

# Mandated Paternity Leave and Fertility: Evidence from South Korea\*

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**PRELIMINARY: PLEASE DO NOT CITE OR CIRCULATE**

## Abstract

As more women strive to balance career and family, policymakers face the challenge of sustaining fertility while supporting female labor force participation. A key policy lever is increasing fathers' involvement in childcare through leave provision, yet the causal effects of paternity leave on fertility remain underexplored. We study a corporate-group mandate in South Korea that, in 2017, required one month of fully paid paternity leave for all male employees. Using rich administrative data and an event study design, we find that the mandate sharply increased fathers' leave-taking by 63.9 percentage points from a 2% baseline and raised the annual probability of having a child by 1.4 percentage points—a 14.7% increase relative to pre-policy levels—adding 1,337 births over six years. Effects are concentrated in dual-earner households and grow with wives' earnings and tenure, while women's employment remains unaffected. Complementary survey evidence indicates that mandating leave shifted workplace norms and normalized paternal caregiving. Treated employees report more supportive workplace attitudes, greater paternal childcare time, and stronger fertility intentions. Together, the results suggest that the mandate raised fertility without reducing women's employment, by changing expectations around fathers' caregiving and easing time constraints faced by dual-earner households.

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# 1 Introduction

As more women seek to combine careers with family life (Goldin, 2021), policymakers face the dual challenge of supporting fertility while sustaining female labor force participation. This issue is particularly acute in low-fertility countries. Figure 1 shows that countries with lower fertility rates also have lower maternal employment probabilities after childbirth.

One promising lever to address this dual challenge is greater paternal involvement in childcare.<sup>1</sup> Cross-country evidence shows that societies where fathers share caregiving more equally tend to exhibit both higher fertility and higher female employment (Feyrer et al., 2008; Doepke et al., 2023). Reflecting this, many high-income countries have introduced or expanded paternity leave policies.<sup>2</sup> The underlying idea is that paternity leave would enable fathers to spend more time on childcare, supporting maternal employment, thereby reducing work–family tensions faced by households, and potentially raising fertility.

Despite growing policy momentum, we know surprisingly little about whether this policy logic holds. First, while a large literature shows that paternity leave improves women’s labor-market outcomes,<sup>3</sup> evidence on fertility is sparse and largely confined to subsequent births, leaving the broader fertility decision—especially the transition into parenthood—unexplored (Farré and González, 2019). Second, even generous entitlements do not guarantee that fathers actually take leave, raising doubts about whether leave provision translates into greater paternal involvement (Kim and Lundqvist, 2023). The persistently low take-up rates in high-income countries suggest that meaningful change may require stronger policy levers to shift caregiving norms and workplace practices (Goldin, 2024). Third, although paternal involvement is correlated with higher fertility across countries, it remains unclear whether increasing involvement through policy interventions causally induces households to have children. Taken together, these gaps mean that it is still uncertain whether paternity leave achieves its intended dual goal: fostering father involvement in ways that both support maternal employment and raise fertility.

This paper provides the first causal evidence on whether paternity leave can increase fertility and evaluates the role of a strong intervention—a mandate—in fostering this change by promoting more cooperative fatherhood. We study a unique natural experiment in which a large South Korean conglomerate (*C Group*)<sup>4</sup> mandated one month of fully paid paternity leave for all male employees with children born after January 2017. The policy was part

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<sup>1</sup>Sociology literature finds that paternal involvement in childcare and housework is linked to higher second-birth rates, largely by easing work–family conflict and supporting maternal employment. See Cooke (2004); Kotila and Kamp Dush (2011); Fanelli and Profeta (2021); Lappegård and Kornstad (2020).

<sup>2</sup>As of 2023, 35 of 38 OECD countries offer paid, father-specific leave, with an average duration of 12.7 weeks.

<sup>3</sup>See Corekcioglu et al. (2024) for a comprehensive review.

<sup>4</sup>For confidentiality, we refer to this firm as *C Group* throughout the paper.

of a broader group-wide initiative to improve workplace culture and aligned with national efforts to support fertility through family-friendly reforms. The decision, made at the holding company level, was applied uniformly across subsidiaries spanning multiple industries. Male employees' exposure to the mandate depended on where they happened to work at the time of implementation, creating exogenous variation in policy exposure. For comparison, we use employees at unaffected firms in other conglomerates as a control group. Importantly, unlike federal policies that leave benefit utilization to individual discretion, this corporate reform required one month of leave. By ensuring actual leave take-up, the mandate generates credible exogenous variation to estimate fertility effects, while also offering an opportunity to test whether a strong intervention like mandates can realign workplace caregiving norms in ways that make fatherhood more compatible with work and increase paternal involvement.

Building on this setting, the paper addresses three core questions: (1) Does a mandate increase leave uptake and lead to more active utilization of paternity leave? (2) Does mandating paternal leave-taking lead to higher fertility? (3) Through which channels does the mandate affect fertility? Is the evidence most consistent with increased paternal availability and shifts in caregiving norms?

To answer these questions, we draw on a novel set of administrative datasets from Statistics Korea, including the Child Registry, Population Census, Parental Leave Registry, Employer-Employee Matched Data, and the Business Registry. These datasets were first released in 2021, and to our knowledge, our study is among the earliest to combine them for research purposes. The Business Registry captures ownership structures across conglomerates and their subsidiaries, which we link to the Employer-Employee Matched Data to identify affected workers. We construct fertility information for these workers by further linking to the Child Registry, Population Census, and Parental Leave Registry using a unique personal identifier. These linked datasets enable us to observe both employees' exposure to the policy and their fertility outcomes. To complement the administrative analysis, we also fielded an original survey of young male employees in firms exposed and not exposed to the mandate. The survey focuses on reported childcare time, workplace culture, and fertility intentions, providing direct evidence on perceptions and mechanisms.

First, we show that the mandate substantially increased paternity-leave uptake, consistent with uniform enforcement across subsidiaries. Prior to the policy, leave take-up within one year of childbirth remained low— 2% among fathers at treated firms and 1.2% at control firms. Following the mandate, uptake among fathers at treated firms increased by 64.5 percentage points, more than 30 times the pre-policy level. While leave-taking at control firms also rose modestly—by 1.8 percentage points in the post-policy period—the increase was substantially smaller. The mandate's effects extended beyond its immediate requirements.

Among treated fathers, the share taking more than one month of leave rose by 3.9 p.p relative to the pre-policy baseline of 1.9%, effectively doubling the share of extended leave users. This is particularly notable given that, beyond the first month, federal wage replacement rates varied between 23–70% depending on leave duration and policy year, implying that men opted into partially paid leave despite limited financial incentives. We also find evidence of spillover effects among fathers at treated firms who were not directly covered by the mandate. Fathers with children born between 2015 and 2016 were excluded from the corporate policy but covered by the federal parental leave scheme. Among this group, the likelihood of being on leave during the post-policy period rose by 2.4 p.p relative to a pre-policy average of 0.9%. By contrast, their counterparts at control firms experienced only a 0.8 percentage point increase during the same period from a similar baseline of 0.6%. Taken together, these findings suggest that the one-month mandate increased uptake among eligible fathers and promoted more active use of paternity leave overall.

Does mandating paternity leave, then, affect households’ fertility decisions? To investigate this question, we implement an event study design that exploits the exogenous timing of the policy. We restrict the sample to male employees who were hired before the policy was under discussion, allowing us to treat the mandate as plausibly exogenous to their job choices. As a control group, we use male employees at other large conglomerates operating in similar industries who were not exposed to the mandate. We further limit the sample to men who were between ages 30 and 45 when the policy was first discussed—targeting individuals in their prime working and childbearing years. This baseline age restriction enables us to follow a stable cohort over time, beginning when the youngest was 27, and examine how their period-specific fertility rates evolved before and after policy implementation.

One potential threat to our identification strategy is selection: firms that adopted the mandate may have already employed men with stronger underlying fertility preferences. If this were the case, we would expect to see higher fertility levels or diverging trends among treated firms even before the policy took effect. Instead, we find that pre-policy fertility rates were slightly lower among treated employees and that fertility rates trended very similarly across treated and untreated firms prior to the policy, diverging only after the mandate is introduced. These patterns provide credence for the parallel trends assumption which underlies our empirical strategy.

Using this design, our analysis finds that the mandate significantly increased the probability of having a baby among affected employees. Specifically, the probability of having an infant increased by 1.4 p.p, representing a 14.7% rise relative to the pre-policy average of 9.5% among treated employees. A back-of-the-envelope calculation suggests the mandate added 1,337 births over six years. We obtain similar results when restricting the outcome to

births occurring while the father remained employed at the same firm. This finding supports the interpretation that the observed fertility increase was a response to the new leave benefit, rather than a result of employees with lower fertility intentions leaving treated firms. Notably, fertility began to rise in the second half of 2016, shortly after the internal survey on policy implementation was circulated. This suggests that households adjusted fertility in anticipation of the policy, even before it formally took effect. These early responses underscore that fertility decisions are forward-looking: households make choices based on the child-rearing environment they expect to face and the anticipated commitment from both parents.

Additionally, we find that the fertility effect operates along both the extensive and intensive margins. The probability of a first birth increased by 0.8 percentage points—17% relative to a 4.7% baseline, while the probability of an additional birth rose by 0.6 percentage points—13% relative to a 4.7% baseline. Roughly half of the overall increase is driven by first births, providing novel evidence that paternity leave mandates can influence the transition into parenthood—a margin that previous studies could not capture given their policy contexts. The remainder reflects higher-order births, indicating that the policy supported both new parents and families expanding further. We also find no evidence of changes in parental age at birth or in birth spacing that would suggest shifts in birth timing. While we cannot yet observe completed fertility, the evidence points to the mandate generating additional fertility rather than simply accelerating births.

How could a one-month leave mandate generate such a large fertility response? We argue that the mandate eased families' time constraints not only through the required month of leave, but also by shifting expectations that fathers would be more available for childcare more generally. When fathers are unable to spend sufficient time on childcare, fertility may be constrained by the total parental time available—particularly when mothers are employed in inflexible jobs. To probe this interpretation, we examine heterogeneity by household characteristics. The effects are concentrated among dual-earner households, especially those in which wives held regular wage jobs at baseline. Within these households, where maternal time constraints are most binding, fertility rose substantially, with larger gains when wives had higher earnings and longer tenure. Importantly, these fertility gains did not come at the expense of wives' labor supply. If higher fertility had reduced maternal employment, we would expect to see declines in labor force participation corresponding to fertility gains. Instead, we find modest increases in both employment rates and months worked. Taken together, these patterns suggest that the mandate did more than provide a month of leave: it shifted households' expectations about fathers' involvement, reduced the effective costs

of childbearing, and enabled time-constrained families to have a child—supporting higher fertility without undermining women’s careers.

To probe this mechanism more directly, we draw on original survey evidence. The survey allows us to examine whether the mandate promoted a more supportive workplace culture for fathers and shifted households’ expectations. A broad literature highlights that social and workplace norms often constrain paternal leave uptake (Dahl et al., 2014; Bartel et al., 2018; Patnaik, 2019), creating barriers to fathers’ involvement in childcare. These slow-to-change norms, especially within workplaces, can further restrict households’ fertility choices (Goldin, 2024). Evidence from a 2024 national survey<sup>5</sup> in Korea underscores this challenge: while fathers view “free use of parental leave” as the most helpful workplace support, many cite concerns about career penalties and discouraging supervisors as reasons for not using it. In this context, a mandate can act as a powerful normalizing device, shifting workplace attitudes toward caregiving and amplifying fertility effects.

To evaluate this mechanism, we fielded an original survey of 450 male employees aged 30–45 from treated and control firms, designed to capture direct evidence on fathers’ childcare time, perceptions of workplace culture, and expectations about leave-taking under both mandated and non-mandated scenarios.

Survey responses indicate that normalizing paternal leave is associated with more family-friendly workplaces. Relative to control firms, men at treated firms are far more likely to have taken leave when eligible and report more supportive norms: they expect higher coworker uptake and encouragement, perceive fewer career penalties for leave-takers and less coworker burden resulting from leave-taking. Treated men also report spending more time on weekday childcare and express stronger fertility intentions.

To isolate the role of the policy environment, we fielded a within-respondent vignette among control workers. When asked to answer the same questions under a mandate assumption, their responses shifted toward greater support for leave-taking—lower perceived penalties and coworker burdens and higher anticipated peer support—and their expected second-birth probabilities also increased. Taken together, the survey evidence is consistent with the mechanism that normalizing leave-taking relaxes constraints on paternal caregiving and raises expected paternal availability, easing time-related barriers to childbearing in dual-earner households.

This paper provides the first causal evidence on the effects of paternity leave on overall fertility. Previous studies on parental leave have largely focused on maternal leave (Lalive

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<sup>5</sup>Presidential Committee on Aging Society and Population Policy (2024), “2024 Survey on Perceptions of Marriage, Fertility, and Childcare,” <https://www.betterfuture.go.kr/front/notificationSpace/pressReleaseDetail.do?articleId=303&listLen=10&searchKeyword=&position=S> (accessed March 21, 2025)

and Zweimüller, 2009; Dahl et al., 2016; Raute, 2019; Kleven et al., 2024). The few that consider paternity leave have been limited to examining the effect of eligibility of paternity leave on higher-order births - often using regression discontinuity designs that compare fathers with children born just before or after a policy change (Kotsadam and Finseraas, 2011; Dahl et al., 2014; Cools et al., 2015; Bartel et al., 2018; Farré and González, 2019), reporting mixed results. While informative, these designs cannot detect effects on having a first child, or responses occurring in anticipation of newly available benefits regardless of their current eligibility. We show that paternity-leave provision can shift entry into parenthood. The binding mandate allows us to estimate the causal effect of guaranteed usage of paternity leave on fertility—capturing behavioral responses to anticipated access, capturing more comprehensive effects.

Second, this paper contributes to the literature on the role of fathers in fertility by providing new causal evidence that paternal involvement is a key channel through which family policies can raise fertility, and that policy design is crucial for activating this channel. A growing literature highlights the role of fathers as central to reconciling low fertility with women’s continued employment (Doepke and Kindermann, 2019; Doepke et al., 2023; Olivetti, 2024), yet empirical evidence on this channel remains limited. Existing studies provide mixed evidence on whether “daddy quotas” increase paternal involvement (Ekberg et al., 2013; González and Zoabi, 2021), and point to workplace culture as a critical factor in promoting or discouraging fathers’ leave-taking (Dahl et al., 2014; Johnsen et al., 2024). This paper shows that a binding mandate compelling leave-taking can overcome workplace barriers, increase paternal involvement, and translate into fertility responses. In doing so, it empirically supports predictions from structural models that emphasize time constraints and stigma around paternal leave as barriers to effective family policy (Erosa et al., 2010; Doepke and Kindermann, 2019; Doepke et al., 2023; Goldin, 2024; Kim and Yum, 2025).

Lastly, the paper complements a large empirical literature on parental leave that has focused primarily on maternal and child outcomes. Prior studies have examined paternity leave in relation to leave uptake (Ekberg et al., 2013; Dahl et al., 2014; Bartel et al., 2018; Patnaik, 2019), household labor division (Ekberg et al., 2013; Almqvist and Duvander, 2014; Tamm, 2019; González and Zoabi, 2021), child outcomes (Farré et al., 2023), and maternal employment and health (Farré and González, 2019; Canaan et al., 2022; Corekcioglu et al., 2024; Persson and Rossin-Slater, 2024). A separate body of work studies maternity leave reforms and their effects on fertility (Lalive and Zweimüller, 2009; Dahl et al., 2016; Raute, 2019; Kleven et al., 2024), often finding short-run increases that fade over time. Our results complement this literature by providing evidence from the father’s side: we show that pa-

ternity leave mandates not only support maternal employment but also generate fertility responses, thus offering a fuller picture of how family policies operate within households.

The paper proceeds as follows. Section 2 describes the institutional setting and the corporate paternity-leave mandate; Section 3 details the administrative data. Section 4 documents the mandate’s effect on leave uptake. Section 5 sets out the empirical strategy for fertility, and Section 6 reports the main fertility effects and heterogeneity analysis. Section 7 provides complementary survey evidence on workplace norms, paternal time, and fertility intentions. Section 8 considers policy implications, and Section 9 concludes.

## 2 Institutional Background

### 2.1 Fertility rate and Parental Leave Policy in Korea

Among high-income countries with low fertility rates, South Korea shows one of the sharpest declines in recent decades. Its total fertility rate (TFR)—the average number of children a woman is expected to have over her lifetime—fell to 0.72 in 2023, far below the replacement level of about 2.1 children per woman needed to maintain a stable population. Other East Asian countries also face extremely low fertility rates, with Hong Kong at 0.75, Japan at 1.30, and China at 1.18 in 2021, compared to 1.67 in the United States.

In response to demographic challenges, the Korean government has expanded parental leave policies to improve work–family compatibility. Both female and male employees with at least six months of tenure are eligible for parental leave until their child reaches age eight, with wage replacement funded by employment insurance. South Korea offers one of the most generous paid parental leave durations among OECD countries—52 weeks—far exceeding the OECD average of 13 weeks for paid paternity leave. However, wage replacement rates have historically been low. Table 1 summarizes the federal parental leave policy between 2015 and 2022, focusing on the case of the second leave user.<sup>6</sup> Initially capped at 1.5 million KRW in 2015, the monthly benefit ceiling for the second parental leave user (typically fathers) was increased to 2 million KRW in 2018 and to 2.5 million KRW in 2019 for the first three months. During 2017–2019, the average monthly post-tax earnings<sup>7</sup> for male workers aged 30–39 was 2.9 million KRW, raising the replacement rate from approximately 52% to 86%. Responding to continued criticism that the benefit ceiling still fell short of fathers’ average wages—and thereby discouraged paternal uptake—the government further increased

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<sup>6</sup>Federal policy grants a higher replacement rate cap for the second leave user, reflecting the fact that in most cases the second user is the father. The policy is designed to promote more active uptake of leave among fathers by providing greater financial incentives.

<sup>7</sup>We compute the replacement rate using post-tax earnings, since the benefit is tax-exempt.



the ceiling to 3 million KRW in 2022 for the first three months of paternity leave. This change made the potential replacement rate reach 100% for the first three months of leave for the average Korean male employee.

Despite the continuous expansion of benefits, paternity leave uptake in Korea remains low. Figure 4 shows parental leave utilization rates by gender for parents of newborns in Korea between 2010 and 2023. In 2017, only 1.8% of eligible fathers used the benefit, compared to 62.2% of mothers. By 2023, fathers' uptake rose modestly to 7.4%, compared to 73.2% for mothers.

## 2.2 Mandatory Corporate Paternity Leave Policy

In line with government efforts, a major Korean conglomerate—"C Group"—implemented a mandatory one-month paternity leave for all male employees with children born from January 2017 onward, offering 100% wage replacement during that month.<sup>8</sup> The leave had to be taken within one year of childbirth, or within two years if both spouses were employed. Figure 3 summarizes the policy timeline. The idea originated in 2015 through an internal contest to improve the workplace environment and was later adopted by the executive board of the holding company. In early 2016, the board surveyed employees across subsidiaries, marking the first time workers learned about the potential mandate. The formal policy announcement was made in December 2016, and the mandate took effect for children born in January 2017 or later.

The corporate mandate complemented the federal parental leave scheme, which already entitled employees to up to one year of leave. Under the federal policy, wage replacement ranged from approximately 36% to 71% of the average monthly post-tax earnings of C Group employees aged 30–45. With the corporate mandate, however, fathers received full wage replacement for the first month of leave. For any leave beyond the first month, compensation reverted to federal rules, offering 36–71% for the next two months and 24–36% thereafter, depending on the year. Because C Group employees in our analysis sample earned above-average wages, their effective replacement rates remained lower than the statutory maximum despite the policy change.

The decision to mandate leave was implemented in a top-down manner, consistent with the governance structure of large Korean conglomerates. C Group, the largest retail employer in Korea, owned 44 companies across nine industries and employed 0.6% of the national

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<sup>8</sup>The C conglomerate has implemented an automatic parental leave policy for female employees since 2012. Under this scheme, women are automatically enrolled in one year of parental leave following the end of their maternity leave. As a result, we do not observe changes in female parental leave usage at C conglomerate firms following the policy change.

labor force in 2016. Like other conglomerates, it consisted of a parent company that set group-wide strategies—such as welfare policies, investment decisions, and brand management—while individual subsidiaries oversaw business operations, including human resources (hiring, compensation, and scheduling), retail and service management, logistics, and production. The Korean Fair Trade Commission (FTC) designates conglomerate status annually based on the total asset value of member firms; as of 2016, 31 groups held this designation, including C Group, which has maintained this status continuously since the category was first introduced.

### **3 Data**

We draw on rich administrative datasets from Statistics Korea that can be linked at both the individual and firm levels for our main analysis. We describe each dataset in more detail below.

#### **3.1 Corporate and firm Data**

We combine the Business Registry and Employer-Employee Matched Data for 2015–2020 to identify male employees working under each conglomerate. The Business Registry offers information on the relationships between conglomerates and their affiliated companies, and on each company including revenue, industry codes, and annual employment size. Because conglomerate status can vary over time based on asset values, we include all companies that have ever been affiliated with a conglomerate during our observation period. In addition, we restrict our sample to companies that are observed continuously from 2015 to 2020, ensuring that companies are not differentially affected by events such as mergers, acquisitions, or business closures. We then link this list of companies with the Employer-Employee Matched Data using hiring date information to identify male employees working at these companies. The Employer-Employee Matched Data provides information on annual earnings and job spells, which we use to construct average monthly earnings.

#### **3.2 Fertility and Childbirth Data**

We integrate data from three sources to construct detailed information on children and fertility. First, we link the Child Registry with the employee dataset at the individual level to obtain data on the number of children and their ages. The Child Registry, which is based on birth certificates and the Population Census, provides information on parental relationships for all children under age 18 on annual basis. To obtain more granular data on birth dates,

we supplement the Child Registry with information from the 1983–1995 Cohort Database<sup>9</sup> and the Parental Leave Registry available for 2015–2022. Both sources provide child birth dates at the year-month level. This linkage process allowed us to identify the birth date for 98% of children born since 2012, which marks the start of our observation period for fertility outcome. By linking these three datasets, we construct an indicator for having an infant.

