------|------|-------|
| $e_f =$               | 1     | 1     | 2    | 2     |
| $e_m =$               | 1     | 2     | 1    | 2     |
| Share                 | 36.4% | 13.3% | 6.7% | 43.5% |

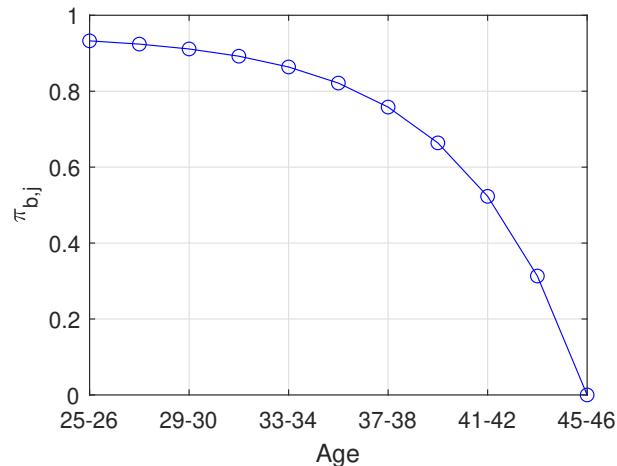
  

| <b>Panel B. Number of Children</b> |    |       |       |       |       |
|------------------------------------|----|-------|-------|-------|-------|
| $e_f =$                            | 1  | 1     | 2     | 2     |       |
| $e_m =$                            | 1  | 2     | 1     | 2     |       |
| No. of children                    | 0  | 27.8% | 37.5% | 42.9% | 61.7% |
|                                    | 1  | 36.1% | 53.1% | 42.9% | 28.3% |
|                                    | 2  | 35.1% | 9.4%  | 14.3% | 10.0% |
|                                    | 3+ | 1.0%  | 0.0%  | 0.0%  | 0.0%  |
| Average                            |    | 1.093 | 0.719 | 0.714 | 0.483 |

Notes: This table presents the initial distribution of education sorting and fertility patterns.  $e_g = 1$  denotes noncollege, and  $e_g = 2$  denotes college. Panel A reports the share of families by education pairing, while Panel B shows the distribution of the number of children across different education groups.

**Fecundity Probabilities** To account for this age-dependent fecundity, we adopt the functional form given by equation (19) and choose the parameters by minimizing the distance between the data points reported in [Leridon \(2004\)](#) and the values implied by the function. The resulting parameter values,  $\tilde{\pi}_0 = 0.890$  and  $\tilde{\pi}_1 = 0.246$ , are plotted in Figure A5.

**Figure A5:** Fecundity by Age Across the Fertile Periods



**Social Norms on Infant Childcare** We assumed parental time input is a function of nonworking hours with the gender-specific social norm for childcare: equation (7). To calibrate the ratio of parental hours to nonworking hours ( $\lambda_g$ ), we use the 2017 KLIPS supplementary data, focusing on households with an infant (age  $\leq 1$ ). We calculate nonworking hours by subtracting daily working time from a 15-hour time endowment.

**Table A2:** Social Norms: Parental Hours

|   | (1)   | (2)                 | (3)                 | (4)                 | (5)                 | (6)                 |
|---|---|---------------------|---------------------|---------------------|---------------------|---------------------|
|   | Dependent variable: Parental hours / nonworking hours |                     |                     |                     |                     |                     |
|   | Female  | Female              | Female              | Male                | Male                | Male                |
| Constant                                | 0.496***<br>(0.018)                                   | 0.498***<br>(0.023) | 0.496***<br>(0.018) | 0.198***<br>(0.016) | 0.186***<br>(0.018) | 0.198***<br>(0.016) |
| Education dummies                       |   |                     |                     |                     |                     |                     |
| $\mathcal{I}_{e_f=0, e_m=0}$            |   | 0.052<br>(0.058)    |                     |                     | -0.024<br>(0.041)   |                     |
| $\mathcal{I}_{e_f=0, e_m=1}$            |   | -0.003<br>(0.050)   |                     |                     | 0.069<br>(0.066)    |                     |
| $\mathcal{I}_{e_f=1, e_m=0}$            |   | -0.055<br>(0.059)   |                     |                     | 0.124<br>(0.096)    |                     |
| Spouse's nonworking time<br>(De-meaned) |   |                     | -0.004<br>(0.004)   |                     |                     | 0.006<br>(0.005)    |
| Observations                            | 166   | 166                 | 166                 | 164                 | 164                 | 164                 |

Notes: \* $p<0.1$ , \*\* $p<0.05$ , \*\*\* $p<0.01$ . Robust standard errors in parenthesis.

