



**ROCKWOOL Foundation Berlin**

Institute for the Economy and the Future of Work (RFBerlin)

**DISCUSSION PAPER SERIES**

**92/25**

---

# **Maternity Leave Extensions and Gender Gaps: Evidence from an Online Job Platform**

Hanming Fang, Jiayin Hu, Miao Yu

# Maternity Leave Extensions and Gender Gaps: Evidence from an Online Job Platform

## Authors

---

Hanming Fang, Jiayin Hu, Miao Yu

## Reference

---

**JEL Codes:** J16, J18, J23, J64, J71

**Keywords:** Maternity Leave; Gender Gaps; Callback Rates; Search Durations

**Recommended Citation:** Hanming Fang, Jiayin Hu, Miao Yu (2025): Maternity Leave Extensions and Gender Gaps: Evidence from an Online Job Platform. RFBerlin Discussion Paper No. 92/25

## Access

---

Papers can be downloaded free of charge from the RFBerlin website: <https://www.rfberlin.com/discussion-papers>

Discussion Papers of RFBerlin are indexed on RePEc: <https://ideas.repec.org/s/crm/wpaper.html>

## Disclaimer

---

*Opinions and views expressed in this paper are those of the author(s) and not those of RFBerlin. Research disseminated in this discussion paper series may include views on policy, but RFBerlin takes no institutional policy positions. RFBerlin is an independent research institute.*

*RFBerlin Discussion Papers often represent preliminary or incomplete work and have not been peer-reviewed. Citation and use of research disseminated in this series should take into account the provisional nature of the work. Discussion papers are shared to encourage feedback and foster academic discussion.*

*All materials were provided by the authors, who are responsible for proper attribution and rights clearance. While every effort has been made to ensure proper attribution and accuracy, should any issues arise regarding authorship, citation, or rights, please contact RFBerlin to request a correction.*

*These materials may not be used for the development or training of artificial intelligence systems.*

## Imprint

**RFBerlin**  
ROCKWOOL Foundation Berlin –  
Institute for the Economy  
and the Future of Work

Gormannstrasse 22, 10119 Berlin  
Tel: +49 (0) 151 143 444 67  
E-mail: [info@rfberlin.com](mailto:info@rfberlin.com)  
Web: [www.rfberlin.com](http://www.rfberlin.com)



# Maternity Leave Extensions and Gender Gaps: Evidence from an Online Job Platform\*

Hanming Fang<sup>†</sup>      Jiayin Hu<sup>‡</sup>      Miao Yu<sup>§</sup>

October 28, 2025

## Abstract

We investigate the unintended consequences of maternity leave extension on gender gaps in the labor market. Using millions of job applications on an online job platform and the staggered extension of maternity leave across Chinese provinces, we find that an average increase (22%) in the length of paid maternity leave led to a 3.7–percentage-point decline in positive callbacks to female applicants relative to their male counterparts, equivalent to 17% of the pre-policy mean. In response, female job seekers shifted toward jobs with 5.4% lower wages than male applicants, submitted 4.4 more job applications (20% of the pre-policy mean) and experienced 2.1 weeks (19% of the pre-policy mean) longer job search duration. We also find that government subsidies that partially cover firms’ wage costs of extended maternity leave help alleviate its adverse impact on gender disparities in hiring.

**Keywords:** Maternity Leave; Gender Gaps; Callback Rates; Search Durations.

**JEL Classification:** J16, J18, J23, J64, J71.

---

\*We would like to thank Aislinn Bohren, Patricia Cortes, Claudia Goldin, Peter Kuhn, Luflade Margaux, Ioana Marinescu, Jessica Pan, Uta Schoenberg, Kailing Shen, Petra Todd, Hanna Wang, Shing-Yi Wang, and participants of the Chinese Economists Society (CES) Annual Conference (2025), the ANU Asian Perspective Seminar (2025), the 8th KOF ETH Zurich and IDSC of IZA Workshop on Matching Workers and Jobs Online, the 3rd National Forum for Doctoral Students in Applied Economics (2025) and the NUS Strategy and Policy Seminar for their valuable comments and suggestions. We also thank Sizhe Li, Xuerui Wang and Manlin Wang for their excellent research assistance. Part of this research was conducted while Yu was a visiting PhD student at the University of Pennsylvania, whose hospitality she gratefully acknowledges. All views and remaining errors are our own.

<sup>†</sup>Department of Economics, University of Pennsylvania, 133 S. 36th Street, Philadelphia, PA 19104, USA; Faculty of Economics, University of Cambridge, UK; and the NBER. Email: [hanming.fang@econ.upenn.edu](mailto:hanming.fang@econ.upenn.edu).

<sup>‡</sup>China Center for Economic Research, National School of Development, Peking University, 5 Yiheyuan Rd, Beijing 100871, China. Email: [jyhu@nsd.pku.edu.cn](mailto:jyhu@nsd.pku.edu.cn).

<sup>§</sup>China Center for Economic Research, National School of Development, Peking University, 5 Yiheyuan Rd, Beijing 100871, China. Email: [myu2021@nsd.pku.edu.cn](mailto:myu2021@nsd.pku.edu.cn).

# 1 Introduction

Governments around the world have adopted increasingly generous maternity leave policies to support working mothers and promote early childhood development. However, the labor market consequences of maternity leave policies remain highly debated, with the existing literature yielding mixed findings and no clear consensus (Olivetti and Petrongolo, 2017). One potential reason for the mixed findings is that most studies rely on equilibrium labor market outcomes, which are jointly determined by employer and employee behaviors and reflect only the net effect. For example, an extension of maternity leave may encourage female labor supply by improving work–family compatibility, but at the same time employers can become more reluctant to hire women of childbearing age. Focusing only on equilibrium outcomes therefore makes it difficult to disentangle the underlying mechanisms and clarify welfare implications.

In this paper, we fill this gap by using detailed job application records to investigate the impact of maternity leave extensions. This unique data set enables us to examine the job search stage—before job matching occurs—where both employer and applicant behaviors are actively revealed. Specifically, we separate the effects on employer-side callback behavior and on applicant-side job application behavior, enabling a more precise identification of the channels through which maternity leave policies affect female labor market outcomes and gender disparities.

Our job application data comes from a leading online job market platform in China. The data set comprises billions of real-time job application records, where each observation links a specific applicant to a specific job posting. For the employer-side sample, we randomly select job postings and include all the corresponding received applications; for the applicant-side sample, we randomly draw job seekers and collect their full application histories. These sampling strategies allow for within-job comparisons in the employer-side analysis and within-individual comparisons in the applicant-side analysis, thereby improving the precision of our treatment effect estimates. The daily granularity of the data enables precise identification of timing around policy shocks.

These records include detailed information on job characteristics (e.g., city where the job is located, wages, benefits), applicant attributes (e.g., city of residence, age, gender, educational background) and employer responses (e.g., callback). We define a callback as a positive response from the employer within 24 hours of application submission, which includes any of the following employer-initiated actions: interview invitation, phone call, contact information exchange, or follow-up conversation initiated by the employer. In addition,

the data set covers a wide range of industries, regions, and applicant profiles, allowing rich heterogeneity analysis and exploration of potential behavioral mechanisms.

In addition to the novel data set, China provides an excellent empirical setting for its recent extension of maternity leave. Before 2021, working women in China, depending on their province, were entitled to 128–188 days of paid maternity leave. Starting in 2021, 10 out of the 31 provinces in mainland China extended their maternity leave by 10 to 50 days, in order to ease childbearing burdens and boost fertility rates. Since extensions are concentrated in regions where maternity leave was initially shorter than 158 days, we restrict our analysis to the ten provinces that implemented extensions to avoid bias arising from potential “always-treated” units. Furthermore, we restrict the analysis to applicants aged 20 to 40 years, who represent about 90% of the platform’s users and are most likely affected by maternity leave policies.

To identify the causal effects of extended maternity leave on labor market outcomes, we exploit the staggered timing of provincial policy changes and different intensities of maternity leave extension. We employ a triple difference (DDD) empirical strategy and compare changes in female-male differences between treated and untreated cities over time, with intensity of treatment measured by the percentage increase in the duration of leaves. The primary analysis focuses on employer callbacks based on the employer sample. We include a rich set of interaction fixed effects to control for potential confounding factors, including city-by-time (calendar week), gender-by-time, gender-by-city, and job fixed effects, as well as applicant characteristics and workday status. In addition to the pooled DDD specification, we estimate separate difference-in-differences (DD) regressions for male and female applicants to trace group-specific responses and implement an event-study framework to assess the dynamics of the policy effect.

Our main finding is that longer maternity leave significantly reduces women’s likelihood of receiving callbacks. Baseline estimates indicate that a 10% increase in the duration of maternity leave reduces callback rates to female applicants by 1.7 percentage points relative to comparable male applicants; this estimate implies that, at the observed average intensity of policy shock, i.e., a 22% increase in the duration of maternity leave, female job seekers of childbearing age experienced an average decrease of 3.7 percentage points in callbacks, representing a 17% reduction in callback rates. This effect remains robust when progressively controlling for job characteristics, job fixed effects, and applicant heterogeneity. Gender-specific regressions show that the widening gender gap in callback rates stems from both a decrease in women’s callback rates and a modest increase in men’s callbacks, with roughly 60% of the gap attributable to the decline among women. Event-study estimates reveal no

evidence of preexisting trends, and further document a persistent widening of the gender gap after the policy shock.

We perform a series of robustness checks to validate our findings. First, we employ the estimator proposed by [Sun and Abraham \(2021\)](#) to address the potential heterogeneity of the treatment effect. Second, estimated effects remain stable after controlling for concurrent gender-related policies (e.g., paternity and childcare leave), COVID-19 outbreaks, and the national three-child policy. Third, we test a range of alternative specifications, including different measures of policy intensity, lunar-calendar-based time fixed effects, the use of untreated provinces as controls, and sample restrictions based on job characteristics, all of which yield consistent results. Fourth, we conduct placebo tests using randomly assigned treatment dates and estimates with applicants older than fertility age (45+), and find that both produce null effects as expected. Fifth, a time-series analysis of Baidu search data suggests limited policy anticipation among the public. Finally, leave-one-out analyses confirm that the main results are not driven by any single province.