### 3.3 Household Composition and Spousal Employment Data

One advantage of our dataset is the ability to identify spouses using household relationship information from the Population Census. We use this information for heterogeneity analysis by wife employment status and for spousal labor supply analysis. The Population Census, available for 2015–2022, provides marital information based on cohabitation as observed every November. The earliest available marital status is from November 2015, which is two months prior to our baseline period.<sup>10</sup> We further link the wife’s identifier from the Census to the Employment Registry to obtain information on the wife’s working status. The Employment Registry covers a longer time series, between 2015–2022, than the Employer-Employee Matched Data, 2015–2020, but does not include information on employers. It provides annual information on employment status, job type, annual earnings, and employment duration.

## 4 The Effect of the Mandate on Leave Uptake

First, we demonstrate that implementing the mandate significantly increased paternity leave uptake and also led to additional leave utilization beyond the mandated one month. Figure 4 illustrates this rise, with uptake reaching 67.6% among new fathers at the affected company. The figure shows the proportion of fathers by leave duration within one year after childbirth, including those who took no leave. The treated group comprises fathers employed by companies within C Group, while the control group includes fathers at companies from other conglomerates within the same industry. The large shift in uptake among treated group indicates that the corporate policy was binding and implemented as intended. Prior to the policy, leave uptake remained low in both treated and control groups- 2% and 1.2% respec-

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<sup>9</sup>The 1983–1995 Cohort Database only covers children born to individuals within that birth cohort, representing about 60% of our analysis sample, while the Parental Leave Registry captures birth dates for children whose parents utilized parental leave.

<sup>10</sup>Because the Census records household members only if they are registered at the same home address at the time of the survey, data on partnerships may be missing when partners are registered at different addresses or when one partner is temporarily abroad. For our purposes, a meaningful relationship is one in which both parents live together and care for the same child. Therefore, in such cases, we treat the individual as unmarried.

tively. Notably, while most fathers initially adhered to the one-month minimum, there is a modest upward trend in fathers taking leave beyond one month over time.<sup>11</sup>

Although the policy was labeled a mandate, uptake in our data did not reach 100%. We observe a take-up rate of about 70%, reflecting both data limitations and some degree of non-compliance. For Figure 4, we exclude daily and temporary contract workers (who were ineligible) and include all workers with contracts longer than one month. However, our data only distinguish regular (longer than one month) versus temporary contracts, without capturing finer distinctions such as part-time versus full-time or permanent versus non-permanent full-time status. This is important in the Korean labor market, where many non-permanent full-time workers—though working full-time hours—are hired on fixed-term contracts that make them ineligible for firm-level benefits like the paternity leave mandate. Because the mandate applied primarily to full-time permanent employees, the observed 30% non-uptake likely reflects both non-compliance among eligible workers and the inadvertent inclusion of ineligible workers in our sample. While understanding the reasons for non-compliance would be an interesting question in its own right, our data do not allow us to distinguish it from eligibility differences. We therefore focus on the policy’s impact on leave usage and fertility behavior.

We formalize the descriptive patterns using an event study framework to estimate the policy’s causal effect on leave-taking behavior of fathers with newborns in each biannual time period. Specifically, we estimate:

$$Y_{ib} = \beta_0 + \sum_{k \neq -1} \beta_{1,k} Treat_{ib} \times \mathbf{1}(b + k = 2017H1) + \tau_b + \theta_{i(j)} + \varepsilon_{ib} \quad (1)$$

where  $Y_{ib}$  is an indicator for whether father  $i$  with a child born in biannual period  $b$  took any leave (or leave longer than one month) within one year of childbirth.  $Treat_{ib}$  equals 1 for fathers employed at C Group firms in period  $b$ —the firms subject to the mandate—and 0 for fathers employed at companies from other conglomerates within the same industry that were not subject to the mandate; this is the same sample used in Figure 4.  $\mathbf{1}(b + k = 2017H1)$  denote event-time indicators relative to the policy implementation, with  $k = -1$ , the period immediately before the policy, omitted as the reference period. The interaction term captures the dynamic effects of the mandate over time. We control for biannual childbirth cohort fixed

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<sup>11</sup>In South Korea, about 80% of mothers spend 2–4 weeks in a postnatal care center after birth. Consistent with this practice, 87% of fathers in our data took paternity leave after their child was at least one month old, and approximately 50% took it when their child was between 1–3 months old. This suggests that fathers often time their leave to coincide with the mother’s return home. Appendix Figure A.1 provides a histogram of leave usage by child age in months.

effects,  $\tau_b$ , and firm fixed effects,  $\theta_{i(j)}$ . Figure 5 presents the dynamic event-study results, and Table 2 reports corresponding average difference-in-differences estimates.

Figure 5a shows a sharp and sustained increase in leave-taking within one year of child-birth at treated firms following the policy. Column 1 of Table 2 indicates that the mandate raised uptake by 63.9 percentage points from a pre-policy baseline of 2% at treated firms. We also find economically meaningful increases in the probability of taking more than the mandated one month of leave. Column 2 shows that, on average, treated fathers were 5.6 percentage points more likely to take extended leave relative to a pre-policy baseline of 1.9%. This estimate may be inflated, however, because the second half of 2020 saw a sharp Covid-related spike in extended leave-taking at C group, visible in Figure 4. To address this, we estimate a version truncated at 2020H2, reported in Column 3, which still shows a 3.9 p.p increase—roughly a doubling in incidence compared to the pre-policy baseline. We present this version in the event-study graph in Figure 5b, which improves visibility of the post-policy trend.

Does the mandate also influence fathers who were not directly covered by the policy? Fathers with children born before January 2017 were ineligible for the corporate mandate but still qualified for the federal parental leave benefit, which could be used until a child turned eight. To test for spillover effects, we estimate a difference-in-differences specification on an unbalanced panel of fathers with births in 2015–2016. The sample is restricted to periods in which these fathers remained employed at the same firm, as the goal is to assess whether leave-taking behavior changed for non-covered workers exposed to a mandate-affected workplace environment. We estimate the following equation:

$$Y_{it} = \beta_0 + \sum_{k \neq -1} \beta_{1,k} Treat_i \times \mathbf{1}(t + k = 2017H1) + \tau_t + \theta_{i(j)} + \varepsilon_{ib} \quad (2)$$

$Y_{it}$  is an indicator for whether father  $i$  took leave in biannual period  $t$ . To focus on ineligible fathers, we code the outcome as zero if leave was taken after the birth of another child born post-2017, since those fathers became eligible under the mandate. This specification is designed to isolate potential spillover effects on ineligible workers who were nevertheless exposed to a mandate-affected workplace environment. We include biannual time fixed effects,  $\tau_t$ , to absorb time-varying common shocks, including changes to federal benefits, and firm fixed effects,  $\theta_{i(j)}$ , to account for persistent differences across firms.

Figure 5c and Column 4 of Table 2 show that ineligible fathers at treated firms were also more likely to take leave following the mandate. On average, their likelihood of taking leave rose by 2.4 percentage points relative to a pre-policy mean of 0.9%. By comparison, their counterparts at control firms saw only a 0.8 percentage point increase, from a similar

baseline of 0.6%. In other words, ineligible fathers at treated firms were nearly twice as likely to take leave post-policy compared to similarly ineligible fathers at control firms.

## 5 Identifying the Effects of the Mandate on Fertility

Having established the policy’s impact on paternity leave uptake, we now turn to fertility behavior. To estimate these effects, we implement an event study design. We first define the treated and control groups, specify the timing of treatment, and establish a pre-policy baseline to capture anticipation effects.

### 5.1 Defining the Treated and Control Group

Our estimation strategy exploits random exposure to treatment via company affiliation at the time of the policy change. To capture both the intensive margin -impact on subsequent births, and the extensive margin-the decision to have a first child, we include all men of reproductive age regardless of their current parental status. For the treatment group, we select male employees who were between 30 and 45 years old at that time. We chose the age range because the average age at first marriage for men in Korea was 32 during the post-policy period. Because the policy was implemented at the company level, an individual’s treatment status depends on their employer. This status could be endogenous if workers joined a treated company after the policy was introduced. To address this, we restrict the sample to employees who were already at their firms before policy information first circulated. For the control group, we include male employees of the same age who, at the time of C group’s policy change, were employed at companies in other conglomerates that did not implement the mandate. Specifically, we include all companies that were part of conglomerates designated by the Korean Fair Trade Commission at any point during our analysis period and operated in the same industries as the treated firms.<sup>12</sup>

### 5.2 Defining Treatment Timing and Baseline Period

We use the first half of 2016—the period when information about the mandate began circulating—as the baseline. Paternity leave can influence fertility behavior not only through actual uptake but also through anticipatory planning, as households may adjust childbearing decisions based on expected access to leave. As outlined in Section 2.2, an internal survey

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<sup>12</sup>We use the section-level industry code from the Korean Standard Industry Code (KSIC) to identify companies operating within the same industry. The KSIC categorizes industries into 21 sections, represented by capital letters A through U.

on the policy was circulated in early 2016, likely raising awareness among employees. If households responded, conceptions would have occurred in early 2016, with births later that year. Accordingly, we set 2016H1 as the reference period for subsequent analysis. To better capture such anticipation effects, we use biannual rather than annual time intervals.

### 5.3 Differences in differences Estimator

Our empirical approach employs an event study design to assess how the probability of having a baby changed among cohorts employed at treated versus control companies during the observation period. Specifically, we use a linear probability model to estimate the relative increase in the probability of having an infant for men at treated firms, compared to men at control firms of the same age, baseline earnings quintile, and baseline tenure. The model is specified as follows:

$$1(\text{infant})_{it} = \beta_0 + \sum_{k \neq -1} \beta_{1,k} \text{Treat}_i \times \mathbf{1}(t + k = 2016H1) + X_i' \Gamma + X_{it}' \delta + \theta_t + \varepsilon_{it} \quad (3)$$

where  $1(\text{infant})_{it}$  is an indicator for whether father  $i$  has an infant (aged 0) during biannual calendar time  $t$ .<sup>13</sup>  $\text{Treat}_i$  equals 1 if father  $i$  was employed by a C Group company at the beginning of the baseline period.  $\mathbf{1}(t + k = 2016H1)$  denote event time dummies relative to the policy announcement, with  $k = -1$  omitted as the reference period. The interaction  $\text{Treat}_i \times \mathbf{1}(t + k = 2016H1)$  captures the differential effect of the policy over time.

The vector  $X_i$  includes time-invariant characteristics such as baseline tenure, baseline monthly earnings quintile indicators, and baseline firm fixed effects.<sup>14</sup> The firm fixed effects absorb time-invariant characteristics at the firm level, ensuring that results are not driven by pre-existing differences across firms—such as preferences for childbearing, career expectations, or work–life balance—that predate the policy change. The vector  $X_{it}$  captures time-varying characteristics. In the main specification, we include age. In robustness checks, we also control for additional demographics, such as an indicator for whether the man had a child in  $(t - 2)$  and indicators for the child’s age groups (0, 1–3, 4–7, and 8 or above). We cluster robust standard errors at the firm level to account for potential within-firm correlation.

<sup>13</sup>This fertility indicator, when aggregated annually, corresponds closely to the conventional birth rate. We use biannual units instead, which better capture immediate fertility responses to the policy. As shown in Figure 6a, fertility increases every six months after the reference period. While annual aggregation yields similar overall patterns, it masks the initial jump that is visible only in the biannual specification.

<sup>14</sup>We define a firm as a combination of a company identifier and a commuting-area pair, where the commuting area is based on employees’ province of residence. This accounts for the fact that a single company in the Business Registry can encompass multiple firms across regions.

Our coefficients of interest,  $\beta_{1,k}$ , capture the causal impact of the paternity leave mandate on the probability of having an infant, a 0-year-old child in period  $k$  relative to the reference period. We track this probability from 2012H1 to 2022H2 using a balanced panel of men who were aged 30–45 at the time of the reference period, regardless of whether they remained at the same firm afterward. By following the same cohort over time—beginning when the youngest was 27 and continuing until the youngest reached 36 and the oldest 51—we observe changes in fertility behavior before and after the policy. This approach allows us to hold the cohort fixed, minimizing concerns about bias from changes in sample composition.

The identifying assumption is that, absent the policy change, fertility behavior in the treated and control groups would have followed similar trends. A potential violation arises if treated firms had systematically employed workers with stronger fertility preferences. In that case, we would expect to see higher fertility levels at the reference period or differential trends even before the policy was introduced. In fact, as shown in Table 3, the average pre-policy fertility rate is slightly lower among treated firms—by about one percentage point—counter to this concern. Moreover, formal tests reveal no evidence of differential pre-policy fertility trends between the two groups, as illustrated in Figure 6a.

## 5.4 Main Analysis Sample

Table 3 presents descriptive statistics for the treated and control groups in our fertility analysis sample, which includes all male incumbents at these firms regardless of their parental status as of the beginning of 2016—as opposed to the father sample used in the leave-taking analysis in Table 2. Characteristics are measured at baseline, with the exception of the birth rate, which is calculated as the average probability of having a child during the full pre-policy period (2012–2015). The treated group comprises fewer individuals ( $N = 17,366$ ) relative to the control group ( $N = 378,689$ ) because the treated group consists of incumbents from a single conglomerate, whereas the control group draws from 30 other conglomerates. Both groups have a similar average age of 37 years and average tenure of about 8 years at baseline. Although both groups earn more than the national average for their age cohort (3.9 million KRW), treated individuals earn, on average, 1.7 million KRW less than control individuals.<sup>15</sup> To account for these differences, we include baseline earnings quintile indicators in our main analysis, along with controls for age and baseline tenure.

Treated individuals were less likely to be married (60% versus 68%), even though the average age of spouses was identical across groups. Consistent with this lower marriage rate, a higher proportion of treated individuals were childless (40% versus 33%) and their pre-

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<sup>15</sup>In 2016, 1 million KRW was equivalent to approximately \$862, and 3.9 million KRW to about \$3,362.



policy birth rate was about one percentage points lower. To address these differences in family characteristics, we conduct robustness checks that control for the number of children and marital status and the results are very similar to our main estimates.

Our main specifications rely on the full sample of eligible control individuals to maximize statistical power and enable heterogeneity analyses. As an additional check, we replicate the analysis on an individually matched sample to improve balance on observed characteristics. Each treated incumbent is matched to a control worker from the same industry, industry-specific income quintile, five-year age bin, marital status group, and commuting area at baseline, using one-to-one propensity score matching with a caliper (see Appendix B.1). While the estimated effect size is somewhat smaller in the matched sample, the results remain statistically significant and directionally consistent with the main findings, suggesting that they are not driven by pre-treatment compositional differences.

## 6 Effects on Household Fertility

We examine whether the mandate affected the likelihood that male incumbents had an infant (a 0-year-old child) in each period. Figure 6a presents estimates from Equation 3, with the first dashed line marking our reference period—when information about the policy began circulating—and the second dashed line marking formal implementation.

Figure 6a shows that the probability of having an infant rose sharply after the policy among treated incumbents and remained consistently higher than that of the control group throughout the post-policy period. Pre-policy estimates are statistically insignificant and centered around zero, confirming that fertility trends evolved in parallel prior to the reform. To ensure that the observed fertility responses are attributable to the mandate, we regress an outcome variable that equals 1 only for births that occurred while fathers remained employed at the same firm, and 0 otherwise. Eligibility for the mandate depended on being employed at the firm at the time of childbirth, so this restriction ensures that the estimated effects reflect actual exposure to the policy. The results, presented in Figure 6b, closely mirror those in Figure 6a, reinforcing that the fertility increase is due to the mandate. We also observe a rise in the probability of having an infant beginning in the second half of 2016, shortly after employees first learned about the policy. This anticipatory response supports our choice of reference period: if households made childbearing decisions in anticipation of the mandate, the resulting births would appear by late 2016, as shown in both Figure 6a and Figure 6b. This pattern underscores that fertility decisions are forward-looking, with households deciding on childbearing based on expected leave availability.

Column 1 and 2 in Table 4 presents the corresponding difference-in-differences estimates - pooled average estimates across post-policy periods. On average, the probability of having an infant increases by 1.4 percentage points—a 14.7% increase relative to the treated group’s pre-policy average of 9.5%. Aggregating over six post-policy years, our back-of-the-envelope calculation yields about 1,337 additional births in the treated group. To our knowledge, this study is the first to find positive effects of paternity leave on fertility. To put our effect size in context, we compare our estimated effect size with those reported in other studies documenting the positive impact of family policy reforms on fertility. Raute (2019) finds that expanding financial incentives for maternity leave increased the fertility of affected women by 16% relative to pre-reform birth rates. Similarly, Lalive and Zweimüller (2009) report that extending the duration of parental leave in Austria—an intervention almost entirely utilized by mothers—resulted in a 21% increase in births among eligible mothers within three years after the reform. Our effect size is broadly comparable to those found in prior studies evaluating family policy reforms targeting mothers.

## 6.1 Extensive vs. Intensive Margin

Next, since the policy could influence fertility both by encouraging first births (extensive margin) and by incentivizing higher-order births (intensive margin), we examine how much of the overall fertility effect comes from each channel. To isolate the extensive margin response, we regress an indicator for whether the infant in a given period is a first child—that is, the outcome variable equals 1 only if the individual has an infant in a given period and the infant is their first-born.

The results are reported in Column 3 of Table 4, with corresponding event study estimates shown in Figure 7. We find that the probability of having a first-born infant increases by 0.8 percentage points, relative to a pre-policy mean of 4.7% in the treated group—representing a 17% increase. The coefficient estimate is directly comparable to the overall fertility effect in Column 1; this estimate is about half the size of the overall effect (Column 1), implying that 53% of the fertility increase is driven by new parents. In other words, about half of the observed increase is driven by childless households having their first child, while the other half reflects households having additional children in the post-policy period. We construct a complementary indicator for second or higher-order births (intensive margin). Column 4 confirms a 0.6 percentage point effect—47% of the total.<sup>16</sup> Together, these results show that

<sup>16</sup>We also examine whether fathers whose first post-policy child was covered by the mandate were more likely to have a subsequent birth than otherwise similar fathers who just missed coverage following prior studies (Dahl et al., 2014; Cools et al., 2015; Bartel et al., 2018; Farré and González, 2019). We find no statistically significant difference. This pattern suggests that households who “just missed” eligibility may still plan an additional child in anticipation of being covered for a future birth. See Appendix B for results.

the policy increased fertility along both margins by similar magnitudes, affecting both new parents and those expanding their families.

## 6.2 Total Fertility vs. Fertility Timing

A key concern in interpreting the effect as a fertility gain is that the patterns might reflect shifts in fertility timing rather than increases in completed fertility. If households merely accelerated births they would have had anyway, our estimates would capture timing adjustments rather than additional childbearing. Under this scenario, we would expect to see three patterns: (i) fertility gains concentrated only among first births, (ii) younger parental ages at childbirth, and (iii) shorter intervals between births for families with existing children. As shown in Section 6.1, our results already rule out the first scenario: fertility gains appear along both the extensive and intensive margins.

We next examine parental age at childbirth and birth spacing, two outcomes that would shift if timing effects were driving the results. For this analysis, we restrict the sample to incumbents at treated and control firms who had a newborn in each period, and estimate the difference-in-differences specification on three outcomes: (i) father’s age at childbirth, (ii) mother’s age at childbirth, and (iii) the age gap between the newborn and the first child. Table 5 reports the results: we find no significant differences between treated and control groups for any of these outcomes (Columns 1–3). Figure 8a illustrates nearly identical trends in paternal age across groups, with no evidence of bunching at younger ages. Similarly, Figure 8b shows no systematic changes in spacing between first and subsequent births, aside from a modest increase in first births in 2022H1.

Overall, these patterns are inconsistent with the view that the mandate simply accelerated births. While we cannot observe completed fertility within our data horizon, the absence of shifts in age or spacing provides supportive evidence that the policy generated additional fertility.

## 6.3 Heterogeneity by Wives’ Employment

How could a one-month leave mandate induce such large changes in fertility behavior? We argue that the mandate worked by relaxing constraints on fathers’ ability to devote time to childcare, constraints that are most binding in households where mothers hold inflexible or demanding jobs. In such settings, limited expectations of paternal involvement can discourage families from having additional children. Our simple household model (Appendix C) formalizes this logic and predicts that effects should be strongest among dual-earner house-

holds and should increase with wives’ opportunity cost of time.<sup>17</sup> Guided by this framework, we examine heterogeneity by wives’ employment characteristics.

We classify households by wives’ baseline employment status prior to the policy introduction using linked administrative data from the Population Census and Employment Registry. This ensures that status is pre-determined and unaffected by the mandate. Table 7 presents descriptive statistics for married households. As in the main sample, treated couples earned somewhat less on average than their control counterparts, though treated wives had higher baseline employment rates. Following Statistics Korea’s classification, we define *any job* as any paid work (daily, temporary, or self-employment) and *regular job* as wage or salary employment with a contract longer than one month.

We estimate the baseline difference-in-differences model separately by wives’ employment status, retaining the full set of controls. Table 8 reports the results and corresponding event study estimates are shown in Figure 10.<sup>18</sup> Fertility responses are concentrated among dual-earner households. Column 1 of Table 8 shows no significant effect among unmarried incumbents. Among married couples, the effects are driven by dual-earner households, as shown in Columns 2 and 3: households with employed wives experience a significant increase in fertility, while those with non-working wives show no response. For households where wives were employed prior to the reference period, treated households exhibit a 1 p.p. increase in fertility, equivalent to an 8.2% rise relative to their pre-policy average of 12.2%. The effect is strongest when the wife held a regular job (Column 4), which typically involves fixed schedules and limited flexibility. In these households, the probability of birth rises by 1.4 p.p., or 11.1% relative to the pre-policy average of 12.6%. By contrast, households with wives in temporary, daily, or self-employed jobs—typically characterized by more flexible work schedules—exhibit no effect. The point estimate for regular job holders is similar to the overall main effect, indicating that the fertility response is almost entirely driven by households where wives were employed in inflexible jobs.