Table A2 provides empirical support for the parameterization of our social norm assumption,  $\lambda_g$ , which the model defines as the ratio of parental hours to nonworking hours (from equation 7). The baseline estimates in Columns (1) and (4) reveal a stark gender disparity. The average ratio for females ( $\lambda_f$ ) is 0.496, while the ratio for males ( $\lambda_m$ ) is 0.198. This finding quantifies the significant gender norm in childcare: the expected proportion of a mother's nonworking time dedicated to childcare is approximately 2.5 times that of a father's.

Crucially, the subsequent columns validate our model's parsimonious assumption that this norm,  $\lambda_g$ , depends only on gender and not on other characteristics.

- *Education:* Columns (2) and (5) introduce interaction dummies for spousal education levels. None of the coefficients for these dummies are statistically significant for either females or males. This indicates that the childcare-to-nonworking-time ratio remains stable regardless of the parents' educational pairing.

- *Spouse's Time*: Columns (3) and (6) test the influence of the spouse's available nonworking time. This variable is also highly statistically insignificant. This result is particularly noteworthy: it suggests that an individual's proportional time commitment to childcare does not adjust even when their partner has more (or less) nonworking time available.

Since these covariates, which proxy for bargaining power or resource availability, do not exhibit statistically significant effects, specifying  $\lambda_g$  as a gender-specific constant in the model ( $\lambda_f = 0.5$ ,  $\lambda_m = 0.2$ ) seems reasonable and broadly in line with the data.

**Promotion and Demotion Transitions** In our model, regular job workers can experience either promotion (an increase in  $\chi$ ) or demotion (a decrease in  $\chi$ ). Empirically, promotion and demotion are determined based on the two-year wage growth, where either a wage increase or decrease exceeding 20% triggers the corresponding event. The probabilities of promotion and demotion vary by gender and age. For female regular workers, the promotion probabilities at  $h_g = 5$  are  $\Pi_{P,f,j \in [1,10]}^u = 12.4\%$  and  $\Pi_{P,f,j \in [11,14]}^u = 5.6\%$  for younger and older age groups, respectively, while the corresponding demotion probabilities are  $\Pi_{P,f,j \in [1,10]}^d = 5.4\%$  and  $\Pi_{P,d,j \in [11,14]}^u = 4.1\%$ . These probabilities are higher for male regular workers, with promotion rates of 20.3% and 12.8%, and demotion rates of 6.3% and 5.0% for the two age groups, respectively.

The transition matrix  $\pi(\chi'|\chi, (P, P), \mathbf{h})$  is specified according to (27), as discussed in Section 5. We estimate the parameter  $\zeta_P^{motion}$  through logistic regression on discretized working hours with fixed effects (household by gender by broad age group) as follows. For promotion ( $u$ ), the regression equation becomes:

$$\text{Prob}(\ln w_{i,g,j+1} - \ln w_{i,g,j} > 0.2 | h_{i,g,j}) = \frac{\exp(\mathbf{fe}_{i,g,\tilde{j}} + \zeta_P^u h_{i,g,j})}{1 + \exp(\mathbf{fe}_{i,g,\tilde{j}} + \zeta_P^u h_{i,g,j-1})}, \quad (\text{A1})$$

where  $i$  and  $\tilde{j}$  index households and broad age groups ([1, 10] and [11, 14]), and  $\mathbf{fe}_{i,g,\tilde{j}}$  denotes the fixed effects defined above. Similarly, for demotion ( $d$ ), we have:

$$\text{Prob}(\ln w_{i,g,j+1} - \ln w_{i,g,j} < -0.2 | h_{i,g,j}) = \frac{\exp(\mathbf{fe}_{i,g,\tilde{j}} + \zeta_P^d h_{i,g,j-1})}{1 + \exp(\mathbf{fe}_{i,g,\tilde{j}} + \zeta_P^d h_{i,g,j-1})}. \quad (\text{A2})$$

The estimated coefficients for  $\zeta_P^u$  and  $\zeta_P^d$  from regression equations (A1) and (A2) are 1.230 (0.158) and -1.366 (0.175), respectively, with standard errors in parentheses, clustered at the level of gender by broad age group. The estimated  $\zeta_P^u$  and  $\zeta_P^d$  are statistically significant at the 1% level.