To explore factors that contribute to the widening gender gap in callbacks, we examine heterogeneity in treatment effects across city, job, firm, industry, and applicant characteristics. Firms likely compare the expected cost of maternity leave with the anticipated productivity of a hire. First, we find that in provinces where the government partially covers the firms' wage costs of extended maternity leave, employers' discriminatory responses toward female applicants in response to the extension of maternity leave are mitigated. Second, we find that high-wage and high-education-requirement jobs exhibit smaller declines in callback rates to females, as these positions target more productive or less easily substitutable workers. Similarly, highly educated women are less affected. Third, jobs with fewer time demands, such as those that offer time-related amenities such as 'weekends off' or 'no overtime', also show milder effects on the gender gap, likely due to the reduced expected costs of leave. Fourth, firms and industries with higher search frictions, measured by low labor market tightness and small firm size (following [Ginja et al., 2023](#)), where replacing employees during leave is more difficult, show larger declines. Fifth, compared to state-owned enterprises, private firms, which face less regulatory oversight, exhibit sharper reductions in callback rates to female applicants. Sixth, the greatest negative effects occur among women of peak fertility probability, aligning with the higher perceived risk of leave-taking by employers for this female group. Lastly, industries more dominated by women see larger reductions in callback rates to female applicants, possibly due to the greater salience of the financial costs of the extension of maternity leave when a larger share of the workforce is affected.

To assess whether these trends come from changes in the composition of posted jobs or the volume of applications, we examine job-level characteristics and applicant counts before and after the policy. We find no significant changes in the number of posted vacancies, wage offers, job amenities, or education requirements. Similarly, the total volume of applications and the gender composition of the applicants remain stable. In summary, the observed decline is unlikely to be driven by shifts in job supply or received applications.

On the applicant side, we analyze how job seekers adjust their search behavior in response to change in callback rates. First, we find that women increasingly apply to lower-paying jobs. According to our estimates, the average wage level of applied jobs decreases by 5.4% compared to men measured at the average intensity of the shock of the maternity leave extension policy. This suggests that women may reduce their wage expectations or strategically target less competitive positions in response to anticipated discrimination. Second, women are 3.7% more likely to apply to jobs offering the aforementioned time-related amenities after the policy shock relative to men. These positions tend to be more female-friendly and are associated with smaller callback penalties after the maternity leave extension. Gender-specific regressions show that these shifts are mainly driven by changes in female behavior, with small and statistically insignificant effects among male applicants.

Finally, we examine the effect of the maternity leave extension on the intensity and duration of the job search. We find that women submit 4.4 additional applications (20% of the pre-policy mean) and extend their job search by 2.1 weeks (19% of the pre-policy mean), calculated at the average intensity of the policy shock, whereas men show no significant change. The larger number of overall job applications submitted by female job seekers is not driven by more frequent weekly applications, but by longer overall search durations. Despite shifting to lower-paying jobs and adjusting their search strategies, women must exert more effort to find a job. The combination of reduced employer interest and intensified job search implies a deterioration in women’s job-matching outcomes, reinforcing gender inequality in the labor market.

Our findings mainly contribute to three strands of literature. First, this paper enriches the existing research on the impact of family policies on female labor market outcomes and the gender gap by providing a direct analysis of how maternity leave extensions separately influence employer hiring behavior and female job application choices. While prior research has documented positive effects of subsidized childcare on women’s employment (e.g., [Baker et al., 2008](#); [Havnes and Mogstad, 2011](#); [Berlinski et al., 2024](#)), the impact of parental leave benefits remains contested ([Olivetti and Petrongolo, 2017](#)). Some papers suggest that family-friendly policies can have positive effects on female employment ([Ruhm, 1998](#); [Zveglic Jr and](#)

van der Meulen Rodgers, 2003; Blau and Kahn, 2013; Byker, 2016), whereas others report null effects (Gruber, 1994; Havnes and Mogstad, 2011; Dahl et al., 2016) or even unintended adverse consequences (e.g., Lalive and Zweimüller, 2009; Dustmann and Schönberg, 2012; Blau and Kahn, 2013; Lalive et al., 2014; Schönberg and Ludsteck, 2014; Prada et al., 2015; Fernández-Kranz and Rodríguez-Planas, 2021).<sup>1</sup> Regarding gender inequality, Antecol et al. (2018) and Timpe (2024) respectively show that the gender gap increased with extension in paid leave and tenure clocks, respectively. However, Kleven et al. (2024) report that large-scale parental leave reforms in Denmark had little effect on narrowing gender inequality. As we discussed earlier, existing studies focus primarily on equilibrium outcomes, which may mask the possibly countervailing forces from the supply side (i.e., job seekers) and the demand side (i.e., employers). The findings in our paper suggest that the overall job market experience of female job seekers can worsen even if the final result in terms of employment is not affected, to the extent that they would have to submit more job applications as a result of the extension of maternity leave.

Recent studies on employers’ response to maternity leave focus mainly on increased wage costs (Ginja et al., 2023; Schmutte and Skira, 2023; Brenøe et al., 2024).<sup>2</sup> These studies highlight the importance of incorporating employer response and the potential for increased discrimination after leave extension. The closest study to ours is by Bapna and Funk (2025), which examines the IT sector in India and finds that extensions in paid leave reduce the likelihood of firms hiring female applicants, particularly in low-profit firms. Our paper complements this work by additionally examining the response from the applicant side. Specifically, we document that women shift their applications toward less competitive jobs and exhibit increased job search intensity and duration, which may further widen gender disparities in wages and labor force participation. In addition, our analysis leverages data that span multiple industries beyond the IT industry, which allows for rich heterogeneity

---

<sup>1</sup>Fernández-Kranz and Rodríguez-Planas (2021) evaluate a 1999 Spanish law that gives employment protection to workers with young children and find that it makes women less likely to be hired and promoted using individual-level data. Prada et al. (2015) show that a Chilean mandate that requires companies to provide and pay for childcare for women with young children resulted in lower wages for newly hired women. Blau and Kahn (2013) find that family-friendly policies in Europe, while increasing female employment, led to women occupying more dead-end jobs and fewer managerial and professional positions compared to the United States. Dustmann and Schönberg (2012) find that three episodes of maternity leave expansion in Germany all reduced maternal employment after the birth of a child. Some authors also find different short- and long-term effects, for example, Lalive and Zweimüller (2009), Lalive et al. (2014), and Schönberg and Ludsteck (2014) find that extended parental leave greatly reduces the chances of returning to work in the short run, while employment and income do not decrease in the long run.

<sup>2</sup>Ginja et al. (2023) find that firms more affected by parental leave expansion hired additional workers and increased co-worker hours, incurring wage costs equivalent to 10 full-time worker months to compensate for absent employees. Schmutte and Skira (2023) find that firms immediately increased hiring when employees took maternity or sick leave. However, Brenøe et al. (2024) find little evidence that parental leave take-up has negative effects on firms and coworkers overall.

analyses that provide deeper insight into the mechanisms underlying the decline in callback rates to female applicants.

Second, our paper contributes to the literature on gender discrimination in hiring (e.g., Goldin and Rouse, 2000; Bertrand and Mullainathan, 2004; Kuhn and Shen, 2013; Kline et al., 2022; Kuhn and Shen, 2023; Mocanu, 2024), particularly discrimination driven by family-related responsibilities (Firth, 1982; Correll et al., 2007; Petit, 2007; Becker et al., 2019; He et al., 2023).<sup>3</sup> While He et al. (2023) examine the effects of lifting fertility restrictions, empirical research directly linking family-friendly labor policies to hiring discrimination remains scarce. To our knowledge, the only related study is by Bapna and Funk (2025) as we mentioned before, which focuses on paid leave extensions in India’s IT sector. Our study complements and extends these works by uncovering the underlying factors that shape the intensity of discrimination. We find that employer responses to maternity leave extensions are tied to the trade-off between expected productivity gains of hiring and the anticipated costs associated with extended leave. Specifically, callback reductions are smaller for women applying to higher-wage or higher-skilled jobs, and larger in settings with high labor market frictions, lower government subsidies, or greater time demands. In addition, women with low education and at the prime-fertility age are less likely to respond, suggesting that the extension of maternity leave may not only increase gender inequality, but also increase the within-gender inequality.

Third, this article offers a novel perspective on the literature on child penalty (e.g., Kuziemko et al., 2018; Kleven et al., 2019; Cortés and Pan, 2023; Boelmann et al., 2025), which highlights the crucial role of childbirth in driving gender disparities in the labor market. Previous research documents that the career trajectories of men and women diverge significantly after the birth of a child, with mothers facing substantial and persistent earnings losses and decreased labor participation. Our study contributes a new dimension to this literature by providing a new perspective on the “child penalty”: a penalty associated *not* with the actual childbirth, but with the *perceived* likelihood of future maternity. We show that women of peak fertility age experience the largest decline in callback rates following maternity leave extensions, regardless of whether they are pregnant or plan to have children.

---

<sup>3</sup>Firth (1982) conducts a correspondence test in the UK accounting sector and finds that females, especially those with children, receive significantly fewer callbacks than comparable males. Correll et al. (2007) combine lab and field experiments in the U.S., showing that mothers are perceived as less competent and committed than childless women or fathers, leading to lower hiring prospects. Petit (2007) uses a similar design in France and finds that younger women—those more likely to have children—face substantial disadvantages in high-skill occupations compared to men. Becker et al. (2019) take a direct approach and explicitly signal the marital status of fictitious applicants and the ages of the children. They find supportive evidence of discrimination in hiring based on both potential and realized fertility. He et al. (2023) use a two-wave correspondence study around China’s 2016 two-child policy change and find that women—but not men—face increased hiring discrimination due to perceived family responsibilities.

Furthermore, we find a positive relationship between the perceived probability of childbirth and the magnitude of the callback decline. These suggest that employers anticipate higher leave-related costs and adjust hiring behavior accordingly. Importantly, this form of latent discrimination occurs before the entry of the labor market and cannot be mitigated by individual fertility choices, underscoring the need to broaden our understanding of child-related penalties beyond postnatal labor market outcomes.