We further test whether the effect increases with wives’ opportunity cost of time, measured by their baseline annual earnings and tenure. To do so, we interact the treatment

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<sup>17</sup>The model treats fertility as a forward-looking decision shaped by three channels: increased paternal time spent at home, reduced utility costs of fathers’ childcare time, and an income effect from full wage replacement. It predicts that effects should be strongest among dual-earner households if the paternal time channels are driving the results.

<sup>18</sup>Because subgroup shares differ between treated and control groups, the weighted average of subgroup estimates is not equivalent to the main effect in Table 4. When  $\Pr(g | T) \neq \Pr(g | C)$ , subgroup treatment effects cannot be linearly combined to recover the overall effect. In our sample, the weighted composite effect matches the full-sample estimate.

indicator with these characteristics, allowing the treatment effect to vary accordingly:

$$Y_{it} = \gamma_0 + \gamma_1(Treat_i \times Post_t)\tilde{\lambda}_i + \gamma_2Treat_i \times Post_t + \gamma_3Treat_i \cdot \tilde{\lambda}_i + \gamma_4Treat_i \\ + \gamma_5Post_t \cdot \tilde{\lambda}_i + \gamma_6Post_t + X_i'\Gamma + \varepsilon_{it}, \quad (4)$$

where  $\lambda_i$  is either the wife’s baseline earnings or tenure, and  $\tilde{\lambda}_i = \lambda_i/SD(\lambda_i)$  standardizes the variable for comparability.

Table 9 reports the results. Columns 1–2 interact the treatment effect with baseline earnings and Columns 3–4 with baseline tenure. We present estimates for both the dual-earner subsample and the full sample of married households. We focus on the dual-earner specification, since the estimates for all wives are qualitatively similar. The interaction term  $\gamma_1$  for employed wives, our coefficient of interest, is significant and positive: a one standard deviation increase in baseline annual earnings—27.6 million KRW, or roughly 2.3 million KRW in average monthly earnings if employed for a full year—is associated with a 0.8 p.p. increase in the likelihood of birth, or 6.7% relative to the pre-policy mean of 12%. Similarly, a one standard deviation increase in baseline tenure—equivalent to 4.5 years—is associated with a 0.9 p.p. increase, or 7.5% relative to the pre-policy mean. Taken together, these results show that fertility responses are driven almost entirely by households where wives face high opportunity costs of time, consistent with the view that expectations of greater paternal availability were central to the effects.

## 6.4 Effects on Spousal Labor Supply

Having shown that fertility responses are concentrated in households where wives face high time costs, we next examine whether these fertility gains came at the expense of women’s employment. If the mandate raised fertility by increasing fathers’ availability at home, wives’ labor supply should remain stable—or even rise—following the policy.

We use the same matched sample of married households from the heterogeneity analysis and track wives’ labor market outcomes over time. Specifically, we test whether wives in treated households experienced relative declines in employment after the policy change compared to those in control households. The dependent variable is the wife’s employment status in each biannual period. We include the same control variables as in the main analysis—age, tenure, earnings quintile dummies, firm fixed effects, and calendar time fixed effects—along with the wife’s age. A limitation of this analysis is the shorter pre-policy window, as Employment Registry data are available only from 2015, providing two pre-policy data points.

The analysis reveals consistently positive effects across several labor supply outcomes. Table 10 presents the regression results and corresponding event study estimates are shown in

Figure 11. Columns 1 and 2 show estimated effects on wives’ probability of being employed in any job and in a regular job (contract duration longer than one month), respectively. Column 3 examines labor intensity, measured as the number of months worked per biannual period. The results indicate that wives of treated incumbents were more likely to remain attached to the labor force. Their probability of being employed in any job increased by 2.1 p.p. from a pre-policy average of 45.4%. The likelihood of holding a regular job rose by 1.9 p.p. from a baseline of 40%. In terms of labor intensity, treated wives worked an additional 0.12 months per biannual period on average—about a 4.3% increase relative to a pre-policy mean of 2.8 months. These effect sizes represent a 4–5% improvement relative to the control group.

Together, these results demonstrate that the mandate not only increased fertility among households with the greatest maternal time constraints, but also supported women’s continued employment. In other words, the policy achieved a dual goal: enabling higher fertility without undermining women’s careers.

## 6.5 Robustness Test

We conduct robustness tests to assess whether baseline demographic differences drive the main results. We report those findings in Figure 9 and Table 6. First, treated incumbents were less likely to be married at baseline. To account for this difference, we additionally control for baseline marital status inferred from the Population Census data collected every November. As reported in Column 2, the results remain unchanged after controlling for baseline marital status.

Second, to adjust for baseline parity differences (treated had fewer children), we include indicators for the number of existing children—having 0, 1, or 2 or more children in period  $t - 2$ —that is, one year prior, given our biannual time units. This adjustment reflects that most individuals have 0 to 2 children at most and that those with two children or more are unlikely to have additional births. As shown in Column 3 of Table 6, including these controls yields estimates very similar to our main results. Additionally, to account for potential birth spacing, we include dummies for the age category of the youngest child in  $t - 2$ —categorized as no child, 0 years, 1–4 years, 5–7 years, and 8 years or above, and find similar results (Column 6). Overall, these robustness checks confirm that our main findings are not driven by baseline differences in marital status or by the number and age of children.

Additionally, some effects may be partly driven by couples in which the wife is also employed at a C Group company, as the conglomerate extended its maternity leave provision to up to two years for female employees at the same time it implemented the paternity leave

mandate. Although C Group ranks fifth nationwide in employment size, dual employment within the group is relatively rare. In our sample, only 6.9% of treated men (1,192 out of 17,366) were ever married to someone employed at a C Group company. To address this concern, we re-estimate the main specifications excluding men ever married to a wife employed at a C Group subsidiary—for both treated and control samples—and the results remain robust (Appendix Figures A.2a and A.2b).

Lastly, we also implement a matched estimator to create a more balanced comparison group, which we discuss in more detail in Appendix B.1. In brief, we match treated firms to control firms based on average monthly earnings within the same industry-area cell and on quartiles of the proportion of young workers. The matched sample is more comparable across all observed characteristics, and results from this estimator remain consistent with our main estimates, supporting the robustness of our findings.

## 7 Survey Evidence on Workplace Norms as a Mechanism

Why would a one-month mandate generate such large fertility responses? Administrative data reveal who responded to the policy and suggest that fertility rose because households expected greater paternal time availability. Yet these data do not directly capture changes in household expectations or concurrent shifts in workplace culture—factors that could amplify effects beyond the formal one-month entitlement. To address this limitation, we turn to survey evidence that directly probes whether the mandate normalized paternal caregiving at work and thereby increased fathers’ effective availability for childcare.

We surveyed 450 male employees aged 30–45—following the age range used in our main analysis—restricted to full-time, permanent-contract workers to ensure eligibility for corporate benefits.<sup>19</sup> The sample includes 216 respondents at treated firms and 234 at control firms. We define treatment using two criteria: (i) the respondent works at a subsidiary of *C Group*, and (ii) the respondent reports that a mandate is in place at their firm. Controls are defined symmetrically: (i) employed at large corporations unaffiliated with *C Group*, and (ii) reporting no mandate in place. This dual definition ensures that individuals categorized as “treated” are both exposed to—and aware of—the policy.

The survey comprised two parts. First, respondents reported their childcare time, perceptions of workplace culture, and experiences with leave-taking at their current workplaces.

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<sup>19</sup>Respondents were recruited through three online survey platforms. Our target was current employees at firms covered in the main analysis, ages 30–45, on permanent contracts. These criteria restricted the available pool, so multiple providers were used to maximize sample size while controlling costs.



Second, we introduced a hypothetical male coworker, *Mingyu* (age 33), whose wife is employed full-time and who is expecting their first child. Respondents indicated (i) whether, on a 10-point scale, they would recommend that Mingyu take paternity leave, (ii) anticipated career penalties if he took leave, and (iii) the perceived likelihood that he would have a second child.

Table 11 presents descriptive statistics for the survey sample. Treated and control groups are similar in marriage rates, the share with infant or pre-K children, wives’ employment, and wives’ regular-job status, with no statistically significant differences. Treated respondents are more likely to have taken leave when eligible—74% compared to 17% in the control group, a difference of 57 percentage points—confirming that they are indeed employed at mandate-covered firms. Treated respondents are 0.8 years older on average (39.0 vs. 38.2, marginally significant at the 10% level). Job rank and tenure distributions are comparable, while own earnings are lower at treated firms: the share earning above 6 million KRW is 20 percentage points lower (0.3 vs. 0.5). By contrast, the share with high-earning spouses (wives earning more than 5 million KRW) is nearly identical. The lower own earnings at treated firms are consistent with our main sample. In subsequent regressions, we include controls for high-income status and age-by-marital group to address these differences.

## 7.1 Perceptions, Childcare, and Fertility Intentions

The survey consisted of two parts. First, we collected information on respondents’ time spent on childcare, perceptions of workplace culture, and experiences with leave-taking at their current workplaces. Second, we introduced a hypothetical male coworker, *Mingyu* (age 33), who works at the same company as the respondent, whose wife is employed full-time, and who is expecting their first child. Respondents reported (i) whether, on a 10-point scale, they would recommend that Mingyu take paternity leave; (ii) anticipated career penalties if he took leave; and (iii) the perceived likelihood that he would have a second child.

Table 11 presents descriptive statistics of the survey sample. Treated and control groups look similar in marriage rates, the share with infant or pre-K children, wives’ employment, and wives’ regular-job status, with no statistically significant differences. Importantly, treated respondents are much more likely to have taken leave when eligible—74% compared to 17% in the control group, a difference of 57 percentage points—confirming that they are indeed employed at firms where leave-taking was compelled by the mandate. Treated respondents are 0.8 years older on average—39.0 vs. 38.2, a difference marginally significant at the 10% level. Job rank and tenure distributions are comparable across groups, while own earnings are lower at treated firms: the share earning above 6 million KRW is 20 percentage points lower-



0.3 versus 0.5. By contrast, the share with high-earning spouses (wives earning more than 5 million KRW) is nearly identical. The lower own earnings at treated firms are consistent with our main sample, where treated incumbents also earn slightly less than controls. In subsequent regressions, we include controls for high-income status and age by marital group to address underlying differences.

## 7.2 Differences in Perception, Childcare and Fertility Intention

First, employees at treated firms were far more likely to have used paternity leave when eligible and were more supportive of leave-taking overall. Figure 12 plots average responses to leave-related questions. Asterisks appear next to the treated-group mean and indicate that the difference from the control mean is statistically significant at the 1% level, with corresponding p-values reported in parentheses. Among eligible employees, 74% at treated firms report having used paternity leave versus 17% at control firms.<sup>20</sup> Treated respondents also report greater willingness to recommend leave to a hypothetical coworker expecting a newborn (*Mingyu*): 8.3 on average versus 6.0 for controls on a 10-point scale. The 2.3-point gap corresponds to 0.83 of the control-group standard deviation. The share willing to recommend (score > 5) is 83.6% for treated versus 54.7% for controls.

Similarly, treated respondents expect broader support from their coworkers. As shown in Figure 12, they believe 7 out of 10 eligible coworkers would take leave at their firm, compared with 2 out of 10 among controls—a difference of about 50 percentage points when expressed as a likelihood, mirroring the observed uptake gap. They also anticipate stronger peer encouragement: treated respondents expect about 7.0 out of 10 coworkers would recommend leave, compared with 4.7 out of 10 among controls. The 2.3-point gap corresponds to 0.8 of the control-group standard deviation.

Treated individuals also perceive fewer penalties and burdens associated with leave-taking. In Columns 1 and 2 of Table 12, we compare the share agreeing with each statement about situations a hypothetical coworker, *Mingyu*, would face if he took paternity leave at the respondent’s company. We control for high-income status and the full set of age-by-marital indicators to account for demographic differences.<sup>21</sup> In Column 1, treated respondents are 45 percentage points less likely than controls to agree that *Mingyu* would face career penalties after leave; 58 percent of control respondents express such concerns. In Column 2, treated

<sup>20</sup>Leave eligibility is defined using reported child ages and tenure at the current employer. A respondent is classified as ever eligible if any child was under age eight during his tenure at the current firm. In our sample, 137 of 236 control employees and 136 of 214 treated employees are ever eligible.

<sup>21</sup>We include four indicators for the  $2 \times 2$  interaction of age (< 37 vs.  $\geq$  37) and marital status (single vs. married), omitting one as the reference. This flexibly adjusts for joint differences in age and marital composition while preserving statistical power in our sample of 450 respondents.

respondents are 52 percentage points less likely to agree that coworkers’ workload would increase due to *Mingyu*’s leave, compared to 74 percent of controls who agree. These gaps suggest that leave-taking is more normalized at treated firms and viewed as less costly for both the leave-taker and coworkers.

We find that differences in perceived workplace support for leave-taking are associated with greater paternal involvement at home and stronger fertility intentions. First, treated men report spending more time on weekday childcare. We elicited childcare time—or expected time if the respondent was childless—in six intervals.<sup>22</sup> Figure 13 shows that a larger share of treated men fall into the highest bracket, spending more than 120 minutes on childcare during weekdays. To compare average time, we converted interval responses to minutes using midpoints. Controlling for high-income status and the full set of age-by-marital indicators, the midpoint OLS estimate (Column 3 of Table 12) indicates that treated respondents spend 6.3 minutes more on childcare than controls, whose mean is 91.9 minutes. Using an interval regression that accounts for censoring at both ends (Column 4), the estimated difference is 8.8 minutes, relative to a control-group mean of 100.2 minutes. Second, treated respondents report higher fertility intentions. Among employees with fewer than two children, they are 7 percentage points more likely than controls to intend to have a child, compared to a control-group mean of 92 percent (Column 5). In addition, their desired number of children is higher by 0.11—about 7.8 percent above the control-group mean of 1.41 (Column 6). While cross-sectional, these patterns are consistent with the interpretation that the mandate acted as a normalizing device, with shifts in norms amplifying fertility effects beyond the one-month leave entitlement.

### 7.3 Mandate Effects in Counterfactual Vignettes

How important is the mandate in shaping more favorable attitudes toward leave-taking? To assess this directly, we re-asked the *control* group the same vignette questions about a hypothetical coworker, *Mingyu* (age 33; wife employed full-time; expecting a first child), but instructed them to answer as if a corporate mandate were in place, analogous to the policy at treated firms. Again, respondents reported (i) whether they would recommend that *Mingyu* take paternity leave, (ii) expected career penalties if he did, (iii) expected coworker workload effects, (iv) expected peer support (share of coworkers who would recommend leave), and (v) the perceived probability that *Mingyu* would have a second child. We plot the within-respondent differences (mandate scenario minus status quo) alongside the initial responses in Figure 14.

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<sup>22</sup>The intervals are: less than 10 minutes; 10–30 minutes; 30–60 minutes; 60–90 minutes; 90–120 minutes; and more than 120 minutes.

The mandate scenario moves attitudes in the direction observed at treated firms. Under the hypothetical mandate, the share of control respondents willing to recommend leave rises by 28.8 percentage points from 54.6% to 83.4%. Expected peer support also increases: the expected share of coworkers who would recommend leave increases by 17.2 p.p. Concerns about penalties and coworker burden decline: the share agreeing that *Mingyu* would face career penalties decreases by 14.8 percentage points from 58%, while agreement that coworkers' workload would increase decreases by 9.7 percentage points from 74%. Finally, fertility expectations shift as well: the perceived probability that the hypothetical couple would have a second child increases by 13.8 percentage points relative to an initial mean of 39%.

These within-respondent counterfactuals illustrate that simply assuming the mandate substantially increases support for leave, reduces perceived penalties and burdens, and raises expected fertility. The pattern aligns with the cross-group differences documented above, reinforcing that the policy environment was a key driver of attitudinal and expectation gaps.

## 8 Discussion and Policy Implications

What lessons do these findings offer for policymakers confronting low fertility in high-income countries—especially where caregiving norms lag behind women's economic progress ([Goldin, 2024](#))?

First, paternal availability matters for fertility, particularly in dual-earner households where maternal time is scarce. Guaranteeing even one month of leave shifted households' expectations of fathers' involvement and led to fertility gains concentrated among dual-earner families. Importantly, these gains did not come at the expense of women's employment. Instead, wives' labor force participation modestly increased, suggesting that well-designed paternity leave can help achieve a dual policy goal: supporting higher fertility while maintaining gender equity in employment.

Second, a binding mandate can help overcome workplace frictions that generous but voluntary benefits alone may not. Administrative evidence shows that fertility gains are concentrated in dual-earner households, while survey evidence demonstrates that the channel operates through shifts in workplace culture. Under the mandate, employees report fewer perceived penalties and concerns about added workload, and stronger peer support. By reducing stigma, career penalties, and coworker burdens, a mandate can transform leave-taking into a normative practice rather than an exception.

Lastly, this normalization carries over into fertility decisions. Treated men not only report spending more time on childcare but also express stronger fertility intentions. Likewise, in within-respondent counterfactuals, control employees asked to assume a mandate shift their expectations in the same direction, reporting more supportive attitudes toward leave-taking and higher predicted probabilities of a second child. Together, these findings suggest that mandates can reshape workplace culture and men’s expectations of their own caregiving role, thereby promoting both greater paternal involvement and higher fertility.

Additionally, scaling a leave mandate raises concerns about firm-level costs. While our data cannot fully capture these outcomes, we explore potential impacts using an event-study design with business registry and matched employer–employee data (see Appendix D). We examine revenue, employment, productivity, retention, and earnings. We find no significant declines in firm performance following the mandate. Instead, firms appear to have partially adjusted through wages and workforce composition: slower wage growth among men aged 30–45, higher retention of men of childbearing age, and a greater likelihood that new male hires had a child soon after joining (consistent with sorting on the value of the benefit). These patterns point to cost-sharing between firms and workers without measurable losses in productivity or headcount in the short to medium run. Future work should assess longer-run effects on wage setting, recruitment, and workforce composition.

## 9 Conclusion

This study leverages a corporate policy change in South Korea—a one-month, fully paid paternity-leave mandate introduced in 2017 at the corporate-group level—to estimate the causal effect of paternal leave mandate on fertility. We show that the mandate substantially increased fathers’ leave-taking and also encouraged leave durations beyond the required month. The policy raised the probability of having an infant among affected employees by 14.7%, with the largest gains in dual-earner households and where wives’ earnings—and thus the opportunity cost of time—were higher, and did so without reducing women’s employment.

Complementary survey evidence shows that men at mandate firms perceive more supportive workplace norms around paternal leave, report spending more time on childcare (or expecting to do so), and express stronger fertility intentions. When control respondents were asked to answer under a mandate scenario, their responses shifted toward higher support for leave, lower perceived penalties and coworker burdens, and higher expected second-birth probabilities. Together, the findings suggest that a binding paternal-leave mandate can help

realign workplace practices with the needs of dual-earner families and lower time-related barriers to parenthood.

These results motivate several extensions. First, while we explore potential costs using an event-study design with business registry and matched employer–employee data (Appendix D), our firm-level evidence is limited to short and medium run outcomes. Assessing the costs of implementing a paternity-leave mandate is important for evaluating its potential as a federal policy. Costs may vary substantially across firms by size and workforce structure, with smaller or less flexible firms potentially facing larger challenges from fathers’ absences. Understanding this heterogeneity is essential for designing equitable and effective family policies. Future work should assess longer-run implications for wage setting, recruitment, and workforce composition, and how any costs vary with firm size and flexibility.

Second, policy discussions would benefit from evidence on whether normalizing fathers’ caregiving helps reduce gender wage and promotion gaps by mitigating the stigma traditionally attached to mothers’ childbearing-related absences. Such downstream benefits would strengthen the public-policy case for paternity-leave mandates by highlighting gains beyond fertility.

Lastly, because the mandate spurred leave beyond the minimum requirement, it is valuable to examine whether corporate policies induce selection and sorting—attracting workers with stronger fertility preferences—and whether these dynamics, in turn, encourage competing firms to adopt similar benefits. Such spillovers could generate broader labor-market effects. Advancing these lines of inquiry will deepen our understanding of how family-friendly mandates shape household decisions, workplace norms, and firm behavior.