## C Recursive Problems in Infertile and Old Periods

**Infertile periods** In infertile periods ( $j = 11, \dots, 14$ ), fertility is not a choice variable, and children leave the household stochastically. The value of an infertile household is:

$$\bar{V}(a, n, \tilde{s}, \chi, \tilde{z}_{-1}, e, j) = \mathbb{E}_\xi \max_s \left\{ \bar{V}_s(a, n, \tilde{s}, \chi, \tilde{z}_{-1}, e, j) - \sum_g \xi_g \mathbb{1}_{\tilde{s}_g=T, s_g=P} \right\}. \quad (\text{A3})$$

The expected value of both working in a regular job before drawing a job-quality shock  $\tilde{z}_g$  is

$$\bar{V}_s(a, n, \tilde{s}, \chi, \tilde{z}_{-1}, e, j) = \mathbb{E}_{\tilde{z}} V_s(a, n, \chi, \tilde{z}, e, j). \quad (\text{A4})$$

The value of working  $s_g$  job after realization of  $\tilde{z}_g$  is

$$V_s(a, n, \tilde{s}, \chi, \tilde{z}_{-1}, e, j) = \max_{\substack{c, a', x_q \geq 0 \\ h_g \in \mathbb{H}_{s_g}}} \left\{ \begin{array}{l} u(c/\Lambda(n)) + \phi(n, x_q^\alpha) - v(\mathbf{h}, e, s_f, n, b, j) - d(\mathbf{l}) \\ + \beta \mathbb{E}_{\chi' | (\chi, s), \tilde{s}} \bar{V}(a', n', \tilde{s}', \chi', \tilde{z}, e, j+1) \end{array} \right\} \quad (\text{A5})$$

subject to

$$c + x_q n + a' = \sum_g w_g h_g + (1+r)a - \mathcal{T}(\mathbf{h}, a, \mathbf{w}) \quad (\text{A6})$$

$$w_g = \omega_{e,j} \gamma_{\chi_g} \tilde{z}_g (1 + \tilde{\omega}_{P,g} \mathcal{I}_{s_g=P}) (1 - \mathcal{I}_{g=f} \varsigma), \quad g = f, m \quad (\text{A7})$$

$$n' \sim B(n, p_n), \quad (\text{A8})$$

where  $B(n, p_n)$  denotes a binomial distribution with parameters  $n$  and  $p_n$ . In other words, each child leaves the household with probability  $1 - p_n$ , so the total number of children in the household in the next period follows a binomial process:  $n' \sim B(n, p_n)$ .

**Old Periods** The household optimization problem simplifies during the old periods, specifically for  $j = 15, \dots, 28$ , as there is no endogenous labor supply and no children in the household. The value functions in these periods can be expressed as:

$$R(a, \chi, e, j) = \max_{c, a' \geq 0} \{u(c/\Lambda(0)) + \beta R(a', \chi, e, j+1)\}$$

subject to

$$c + a' = \sum_g \mathcal{P}(\chi_g, e_g) + [1 + (1 - \tilde{\tau}_k)r]a$$

where  $\mathcal{P}(\chi_g, e_g) = \vartheta \times \tilde{\omega}_0 \exp(\tilde{\omega}_1(15 - 1))(1 + \tilde{\gamma}_g)^{(\chi_g - 1)}(1 + \tilde{\omega}_e \mathcal{I}_{e_g=2})$  represents old-age income, which is assumed to be proportional to final working-age income, depending on education and career stage, with a scaling parameter  $\vartheta$ .

## D Parental Leave Policy Reforms in Korea

The PL policy in Korea dates back to 1988, when the Equal Employment Act granted female workers eligibility for unpaid leave for up to one year. In 1995, the Labor Standards Act allowed male workers to take leave only as a substitute for mothers. It was not until 2001 that both mothers and fathers were allowed to take leave, with a small flat monetary benefit introduced at a modest level (approximately 200K KRW per month). Benefit amounts gradually increased over time, reaching 300K KRW in 2002, 400K KRW in 2004, and 500K KRW in 2007.

Maternity leave has existed for decades, first introduced in 1953 under the Labor Standards Act, with a maximum duration of 60 days. In 2001, the same act extended the duration to 90 days, with a 100% replacement rate, subject to a cap of 1,350K KRW for the final month. Paternity leave was introduced in 2008 under the Equal Employment Act, initially allowing a maximum of three days, which was later extended to 10 days in 2019.