## 2 Policy Background

### 2.1 Maternity Leave Policy in China

The length of maternity leave in China is determined mainly by the local governments, as long as it is above the national minimum requirement. As of January 1, 2021, depending on the provinces, working women in China have a right to 128 to 188 days of maternity leave, comprising 98 days of national leave and an additional 30 to 90 days granted by provincial governments.<sup>4</sup> As shown in Figure 1(a), most provinces provide a total of 158 days.<sup>5</sup> Provinces such as Hainan and Henan offer up to 188 days, indicating a more generous approach compared to the national standard; in contrast, provinces (or provincial level municipalities) such as Zhejiang, Guangxi and Shanghai provide shorter durations, ranging from 128 to 148 days.

The right to maternity leave is legally protected, and all working women who give birth are eligible. During this period, female employees are exempted from work duties and receive a maternity allowance equal to their average pre-leave salary.<sup>6</sup> By law, employers are prohibited from reducing wages, dismissing employees, or terminating contracts due to pregnancy, childbirth, or breastfeeding. If employers violate this, employees have the right to legal recourse, with a high success rate of 82%.<sup>7</sup>

[Insert Figure 1 about here]

---

<sup>4</sup>Consistent with the regression sample, we don't present policy background for locations outside mainland China or for ethnic minority regions (e.g., Tibet, Xinjiang, Qinghai, and Ningxia), where fertility regulations differ substantially.

<sup>5</sup>In Figure 1, we refer to the maximum maternity leave for the first child. Note that Fujian province offers 158-180 days of maternity leave for the first child, and we use the maximum number of 180 days in this figure.

<sup>6</sup>Specifically, the allowance is calculated as the employee's monthly salary before maternity leave divided by 30 days, multiplied by the number of leave days.

<sup>7</sup>This data is from a judicial document sample on maternity leave rights claims during 2021 to 2023. The sample contains more than 2000 cases, and 82% of the cases are won by employees.

## 2.2 Costs Faced by Firms for Paid Leave

Compared to other countries, maternity leave in China is characterized by full pay and long paid duration, which can place a greater financial burden on employers.<sup>8</sup> Firms face two primary costs associated with maternity leave. The first is the wages for employees during paid leave. For the 98-day national leave, if the firm has contributed to the maternity insurance scheme for at least one year, the government covers the employee’s wages based on the firm’s average monthly salary from the previous year. If the employee’s pre-leave salary exceeds this average, the employer is required to cover the difference, ensuring that the employee continues to receive her regular income.<sup>9</sup> Firms that do not participate in the maternity insurance scheme must fully cover the employee’s salary during leave.<sup>10</sup>

Who is responsible for paying the wage costs associated with maternity leave extensions varies by provinces. Between 2021 and 2022, among the provinces that extended maternity leave, Shanghai, Zhejiang, and Jiangsu issued official documents confirming that the additional wage costs associated with extended maternity leave will be covered by the city government maternity insurance fund, similar to how the nationally mandated maternity leave; other provinces that extended their maternity leave during this period did not announce any such policy and it is typically assumed that additional wage costs are to be borne by employers.

The second cost arises from the need to maintain operations during the absence of the employee. Firms may need to hire and train temporary replacements or reassign workloads, incurring additional labor costs. For example, [Ginja et al. \(2023\)](#) found that firms more affected by parental leave expansions hired additional workers and extended the hours of their coworkers, resulting in labor costs equivalent to ten full-time worker-months. [Schmutte and Skira \(2023\)](#) also documented that firms increased hiring immediately when employees took maternity or sick leave. In response to these increased costs, firms may reduce callback rates for female applicants, particularly those of prime childbearing age, to mitigate the financial risks associated with extended maternity leave.

---

<sup>8</sup>For example, the US, Switzerland, Japan, and Korea offer 0, 98, 98, and 90 days of paid maternity leave, respectively. In Switzerland, the government provides 80% of the wage during paid leave, with a daily limit of USD 219.6. Japan provides 67% of the wage during maternity leave, while Korea covers 100% of the wage for the first 60 days and 50% for the following 30 days.

<sup>9</sup>If an employee’s pre-leave salary is below this average, she will receive the average wage.

<sup>10</sup>As we show in Section 3, approximately 66% of the firms in our sample provide social insurance benefits that include maternity insurance.

## 2.3 Maternity Leave Extension from 2021 to 2022

Over the past decade, the Chinese government has introduced a series of family-friendly policies to address declining fertility rates. Between 2021 and 2022, several provinces extended maternity leave. These changes were implemented immediately after the announcement and were specified in official policy documents, which often included other family and fertility support measures. The announcements were usually sudden and unanticipated.<sup>11</sup>

All changes were implemented at the provincial level, each of which issued its own policy.<sup>12</sup> Figure 1(b) illustrates regional changes in maternity leave from 2021 to 2022. Ten provinces extended their maternity leave by 10 to 50 days between September 2021 and March 2022.<sup>13</sup> Chongqing saw the largest increase, adding 50 days. Tianjin, Beijing, Shanghai, Jiangxi, Hubei, Zhejiang, and Jiangsu each added 30 days. Jilin province extended its maternity leave by 22 days, and Guangxi by 10 days. No other provinces implemented changes during this period. Most reforms occurred in November 2021, although some (e.g., Jiangxi and Jilin) took effect in September 2021, and Jiangsu and Guangxi in February and March 2022, respectively.

The extensions were concentrated in regions where the maternity leave was initially shorter than 158 days, as shown in dark blue in Figure 1(b). Therefore, provinces that did not implement new extensions may have already offered sufficiently long leave and thus cannot serve as untreated controls. It is hard to define whether these regions without extension belong to the “never-treated” or “always-treated” group. To avoid bias arising from “always-treated” units (as discussed in Goodman-Bacon (2021), Sun and Abraham (2021), and Baker et al. (2022)), we restrict our analysis to provinces that implemented new extensions during this period.<sup>14</sup> That is, the 10 regions shown in Figure 1(b).

Given the variation in both the baseline leave duration and the length of extensions

---

<sup>11</sup>This is supported by a sharp increase in the Baidu Search Index for “maternity leave” during the policy week, as shown in Appendix Figure A5. Before policy announcement week, the search frequency was low and stable, but increased after policy announcement week, suggesting limited public anticipation.

<sup>12</sup>For expositional simplicity, we also refer to the four provincial-level municipalities, Beijing, Shanghai, Tianjin and Chongqing, as provinces.

<sup>13</sup>Figure 1(b) refer to the changes in maternity leave for the first child. In some regions, the number of leave days varies by the number of children to encourage more childbirth. Between 2021 and 2022, provinces such as Hebei, Inner Mongolia, Zhejiang, and Guangxi extended maternity leave by an additional 20-30 days for the third child compared to the first. Specifically, Hebei grants 158 days of leave for both the first and second child, but 188 days for the third child. Inner Mongolia grants 158 days of leave for the first and second child, and 188 days for the third. Zhejiang offers 158 days for the first child and 188 days for the second or third child. In Guangxi, the leave days are 158 for the first child, 168 for the second, and 178 for the third.

<sup>14</sup>Prior studies emphasize that always-treated units do not serve as valid controls (Goodman-Bacon, 2021; Sun and Abraham, 2021; Baker et al., 2022). Their inclusion may lead to unclear pre-trends and improper weighting, thereby biasing the estimation.

across provinces, we use the ratio of additional days ( $\Delta ML_c$ ) to the 2021 baseline ( $ML_{c,2021}$ ),  $\Delta ML_c / ML_{c,2021}$ , as our primary measure of *policy intensity*. This variable of policy intensity for the ten provinces that we study ranges from 0.07 to 0.39, with an average value of 0.22. We discuss the alternative measure of policy intensity in Section 5.3, such as the absolute number of additional leave days.

In addition to maternity leave extensions, many local governments also introduced childcare leave during this period. Prior to 2021, China did not have a formal childcare leave policy. Under the new rules, parents of children aged 0 to 3 were entitled to 5 to 10 days of leave per year. Some provinces also extended paternity leave by 5 to 15 days. In Section 5.3, we control for the potential impacts of childcare and paternity leave extensions and then examine their effects separately.

## 3 Data

### 3.1 Data Source and Sample

Our analysis draws on high-frequency job application data from a top online job market platform in China, covering the period from January 1, 2021, to December 31, 2022. It spans nearly all industries, a wide range of regional economic conditions, and job seekers with diverse levels of human capital, allowing for rich heterogeneity analyses. However, this online job platform tends to attract young and highly educated individuals seeking well-paid positions in the private sector. Thus, while comprehensive, the data may not be fully representative of the overall Chinese labor market.

Compared to traditional survey data or employer–employee matched datasets, online application records do not track final hiring outcomes. However, they offer a key advantage: the ability to capture the dynamics of job application and recruitment before matching. This feature is crucial for separately identifying the responses on the supply side (applicant) and the demand side (employer). The data set includes both employer callbacks and applicant behavior, enabling us to observe the immediate effects of maternity leave extensions on both sides of the labor market.

In addition, its daily frequency allows for precise identification of the timing around policy shocks. Although some provinces may have anticipated the policy due to their initially shorter maternity leave, the exact month/week of the announcement is generally unanticipated, providing a plausibly exogenous source of variation. This feature allows us to define the post-policy period using exact announcement dates rather than annual indica-

tors, thereby guaranteeing the relative randomness of policy timing and improving causal identification.

### 3.2 Data Structure and Main Variables

Each observation in the data set corresponds to an application-job pair that links information about the applicant, the job, and the employer’s response. For applicants, the data include the application date, gender, age, education, work experience, and city of residence. For job postings, we observe the job title, location, industry and occupation categories, wage range, required qualifications, and benefit descriptions (e.g., flexible scheduling, social insurance, wage bonus). The employer’s response is captured by two indicators: whether a response is sent within 24 hours and whether this response is “positive.” A positive response is defined as any of the following: interview invitation, phone call, contact exchange, or follow-up conversation about the job. Detailed examples are shown in Appendix Figure A1.