## References

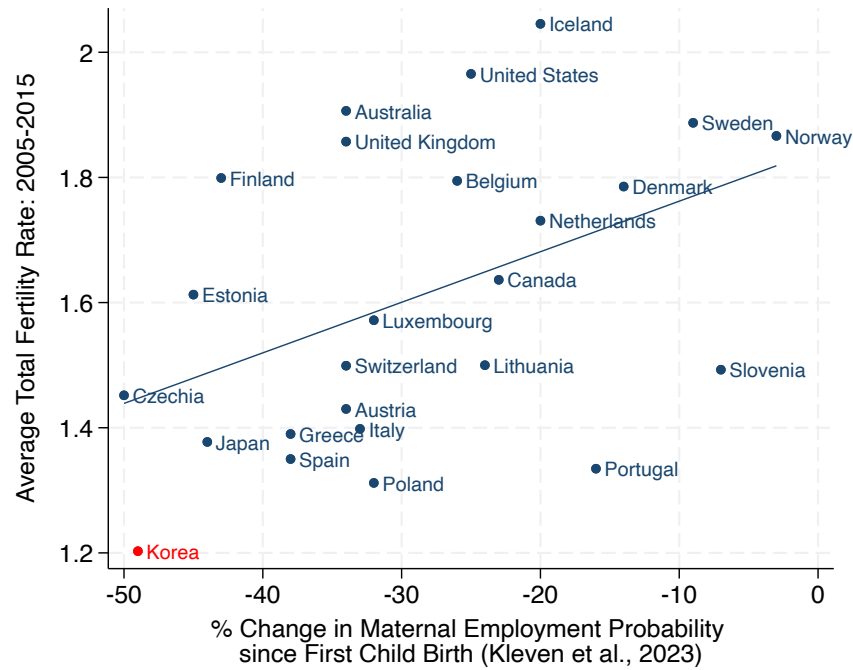
- Almqvist, A.-L. and A.-Z. Duvander (2014). Changes in gender equality? swedish fathers' parental leave, division of childcare and subsequent behavior. *Work, Employment and Society* 25, 234–256.
- Bartel, A. P., M. Rossin-Slater, C. J. Ruhm, J. Stearns, and J. Waldfogel (2018). Paid family leave, fathers' leave-taking, and leave-sharing in dual-earner households. *Journal of Policy Analysis and Management* 37(1), 10–37.
- Becker, G. S. and H. G. Lewis (1973). On the interaction between the quantity and quality of children. *Journal of political Economy* 81(2, Part 2), 279–288.
- Canaan, S., A. Lassen, P. Rosenbaum, and H. Steingrimsdottir (2022). Maternity leave and paternity leave: Evidence on the economic impact of legislative changes in high income countries. Working Paper.
- Cooke, L. P. (2004). Persistent policy effects on gender equity. *Journal of Social Policy* 33(2), 191–211.
- Cools, S., J. H. Fiva, and L. J. Kirkebøen (2015). Causal effects of paternity leave on children and parents. *The Scandinavian Journal of Economics* 117(3), 801–828.
- Corekcioglu, G., M. Francesconi, and A. Kunze (2024). Expansions in paid parental leave and mothers' economic progress. *European Economic Review* 169.
- Dahl, G. B., K. V. Løken, M. Mogstad, and K. V. Salvanes (2016). What is the case for paid maternity leave? *Review of Economics and Statistics* 98(4), 655–670.
- Dahl, G. B., K. V. Løken, and M. Mogstad (2014). Peer Effects in Program Participation. *American Economic Review* 104(7), 2049–2074.
- Doepke, M., A. Hannusch, F. Kindermann, and M. Tertilt (2023). The economics of fertility: A new era. In *Handbook of the Economics of the Family*, Volume 1, pp. 151–254.
- Doepke, M. and F. Kindermann (2019). Bargaining over babies: Theory, evidence, and policy implications. *American Economic Review* 109(9), 3264–3306.
- Ekberg, J., R. Eriksson, and G. Friebel (2013). Parental leave—a policy evaluation of the swedish “daddy-month” reform. *Journal of Public Economics* 97, 131–143.

- Erosa, A., L. Fuster, and D. Restuccia (2010). A general equilibrium analysis of parental leave policies. *Review of Economic Dynamics* 13(4), 742–758.
- Fanelli, E. and P. Profeta (2021). Fathers’ involvement in the family, fertility, and maternal employment. *Demography* 58(5), 1931–1951.
- Farré, L., C. Felfe, L. González, and P. Schneider (2023). Changing gender norms across generations: Evidence from a paternity leave reform.
- Farré, L. and L. González (2019). Does paternity leave reduce fertility? *Journal of Public Economics* 172, 52–66.
- Feyrer, J., B. Sacerdote, and A. D. Stern (2008). Will the stork return to europe and japan? understanding fertility within developed nations. *Journal of Economic Perspectives* 22(3), 3–22.
- Goldin, C. (2021). *Career and family: Women’s century-long journey toward equity*. Princeton University Press.
- Goldin, C. (2024). Babies and the macroeconomy. Working Paper.
- Goldschmidt, D. and J. F. Schmieder (2017). The rise of domestic outsourcing and the evolution of the german wage structure. *Quarterly Journal of Economics* 132(3), 1165–1217.
- González, L. and H. Zoabi (2021). Does paternity leave promote gender equality within households?
- Johnsen, J. V., H. Ku, and K. G. Salvanes (2024). Competition and career advancement. *Review of Economic Studies* 91(5), 2954–2980.
- Kim, D. and M. Yum (2025). Parental leave policies, fertility, and labor supply. *Fertility, and Labor Supply*.
- Kim, Y. and Å. Lundqvist (2023). Parental leave reforms in south korea, 1995–2021: Policy translation and institutional legacies. *Social Politics: International Studies in Gender, State & Society* 30(4), 1113–1136.
- Kleven, H., C. Landais, and G. Leite-Mariante (2024). The child penalty atlas. *Review of Economic Studies*.

- Kleven, H., C. Landais, J. Posch, A. Steinhauer, and J. Zweimuller (2024). Do family policies reduce gender inequality? evidence from 60 years of policy experimentation. *American Economic Journal: Economic Policy* 16(2), 110–49.
- Kotila, L. E. and C. M. Kamp Dush (2011). Fhigh father involvement and supportive co-parenting predict increased same-partner and decreased multipartnered fertility. Working Paper No.1311.
- Kotsadam, A. and H. Finseraas (2011). The state intervenes in the battle of the sexes: Causal effects of paternity leave. *Social Science Research* 40(6), 1611–1622.
- Lalive, R. and J. Zweimüller (2009). How does parental leave affect fertility and return to work? evidence from two natural experiments. *The Quarterly Journal of Economics* 124(3), 1363–1402.
- Lappegård, T. and T. Kornstad (2020). Social norms about father involvement and women’s fertility. *Social Forces* 99(1), 398–423.
- Olivetti, C. (2024). Gender, work, and family: Progress and ongoing challenges. *NBER Reporter* (4), 13–16.
- Patnaik, A. (2019). Reserving time for daddy: The consequences of fathers’ quotas. *Journal of Labor economics* 37(4), 1009–1059.
- Persson, P. and M. Rossin-Slater (2024). When dad can stay home: fathers’ workplace flexibility and maternal health. *American Economic Journal: Applied Economics* 16(4), 186–219.
- Raute, A. (2019). Can financial incentives reduce the baby gap? evidence from a reform in maternity leave benefits. *Journal of Public Economics* 169, 203–222.
- Smith, M., D. Yagan, O. Zidar, and E. Zwick (2019). Capitalists in the twenty-first century. *Quarterly Journal of Economics* 134(4), 1675–1745.
- Tamm, M. (2019). Fathers’ parental leave-taking, childcare involvement and labor market participation. *Labour Economics* 59, 184–197.

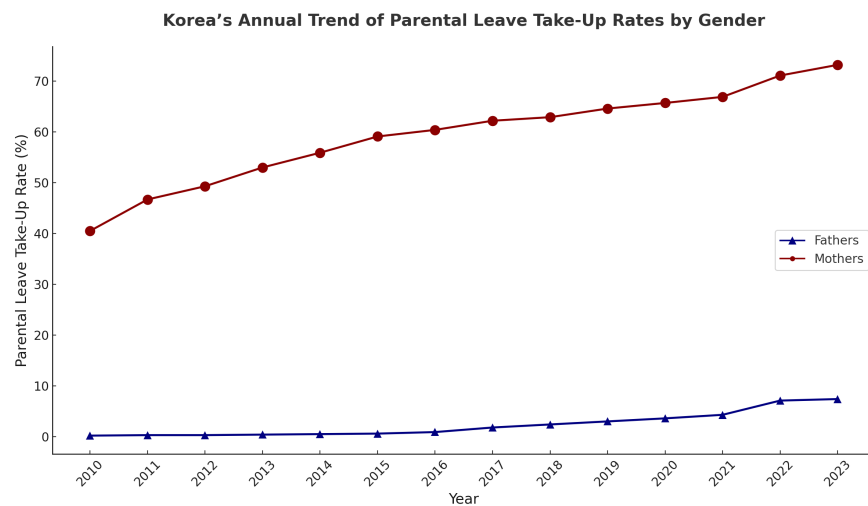


Figure 1: Average Fertility Rate and Child Penalty in Employment



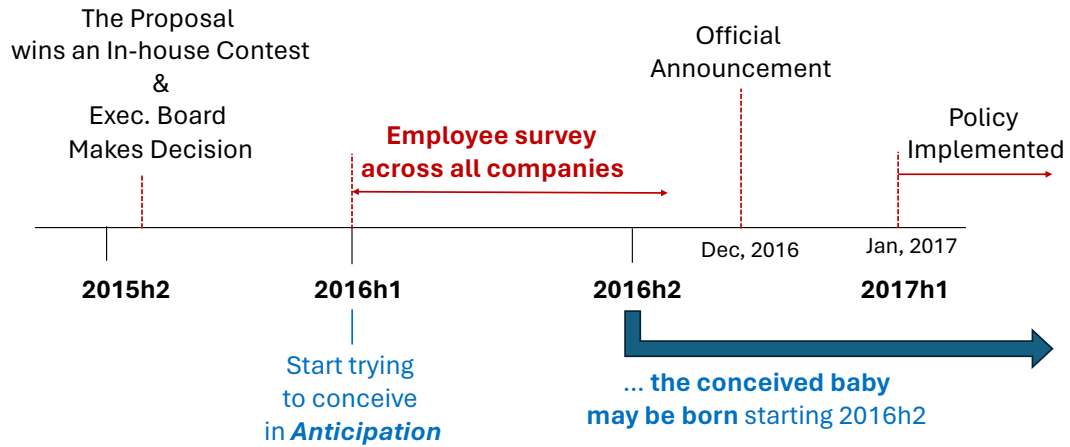
Note: The figure shows the average total fertility rate (Source: World Bank) and the percentage change in mothers' employment probability after the birth of their first child, relative to men, as estimated by [Kleven et al. \(2024\)](#).

Figure 2: Parental Leave Utilization Rate in Korea by Gender



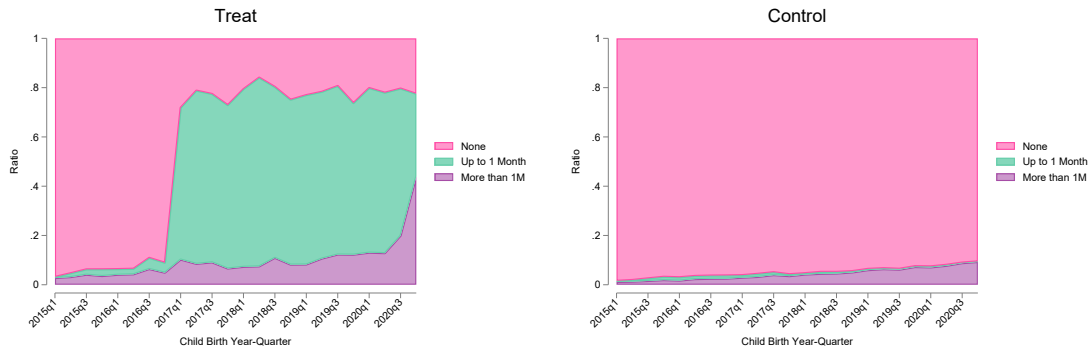
Note: The figure plots the average parental leave utilization rate by gender in Korea from 2010 to 2023. The utilization rate is calculated as the proportion of parents of newborns who used parental leave in a given year. Source: Statistics Korea.

Figure 3: Paternity Leave Mandate Policy Introduction



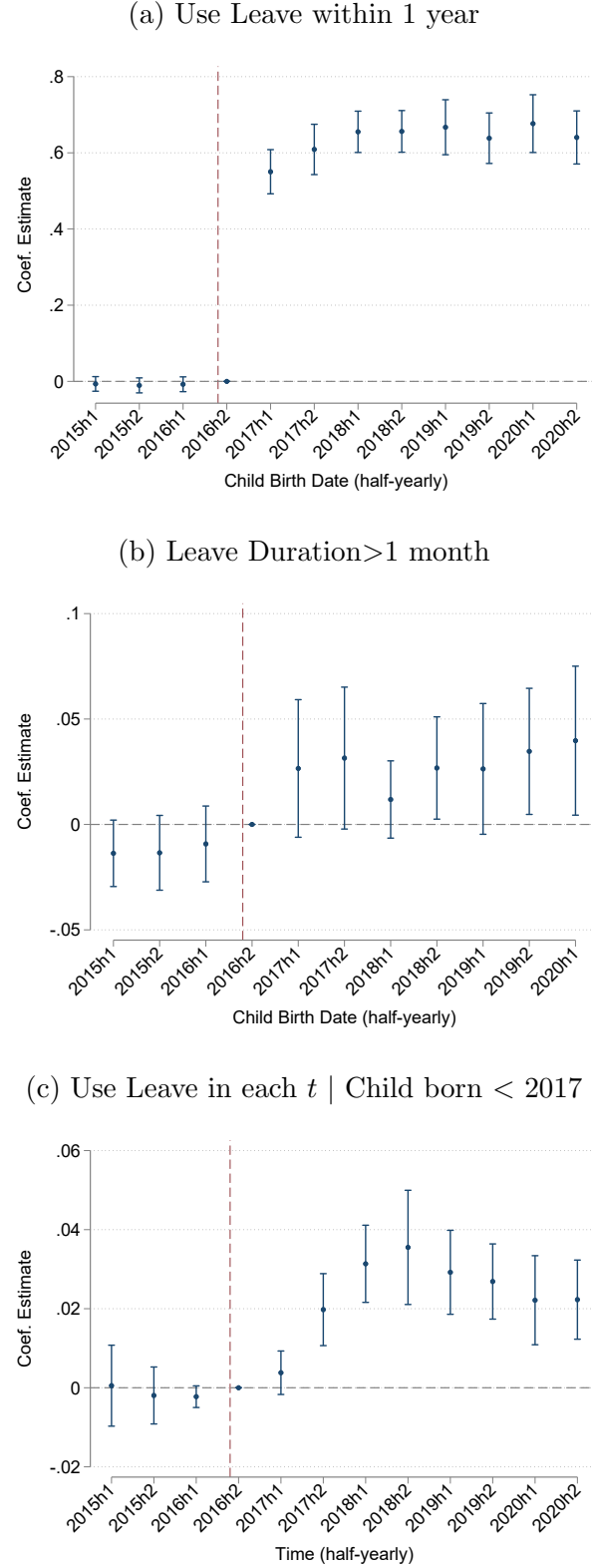
Note: The graph illustrates the timeline of C Group's corporate policy change, along with the expected timeline for conceived births among male incumbents in response to the new corporate paternity leave mandate. See Section 2.2 and Section 5.2 for further details.

Figure 4: Leave Utilization among Newborn Fathers



Note: The stacked area chart illustrates the proportion of fathers with newborns who took no leave (pink), up to one month of leave (green), or more than one month of leave (purple). The treated group consists of fathers employed by C group companies, while the control group includes fathers working at other conglomerates designated by the Korea Fair Trade Commission in the same industry as C group.

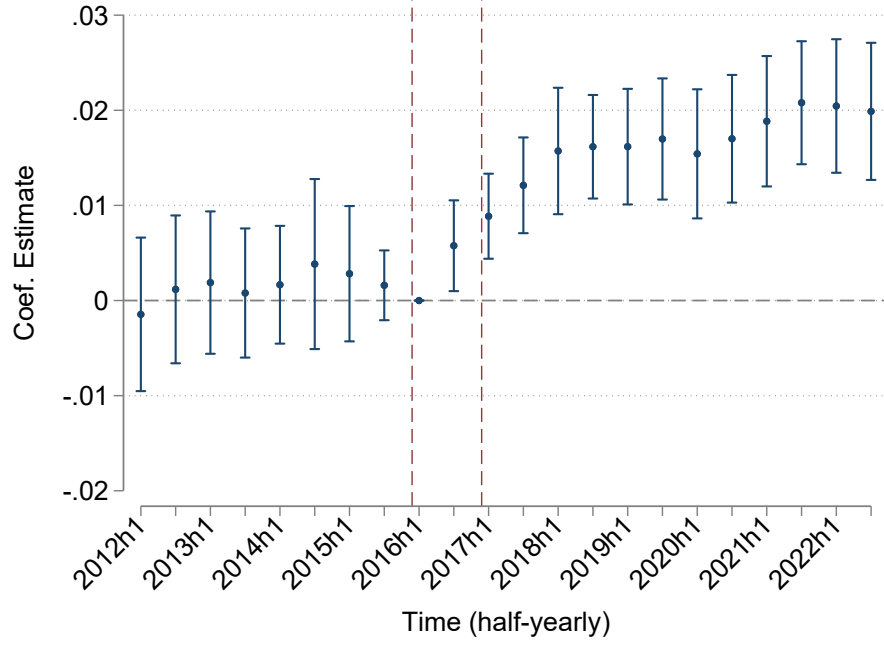
Figure 5: The Effect of the Mandate on Paternity Leave Taking



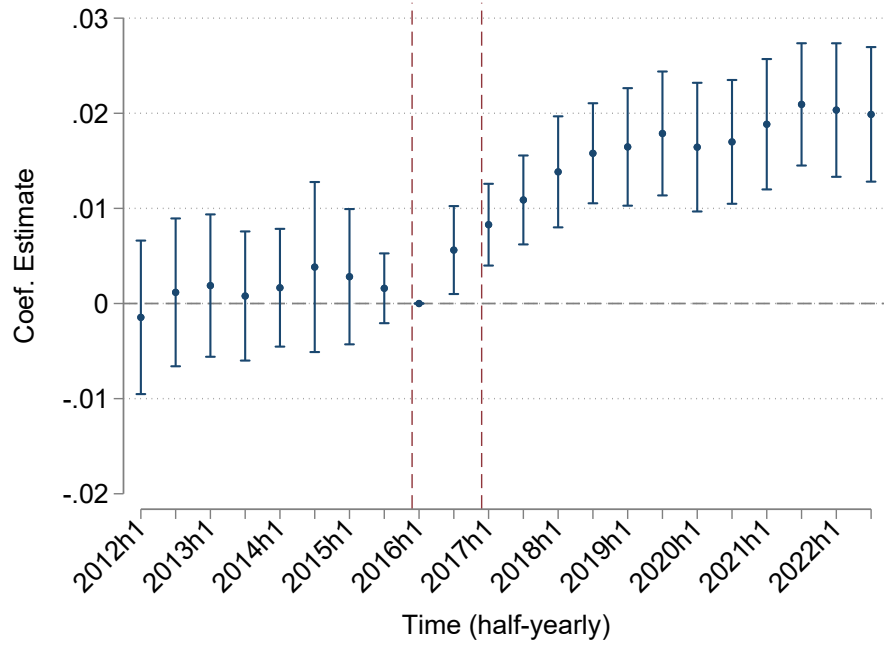
Note: The figures present event study estimates of the effects of the paternity leave mandate on male employees' leave-taking behavior. Panel (a) and (b) plot event time coefficients for fathers whose child was born in each period (x-axis) with (a) showing the probability of taking any paternity leave within one year of childbirth, and (b) the probability of taking leave longer than one month. Panel (c) shows leave usage in each period for fathers whose child was born before 2017. See Table 2 for more detail. Robust standard errors are clustered at the baseline firm level.

Figure 6: The Effect of the Paternity Leave Mandate on Fertility

(a) Probability to have an infant



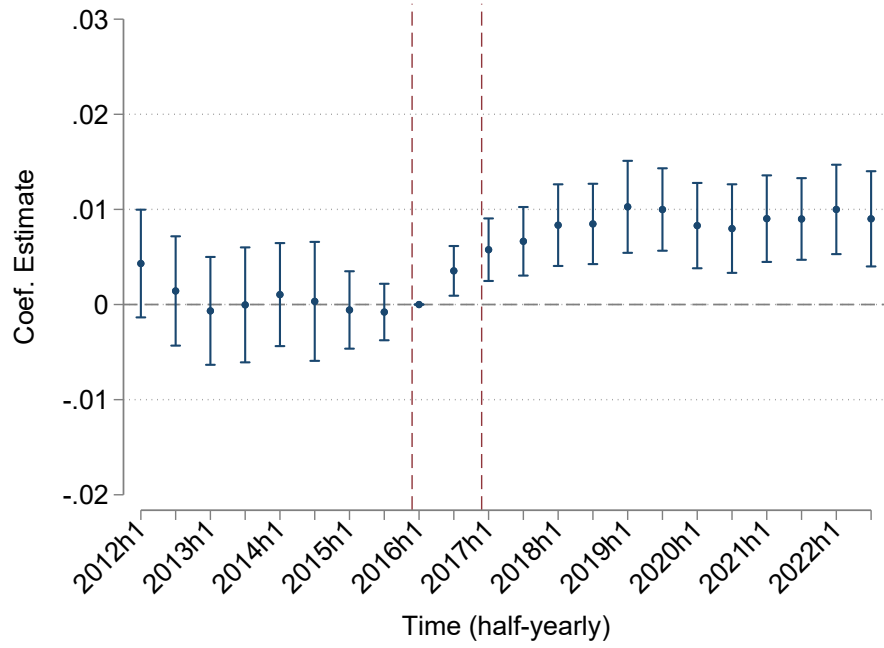
(b) Probability to have an infant and still employed at the same company



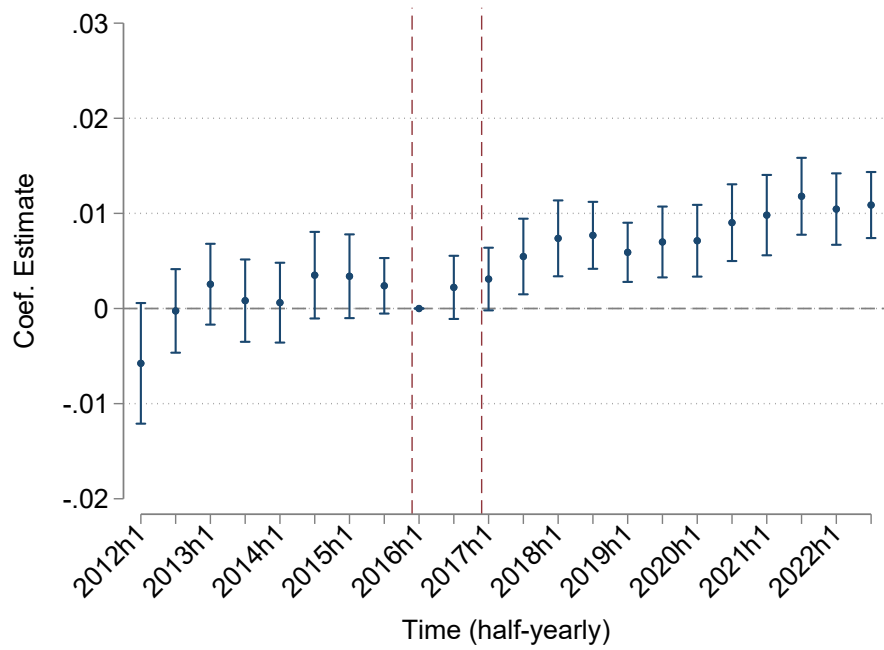
Note: The figures show event study estimates of the effects of the paternity leave mandate on the probability that male incumbents have an infant (age 0) in each period. Panel (a) uses an indicator for having an infant in each and (b) an indicator for having an infant and remaining at the same baseline firm. Each point plots the estimated coefficients corresponding to  $\beta_{2,k}$  in Equation 3 and associated 95% confidence intervals. Robust standard errors are clustered at the baseline firm level.