In 2011, PL benefits transitioned from a flat-rate system to a wage-dependent structure, covering 40% of the worker's salary. The benefit was capped at approximately 2.5 times the prior flat rate, with a minimum of 500K KRW and a maximum of 1,000K KRW per month ([Kim et al., 2023](#)). In 2017, PL benefits became more generous. The replacement rate was sharply increased to 80% for the first three months and 50% for the remainder of the leave period. Moreover, the benefit cap rose by 50% to 1,500K KRW, while the minimum increased by 40% to 700K KRW. In 2020, both mothers and fathers in Korea became eligible to take PL simultaneously; prior to this change, parents were required to take leave sequentially without overlap.

In 2022, PL benefits were further expanded, with new benefit amounts set at a minimum of 700K KRW and a maximum of 1,500K KRW per month, while maintaining the replacement rates. Adjusting for a 2% average annual inflation rate, these amounts are equivalent to 583K KRW and 1,250K KRW in baseline terms. Compared to the baseline value of 400K KRW, the 2022 Reform increased the minimum benefit by 50% and the maximum benefit by 210%. Additionally, the maternity leave cap for the third month was raised to 2,000K KRW, representing a 20% increase from the baseline. Notably, the 3+3 program was introduced to encourage joint PL usage in response to low take-up

rates among fathers. Under this program, the replacement rate increases to 100% when both parents take PL for three months, either simultaneously or sequentially within a year of birth, and the benefit cap was significantly raised to 3,000K KRW per parent, approximately 6.3 times the baseline amount after inflation adjustment. These form the basis for the policy parameter choices in the 2022 *Reform* discussed and analyzed in Section 6.

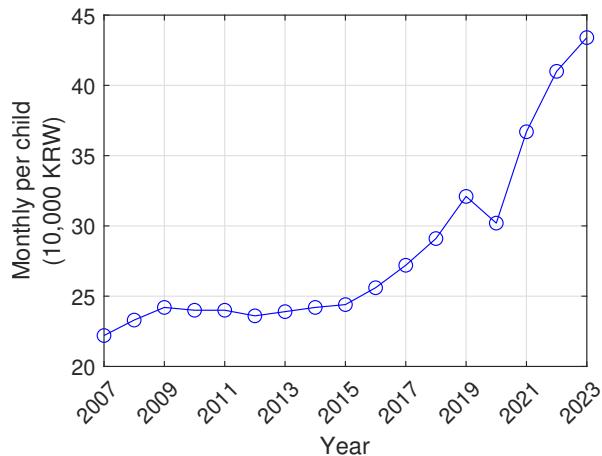
Despite these expansions, ongoing policy debates suggest that the benefit cap remains insufficient. A recent reform, scheduled for implementation in 2025, will introduce a more generous but gradually diminishing cap structure, with a cap of 2,500K KRW and 2,000K KRW in the first and second quarters, respectively, and 1,600K KRW from the third quarter onward. The policy parameter choices in the 2025 *Reform* in Section 6 are based on these changes. In practice, the government also considered other programs that are not incorporated in our analysis to maintain a focused scope. These include the expansion of the 3+3 program, aimed at increasing fathers' PL uptake further, and an extension of the maximum leave duration to 1.5 years.

## E Additional Figures and Tables

**Table A3:** Choices and Household Structures Over Model Periods

| Female Age:<br>$j =$  | Fertile Periods |       |     |       | Infertile Periods |     |       |       | Old Periods |       |  |
|-----------------------|-----------------|-------|-----|-------|-------------------|-----|-------|-------|-------------|-------|--|
|                       | 25–26           | 27–28 | ... | 43–44 | 45–46             | ... | 51–52 | 53–54 | ...         | 79–80 |  |
|                       | 1               | 2     | ... | 10    | 11                | ... | 14    | 15    | ...         | 28    |  |
| Consumption-Savings   | Yes             |       |     |       | Yes               |     |       |       | Yes         |       |  |
| Labor-Career Choices  | Yes             |       |     |       | Yes               |     |       |       | No          |       |  |
| New Child (Birth)     | Possible        |       |     |       | No                |     |       |       | No          |       |  |
| Children in Household | Possible        |       |     |       | Possible          |     |       |       | No          |       |  |

**Figure A6:** Recent Change in Private Education Expenditure



Source: Private Education Expenditures Survey, Statistics Korea