In this paper, we use “whether the employer gives a positive reply within 24 hours (Yes=1)” as the measurement for callbacks. Although our outcome variable only captures responses within 24 hours, this is a strong proxy for employer interest. According to internal data from the job platform, 80% of the applications that eventually receive a positive response (within one year) are contacted within the first 24 hours.

### 3.3 Data Sampling and Selection

We draw random subsamples from the full database for empirical analysis. We design different sampling strategies for the employer and applicant side analyses, resulting in two separate samples. For the employer-side sample, we randomly select 20,000 job postings per year and include *all* application records received by those postings during the same year, yielding 1,089,546 application-level observations; and for the applicant-side sample, we randomly draw 15,000 job seekers per year and collect their *complete* application history for that year, resulting in 886,727 observations. Each sample is used independently to analyze the respective side of the labor market. The employer-side sample allows us to examine how callback rates vary across applicants for the same job, as job fixed effects can be controlled for. Similarly, the applicant-side sample enables us to study changes in job search behavior, such as the number of applications submitted, the duration of the application, and the wage level of the jobs applied.

For both samples, we restrict the analysis to applicants aged 20 to 40 years. This age

range captures the primary childbearing population in China, which is more likely to be affected by maternity leave policies, and also represents 90% of all job seekers on the platform.<sup>15</sup> We exclude observations from outside mainland China and from ethnic minority regions such as Tibet, Xinjiang, Qinghai and Ningxia, where fertility regulations differ substantially. These regions are also underrepresented on the platform, accounting for only 1.4% of the applicant-side sample. As discussed in Section 2.3, we keep regions with extension during 2021-2022 in our baseline regressions.<sup>16</sup>

For the employer-side sample, we further exclude applications submitted on a non-working day that is followed by another non-working day, since the outcome variable is based on employer responses within 24 hours, which are unlikely to occur during consecutive holidays.

### 3.4 Data Description

Table 1 presents descriptive statistics from the employer-side sample, which consists of 333,608 application records submitted to 11,250 distinct job postings. On average, the advertised monthly wage is 10,076 RMB, a level markedly higher than the national average, reflecting the platform’s focus on white collar job seekers. In particular, since job postings only report wage ranges, we use the midpoint of the range as the measure of wage. About 29% of jobs include time-related amenities we previously mentioned: to recall, a job is considered as “with time amenity” if there are phrases like “no required overtime work” or “weekend off” in the job description. Approximately 66% of jobs provide social insurance benefits, referring to China’s “Five Insurances and One Housing Provident Fund” system, which includes pension, medical, unemployment, work injury, and maternity insurances, and the housing provident fund. Furthermore, 30% of the jobs require a higher education degree (defined as a bachelor’s degree or higher), again underscoring the platform’s white-collar orientation. The average probability of receiving a positive reply within 24 hours is 26%, suggesting that employers on this platform are relatively responsive. Before the policy change, female and male applicants had similar callback rates, but in the post-policy period, the callback rate to male applicants increased by approximately one percentage point compared to female applicants. On average, each job receives 30 applications, with a nearly equal distribution between male and female applicants, though more applications from male.

Table 2 reports summary statistics from the applicant-side sample, which includes 295,592

---

<sup>15</sup>This statistic is obtained from the applicant-side sample.

<sup>16</sup>We use the regions without extension during 2021-2022 as the “control” group in the robustness section, and the results are shown in A4.

application records, 150,785 submitted by female applicants and 144,807 by male applicants. These applications correspond to 6,002 unique female applicants and 6,120 male applicants. On average, female job seekers are younger, have higher educational attainment, but have less work experience than males on average. In terms of the characteristics of applied jobs, on average, women apply to positions with lower posted wages and a higher likelihood of offering time-related amenities, while there is little difference between genders in the probability of applying to jobs that provide social insurance.

Female applicants, on average, submit more applications than male applicants, although the average search duration is similar between genders. Comparing the pre- and post-policy periods, female applicants show a larger decline in the wage level of applied jobs, and both their total number of applications and search duration increase after the policy. In contrast, for male applicants the average number of applications submitted decreases post-policy, and their average search duration remains largely unchanged.

[Insert Tables 1 and 2 about here]

## 4 Empirical Strategy

To estimate the causal effects of maternity leave extensions on employer callback behavior and applicant job search decisions, we utilize the staggered implementation of provincial-level policy changes between 2021 and 2022. We adopt a staggered DDD design to estimate the average treatment effects, and complement this with event-study analyses to assess the dynamic effects. We analyze employer-side and applicant-side outcomes separately, with greater emphasis on employers' responses due to their central role in identifying potential gender discrimination.

### 4.1 Employer-Side Analysis

#### 4.1.1 Average Treatment Effect

We begin by estimating the average effect of maternity leave extensions on the probability that an employer gives a callback (positive response) to a job application. The main estimating equation is:

$$Y_{ijct} = \alpha + \beta D_{ct} \times \Delta \% ML_c \times Female_i + \delta_{c*t} + \delta_{female*t} + \delta_{female*c} + \delta_j + X_i + Workday_t + \varepsilon_{ijct}, \quad (1)$$

where the dependent variable  $Y_{ijct}$  is an indicator equal to 1 if the job posting  $j$  in city (city of employment)  $c$  responds positively to the applicant  $i$  at time  $t$ ; the variable  $D_{ct}$  equals 1 if a maternity leave extension policy has been implemented in city  $c$  by time  $t$ , and  $\Delta\%ML_c$  denotes the percentage increase in the duration of the maternity leave relative to the 2021 baseline in city  $c$ , denoted by  $ML_{c,2021}$ :

$$\Delta\%ML_c = \frac{\Delta ML_c}{ML_{c,2021}}. \quad (2)$$

The coefficient  $\beta$  of the triple interaction term  $D_{ct} \times \Delta\%ML_c \times Female_i$  captures the differential impact of the policy on female applicants compared to males, and measures the relative change in the callback rates associated with a 100% increase in the duration of maternity leave in the post period.

This DDD design allows us to flexibly control for high-dimensional confounders. Specifically, we include interaction fixed effects:  $\delta_{c*t}$  (city-by-calendar week),  $\delta_{female*t}$  (gender-by-calendar week), and  $\delta_{female*c}$  (gender-by-city). These controls absorb time-varying shocks at the city level (e.g., changes in industrial policy or COVID-19 outbreaks), gender-specific national trends (e.g., unified national family policy reforms), and city characteristics that may differentially affect callback rates to female and male (e.g., occupational composition or local gender norm). We also include the job posting fixed effects  $\delta_j$  to control for time-invariant job attributes such as the baseline callback propensity or the response speed.

To further ensure comparability between male and female applicants, we control for observable characteristics for the applicant,  $X_i$ , including age, education, and work experience. Since callback outcomes are defined based on whether a positive response occurs within 24 hours, response rates may vary with the day of application; therefore, we include a categorical variable  $Workday_t$  indicating the configuration of working and non-working days, where  $Workday_t = 1$  if both the application day and the following day are working days;  $Workday_t = 2$  if only the application day is a working day; and  $Workday_t = 3$  if only the following day is a working day. In the regression, we control for  $X_i$  and  $Workday_t$  through a set of education-by-age-by-experience fixed effects and workday indicator fixed effects.<sup>17</sup> Although the duration of maternity leave is determined at the provincial level, specific implementation details, such as government subsidies, vary slightly across cities. Therefore, standard errors are clustered at the city of employment level to account for within-city

---

<sup>17</sup>Education is classified into six categories based on the applicant's most recent degree: (1) middle school or below; (2) vocational or technical secondary school; (3) high school; (4) junior college (associate degree); (5) bachelor's degree; and (6) master's degree. Work experience is grouped into seven categories: (1) no experience; (2) less than 1 year; (3) 1–3 years; (4) 3–5 years; (5) 5–10 years; (6) 10–20 years; and (7) more than 20 years.

correlation in policy enforcement and employer responses.

We also estimate gender-specific regressions to assess how employers respond to maternity leave extensions separately for male and female applicants. This approach helps to assess whether the observed change in the gender gap in the probability of receiving callbacks is primarily driven by a decrease in callback rates to female applicants, an increase in callback rates to male applicants, or both.

Specifically, we estimate the following equation for each gender group  $g \in \{female, male\}$ :

$$Y_{ijct}^g = \alpha^g + \gamma^g D_{ct} \times \Delta \% ML_c + \delta_t^g + \delta_j + X_i + Workday_t + \varepsilon_{ijct}^g, \quad (3)$$

where  $Y_{ijct}^g$  is an indicator for whether job posting  $j$  in city  $c$  responds positively to applicant  $i$  of gender  $g$  at time  $t$ . The coefficient  $\gamma^g$  captures the treatment effect on the callback rate to gender  $g$ .

We include gender-specific time fixed effects  $\delta_t^g$  to absorb time-varying shocks, and job fixed effects  $\delta_j$  to control for time-invariant job characteristics. Note that city fixed effects are absorbed by job fixed effects, as each job is associated with a unique city. As in Equation 1, we control for applicant-level characteristics  $X_i$  and  $Workday_t$ .<sup>18</sup> Standard errors are also clustered at the city of employment level.

#### 4.1.2 Dynamic Treatment Effects

To investigate the evolution of gender-specific callback responses over time, we estimate an event-study specification centered on the month of policy implementation. This specification enables us to test for pre-trends, as well as to examine the persistence and timing of policy-induced changes in employer behavior. The regression equation is as follows:

$$Y_{ijct} = \alpha + \sum_{r=-6, r \neq -1}^8 \theta_r \mathbf{I}_r \times \Delta \% ML_c \times Female_i + \delta_{c*t} + \delta_{female*t} + \delta_{female*c} + \delta_j + X_i + Workday_t + \varepsilon_{ijct}, \quad (4)$$

where  $\mathbf{I}_r$  is a set of event-time dummies equal to one if the observation occurs in month  $r$  relative to the month of policy implementation, with  $r = -1$  omitted as the reference period. The coefficients  $\theta_r$  capture the dynamic changes in the callback gender gap (female – male) at each event time (month) relative to the reference month. The control variables are similar

---

<sup>18</sup>As in Equation 1, we assume that time fixed effects are gender-specific, whereas job fixed effects, applicant-level characteristics, and workday effects are gender-invariant. In the gender-specific regressions, we control for the same set of fixed effects for job, applicant characteristics, and workday indicators for both genders.

to Equation 1 settings. Standard errors are, again, clustered at the city of employment level.