Figure 7: The Effect of the Paternity Leave Mandate on Fertility by Birth Parity

(a) Probability to have an infant & first child



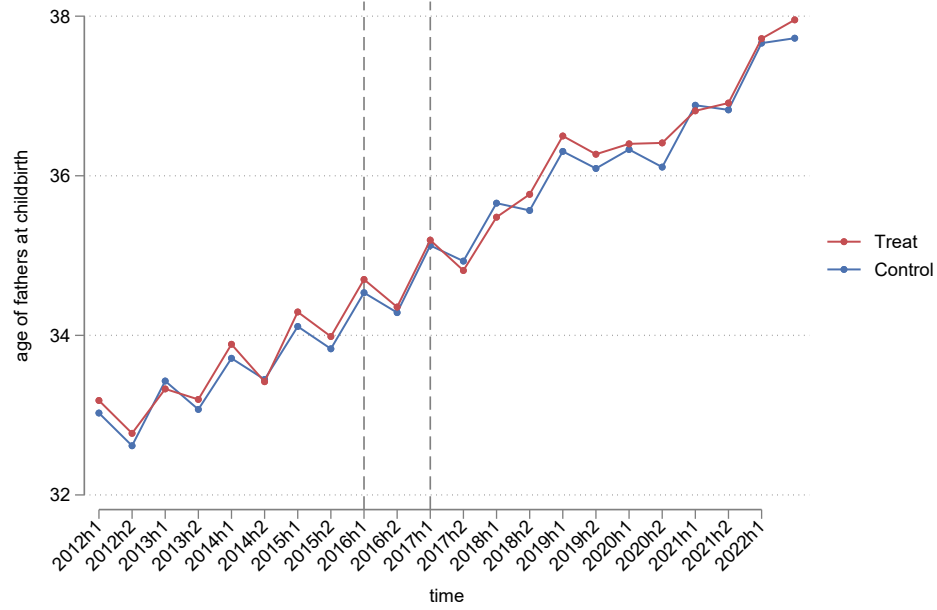
(b) Probability to have an infant & second or higher order birth child



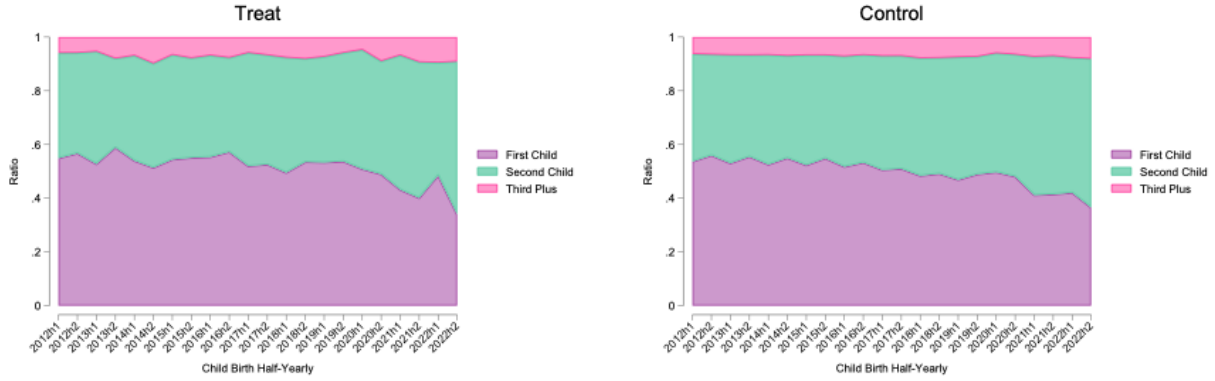
Note: The figures show event study estimates of the effects of the paternity leave mandate on the probability that male incumbents have an infant (0 years old) in a given period. Panel (a) uses an indicator for first-born infants and (b) an indicator for second or higher-order infants. Each point shows the estimated coefficients, corresponding to  $\beta_{2,k}$  in equation 3 and associated 95% confidence intervals. Robust standard errors are clustered at the baseline firm level.

Figure 8: Average Paternal Age at Childbirth and Distribution of Birth Orders

(a) Average paternal age at child birth

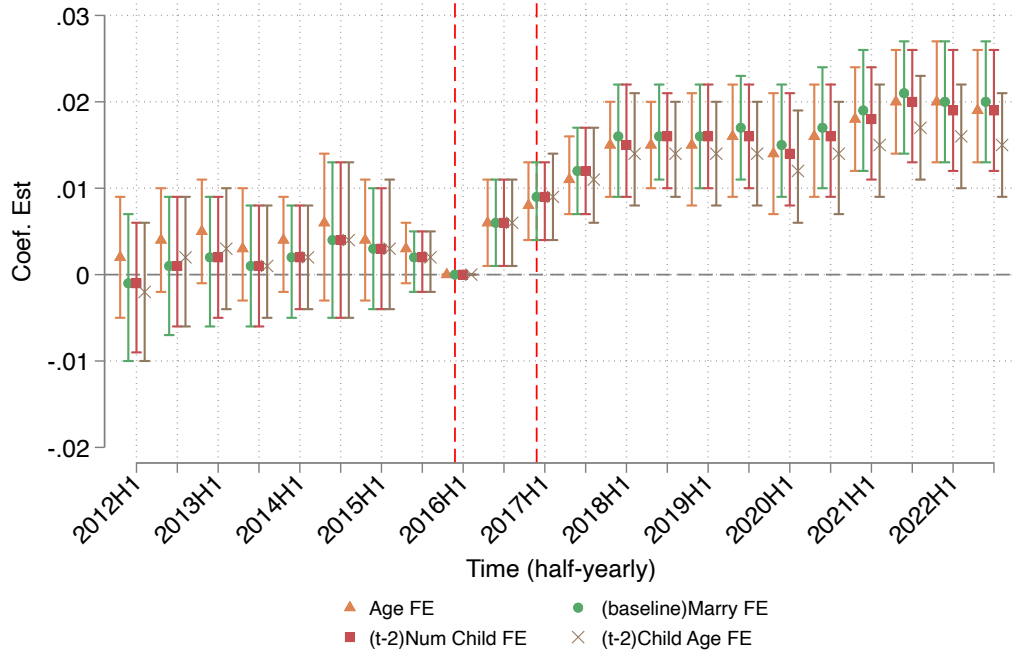


(b) The distribution of birth orders



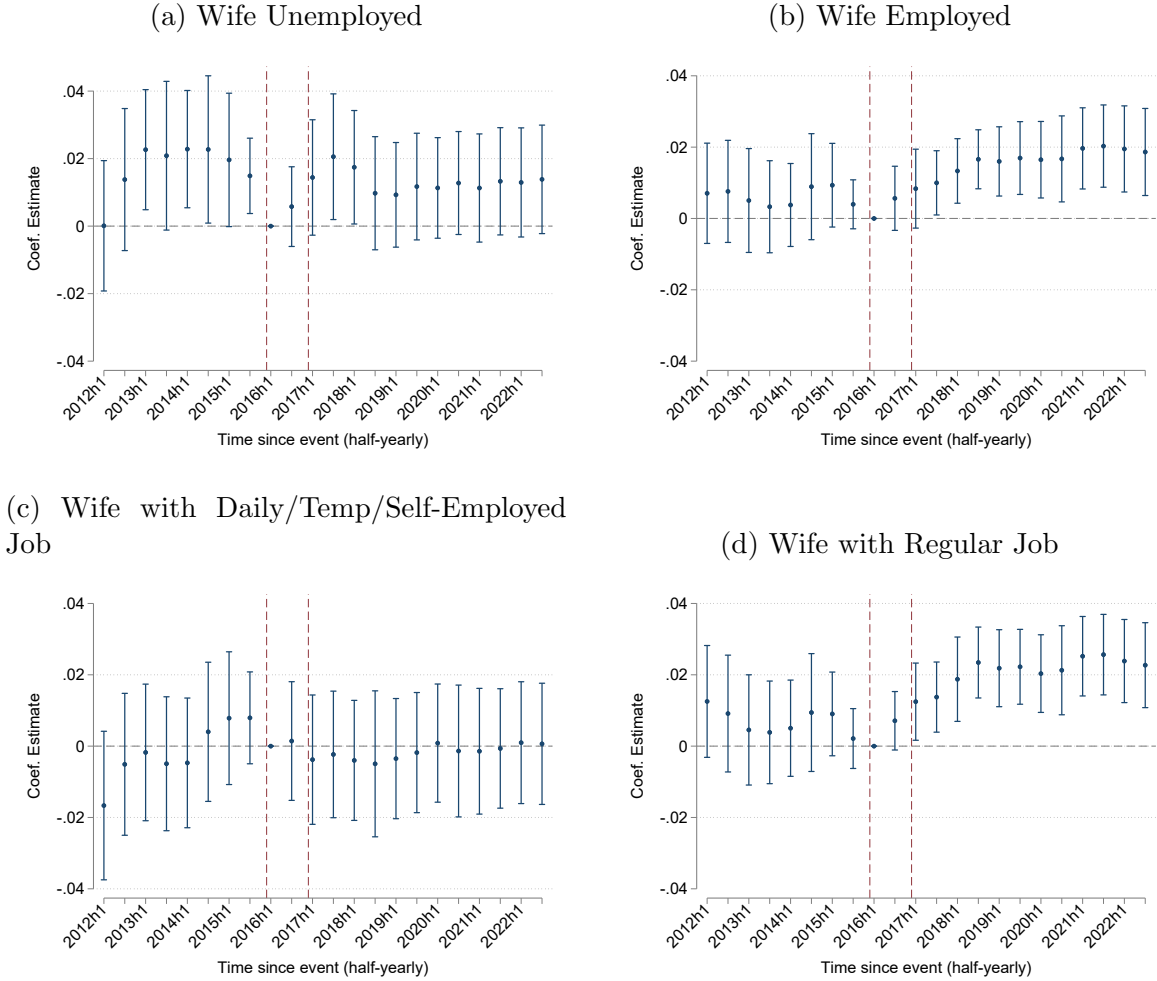
Note: Panel (a) plots the average paternal age at birth in each period for treated and control groups. Panel (b) shows the distribution of birth order among fathers with newborns—first births (purple), second births (green), and third or higher-order births (pink)—for treated and control firms in each period.

Figure 9: The Effect of the Paternity Leave Mandate on Fertility: Robustness



Note: The figures show event study estimates of the effects of the paternity leave mandate on the probability that male incumbents have an infant (0 years old) in a given period, using alternative sets of time-varying fixed effects. Each point plots the estimated coefficients corresponding to  $\beta_{2,k}$  in Equation 3 and associated 95% confidence intervals. See Table 6 for included controls in each specification. Robust standard errors are clustered at the baseline firm level.

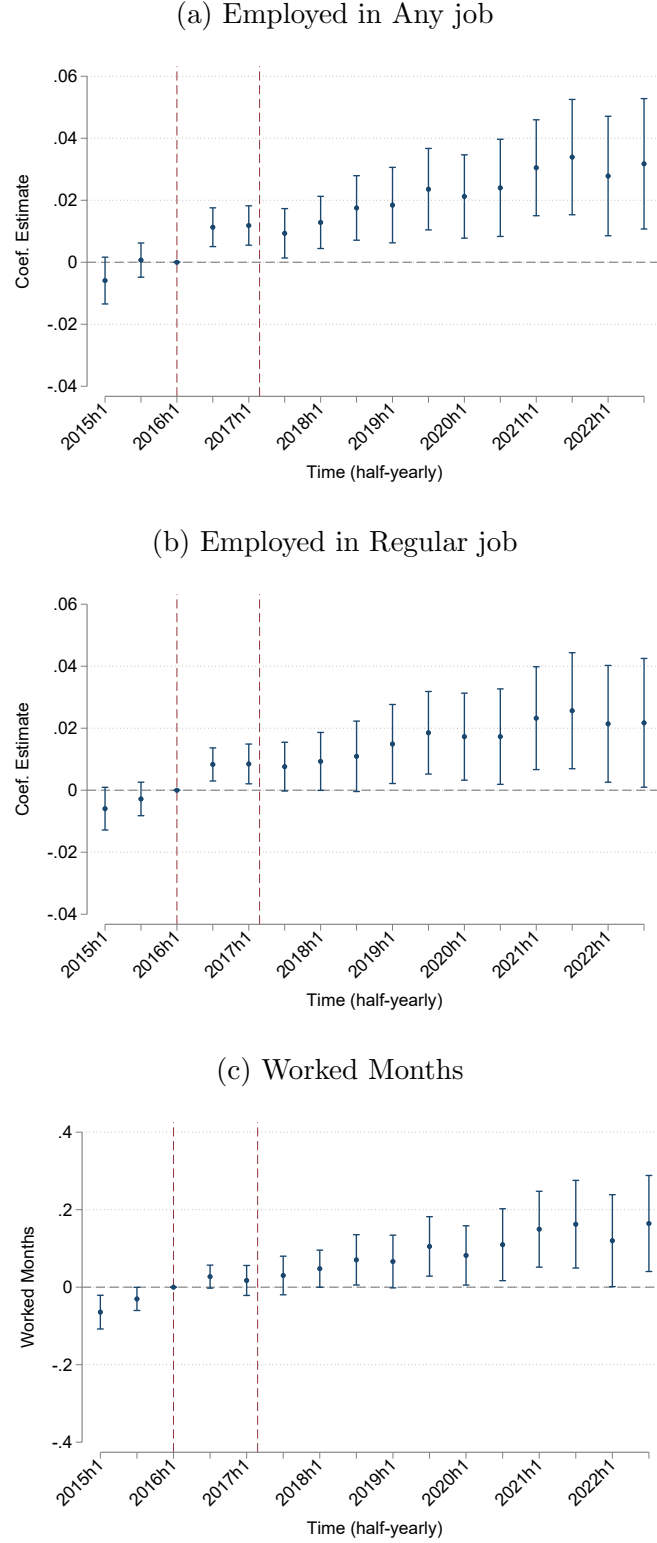
Figure 10: The Effect of the Paternity Leave Mandate on Fertility by Wife Employment



Note: The figure shows event-study estimates of the paternity leave mandate's effect on spousal labor supply of male incumbents. Panel (a) restricts to incumbents whose spouses were not employed at baseline; Panel (b) to those with spouses employed in any job; Panel (c) to those with spouses in daily, temporary, or self-employed work; and Panel (d) to those with spouses in wage and salary jobs in 2015. Each point plots the estimated coefficients  $\beta_{2,k}$  from equation 3, with 95% confidence intervals. Standard errors are clustered at the baseline firm level.

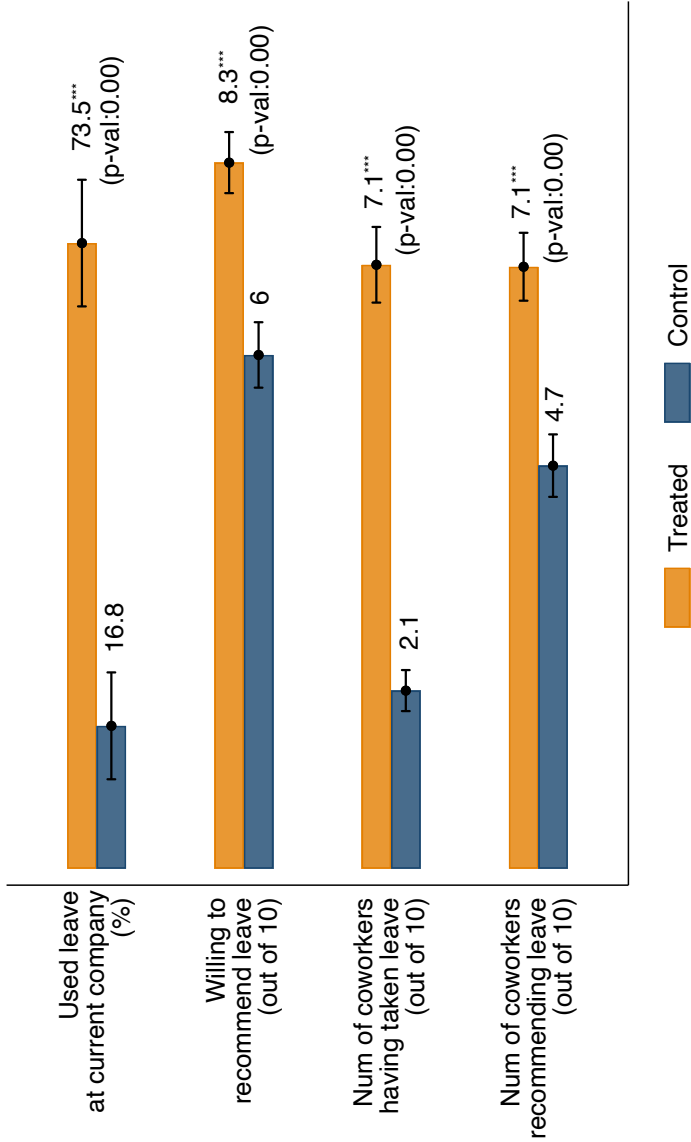


Figure 11: The Effect of the Paternity Leave Mandate on Spousal Labor Supply



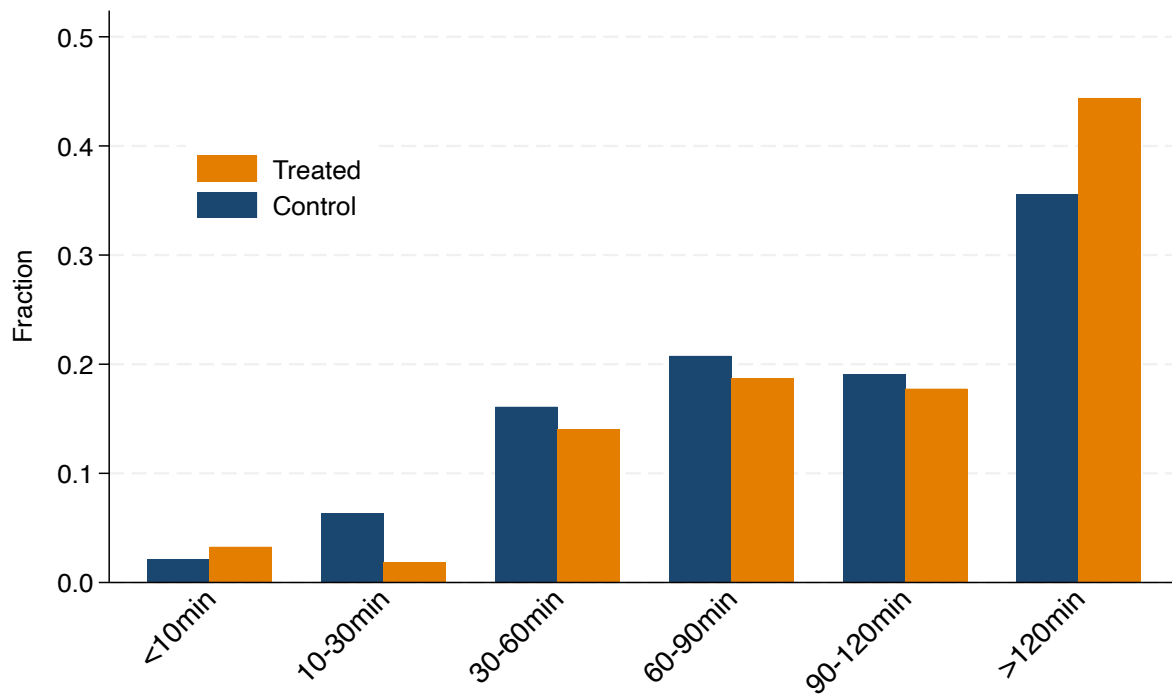
Note: The figure shows event-study estimates of the paternity leave mandate's effect on wives' labor supply. The sample includes wives matched to male incumbents in 2015. Panel (a) reports estimates for an indicator of employment in any job, Panel (b) for employment in wage and salary jobs, and Panel (c) for total months worked in biannual period  $t$ . Each point plots the estimated coefficient  $\beta_{2,k}$  from equation 3, with 95% confidence intervals. Standard errors are clustered at the husband's baseline firm level. See Table 10 for additional results.