## 4.2 Applicant-Side Analysis

For the applicant-side analysis, we focus on two sets of outcomes related to application behavior: (1) the characteristics of jobs applied to; and (2) measures of search intensity, including the number of applications and the duration of job search. In this section, we focus on the first set, job characteristics, while the analysis of search intensity is presented in the corresponding section. The job characteristics taken into account include the posted wage, the presence of time-related amenities, and whether the job offers social insurance.

### 4.2.1 Average Treatment Effects

The baseline specification is given by:

$$Y_{ijct} = \alpha + \kappa D_{ct} \times \Delta \% ML_c \times Female_i + \delta_{c*t} + \delta_{female*t} + \delta_i + \varepsilon_{ijct}, \quad (5)$$

where the dependent variable  $Y_{ijct}$  denotes a characteristic of job posting  $j$ , such as the offered wage or the presence of job amenities, applied to by applicant  $i$  residing in city  $c$  at time  $t$ . Note that the city  $c$  for applicant-side analysis is the residence city of the applicant. The key coefficient of interest,  $\kappa$ , captures the differential response of female applicants to the extension of maternity leave relative to male applicants in the application behavior.

Following Equation 1, we include a rich set of interaction fixed effects: city-by-week fixed effects ( $\delta_{c*t}$ ), gender-by-week fixed effects ( $\delta_{female*t}$ ), and individual fixed effects ( $\delta_i$ ). Note that gender-by-city fixed effects are absorbed by the inclusion of individual fixed effects and therefore are not separately included. Standard errors are clustered at city of residence level.

Similarly, we estimate the following equation for each gender group  $g \in \{\text{female}, \text{male}\}$ :

$$Y_{ijct}^g = \alpha^g + \kappa^g D_{ct} \times \Delta \% ML_c + \delta_t^g + \delta_i + \varepsilon_{ijct}^g, \quad (6)$$

where the coefficient  $\kappa^g$  captures the treatment effect on the application behavior for applicants of gender  $g$ .  $\delta_t^g$  and  $\delta_i$  are time and individual fixed effects, respectively.

### 4.2.2 Dynamic Treatment Effects

To examine the timing and trajectory of the behavioral responses of the applicants, we adopt an event-study framework that accommodates the unbalanced panel nature of the application data. Unlike job postings, which typically remain online for extended durations, individual job search episodes are short-lived. The median duration between the start and end dates of an applicant is approximately 1.5 months. Moreover, the median number of active application days is 5.

These characteristics make it challenging to define applicant-level event windows using calendar months. Even with weekly windows, most applicants are only observed in a few weeks and are not continuous, leading to severe imbalance. To address this issue, we redefine the event time based on the application history of each individual. Specifically, event time  $r = -1$  refers to the last week in which an applicant submitted a job application prior to the policy change, rather than the last calendar week before the policy. This approach allows us to build a more balanced event panel centered around the job seeker’s actual application behavior. The estimating equation is as follows:

$$Y_{ijct} = \alpha + \sum_{r=-5, r \neq -1}^5 \mu_r \mathbf{I}_r \times \Delta \% ML_c \times Female_i + \delta_{c* t} + \delta_{female* t} + \delta_i + \varepsilon_{ijct}, \quad (7)$$

where  $\mathbf{I}_r$  are event time indicators indexed by  $r$ , where  $r = -1$  denotes the last application week before policy implementation, which serves as the reference period. The other control variables are similar to those in Equation 5. Standard errors are clustered at the city of residence level.

## 5 Employer-Side Results: Impact of Extension on Callback Response

### 5.1 Baseline Results

Table 3 reports the effects of maternity leave extensions on employers’ callback responses. Columns (1)–(3) use the full sample and adopt a Staggered DDD design, as described by Equation (1), to estimate changes in the gender gap in callback rates following the policy change.

In Column (1), we control for job characteristics, including the number of openings,

industry, firm size, and ownership type fixed effects, allowing comparisons across similar types of jobs. Column (2) includes job fixed effects, which absorb unobserved, time-invariant job-level heterogeneity. Column (3) further adds applicant characteristics (age, education, and work experience), allowing comparisons within the same job and among similar applicants. The coefficients become smaller after controlling for job fixed effects but remain stable when applicant characteristics are added.

We take the specification in Column (3) as our baseline results. The estimate suggests that a 10% increase in maternity leave duration reduces callback rates to females by 1.7 percentage points relative to males, corresponding to 7.8% of the pre-policy mean callback rate for female job applicants (0.217). Given an average intensity of the policy shock of 22%, this implies that the reform reduced callback rates to females by approximately 3.7 percentage points on average, or 17% of the baseline level.

Columns (4) and (5) present separate estimates for female and male applicants, controlling for job fixed effects, time fixed effects, workday indicators, and applicant characteristics. The results show that the widening gender gap in callback rates stems from both a decline in women’s callback rates and an increase in men’s callbacks, with the decline among women accounting for the larger share—roughly 60% of the total gap.

[Insert Table 3 about here]

## 5.2 Dynamic Effect

Figure 2 plots the dynamic effects of maternity leave extensions on the gender gap in callback rates (Female – Male), with all coefficients measured relative to the last month prior to policy implementation. The vertical line marks the baseline month. Estimates before the reform fluctuate around zero and are statistically insignificant. After implementation, the coefficients become persistently negative and remain so for at least seven months. Consistent with Column (3) of Table 3, the average post-policy effect is approximately 0.17. The smaller magnitude observed in the policy month likely reflects an initial adjustment or learning phase on the part of employers.

We further examine the dynamics using alternative specifications. First, we replace the policy intensity measure with the number of additional days of maternity leave. As shown in Appendix Figure A2(a), the estimates become less noisy and indicate more precisely estimated negative effects. Second, we restrict the sample to provinces that initially offered 128 days of leave and later extended it uniformly by 30 days, ensuring consistent treatment across

regions. For this sample, we use a binary indicator for extension. Appendix Figure A2(b) shows that the gender gap in callback rates remains flat before implementation, but broadens markedly after month 0 and persists. Despite differences in model specifications and sample restrictions, the magnitude of the estimated average effect is similar to the baseline, around 4 percentage points.

[Insert Figure 2 about here]

### 5.3 Robustness Checks

**Treatment Effect Heterogeneity.** We estimate dynamic treatment effects using the method proposed by Sun and Abraham (2021), which accounts for treatment effect heterogeneity and avoids biases present in traditional two-way fixed effects estimators under staggered adoption. Because our sample consists exclusively of treated provinces, we do not observe a never-treated control group. To address this, we retain the pre-treatment period of late-treated provinces and treat them as if they were never treated. Specifically, we restrict the sample to observations before February 2022 and designate Jiangsu (policy implemented on February 10, 2022) and Guangxi (March 24, 2022) as the never-treated control group.

Figure A3 plots the event time coefficients, showing a clear decline in callback rates to female applicants compared to males in the months following the implementation of maternity leave extensions. The absence of significant pre-trends further supports the validity of the parallel trends assumption.

**Concurrent Policy Controls.** Although our baseline regressions include city-by-week fixed effects, which absorb time-varying shocks at the city of employment level, including most local policy changes, these controls do not capture heterogeneity in policy effects across genders. If concurrent policies have differential impacts on male and female applicants, failing to control for such interactions could bias our estimates.

To address this concern, we incorporate additional controls for two key sources of gendered policy variation across regions: COVID-19 outbreaks and other family-related policies. First, the COVID-19 pandemic can influence callback rates to females through mechanisms such as increased work-from-home arrangements or increased family responsibilities. To account for this, we control for the number of newly confirmed and currently active COVID-19 cases at the city-week level and interact these measures with the female dummy. Second, we consider potential interactions between our main policy and concurrent expansions in family

leave benefits, specifically paternity leave and childcare leave. We control for the durations of paternity and childcare leave at the provincial level and include interactions with the female indicator to isolate their differential impacts.

Table A1 presents the estimation results. Our findings remain robust, confirming that the observed decline in callback rates to females is not driven by these concurrent policy changes. Furthermore, Table A2 further examines the standalone effects of paternity and childcare leave extensions, finding no statistically significant gender-specific effects on employer responses.

Moreover, to further rule out the possible confounding effects of national fertility policy, we account for the implementation of China’s “three-child policy.”<sup>19</sup> While female-by-week fixed effects absorb most of its time-specific impacts, we conduct an additional robustness check restricting the sample to observations after May 31, 2021 (policy time). This restriction ensures that all applicants were subject to the same fertility restriction during the sample period. As reported in Table A1, the results remain robust under this specification.

**Alternative Specifications.** We test the robustness of our findings under a series of alternative model specifications. First, instead of using the percentage increase in the duration of maternity leave relative to the 2021 baseline, we redefine policy intensity as the absolute number of added days. Second, we use the lunar calendar for fixed effects related to time. This adjustment helps mitigate confounding effects of the holidays, especially around the Spring Festival, which can influence employer behavior. As reported in Table A4, our key results remain stable in all these specifications.

Table A3 further examines robustness under alternative sample restrictions. We use untreated provinces as control groups and impose restrictions on job characteristics. In particular, we restrict the sample to jobs that receive more than 10 applications and advertise fewer than 30 vacancies.<sup>20</sup> In all alternative specifications, the estimated effects remain consistent, reinforcing the robustness of our baseline results.

**Placebo Test Results.** To assess whether our findings could be driven by spurious correlations or random shocks, we conduct placebo simulations by randomly assigning treatment

---

<sup>19</sup>This policy is officially announced on May 31, 2021. This policy allows each couple to have up to three children and was uniformly adopted nationwide.

<sup>20</sup>Approximately 5% of jobs have more than 30 vacancies. Jobs with a large number of openings, such as delivery or factory piecework positions, often reflect outsourced or informal employment. These postings typically receive high application volumes, but may not be representative of general labor market dynamics. Removing these observations helps ensure that our findings are not driven by a small subset of atypical postings.

timing across provinces. Figure A4 plots the distribution of placebo effects, with the actual estimated effect lying far in the tails, indicating that it is unlikely to occur by chance. In addition, we conduct a falsification test using applicants aged over 45 years, who are unlikely to be affected by maternity leave policies. As reported in Table A3, we find no significant treatment effect in this placebo group.

**Anticipation Effects.** To test for policy anticipation, we examine public search behavior around the policy period, which is measured by the Baidu Search Index.<sup>21</sup> Figure A5 shows a sudden and sharp increase in the Baidu Search Index for the term “maternity leave” during the week of policy announcement. The lack of elevated search activity prior to the announcement suggests limited public awareness or anticipation of the policy, supporting the exogeneity of policy timing.

**Leave-One-Out Analysis.** Finally, to ensure that our findings are not driven by a single influential province, we implement a leave-one-out procedure by reestimating the main regression while sequentially excluding one treated province at a time. As illustrated in Figure A6, the estimated effects remain significant and consistent across all regressions, confirming that the main results are not driven by a single province.

## 5.4 Heterogeneity Analysis

To better understand the underlying mechanisms behind the decline in callback rates to females, we conduct a series of heterogeneous analyses. We first examine how employers’ responses to maternity leave extension is impacted by whether the local government pays for the wage costs associated with the leave extension; we then explore variation across the job characteristics (wage, job requirements, and amenities), firm and industry attributes (labor market frictions, firm ownership and industry female share), and applicant profiles (age and education).

**Government Coverage for Wages During the Extended Maternity Leave.** As mentioned in Section 2.2, among the ten provinces that extended maternity leave, only Shanghai, Zhejiang, and Jiangsu issued official documents stating that additional wages during the extended leave period would be covered by the city’s maternity insurance fund in the same way as the national maternity leave. This institutional variation enables us to

---

<sup>21</sup>Baidu is the largest search engine in China. The Baidu Search Index, similar to Google Trends, captures time series data on search frequency for different terms.

test whether shifting the financial burden of maternity leave from firms to the government alters the hiring responses of employers. Specifically, we divide the sample into “cover” and “no cover” groups based on whether the local government subsidizes the wage costs for extension of maternity leave. Using the same specification as in Equation 1, we estimate the model separately for each group. Table 4 shows that employers in “no cover” provinces exhibit almost twice the increase in gender gaps in callback rates compared to the “cover” provinces; moreover, the effect is statistically significant at the 10% level in the “no-cover” provinces, but not in the “cover” provinces. These findings suggest that government-funded maternity leave extensions can partially mitigate discriminatory responses by reducing the perceived wage cost burden on employers.

[Insert Table 4 about here]

**Job Wage and Requirements.** Panel (a) of Figure 3 examines heterogeneity by job wage and education requirements. We find that the widening gender gap in callbacks is more pronounced in low-wage jobs and jobs requiring lower educational qualifications, whereas high-wage, high-education jobs show little to no change. Although high-wage jobs are associated with greater potential wage costs during maternity leave, they also demand higher worker productivity. The expected productivity of highly educated or highly paid applicants may offset the increased costs related to leave extension, leading to less discrimination.

**Job Amenities.** We focus on two job amenities that are closely related to firm costs: time flexibility and social insurance coverage. As we previously mentioned, a job is coded as having time amenities if the posting includes phrases such as “no overtime” or “weekends off,” suggesting reduced work intensity and shorter working hours. Such positions likely impose lower costs on firms during maternity leave, which may explain the smaller decline in callback rates to females. This finding is consistent with Goldin (2014), who argues that gender inequality would diminish if firms had fewer incentives to reward long or rigid work hours.

As we previously mentioned, social insurance refers to China’s “Five Insurances and One Housing Provident Fund” (pension, medical, unemployment, work injury, maternity insurances, and the housing provident fund). Jobs offering full social insurance indicate higher firm formality and suggest that maternity-related wage costs are largely covered by government insurance. These firms may also face stronger regulatory oversight. Consequently, formal firms offering social insurance benefits exhibit weaker discriminatory responses to the extension of maternity leave.

**Labor Market Frictions.** Following [Ginja et al. \(2023\)](#), we consider labor market frictions as a key driver of firm responses to parental leave policies. If firms face minimal friction, they can replace employees more easily, reducing the cost impact of temporary absences. We use two proxies for frictions: industry tightness and firm size. Industry tightness is measured as the ratio of applicants to vacancies in a given city–industry cell; higher tightness implies easier hiring. Larger firms are assumed to have more structured internal labor markets and better capacity to reallocate tasks. As shown in Panel (b) of Figure 3, we find that jobs in high-tightness industries and large firms—i.e., those with lower labor market frictions—exhibit smaller reductions in callback rates to females.

**Firm Ownership.** More than 43 million workers in China are employed by state-owned enterprises (SOEs), which typically shoulder greater public responsibilities, are less responsive to short-term cost fluctuations and possess stronger buffers against financial losses. In addition, SOEs are subject to stricter regulatory oversight. We find that the decline in callback rates to female applicants is concentrated among private firms, whereas SOEs exhibit little to no change in response to maternity leave extensions.

**Industry Female Share.** It is often hypothesized that female-dominated industries are more accommodating to women, especially during periods of expansion of maternity leave. To examine this, we classify industries into high-female-share (above 50%, top quartile) and low-female-share (below 30%, bottom quartile) groups based on the proportion of female workers.<sup>22</sup> Contrary to expectations, we find that industries with a higher female share experience larger reductions in callback rates to female applicants. This pattern may reflect the greater financial salience of leave-related costs when a larger share of the workforce is likely to take advantage of such benefits.

**Applicant Characteristics.** We focus on two characteristics of the applicants: age and education. Based on 2020 Census data, we categorize female applicants aged 20–40 into pre-peak (20–25), peak (26–30), and post-peak (31–40) fertility groups.<sup>23</sup> As shown in Panel (c) of Figure 3, women in the peak fertility age group experience the largest relative decrease in

---

<sup>22</sup>Data on the share of female employment by industry are obtained from the 2020 Census, which reports employment by gender and broad industry categories at the regional level. We calculate the proportion of female workers within each industry and match these categories to our sample based on the corresponding industry classifications.

<sup>23</sup>We use data from the 2020 China Population Census, focusing on the fertility status of women of childbearing age in urban areas. The fertility rate is defined as the number of births divided by the number of women of childbearing age. We define the peak fertility group as the age group with a fertility rate equal to or above 8 per 1,000 women, which corresponds to women aged 26–30 in our data.

the probability of receiving callbacks compared to men of the same age. To further validate the relationship between the decline in callback rates and fertility probability, we interact the predicted probability of childbirth within the next three years with the policy shock among female applicants.<sup>24</sup> As shown in Table A5, at the average policy shock intensity (22%), a 10–percentage-point increase in the predicted fertility probability is associated with an additional 1.24–percentage-point decline in employers’ callback rates after the policy relative to the pre-policy period.<sup>25</sup> This finding suggests that perceived fertility risk—and the associated potential increase in maternity leave costs—plays an important role in employers’ adjustment of hiring behavior.

Highly educated women, on average, experience significantly smaller negative effects. Their higher productivity may compensate for the cost of leave, and their skills are often less substitutable. For example, while a factory assembler can be easily replaced by a male counterpart, a senior female AI engineer may be more difficult to replace. These findings suggest that maternity leave extensions not only exacerbate gender inequality, but also increase within-gender inequality, placing low-skilled women at a greater disadvantage. Given their lower earnings, this can increase their likelihood of exiting the labor force in favor of home production.

[Insert Figure 3 about here]

## 5.5 Changes in Job Characteristics and Application Counts

The observed widening of the gender gap in callback rates may not be entirely attributable to shifts in employer preferences during recruitment. In this section, we explore two alternative mechanisms that could also contribute to the decline in callback rates to female applicants: changes in job composition and changes in application volume and gender mix.

---

<sup>24</sup>The fertility probability is obtained from the 2020 China Population Census Micro Database. The dataset represents approximately 0.98‰ random sample of national population. We construct an individual–age panel from ages 20 to 40 and define a variable *childbirth* that equals one for the age at which childbirth occurs, zero otherwise, and missing for ages not yet reached by 2020. We retain observations for 2016–2020 and aggregate the *childbirth* variable at the province–education–age level to obtain the average fertility rate of individuals in each group. To capture employers’ concern about near-term maternity risk, we further compute the average fertility rate over the next three years for use in the interaction. Finally, we match this fertility probability to our online job applications data.

<sup>25</sup>There exists a positive correlation between average fertility probability and productivity at the province–education–age level. To isolate the effect of fertility probability, we restrict the regression sample to female applicants with a bachelor’s degree and less than one year of work experience. This group is chosen for two reasons: first, the applicants with bachelor’s degree accounts for the largest share of applicants on the platform (56%); second, work experience in other groups is recorded in intervals (e.g., 3–5 years), making it impossible to precisely identify actual experience.

First, if the composition of posted jobs changes after the maternity leave extension, for example, if the share of positions offering time-related amenities decreases, then a mechanical decline in average callback rates to female applicants may occur, as such jobs are typically more friendly to women.

Second, callback rates may decline if the total number of applications per job increases, particularly from female applicants. If employers aim to hire a certain number of women, an increase in female applicants without a corresponding rise in vacancies would mechanically lower the callback rate, even in the absence of any change in gender preferences.

Table 5 reports the effects of maternity leave extensions on the characteristics of the job posted and the volume of applications using data from employers. For regressions on job characteristics and total application counts, we include one observation per job and define treatment status based on whether the job was posted after the policy implementation. These regressions control for city and calendar week (the week of job posting) fixed effects. For regressions on weekly application volumes, we construct the data at the job-week level. Since our data set only records job-week observations with at least one application, we impute weeks with zero applications by generating job-week entries with application count equal to 0. A job is considered treated when the corresponding week is after the policy implementation date. These regressions include job fixed effects and calendar week fixed effects.