Figure 12: Paternity leave usage and attitudes toward paternity leave



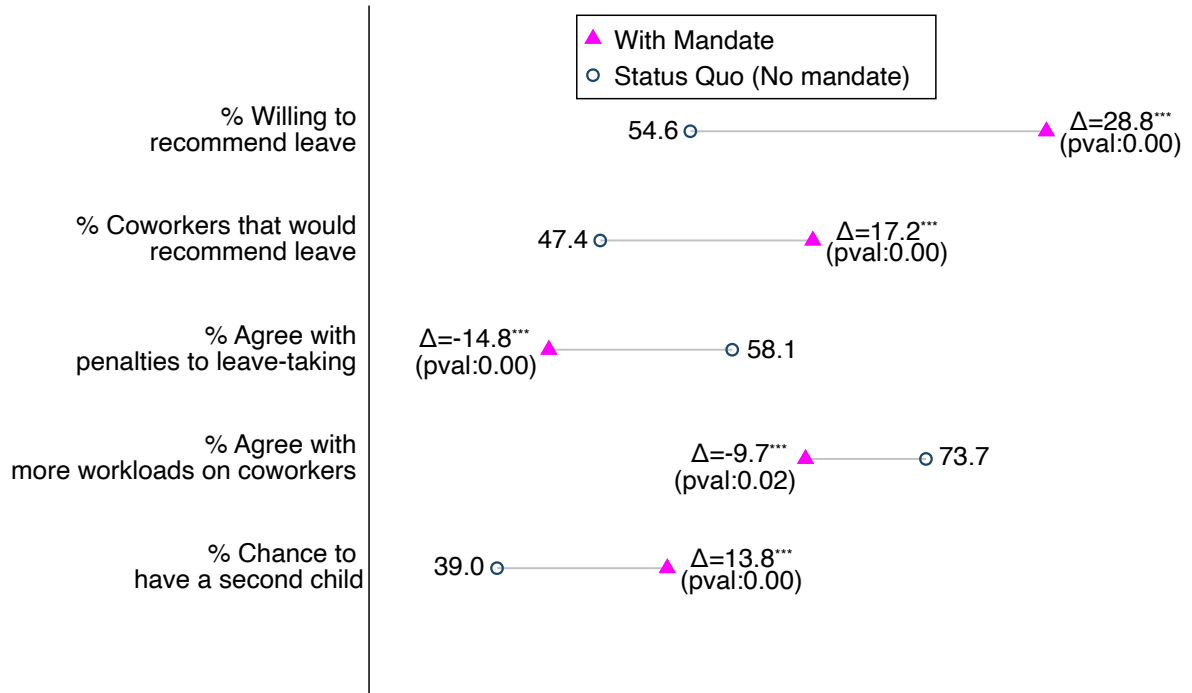
Note: The figure shows mean responses of treated and control individuals to survey questions on paternity leave-taking at their current companies. The y-axis lists each question, and bars represent group means with 95% confidence intervals shown as capped black lines. Asterisks next to the treated-group means indicate statistical significance of the difference from controls at the 1% level, with corresponding p-values reported in parentheses. See Section 7 for details.

Figure 13: Weekday time spent on childcare



Note: The figure shows the distribution of responses to the survey question on weekday childcare time, comparing treated and control groups. Each bar represents the share of respondents in a given time category. See Section 7 for details.

Figure 14: Effects of a Mandate Scenario on Leave Norms and Subsequent Fertility



Note: The figure reports control-group responses to a vignette about a hypothetical coworker (“Mingyu”). For each outcome, the hollow circle shows the mean response under the status quo (no mandate), and the magenta triangle shows the mean response when the same question is answered assuming a mandate is in place. The average within-respondent difference is labeled as  $\Delta$ , with p-values in parentheses. Asterisks (\*\*\*) indicate significance at the 1% level. The survey questions are summarized on the y-axis. See Section 7 for details.

Table 1: Federal Parental Leave Policy (2015-2022)

Condition		Eligible while child is aged 0–8 years; maximum duration: 12 months			
Earnings Replacement Basis		Calculated based on maximum benefit cap for second parental leave user for the same child.			
Year		2015–2017	2018	2019	2022
1–3 months	Maximum Monthly Benefit (KRW)	1.5 million	2.0 million	2.5 million	3.0 million
	<i>Benefit Relative to Average Post-tax Earnings (%)</i>				
	Male Employees, ages 30–39 (2.9 million)	52%	69%	86%	100%
	C group Male Employees, ages 30–45 (4.2 million)	36%	48%	60%	71%
4–12 months	Maximum Monthly Benefit (KRW)	1.0 million	1.0 million	1.2 million	1.5 million
	<i>Benefit Relative to Average Post-tax Earnings (%)</i>				
	Male Employees, ages 30–39 (2.9 million)	34%	34%	41%	52%
	C group Male Employees, ages 30–45 (4.2 million)	24%	24%	29%	36%

Note: This table summarizes the federal parental leave scheme including maximum monthly benefits and income replacement rates by year. Replacement rates are calculated as the percentage of average annual post-tax earnings of male employees aged 30 to 39 and of male employees aged 30 to 45 at C Group during the observation period.

Table 2: Paternity Leave Utilization: Differences-in-differences estimates

Dep. Var.	Leave Used within 1 year	1(Leave > 1 month)	1(Leave > 1 month) child born < 2020H2	Leave Used in each $t$ child born < 2017
	(1)	(2)	(3)	(4)
Treat $\times$ Post	0.645*** (0.026)	0.056*** (0.008)	0.039*** (0.009)	0.024*** (0.003)
Pre Avg (Treat)	0.0197	0.0191	0.0191	0.0091
Observations	182,644	182,644	173,121	1,409,187
Unit	Individual	Individual	Individual	Individual $\times$ Time
Child Birth Date FE	Y	Y	Y	
Time (Bi-annual) FE				Y
Firm FE	Y	Y	Y	Y

Note: This table presents difference-in-differences estimates of paternity leave utilization by fathers of newborns employed at C group firms (treated) and other conglomerates (controls). The Treat dummy indicates C group firm employees, and the Post dummy indicates periods since the first half of 2017, when the policy was first implemented. Columns 1–3 use samples of fathers with children born in each corresponding period. Column 1 estimates the probability of taking any paternity leave within one year of childbirth. Columns 2 and 3 estimate the probability of taking more than one month of leave, with Column 3 restricting the sample to births before the second half of 2020. Column 4 uses a sample of fathers with children born before 2017 and regresses an indicator for any leave-taking during a given period. The unit of analysis is the individual in Columns 1–3, and an unbalanced individual-by-time panel in Column 4. Columns 1–3 control for bi-annual childbirth fixed effects and firm fixed effects. Column 4 includes bi-annual time fixed effects. Robust standard errors clustered at the firm level are reported in parentheses. \*\*\* indicates significance at the 1%.

Table 3: Descriptive statistics

	(1) Treat mean (sd)	(2) Control mean (sd)	(3) (1) - (2) mean (se)
<i>Panel A: Individual Characteristics</i>			
Number of Individuals	17,366	378,689	
Age	37.0 (4.5)	37.2 (4.6)	-0.3 (0.2)
Monthly Earnings (10,000KRW)	509.6 (172.0)	680.9 (280.0)	-171.3*** (34.8)
Tenure (years)	8.03 (4.95)	8.62 (5.47)	-0.59 (0.31)
Birth Rate (Pre-policy)	0.10	0.11	-0.01***
Married	0.60	0.68	-0.09***
Wife Age   Married	35.5 (4.5)	35.5 (4.5)	0.00 (4.5)
<i>Number of Children</i>			
Childless	0.40	0.33	0.07***
One Child	0.24	0.25	0.01
Two or more	0.36	0.41	-0.05***
<i>Panel B: Firm Characteristics</i>			
Number of Firms	104	1928	
Employment Size (establishment)	456.3 (1289.2)	436.2 (1997.3)	20.1 (133.8)
Revenue per Employee (1 billion KRW)	1.05 (0.80)	1.02 (2.00)	-0.03 (0.18)

Note: Panel A reports baseline individual characteristics by treatment status. Columns 1 and 2 display means and standard deviations for treated and control groups, respectively, while Column 3 reports the mean difference (and the standard error for the difference in means) between the groups. Age, monthly earnings, and tenure are sourced from the Matched Employer-Employee dataset; child information is from the 2015 Child Registry, and marriage data are drawn from the 2015 Population Census. Panel B presents characteristics of the baseline firms employing these individuals. Firm-level employment size is calculated using matched employer-employee data, and revenue per employee is derived from the Business Registry. \*\*\* indicates significance at the 1% level.

Table 4: Probability to have an infant: Differences-in-differences estimates

Dep Var	(1) 1(Infant)	(2) 1(Infant) × 1(same company)	(3) 1(Infant) × 1(First child)	(4) 1(Infant) × 1(Second+ child)
Treat x Post	0.014*** (0.003)	0.014*** (0.003)	0.008*** (0.002)	0.007*** (0.002)
Age	-0.009*** (0.000)	-0.008*** (0.000)	-0.006*** (0.000)	-0.003*** (0.000)
Baseline Tenure (years)	-0.001*** (0.000)	-0.001*** (0.000)	-0.000*** (0.000)	-0.000* (0.000)
Constant	0.413*** (0.005)	0.395*** (0.006)	0.248*** (0.003)	0.165*** (0.004)
Observations	8,713,232	8,713,232	8,713,232	8,713,232
Pre-policy Mean (Treat)	0.095	0.095	0.047	0.047
% rel. to Pre-Mean	14.7%	14.7%	17.0%	14.9%
Included Fixed Effects	Calendar Time, (baseline) Income Quintile, (baseline) Firm			

Note: This table reports differences-in-differences estimates from a linear probability model assessing the impact of a corporate policy change on the probability that male incumbents aged 30–45 have an infant. The sample includes men employed at subsidiary firms under conglomerates as of the first half of 2016. The Treat indicator identifies individuals at firms subject to the corporate policy change, while the control group comprises men at firms in other conglomerates. The interaction of Post and Treat indicators captures differential time trends between these groups. Column 1 reports estimates for having an infant; Column 2 adds the condition of remaining at the same baseline company; Column 3 focuses on having an infant who is the first child; and Column 4 covers having an infant of second or higher parity. All specifications control for biannual calendar time dummies, baseline monthly earnings quintile dummies, and baseline firm dummies. Robust standard errors clustered at the baseline firm level are reported in parentheses. \*\*\* indicates significance at the 1% level.



Table 5: Parental Age, Birth Order, and Age Difference: Differences-in-differences estimates

	(1)	(2)	(3)
	Father Age	Mother Age	Age Gap
Treat $\times$ Post	-0.033 (0.084)	-0.024 (0.084)	0.003 (0.045)
Treat	0.118 (0.178)	-0.060 (0.166)	0.063 (0.053)
Post	2.029*** (0.043)	0.310*** (0.031)	0.539*** (0.013)
Constant	33.519*** (0.080)	33.109*** (0.076)	2.459*** (0.012)
Observations	255,834	255,834	116,255

Note: This table reports differences-in-differences estimates for parental age and the age gaps between children in households with a newborn in each period. The sample comprises households of male incumbents aged 30–45 who were employed at firms under C Group or other conglomerates as of the first half of 2016 and who subsequently had a newborn. The Treat indicator identifies firms affiliated with C Group, while Post marks the time since the first half of 2016, when information about the policy began circulating. The interaction term  $Treat \times Post$  captures differential trends in these outcomes among treated households. Columns 1 and 2 estimate the effects on the ages of the father and mother of the newborn, respectively. Column 3 estimates the age difference between the newborn and the next oldest child (for non-firstborns). Robust standard errors, clustered at the baseline firm level, are reported in parentheses. \*\*\* indicates significance at the 1% level.

Table 6: Probability to have an infant: Differences-in-differences estimates

Dep Var	(1) 1(Infant)	(2) 1(Infant)	(3) 1(Infant)	(4) 1(Infant)
Treat x Post	0.014*** (0.003)	0.014*** (0.003)	0.013*** (0.003)	0.012*** (0.002)
Age		-0.010*** (0.000)	-0.009*** (0.000)	-0.006*** (0.000)
(baseline) tenure	-0.000*** (0.000)	-0.001*** (0.000)	-0.000*** (0.000)	-0.000*** (0.000)
Constant	0.084*** (0.001)	0.464*** (0.004)	0.392*** (0.004)	0.278*** (0.003)
Observations	8,713,232	8,713,232	8,713,232	8,713,232
Pre Avg (Treat)	0.095	0.095	0.095	0.095
% relative to Pre Avg	14.7%	14.7% (baseline)	13.7% (t-2)	12.6% (t-2)
Additional Fixed Effects	Age	Marital Status	Num. of children	Age of youngest child)
Included Fixed Effects	Time, (baseline)	Income Quintile, Firm		

Note: This table presents differences-in-differences estimates from a linear probability model examining the effect of a corporate policy change on the likelihood that male incumbents aged 30–45 have an infant. The sample includes men employed at subsidiary firms under conglomerates in the first half of 2016. The *Treat* indicator identifies firms affected by the corporate policy change, while the control group consists of men employed at firms belonging to other conglomerates. The interaction term  $Treat \times Post$  captures differential trends in fertility outcomes across groups. All columns use an indicator for having an infant as the dependent variable. All specifications control for bi-annual calendar time dummies, baseline monthly earnings quintile dummies, and baseline firm dummies. Column (1) additionally controls for age group dummies (rather than the continuous measure used in the main specification). Column (2) controls for a baseline married dummy. Column (3) includes dummies for the number of children at time  $t - 2$  (0, 1, or 2+). Column (4) includes dummies for the age category of the youngest child at time  $t - 2$  (no child, 0, 1–4, 5–7, or 8+ years). Robust standard errors are clustered at the baseline firm level and reported in parentheses. \*\*\* indicates significance at 1% level.

Table 7: Descriptive statistics: Households Characteristics

	(1) Treat mean (sd)	(2) Control mean (sd)	(3) (1) - (2) mean (se)
Wife age	36.61 (4.52)	36.65 (4.51)	-0.05 (0.18)
Husband age	38.20 (4.24)	38.16 (4.29)	0.00 (0.19)
Husband tenure	107.79 (61.68)	113.64 (67.23)	-5.49 (4.33)
Husband monthly earnings (10,000KRW)	545.64 (173.28)	721.56 (281.23)	-174.78*** (36.84)
Wife annual earnings (10,000KRW)	1,213.16 (1,947.08)	1,371.23 (2,430.08)	-157.06 * (95.38)
Wife annual earnings   Employed	1,865.73 (2,148.21)	2,297.91 (2,786.88)	-429.18 *** (152.93)
<i>Employment Status in 2015</i>			
Wife with no job	0.35	0.40	-0.05***
Wife with any job	0.65	0.60	0.05***
Wife with regular job	0.47	0.45	0.02

Note: The table reports baseline household characteristics by treatment status. Columns 1 and 2 present the mean and standard deviation for treated and control incumbent households with matched spouse information. Age, monthly earnings, annual earnings data are sourced from the Employment Registry data. Information on marriage are drawn from the 2015 Population Census.

Table 8: Probability to have an infant by Wife Employment

Sample	(1) No spouse id	(2) Wife unemployed	(3) Wife employed	(4) Wife daily/temp/self-employed	(5) Wife regular wage job
Treat x Post	-0.003 (0.004)	-0.003 (0.005)	0.010*** (0.003)	-0.000 (0.005)	0.014*** (0.004)
Age	-0.006*** (0.000)	-0.013*** (0.000)	-0.012*** (0.000)	-0.011*** (0.000)	-0.012*** (0.000)
(baseline) tenure	-0.000*** (0.000)	-0.000*** (0.000)	-0.000*** (0.000)	-0.000*** (0.000)	-0.000*** (0.000)
Constant	0.261*** (0.004)	0.581*** (0.005)	0.553*** (0.004)	0.517*** (0.005)	0.557*** (0.004)
Pre Avg (Treat)	0.029	0.164	0.122	0.113	0.126
% relative to Pre Avg	-10.3%	-2.9%	8.2%	-0%	11.1%
R-squared	0.022	0.104	0.070	0.081	0.068
Observations	2785054	2363658	3567520	884158	2683362
Include FE	Time, (baseline) Earnings Quintile, (baseline) Establishment				

Note: This table presents differences-in-differences estimates from a linear probability model examining the effect of a corporate policy change on the likelihood of male incumbents aged 30-45 having an infant. The sample include men employed at subsidiary firms under conglomerates in the first half of 2016. The Treat dummy indicates whether an individual works for firms affected by the corporate policy change, with the control group consisting of men working at firms belonging to other conglomerates. The interaction of Post and Treat indicators tests for differential time trends between these groups. All columns regress on an indicator for having an infant. In Column 1, the sample includes incumbents that are not matched to spouses at baseline. In Column 2, the sample includes incumbents whose matched spouses were not employed at the baseline. In Column 3 to 5, the sample includes incumbents whose matched spouses were employed in (3) any jobs, (4) daily, temporary contract jobs, or self-employed, and (5) wage and salary job in 2015. We control for bi-annual calendar time dummies, baseline monthly earnings quintile dummies, and baseline firm dummies. Robust standard errors are clustered at the baseline firm level and reported in parentheses. \*\*\* indicates significance at 1% level.

Table 9: Probability to have an infant by Wife Employment Characteristics

Wife Characteristics	Annual Earnings		Tenure (months)	
	(1)	(2)	(3)	(4)
Sample	Employed wives	All wives	Employed wives	All wives
Dep. Var	1(Infant)	1(Infant)	1(Infant)	1(Infant)
Treat x Post x $\tilde{\lambda}_i$	0.008** (0.003)	0.011** (0.003)	0.009*** (0.002)	0.006*** (0.002)
Treat x Post	0.007* (0.004)	0.004 (0.004)	0.002 (0.003)	0.005 (0.003)
Treat x $\tilde{\lambda}_i$	-0.003 (0.002)	-0.007*** (0.002)	-0.006*** (0.002)	-0.006*** (0.001)
Post x $\tilde{\lambda}_i$	0.015*** (0.001)	0.022*** (0.002)	-0.018*** (0.001)	-0.001 (0.001)
Pre Avg(Treat)	0.12	0.14	0.12	0.14
% change associated with 1SD increase	6.7%	7.9%	7.5%	4.3%
Observations	3,567,520	5,931,178	3,567,520	5,931,178
Included Controls	Husband age, (baseline) Husband tenure, (baseline) Husband Earnings Quintile			

Note: This table presents difference-in-differences estimates from a linear probability model examining the effect of a corporate policy change on the likelihood of male incumbents aged 30–45 having an infant. The sample includes men employed at subsidiary firms under conglomerates in the first half of 2016 and whose matched spouses were employed in 2015. The Treat dummy indicates whether an individual works for firms affected by the corporate policy change, with the control group consisting of men employed at firms in other conglomerates. All columns regress on an indicator for having an infant. In Columns 1 and 3, the sample is restricted to dual-earner households where the wife was employed in 2015; Columns 2 and 4 use the full sample of married incumbents. Columns 1 and 2 interact the treatment effect with the wife's total baseline annual earnings, while Columns 3 and 4 use her tenure at baseline. Both characteristics are normalized by their sample standard deviation for ease of interpretation. We control for bi-annual calendar time dummies, baseline monthly earnings quintile dummies, and baseline firm dummies. Standard errors are clustered at the firm level. \*\*\* indicates significance at 1% level.

Table 10: Effects on Wives' Labor Market Outcomes

	(1) 1(any job)	(2) 1(regular job)	(3) Worked months
Treat $\times$ Post	0.023*** (0.007)	0.019*** (0.007)	0.12*** (0.040)
wife age	-0.004*** (0.001)	-0.006*** (0.001)	-0.023*** (0.006)
husband age	0.000 (0.001)	-0.001* (0.001)	0.001 (0.004)
husband tenure	0.000** (0.000)	0.000 (0.000)	0.001** (0.000)
Constant	0.618*** (0.051)	0.689*** (0.051)	3.598*** (0.304)
Pre avg treated	0.45	0.4	2.79
% rel. to pre avg	5.1%	4.8%	4.3%
Observations	4,313,584	4,313,584	4,313,584
Included FE: time, (baseline) husband firm, (baseline) husband earnings quintile			

Note: This table reports difference-in-differences estimates of the paternity-leave mandate's effect on wives' labor supply. The sample includes wives matched to male incumbents employed in 2015 at either treated or control firms. Column (1) reports results for an indicator of employment in any job, Column (2) for employment in a regular job (defined as wage or salary employment with contract duration longer than one month), and Column (3) for the total number of months worked in biannual period  $t$ . All specifications include biannual time fixed effects, baseline husband firm fixed effects, and baseline husband earnings-quintile fixed effects. Standard errors are clustered at the husband's baseline firm level. \*\*\* indicates significance at the 1% level, \*\* at 5%, and \* at 10%.

Table 11: Descriptive Statistics of Survey Sample

	(1)	(2)	(3)	(4)
	Treated	Control	Difference	SE of Difference
Number of Respondents	214	236	450	
Age	39.04	38.21	0.84*	0.38
Married	0.82	0.75	0.07	0.04
Number of Children	0.98	0.96	0.02	0.08
Have an Infant	0.19	0.13	0.06	0.03
Have Age $\leq$ 8 old	0.55	0.48	0.06	0.05
Wife Employed in Wage Job	0.51	0.45	0.06	0.05
Wife Non-Employed	0.23	0.23	0.00	0.04
Monthly Income $\geq$ 6M KRW	0.30	0.50	-0.20***	0.05
Wife Monthly Income $\geq$ 5M KRW	0.13	0.14	-0.01	0.03
Leave Used in current company	0.74	0.17	-0.57***	0.05
<b>Tenure (years)</b>				
Less than 1 year	0.02	0.01	0.01	0.01
1–4 years	0.23	0.16	0.07	0.05
5–8 years	0.19	0.21	-0.02	0.06
9 years or longer	0.56	0.61	-0.05	0.05
<b>Job Level</b>				
Staff/Associate	0.28	0.32	-0.04	0.04
Team Manager	0.22	0.15	0.07	0.04
Middle Manager	0.50	0.53	-0.02	0.05

Note: This table reports descriptive statistics for the survey sample of 450 male employees aged 30–45 on permanent contracts. The treated group is defined as employees at C Group firms where the paternity-leave mandate applied, and the control group as employees at large non-C Group firms without a mandate. Columns (1) and (2) present means for treated and control groups, Column (3) shows their differences, and Column (4) reports the standard errors of those differences. Variables cover demographic characteristics, spousal employment, income, leave use, tenure, and job level.