Panel A examines changes in job postings and finds no significant effects on the number of openings, wage offers, time-related benefits, social insurance coverage, or education requirements. Panel B assesses application volumes and gender composition. While total application numbers increase slightly, the number of female applicants shows a small decline. Weekly application data yield similar patterns, but none of the effects are statistically significant. Taken together, these results suggest that neither shifts in job characteristics nor changes in the applicant pool are sufficient to explain the widening gender gap in callback rates.

[Insert Table 5 about here]

## 6 Applicant-Side Results: Impact of the Extension on Application Behavior

### 6.1 Changes in the Characteristics of Applied Jobs

In addition to employer responses, job seekers may also adjust their application behavior in response to maternity leave extensions. First, female applicants may revise their application strategies based on perceived changes in the likelihood of hiring. For example, anticipating increased wage costs for firms, women may view themselves as less competitive and shift toward less competitive, more female-friendly jobs. Second, extension of maternity leave can make female applicants more likely to seek positions that offer formal benefits, such as social insurance coverage, to fully access the new entitlements. In addition, changes in fertility intentions induced by the maternity leave extensions may shape women’s job preferences.

In this section, we focus on how the characteristics of applied jobs changed after the extension of maternity leave, with particular attention to three outcomes: wage level, time-related amenities, and provision of social insurance. Table 6 presents estimates of the effect of extensions of maternity leave on applied job characteristics, based on Equation 5, using the sample data from the applicant’s side.

**Wages.** The results indicate that, following the extension of the maternity leave, the posted wages of the jobs that female applicants apply for are significantly lower than those of male applicants; the estimated coefficient of  $-0.234$  implies that, at the average policy intensity of 22%, the female applicants witness a 5.4% reduction in the wage level of the jobs applied compared to males. This pattern suggests that women may partially offset the expected increase in employers’ costs due to the maternity leave extension by applying to lower-paying positions, potentially reinforcing gender disparities in hiring and earnings.

Several mechanisms may contribute to this decline in applied job wages. First, as shown in Table 3, conditional on similar characteristics, women face a lower probability of receiving callbacks than men. Anticipating higher barriers to employment or learning from repeated rejections, female applicants may revise their wage expectations downward. Second, the reduction in employer responses may prolong women’s job search duration, which has been shown to lower wage expectations over time.<sup>26</sup> A third possible explanation is that extended

---

<sup>26</sup>Table A7 shows the relationship between the search length and the wages of the applied job. For the full sample, the wage level of the jobs applied for is significantly associated with the length of the job search.

maternity leave shifts the preferences of women seeking work toward non-wage job attributes. In particular, women may increasingly prioritize benefits such as flexible working hours or access to social insurance, accepting lower wages in exchange for these amenities.

To evaluate the relative importance of these channels, we control for length of time (in days) since the applicant began their first job search and the characteristics of the job, specifically the presence of time-related amenities and social insurance, in Appendix Table A6. The estimated coefficients change negligibly under these alternative specifications, suggesting that neither changes in preferences nor longer search durations can account for the decline in wages of applied jobs among women.

**Time-related Amenities and Social Insurance.** Table 6 also shows that women are 3.7% more likely to apply to jobs offering time-related amenities (e.g., “weekends off” or “no overtime”) after the extension of maternity leave, relative to men. This shift may be driven by three mechanisms. First, it may reflect a growing preference for work–life balance in response to the policy change. Second, given that such jobs exhibit smaller declines in callback rates to female applicants after the reform (see Figure 3), women may strategically shift toward these positions to avoid discrimination. Third, one might suspect that this shift is mechanically driven by the move toward lower-paying jobs, as time-related amenities are negatively correlated with wages in our sample. However, the third explanation appears unlikely, as the increase in applications to jobs offering time-related amenities remains virtually unchanged after controlling for wage levels (see Appendix Table A6).

In contrast, in Table 6 we find no significant effect on the gender gap in the likelihood of applying to jobs that offer social insurance. Panel B of Table 6 shows that the observed behavioral changes are concentrated among women. Male applicants appear to target jobs with greater amenities, yet show no significant changes in job search behavior across dimensions.

Taken together, these findings suggest that maternity leave extensions may widen gender disparities not only in callback rates, but also in expected earnings. Women appear to adjust their search strategies with respect to wage levels and job types, potentially reinforcing occupational segregation and income inequality in the labor market.

[Insert Table 6 about here]

---

Gender-specific regressions reveal that this relationship is statistically significant for male applicants but not for female applicants. This suggests that the longer duration of search among women contributes little to the observed decline in the wages of applied jobs.

**Dynamic Effects.** Figure 4 illustrates the dynamic effects on the gender gap (Female – Male) in the characteristics of applied jobs. Several patterns emerge from the figure. Following the policy change, the gender gap in log wages becomes increasingly negative, indicating that women gradually shift toward lower-paying jobs relative to men. At the same time, women become more likely than men to apply for jobs with time-related amenities. In contrast, the gender gap in applications to jobs with social insurance benefits remains flat.

[Insert Figure 4 about here]

## 6.2 Changes in Application Frequency, Number and Duration

Given that both employers and applicants adjust their behavior in response to the policy shock, a natural question arises: How do these adjustments affect overall application intensity and job search duration? In Table 7 we examine this by estimating the effects of maternity leave extensions on four key outcomes for male and female applicants, using applicant-side data: (1) the weekly probability of submitting any job application, (2) the number of applications submitted per week, (3) the total number of applications submitted during the observation period, and (4) the total duration of the job search, measured as the number of weeks between the first and last applications.

For regressions on weekly search behavior, as discussed in Section 5.5, our data set only includes applicant-week observations with at least one application. To account for weeks without applications, we impute zero-application weeks by constructing applicant-week entries with an application count of zero. Then we construct the data at the applicant-week level. An applicant is defined as treated when the corresponding week falls after the maternity leave policy implementation date. These regressions include individual fixed effects and calendar-week fixed effects.

For total application counts and job search duration, the unit of observation is the individual applicant. The treatment status is determined based on whether the midpoint of the applicant’s job search period falls after the policy announcement date. We control for city fixed effects and calendar week (the week of first application) fixed effects, as well as applicant characteristics (education by age by experience fixed effects).

Table 7 reports the results. It reveals substantial gender differences in behavioral responses. Among women, both the total number of applications and the search duration increase significantly following the reform. At the average policy intensity of 22%, women submit approximately 4.4 additional applications (20% of the pre-policy mean) and extend

their search by 2.1 weeks (19% of the pre-policy mean). However, we do not observe a significant change in the probability or volume of weekly applications, implying that the increase in total applications is primarily driven by a longer search duration rather than a higher application frequency. In contrast, male applicants do not show statistically significant changes in any of the four outcomes.

Despite lowering their wage expectations (as shown in Table 6), female applicants face longer and more intensive job searches, likely reflecting increased frictions or diminished opportunities driven by employer-side responses. The combination of greater search effort and lower applied wages suggests a deterioration in job match quality for women after the reform. In comparison, male applicants remain largely unaffected. These patterns further amplify gender disparities in labor market outcomes.

[Insert Table 7 about here]

## 7 Conclusion

We show that extended maternity leave unintentionally worsens gender disparities in the labor market. Using high-frequency job application data from China and exploiting the staggered policy roll-out between 2021 and 2022, we find that longer maternity leave significantly reduces callback rates to female applicants relative to males. On average, the policy shock decreases women’s probability of receiving callbacks by an additional 3.7 percentage points. This adverse effect is stronger among women of childbearing age and those with lower education levels. In response, female job seekers shift their applications toward lower-wage, more flexible positions. Still, the durations of their job searches and total number of applications increase.

Importantly, our results reveal that motherhood penalties emerge even before childbirth, as employers penalize women at the hiring stage in anticipation of maternity leave costs rather than in response to actual leave-taking. These findings underscore the importance of accounting for pre-hiring employer biases when designing family-friendly policies.

Our analysis highlights two channels through which extended maternity leave may unintentionally exacerbate gender disparities in the labor market. First, employers appear to respond to the higher expected costs associated with female hires by reducing callbacks to women of childbearing age. Second, women adjust their application behavior by targeting less competitive and lower-paying jobs, thus reinforcing existing wage gaps. Even after lowering their wage expectations, women continue to experience longer search durations.

Beyond gender inequality, the policy also amplifies disparities within the female population: women with lower education levels experience the largest declines in callbacks, whereas more highly educated women are less affected, potentially due to higher perceived productivity and limited extent that employers can substitute high-skilled workers.

Although generous leave policies are designed to support working mothers, they may reduce women’s labor market access if costs are borne by firms. To safeguard both family welfare and gender equity, governments may want to consider shifting the financial burden of leave coverage from employers to public funds. Finally, our study points to the need for more research on employer-side responses to family policies. Understanding how employers interpret and react to these reforms is essential for designing family-friendly policies that promote, rather than hinder, gender equality in the workplace.

## References

- Antecol, Heather, Kelly Bedard, and Jenna Stearns**, “Equal but Inequitable: Who Benefits from Gender-Neutral Tenure Clock Stopping Policies?,” *American Economic Review*, 2018, *108* (9), 2420–2441.
- Baker, Andrew C., David F. Larcker, and Charles C.Y. Wang**, “How Much Should We Trust Staggered Difference-in-Differences Estimates?,” *Journal of Financial Economics*, 2022, *144* (2), 370–395.
- Baker, Michael, Jonathan Gruber, and Kevin Milligan**, “Universal Child Care, Maternal Labor Supply, and Family Well-being,” *Journal of Political Economy*, 2008, *116* (4), 709–745.
- Bapna, Sofia and Russell J. Funk**, “Does Employer-Paid, Job-Protected Maternity Leave Help or Hurt Female IT Workers? Evidence from Millions of Job Applications,” *Management Science*, 2025. <https://doi.org/10.1287/mnsc.2021.00380>.
- Becker, Sascha O., Ana Fernandes, and Doris Weichselbaumer**, “Discrimination in Hiring Based on Potential and Realized Fertility: Evidence from a Large-Scale Field Experiment,” *Labour Economics*, 2019, *59*, 139–152.
- Berlinski, Samuel, Maria Marta Ferreyra, Luca Flabbi, and Juan Diego Martin**, “Childcare Markets, Parental Labor Supply, and Child Development,” *Journal of Political Economy*, 2024, *132* (6), 2113–2177.