Table 12: Effects of the Mandate on Workplace Culture, Childcare Time, and Fertility Intentions

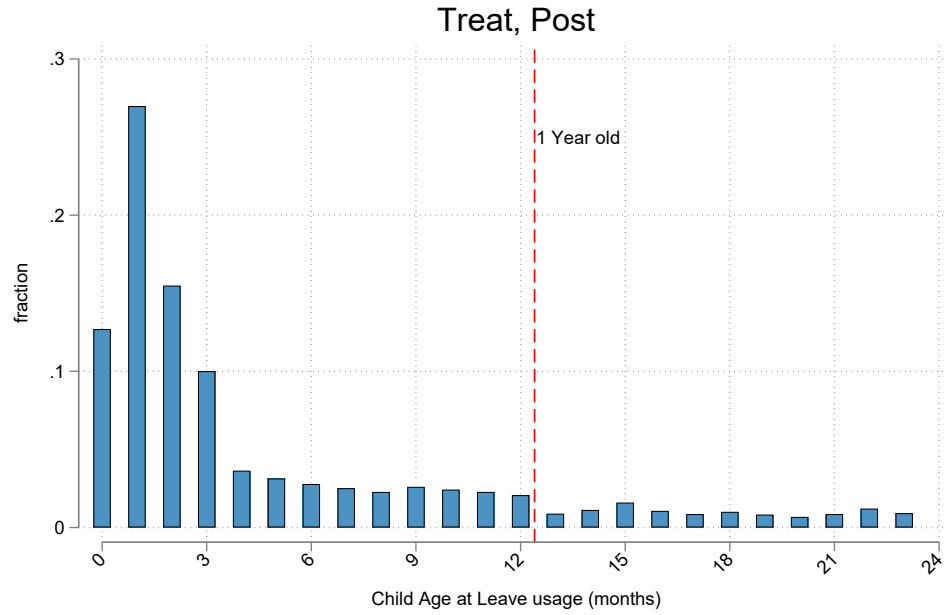
	(1) Experience penalties after leave-taking (Agree, or Strongly Agree)	(2) Coworkers' workload will increase (Agree, or Strongly Agree)	(3) Time on childcare OLS (midpoint)	(4) Time on childcare Interval regression (MLE)	(5) Intend to have a child	(6) Desired number of children
Treated	-0.45*** (0.04) 450	-0.52*** (0.04) 450	6.34* (3.83) 450	8.80* (5.29) 450	0.07** (0.03) 313	0.11* (0.07) 313
Observations						
Treat mean	0.13	0.23	99.35	109.02	0.98	1.50
Control mean	0.58	0.74	91.95	100.22	0.92	1.41
Control SD	0.49	0.44	40.62	3.69	0.27	0.64
Demographic Controls: Age-by-marital status, High-income status						

Note: This table reports regression estimates comparing survey responses of treated and control respondents. Columns (1)–(2) show the share agreeing that a hypothetical male coworker would face career penalties after leave-taking or increase coworkers' workload. Column (3) reports average weekday childcare minutes using OLS with midpoint coding; and Column (4) reports an interval regression (MLE) that accounts for censoring. Columns (5)–(6) present fertility intentions among respondents with fewer than two children. "Treated" equals 1 for respondents employed at mandate-covered firms and aware of the policy. Demographic controls include high-income status and four indicators for the age-by-marital interaction. Robust standard errors are in parentheses. \*\*\* indicates significance at the 1% level, \*\* at 5%, and \* at 10%.



## A Additional Figures and Tables

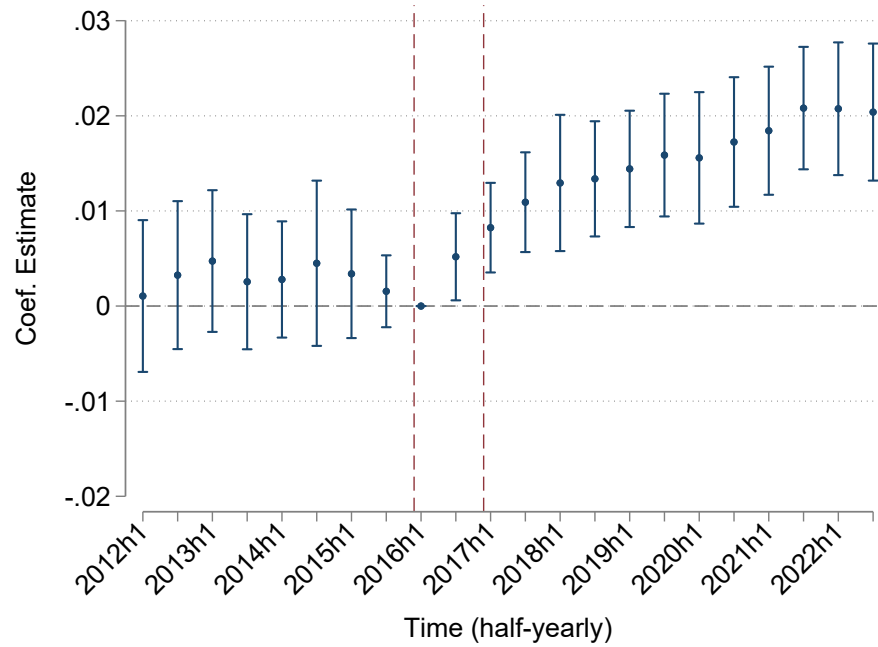
Figure A.1: Child Age at Leave Usage



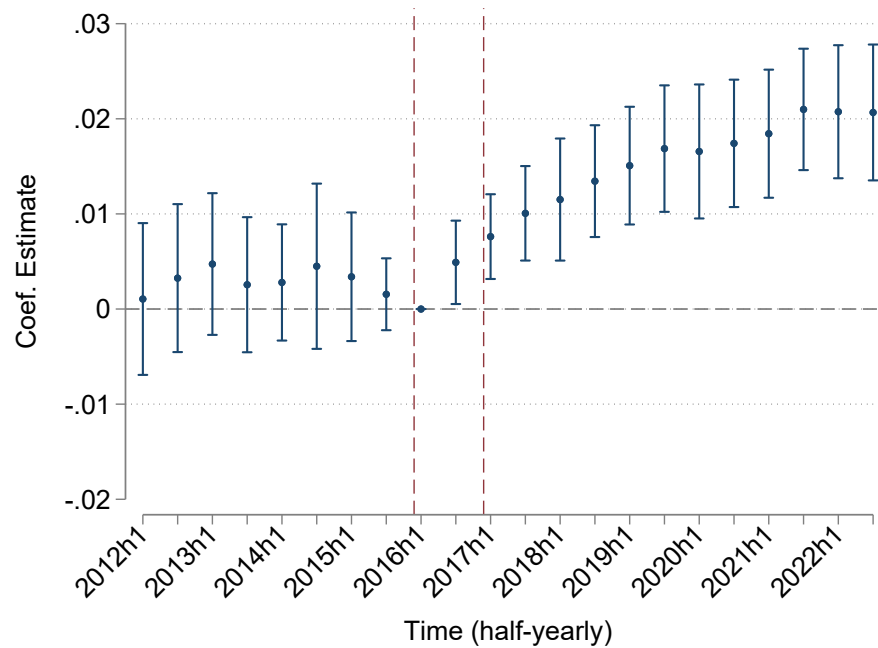
Note: The figure shows the distribution of child age at the time of leave-taking among fathers with newborns during 2017–2022 at treated firms. Treated firms refer to subsidiaries of conglomerate C Group, which implemented a mandatory one-month paternity leave policy in 2017.

Figure A.2: The Effect of the Paternity Leave Mandate on Fertility: Excluding those with wives working at the treated firms

(a) Probability to have an infant



(b) Probability to have an infant and still employed at the same company



Note: These event study figures show event study estimates of the impact of the paternity leave mandate on the probability that male incumbents have an infant (age 0) in a given period excluding incumbents who are ever married to wife working at the treated firms. Panel (a) uses an indicator for having an infant in a given period, and (b) uses an indicator for having an infant and remaining at the same baseline firm. Each point plots the estimated coefficients corresponding to  $\beta_{2,k}$  in Equation 3. Robust standard errors are clustered at the baseline firm level.

## B Do Expectations or Experiences Drive the Effect?

In this section, we assess how much of the observed fertility response reflects forward-looking behavior (changes in expectations before any leave is taken) versus ex-post effects from the lived experience of taking leave. A paternity-leave mandate can influence fertility either by shifting expectations about future paternal availability (*ex ante*) or by changing preferences after fathers experience leave (*ex post*). Prior work has largely targeted the latter and typically finds null or negative effects.

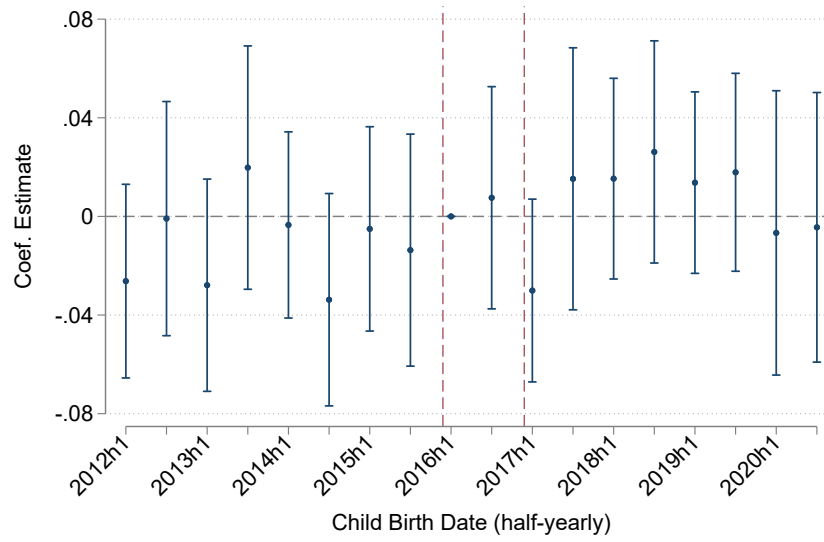
To isolate the ex-post channel, we follow the spirit of designs that study higher-order births around timing cutoffs and compare fathers whose current birth was covered by the mandate with otherwise similar fathers who just missed coverage. Concretely, within treated firms, we form cohorts of fathers with an infant whose birth occurred shortly after the mandate’s start (covered) and those with an infant born shortly before (just missed). Rather than a sharp regression discontinuity—which is underpowered here—we implement an event-study centered on the mandate start, tracking the probability of an additional birth following the current birth. We include father covariates (age, tenure, earnings-quintile fixed effects), firm fixed effects, and calendar-time fixed effects, in line with our main specification. This setup parallels prior “ex-post” tests while maintaining consistency with our baseline design.<sup>23</sup>

Figure B.1 shows no statistically significant increase in the likelihood of a subsequent birth for the covered cohort relative to the just-missed cohort. This suggests that the fertility response we document is not primarily driven by the experience of taking leave. Instead, the pattern is consistent with forward-looking fertility decisions: households that just missed coverage for the current child may still plan an additional birth in anticipation of being covered in the future. These findings align with our main evidence that expectations about paternal availability—rather than realized leave experiences—play a central role in the mandate’s fertility effects.

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<sup>23</sup>We also benchmark against control firms to absorb seasonality and broader trends via time fixed effects; results are unchanged.

Figure B.1: Probability of subsequent births of fathers with newborn



Note: The figures present difference-in-differences estimates of the effect of the paternity leave mandate on subsequent births. The sample consists of male incumbents with infants in each time period. The outcome variable is an indicator for having another child. The treat dummy indicates whether a father is working at treated firms at the time of childbirth. We control for biannual calendar time dummies, firm fixed effects, monthly earnings of fathers, and number of children at the time. Each point represents the estimated coefficient on the interaction between the treatment indicator and biannual calendar time dummies (as shown on the x-axis) along with the associated 95% confidence intervals. Robust standard errors are clustered at the individual level.

## B.1 Robustness Check: Matched Sample

To assess the robustness of our findings to differences in worker and firm characteristics between treated and control groups, we replicate the main analysis using an individually matched sample, following the approach of [Goldschmidt and Schmieder \(2017\)](#) and [Smith et al. \(2019\)](#).

Specifically, for each treated incumbent, we identify a potential control from the pool of incumbents at control firms who: (i) work in the same industry, (ii) fall in the same industry-specific quintile of baseline monthly earnings, (iii) are in the same five-year age bin, (iv) reside in the same commuting area at baseline, and (v) share the same marital status. Among these candidates, we select the control with the closest propensity score—estimated via a linear probability model including quadratic terms in earnings, age, and tenure (in  $t - 1$ )—using one-to-one caliper matching.

Table [B.1](#) presents descriptive statistics for the matched sample. The treated and control incumbents are more comparable on matched covariates, and we also observe improved balance in unmatched characteristics, including number of children and pre-policy fertility rates (i.e., pre-period means of the outcome variable).

We then re-estimate our main event-study and difference-in-differences specifications on the matched sample. The key change is that we now include baseline firm fixed effects and cluster standard errors at the matched pair level. The inclusion of firm fixed effects helps control for time-invariant firm-level unobservables that may correlate with fertility outcomes. Clustering at the matched pair level accounts for potential correlation in unobserved fertility preferences related to the variables used in matching (e.g., age, marital status, income).

Figure [B.2a](#) shows broadly similar trends to those in Figure [6a](#), albeit with greater fluctuations due to reduced sample size. Table [B.2](#) reports treatment effect estimates that remain statistically and substantively similar to our main results. Although the effect sizes are slightly smaller, the findings reinforce that our main conclusions are not driven by pre-existing differences in worker or firm composition.

Table B.1: Descriptive statistics: : Matched Sample

	(1) Treat mean (sd)	(2) Control mean (sd)	(3) (1) - (2) mean (se)
<i>Panel A: Individual Characteristics</i>			
N of Individuals	17,352	17,352	
Age	36.95 (4.54)	36.85 (4.52)	0.10 (0.61)
Monthly Earnings (10,000KRW)	509.76 (171.94)	517.37 (181.13)	-7.61 (14.81)
Tenure (years)	8.04 (4.95)	7.73 (4.95)	0.32 (0.29)
Birth Rate (Pre-policy)	0.09	0.10	-0.006* (0.003)
Married	0.637	0.637	0.00
<i>Number of Children</i>			
No child	0.40	0.40	0.000
One child	0.24	0.25	-0.005
Two or more	0.356	0.351	0.005
<i>Panel B: Establishment Characteristics</i>			
Number of Establishments	102	1218	
Employment Size (establishment)	4606.7 (1754.9)	720.2 (2652.4)	-113.5 (189.0)
Revenue per Employee (1 billion KRW)	1.05 (0.80)	1.04 (1.61)	0.01 (0.18)

Note: The table reports baseline characteristics of individually matched sample as described in Section B.1. Panel A reports baseline individual characteristics by treatment status. Columns 1 and 2 display means and standard deviations for treated and control groups, respectively, while Column 3 reports the mean difference (and the standard error for the difference in means) between the groups. Age, monthly earnings, and tenure are sourced from the Matched Employer-Employee dataset; child information is from the 2015 Child Registry, and marriage data are drawn from the 2015 Population Census. Panel B presents characteristics of the baseline firms employing these individuals. Firm-level employment size is calculated using matched employer-employee data, and revenue per employee is derived from the Business Registry.

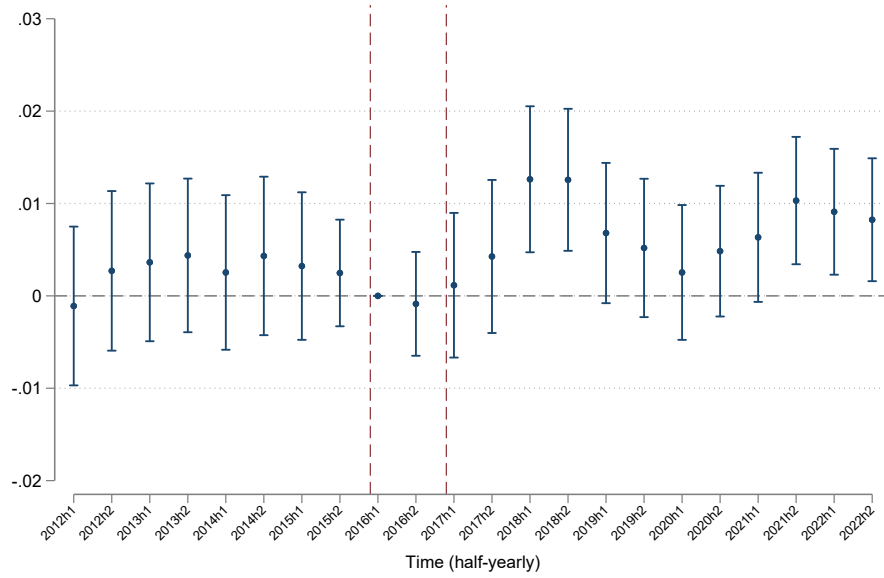
Table B.2: Differences-in-differences estimates: Matched Sample

Dependent Variable	(1) 1(Infant)	(2) 1(Infant) $\times$ 1(Same Firm)
Treat $\times$ Post	0.0039** (0.0019)	0.0051*** (0.0019)
Age	-0.0075*** (0.0001)	-0.0071*** (0.0001)
Tenure (baseline, months)	-0.0000* (0.0000)	-0.0000 (0.0000)
Constant	0.357*** (0.0051)	0.335*** (0.0050)
Observations	763,488	763,488
Pre Avg (Treat)	0.0945	0.0945
% Relative to Pre Avg	4.2%	5.4%
Included Fixed Effects	Time, (baseline) Income Quintile, (baseline) Firm	
R-squared	0.032	0.033

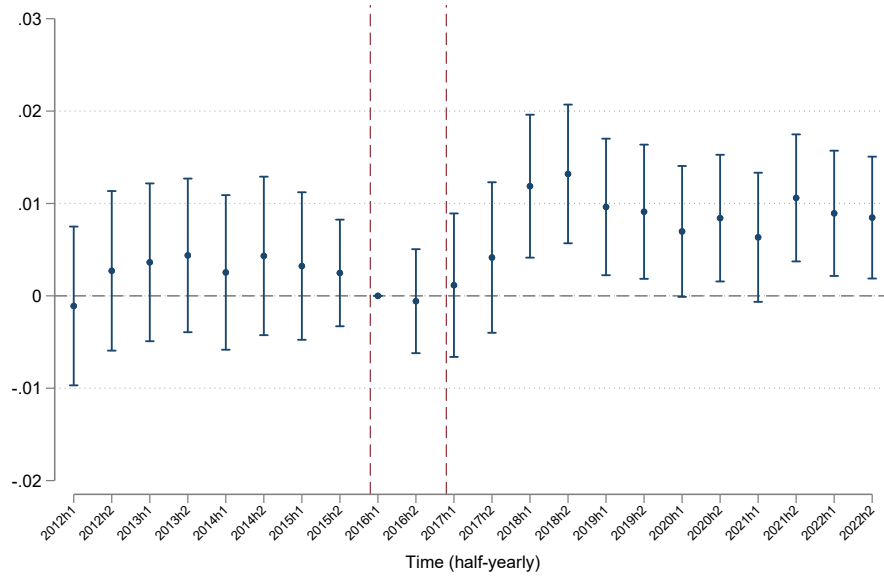
Note: This table reports differences-in-differences estimates from a linear probability model assessing the impact of a corporate policy change on the probability that male incumbents aged 30–45 have an infant. The sample includes men employed at subsidiary firms under conglomerates as of the first half of 2016 and those who are matched based on observables. See Section B.1. The Treat indicator identifies individuals at firms subject to the corporate policy change, while the control group comprises men at firms in other conglomerates. The interaction of Post and Treat indicators captures differential time trends between these groups. Column 1 reports estimates for having an infant; Column 2 adds the condition of remaining at the same baseline company. All specifications control for biannual calendar time dummies, baseline monthly earnings quintile dummies, and baseline firm dummies. Robust standard errors clustered at the matched pair level are reported in parentheses. \* indicates significance at the 10% level; \*\* at 5%; and \*\*\* at 1%.

Figure B.2: The Effect of the Paternity Leave Mandate on Fertility: Matched Sample

(a) Probability to have an infant



(b) Probability to have an infant and still employed at the same company



Note: These event study figures show dynamic difference-in-differences estimates of the impact of the paternity leave mandate on the probability that male incumbents have an infant (age 0) and those who are matched based on observables. See Section B.1. Figure 6a uses an indicator for having an infant in a given period, while Figure B.2b uses an indicator for having an infant and remaining at the same baseline firm. Each point plots the estimated interaction coefficient between treatment and period, corresponding to  $\beta_{2,k}$  in Equation 3 (see Table B.2 for estimates). Robust standard errors are clustered at the matched pair level.



## C Formal Model of Fertility Decisions

This appendix presents the full household decision-making model that underlies the heterogeneity analysis in the main text (Section ??). We analyze household fertility decisions using a two-period utility maximization framework, following [Becker and Lewis \(1973\)](#). The household is modeled as a unitary decision maker. For clarity, we frame the problem as a two-stage decision solved by backward induction. Intuitively, the household first anticipates its situation if it were to have a child—how much time each parent would allocate, how much income would be forgone, and what additional costs would arise. Based on this anticipated allocation, the household then decides whether to have a child. Thus, the fertility decision reflects not only the desire to have a child but also the expected trade-offs between the benefits of childrearing and the associated costs. We begin with the second-stage problem: a utility maximization exercise conditional on having a child versus not. We then turn to the first-stage problem, which yields an inequality condition characterizing the fertility decision.

### Second Stage: Utility Maximization Conditional on Fertility

Conditional on having a child ( $b = 1$ ), the household allocates consumption  $c$ , maternal time  $t_f$ , and paternal time  $t_m$  to maximize utility:

$$U(1) = \delta c + \nu h(t_f, t_m) - \alpha t_m,$$

where  $\delta$  is the marginal utility of consumption,  $h(t_f, t_m)$  denotes child quality (concave in both inputs), and  $\alpha$  captures stigma costs associated with paternal leave-taking.

The household faces both time and budget constraints. Each parent  $g \in \{f, m\}$  has 12 months available, so  $t_g \leq 12$ . Earnings are reduced by foregone labor income  $\lambda(t_g)w_g$ , where  $w_g$  is the monthly wage and  $\lambda(t_g)$  is the proportion of time withdrawn from market work. The budget constraint is:

$$c = 12w_f + 12w_m - \lambda(t_f)w_f - \lambda(t_m)w_m - \theta,$$

where  $\theta$  captures fixed monetary costs of childrearing. Solving this problem yields the optimal allocation  $(t_f^*, t_m^*)$  of maternal and paternal time.

In the absence of a child ( $b = 0$ ), the household maximizes:

$$U(0) = \delta c,$$

subject to the budget constraint:

$$c = 12w_f + 12w_m,$$

since no childrearing costs are incurred and no time is withdrawn from market work.

## First Stage: Fertility Decision

Given the optimal allocation of parental time, the household chooses to have a child in the first period if and only if the expected utility from child rearing in the second period exceeds the utility from remaining childless. Analytically, the household chooses fertility to maximize expected utility:

$$b^* = \arg \max_{b \in \{0,1\}} \mathbb{E}[U(b) | \Omega],$$

where  $\Omega$  denotes the information set, including wages  $(w_f, w_m)$ , stigma costs  $\alpha$ , and fixed childrearing costs  $\theta$ .

Fertility occurs if and only if:

$$U(1) \geq U(0).$$

Reordering terms yields the following fertility condition:

$$\nu h(t_f^*, t_m^*) \geq \delta [\lambda(t_f^*)w_f + \lambda(t_m^*)w_m] + \theta + \alpha \cdot t_m^*, \quad (5)$$

where  $t_m^*$  is the utility-maximizing paternal time input. The left-hand side represents the utility from time spent with a child, while the right-hand side reflects forgone consumption due to reduced earnings, direct child-related costs, and stigma costs. Intuitively, fertility occurs when the value of time spent with a child outweighs the forgone earnings and associated costs.

## Fertility Threshold and the Role of Paternal Time

The household chooses to have a child if and only if the expected utility with a child exceeds that without one. Substituting the optimal allocation  $(t_f^*, t_m^*)$  into the budget constraints gives:

$$\begin{aligned} \delta [(12 - \lambda(t_f^*))w_f + (12 - \lambda(t_m^*))w_m - \theta] + \nu h(t_f^*, t_m^*) - \alpha t_m^* &\geq \delta [12w_f + 12w_m] \\ \iff \nu h(t_f^*, t_m^*) &\geq \delta [\lambda(t_f^*)w_f + \lambda(t_m^*)w_m] + \theta + \alpha t_m^*. \end{aligned}$$

The left-hand side captures the benefit from parental time spent with the child, while the right-hand side represents the costs of childbearing: foregone consumption from reduced labor supply, fixed childrearing expenses, and stigma costs associated with paternal leave.

The concavity of  $h(t_f, t_m)$ , combined with the linearity of the opportunity costs  $\lambda(t_g)w_g + \alpha t_m$ , generates a threshold level of paternal involvement,  $\bar{t}_m$ , such that households with  $t_m^* > \bar{t}_m$  optimally choose not to have a child. Intuitively, beyond  $\bar{t}_m$ , the marginal cost of additional paternal time exceeds the marginal gain in child quality. Formally, let  $\bar{t}_m = T$  satisfy

$$\nu h(t_f^*, T) = \delta[\lambda(t_f^*)w_f + \lambda(T)w_m] + \theta + \alpha T.$$

For any  $t_m^* = T + \varepsilon$  with  $\varepsilon > 0$ , the additional benefit is

$$\nu[h(t_f^*, T + \varepsilon) - h(t_f^*, T)] \simeq \nu h_{t_m}(t_f^*, T)\varepsilon,$$

while the additional cost is

$$\delta\lambda_t(T)w_m\varepsilon + \alpha\varepsilon.$$

The first-order condition for  $t_m$  implies

$$\nu h_{t_m}(t_f^*, T) = \delta\lambda_t(T)w_m + \alpha,$$

so by concavity of  $h(\cdot)$ ,

$$\frac{\nu h(t_f^*, T + \varepsilon) - \nu h(t_f^*, T)}{\varepsilon} \not\geq \nu h_{t_m}(t_f^*, T).$$

Thus, for  $\bar{t}_m$ ,  $U(1|t_m = \bar{t}_m + \varepsilon) < U(0)$  for all  $\varepsilon > 0$ , defining the threshold paternal time beyond which fertility is not optimal.

This formulation defines a threshold paternal time input,  $\bar{t}_m$ , conditional on  $t_f^*w_f, w_m$ , above which the marginal costs of childbearing outweigh the benefits. Households with  $t_m^* > \bar{t}_m$  optimally choose not to have a child. Prior to the mandate, fertility was concentrated among households with  $t_m^* = 0$ , consistent with stigma and low wage replacement deterring even modest paternal leave-taking. By reducing the effective costs of early leave-taking, the mandate raises this threshold  $\bar{t}_m$ , expanding the set of households for whom childbearing is optimal.

As documented in Section 4, the share of fathers taking more than one month of leave also rises after the mandate. This suggests that by lowering the first-month leave cost, the policy shifted the paternal-time cutoff from  $\bar{t}_m^{\text{pre}} = 0$  to  $\bar{t}_m^{\text{post}} > 0$

## Distinguishing Time vs. Income Channels: Single vs. Dual-Earner Households

Equation 5 shows that the policy lowers the fertility threshold through two distinct mechanisms: (i) an *income channel*—full wage replacement for one month—and (ii) a *time channel*—mandated leave-taking that reduces stigma. The importance of each channel depends on the mother’s availability of time for childcare. In single-earner households—where the mother is not employed and provides maximum childcare input ( $t_f = \bar{t}_f^{\max}$ )—the marginal utility from additional paternal time is negligible. In this case, the policy primarily operates through the income channel. In contrast, in dual-earner households, where maternal time is constrained, both channels are operative, with the time channel expected to be particularly important.

### Single- versus Dual-Earner Households

The relevance of the time versus income channels depends critically on maternal time input  $t_f$ , which is shaped by the mother’s employment status. In single-earner households, where the mother allocates her maximum time  $\bar{t}_f^{\max}$  to childcare, the marginal value of paternal time is near zero. In such cases, the policy primarily affects fertility through the income channel. By contrast, in dual-earner households—where maternal time is limited due to employment—the marginal value of paternal involvement is higher, and both channels are operative.

#### Case 1: $t_m^* = 0$ (No Paternal Leave Pre-Policy)

For these households, pre-policy utility with a child was below utility without one, since the threshold  $\bar{t}_m$  was effectively zero. The policy can induce fertility if the combined benefit of one month of paternal time and wage replacement exceeds the pre-policy utility gap:

$$\nu [h(t_f, 1) - h(t_f, 0)] + \delta w_m \geq \nu h(t_f, 0) - \delta \lambda(t_f) w_f - \theta.$$

Because these households did not previously plan for paternal leave, the stigma component  $\alpha$  is irrelevant. For single-earner households with  $t_f = \bar{t}_f^{\max}$ , the marginal gain from paternal time is negligible ( $h_{t_m}(\bar{t}_f^{\max}, t_m) \approx 0$ ), so the effect operates almost entirely through wage replacement. In contrast, dual-earner households benefit from both channels, as paternal time has a higher marginal value when maternal involvement is constrained.

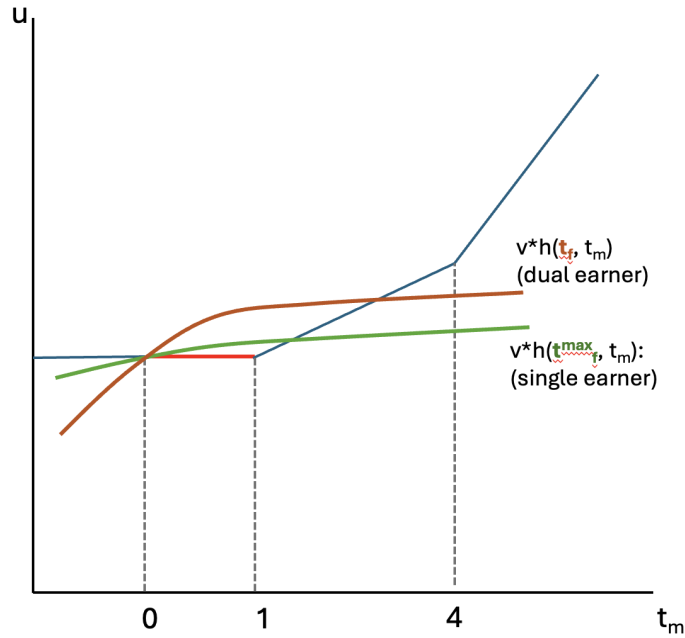
**Case 2:  $t_m^* > 0$  (Positive Paternal Leave Pre-Policy)**

These households were previously deterred by the joint cost of forgone wages and stigma. The mandate reduces both components by  $\delta w_m + \alpha$ , shifting the fertility threshold  $\bar{t}_m^*$  defined by:

$$\nu h(t_f^*, \bar{t}_m^*) = \delta [\lambda(t_f^*)w_f + \lambda(\bar{t}_m^*)w_m] + \theta + \alpha \bar{t}_m^* - \delta w_m - \alpha.$$

Households with  $t_m^* \leq \bar{t}_m^*$  may now optimally choose to have a child. The effect is again stronger in dual-earner households, where the marginal return to paternal time is higher. This is illustrated in Figure C.1.

Figure C.1: Policy Effects on Fertility Decision Threshold by Household Type



Finally, the model predicts that fertility responses increase with the mother's wage. Higher  $w_f$  raises the opportunity cost of maternal time, lowering maternal involvement ( $\partial t_f / \partial w_f < 0$ ) and increasing the marginal value of paternal time ( $\partial h_{t_m}(t_f(w_f), t_m) / \partial w_f \geq 0$ ). As a result, the availability of paternal leave is especially valuable in households where mothers face strong labor market incentives, amplifying fertility responses to the policy.

This framework yields two key testable predictions which are tested in Section 6.3. First, if the time channel is the dominant mechanism, fertility responses should be stronger among dual-earner households. Second, the effect should increase with the wife's market wage  $w_f$ ,

as higher wages imply a greater opportunity cost of maternal time and a correspondingly higher marginal return to paternal involvement. Formally,  $h_{t_m}(t_f(w_f), t_m)$  is increasing in  $w_f$ , making the time channel more valuable in high-wage households. We test these predictions by examining heterogeneity in fertility responses by wives' employment status and earnings.

## D Descriptive Evidence on Firm-Level Outcomes

While the primary focus of this paper is on household fertility responses to a paternity leave mandate, the policy’s implementation at the corporate level motivates an examination of its potential implications for firms. Since the decision to adopt the policy was made at the conglomerate level rather than at individual firms, our firm-level results are descriptive and not interpreted as causal.

Offering paternity leave can impose costs on firms through temporary worker absences. However, firms might offset these costs by adjusting payroll—such as lowering wages or reducing headcount—or by retaining experienced workers with high firm-specific productivity who value the benefit. To explore these potential adjustments, we use company-level data from the Business Registry between 2014 and 2020, focusing on log revenue, log employment, and revenue per employee. We estimate the following event study specification:

$$Y_{jy} = \beta_0 + \sum_{k \neq -1} \beta_{1,k} \text{Treat}_j \times D_{y,k} + \sum_{k \neq -1} \beta_{2,k} D_{y,k} + \theta_j + \varepsilon_{jy},$$

where  $Y_{jy}$  is the outcome for company  $j$  in year  $y$ ,  $\theta_j$  is a company fixed effect, and  $D_{y,k}$  are event time indicators (with  $k = -1$  omitted). Standard errors are clustered at the company level.

Figure D.1 shows no statistically significant changes in revenue, employment, or productivity following the mandate. Although estimates are somewhat noisy, the absence of discernible negative effects suggests that firms may have partially offset costs.

Turning to matched employer–employee data (2015–2020), we examine changes in workforce composition. Figure D.2b shows an increase in the share of male employees aged 30–45 in treated firms post-mandate, driven primarily by higher retention rather than new hires (Figure D.2c). Firm-level headcount remained stable (Figure D.2a), suggesting compositional shifts rather than overall growth.

Next, we assess whether firms shifted costs onto workers. Figures D.2d and D.2e reveal that treated male workers earned persistently less than their control group counterparts, despite higher retention. This pattern suggests that firms may have passed on some of the cost of the mandate via lower wages while retaining workers who valued the benefit.

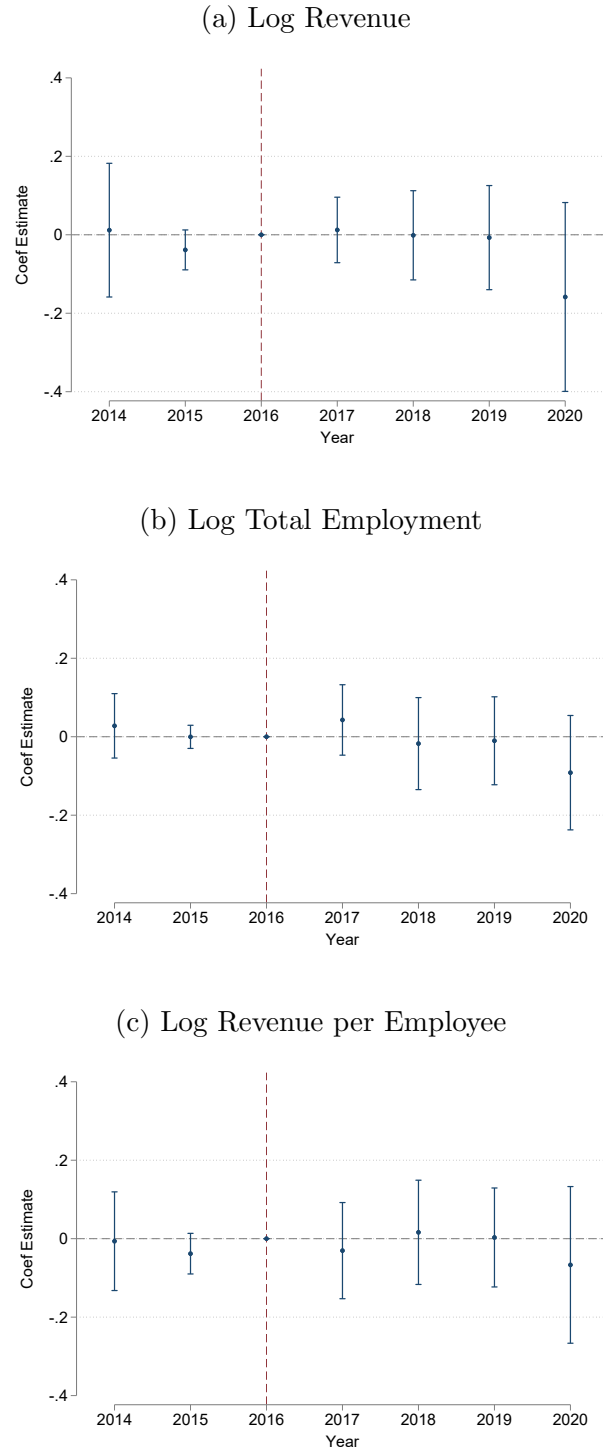
We also find suggestive evidence that the mandate attracted men who valued this benefit. Among new hires after the policy announcement in the second half of 2016 (our baseline), we observe higher probabilities of having a child or an additional child compared to pre-policy hires (Figures D.3a and D.3b). Because this analysis focuses on new hires, the immediate

increase post-announcement suggests that selection—rather than peer effects—drove this result.

In summary, the paternity leave mandate did not harm firm-level performance and may have improved workforce stability among men of childbearing age. While exploratory, these findings highlight how firms and workers share the costs of family-friendly policies and how such benefits can shape workforce composition. These insights complement our main analysis by illustrating the firm-level context in which the policy was implemented.

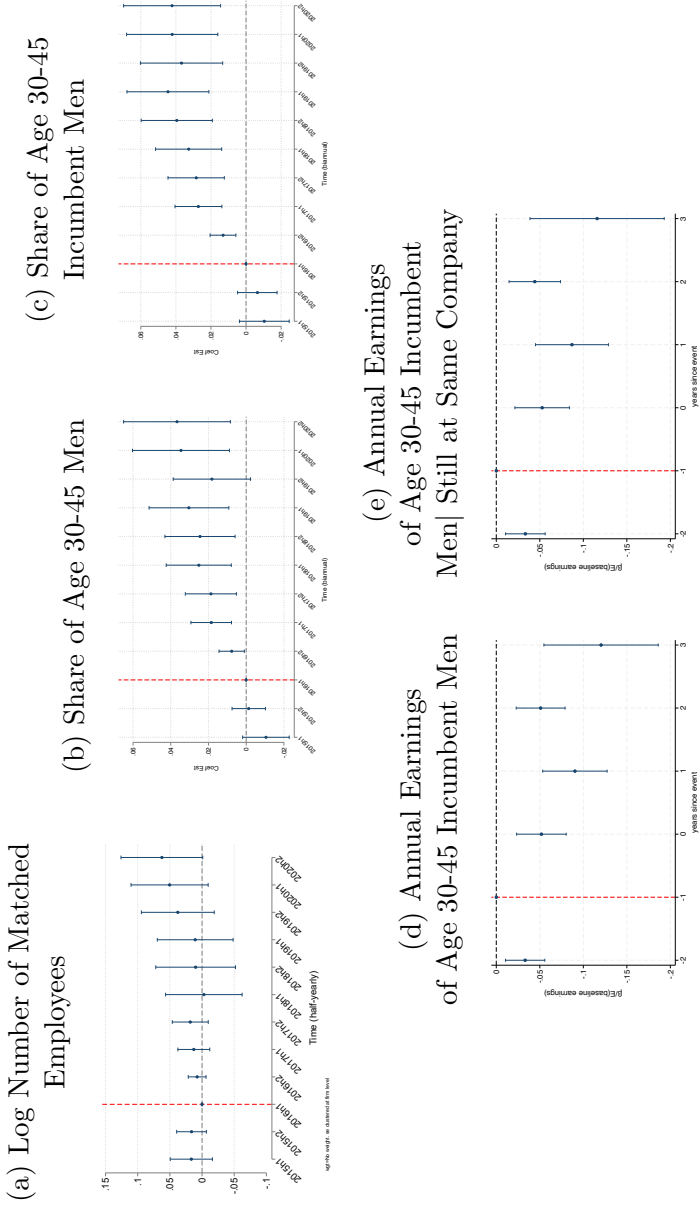


Figure D.1: Company Level Outcomes



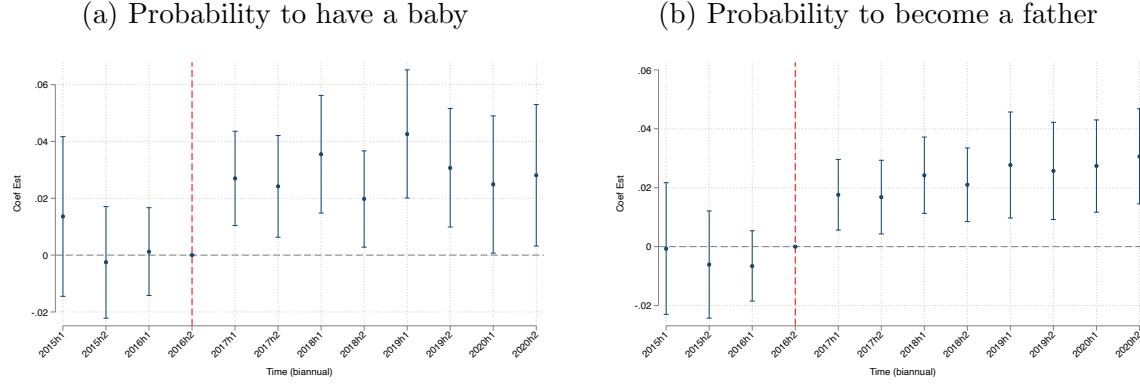
Note: The figures present difference-in-differences estimates of the effect of the paternity leave mandate on company level outcomes. The sample consists companies owned by conglomerates. The outcome variables are observed at annual frequency on Business Registry 2014-2020, and are log revenue (Panel a), log total employment size (Panel b), and log revenue per employee (Panel c). The Treat dummy indicates whether a company is affected by the corporate policy change in 2017. We control for year dummies and company fixed effects. Each point represents the estimated coefficient on the interaction between the treatment indicator and year dummies (as shown on the x-axis) along with the associated 95% confidence intervals. Robust standard errors are clustered at the company level.

Figure D.2: Effects on Firm Compositions and Employee Earnings



Note: The figures present difference-in-differences estimates of the effect of the paternity leave mandate on firms. The sample consists of firms owned by conglomerates (Figure (a)-(c)) and age 30 to 45 male employees hired before 2017 (Figure (d)-(e)). In Figure (a)-(c), the outcome variables are aggregated at biannual frequency based on Matched Employee Employer data. In Figure (a), the outcome variable is log of number of matched employees in each time period. In Figure (b), the outcome variable is the share of age 30-45 male employees among current employees in each given time period; In Figure (c), the outcome variable is the share of age 30-45 male employees who were hired before 2017 among current employees in each given time period. In Figure (d), the outcome variable is annual earnings of age 30-45 male and we control for individual fixed effects. In Figure (e), we estimate the same regression as (d) but using employees who are still working at the same baseline company in a given period. The Treat dummy indicates whether a firm is affected by the corporate policy change in 2017. We control for biannual calendar time dummies and firm fixed effects. Each point represents the estimated coefficient on the interaction between the treatment indicator and biannual calendar time dummies (as shown on the x-axis) along with the associated 95% confidence intervals. Robust standard errors are clustered at the firm level.

Figure D.3: Probability of having a baby upon entry



Note: The figures present difference-in-differences estimates of the effect of the paternity leave mandate on male new hires' probability to have a baby upon entry. The sample consists of male new hires entering firms in each time period. In Figure D.3a, the outcome variable is an indicator for ever having a baby upon entry and while staying at firm; In Figure D.3b, the outcome variable is an indicator for becoming a father upon entry and while staying at firm. The Treat dummy indicates whether a firm is affected by the corporate policy change in 2017. We control for biannual calendar time dummies, firm fixed effects, age of a newhire, and starting monthly earnings. Each point represents the estimated coefficient on the interaction between the treatment indicator and biannual calendar time dummies (as shown on the x-axis) along with the associated 95% confidence intervals. Robust standard errors are clustered at the firm level.