- Bertrand, Marianne and Sendhil Mullainathan**, “Are Emily and Greg More Employable than Lakisha and Jamal? A Field Experiment on Labor Market Discrimination,” *American Economic Review*, 2004, *94* (4), 991–1013.
- Blau, Francine D. and Lawrence M. Kahn**, “Female Labor Supply: Why Is the US Falling Behind?,” *American Economic Review*, 2013, *103* (3), 251–256.
- Boelmann, Bastian, Anna Raute, and Uta Schönberg**, “Wind of Change? Cultural Determinants of Maternal Labor Supply,” *American Economic Journal: Applied Economics*, 2025, *17* (2), 41–74.
- Brenøe, Anne Ardila, Serena Canaan, Nicole A. Harmon, and Heather N. Royer**, “Is Parental Leave Costly for Firms and Coworkers?,” *Journal of Labor Economics*, 2024.
- Byker, Tanya S.**, “Paid Parental Leave Laws in the United States: Does Short-Duration Leave Affect Women’s Labor-Force Attachment?,” *American Economic Review*, 2016, *106* (5), 242–246.
- Correll, Shelley J., Stephen Benard, and In Paik**, “Getting a Job: Is There a Motherhood Penalty?,” *American Journal of Sociology*, 2007, *112* (5), 1297–1339.
- Cortés, Patricia and Jessica Pan**, “Children and the Remaining Gender Gaps in the Labor Market,” *Journal of Economic Literature*, 2023, *61* (4), 1359–1409.
- Dahl, Gordon B, Katrine V Løken, Magne Mogstad, and Kari Vea Salvanes**, “What is the Case for Paid Maternity Leave?,” *Review of Economics and Statistics*, 2016, *98* (4), 655–670.
- Dustmann, Christian and Uta Schönberg**, “The Effect of Expansions in Maternity Leave Coverage on Children’s Long-Term Outcomes,” *American Economic Journal: Applied Economics*, 2012, *4* (3), 190–224.
- Fernández-Kranz, Daniel and Núria Rodríguez-Planas**, “Too Family Friendly? The Consequences of Parent Part-Time Working Rights,” *Journal of Public Economics*, 2021, *197*, 104407.
- Firth, Michael**, “Sex Discrimination in Job Opportunities for Women,” *Sex Roles*, 1982, *8* (8), 891–901.
- Ginja, Rita, Arizo Karimi, and Pengpeng Xiao**, “Employer Responses to Family Leave Programs,” *American Economic Journal: Applied Economics*, 2023, *15* (1), 107–135.

- Goldin, Claudia**, “A Grand Gender Convergence: Its Last Chapter,” *American Economic Review*, 2014, *104* (4), 1091–1119.
- **and Cecilia Rouse**, “Orchestrating Impartiality: The Impact of ”Blind” Auditions on Female Musicians,” *American Economic Review*, 2000, *90* (4), 715–741.
- Goodman-Bacon, Andrew**, “Difference-in-Differences with Variation in Treatment Timing,” *Journal of Econometrics*, 2021, *225* (2), 254–277.
- Gruber, Jonathan**, “The Incidence of Mandated Maternity Benefits,” *American Economic Review*, 1994, *84* (3), 622–641.
- Havnes, Tarjei and Magne Mogstad**, “Money for Nothing? Universal Child Care and Maternal Employment,” *Journal of Public Economics*, 2011, *95* (11-12), 1455–1465.
- He, Haoran, Sherry Xin Li, and Yuling Han**, “Labor Market Discrimination against Family Responsibilities: A Correspondence Study with Policy Change in China,” *Journal of Labor Economics*, 2023, *41* (2), 361–387.
- Jr, Joseph E Zveglic and Yana van der Meulen Rodgers**, “The Impact of Protective Measures for Female Workers,” *Journal of Labor Economics*, 2003, *21* (3), 533–555.
- Kleven, Henrik, Camille Landais, and Jakob Egholt Sogaard**, “Children and Gender Inequality: Evidence from Denmark,” *American Economic Journal: Applied Economics*, 2019, *11* (4), 181–209.
- , — , **Johanna Posch, Andreas Steinhauer, and Josef Zweimüller**, “Do Family Policies Reduce Gender Inequality? Evidence from 60 Years of Policy Experimentation,” *American Economic Journal: Economic Policy*, 2024, *16* (2), 110–149.
- Kline, Patrick M., Evan K. Rose, and Christopher R. Walters**, “Systemic Discrimination Among Large U.S. Employers,” *Quarterly Journal of Economics*, 2022, *137* (4), 1963–2036.
- Kuhn, Peter and Kailing Shen**, “Gender Discrimination in Job Ads: Evidence from China,” *Quarterly Journal of Economics*, 2013, *128* (1), 287–336.
- Kuhn, Peter J. and Kailing Shen**, “What Happens When Employers Can No Longer Discriminate in Job Ads?,” *American Economic Review*, 2023, *113* (4), 1013–1048.
- Kuziemko, Ilyana, Jessica Pan, Jenny Shen, and Ebonya Washington**, “The Mommy Effect: Do Women Anticipate the Employment Effects of Motherhood?,” NBER Working Paper 24740, National Bureau of Economic Research 2018.

- Lalive, Rafael, Analía Schlosser, Andreas Steinhauer, and Josef Zweimüller**, “Parental leave and mothers’ careers: The relative importance of job protection and cash benefits,” *Review of Economic Studies*, 2014, 81 (1), 219–265.
- **and Josef Zweimüller**, “How Does Parental Leave Affect Fertility and Return to Work? Evidence from Two Natural Experiments,” *The Quarterly Journal of Economics*, 2009, 124 (3), 1363–1402.
- Mocanu, Tatiana**, “Designing Gender Equity: Evidence from Hiring Practices,” *Unpublished Manuscript*, 2024. IZA Discussion Paper No. 17480 / CESifo Working Paper No. 11523. Available at: <https://ssrn.com/abstract=5038222>.
- Olivetti, Claudia and Barbara Petrongolo**, “The Economic Consequences of Family Policies: Lessons from a Century of Legislation in High-Income Countries,” *Journal of Economic Perspectives*, 2017, 31 (1), 205–230.
- Petit, Pascale**, “The Effects of Age and Family Constraints on Gender Hiring Discrimination: A Field Experiment in the French Financial Sector,” *Labour Economics*, 2007, 14 (3), 371–391.
- Prada, Maria Fernanda, Graciana Rucci, and Sergio S. Urzúa**, “The Effect of Mandated Child Care on Female Wages in Chile,” NBER Working Paper 21080, National Bureau of Economic Research 2015.
- Ruhm, Christopher J.**, “The Economic Consequences of Parental Leave Mandates: Lessons from Europe,” *Quarterly Journal of Economics*, 1998, 113, 285–317.
- Schmutte, Ian M. and Meghan M. Skira**, “The Response of Firms to Maternity Leave and Sickness Absence,” *Journal of Human Resources*, 2023. 0522-12352R2; DOI: 10.3368/jhr.0522-12352R2.
- Schönberg, Uta and Johannes Ludsteck**, “Expansions in Maternity Leave Coverage and Mothers’ Labor Market Outcomes after Childbirth,” *Journal of Labor Economics*, 2014, 32 (3), 469–505.
- Sun, Liyang and Sarah Abraham**, “Estimating Dynamic Treatment Effects in Event Studies with Heterogeneous Treatment Effects,” *Journal of Econometrics*, 2021, 225 (2), 175–199.
- Timpe, Brenden**, “The Labor Market Impacts of America’s First Paid Maternity Leave Policy,” *Journal of Public Economics*, 2024, 231, 105067.

# Tables

**Table 1: Summary Statistics: Employer Sample**

|                                                           | All<br>(1)            | Pre<br>(2)           | Post<br>(3)           |
|-----------------------------------------------------------|-----------------------|----------------------|-----------------------|
| <b><u>Job Characteristics:</u></b>                        |                       |                      |                       |
| Required Number of Employees                              | 12.47<br>[72.70]      | 9.18<br>[56.48]      | 14.88<br>[82.52]      |
| Wage                                                      | 10075.90<br>[5250.09] | 9898.45<br>[5180.68] | 10206.20<br>[5297.08] |
| With Time Amenity                                         | 0.29<br>[0.45]        | 0.28<br>[0.45]       | 0.29<br>[0.45]        |
| With Social Insurance                                     | 0.66<br>[0.47]        | 0.71<br>[0.46]       | 0.63<br>[0.48]        |
| High Education Requirement                                | 0.30<br>[0.46]        | 0.33<br>[0.47]       | 0.28<br>[0.45]        |
| <b><u>Give a positive reply (<math>Y = 1</math>):</u></b> |                       |                      |                       |
| All Sample                                                | 0.26<br>[0.44]        | 0.22<br>[0.41]       | 0.28<br>[0.45]        |
| Female                                                    | 0.26<br>[0.44]        | 0.22<br>[0.41]       | 0.28<br>[0.45]        |
| Male                                                      | 0.26<br>[0.44]        | 0.22<br>[0.41]       | 0.29<br>[0.45]        |
| <b><u>Number of Applications Received:</u></b>            |                       |                      |                       |
| Weekly Number                                             | 1.67<br>[6.76]        | 1.48<br>[5.23]       | 1.79<br>[7.57]        |
| Weekly Number from Female                                 | 0.83<br>[4.55]        | 0.73<br>[3.48]       | 0.89<br>[5.11]        |
| Total Number                                              | 29.65<br>[88.25]      | 22.77<br>[62.95]     | 34.71<br>[102.65]     |
| Total Number from Female                                  | 14.69<br>[59.63]      | 11.31<br>[38.90]     | 17.17<br>[71.00]      |

*Notes:* This table reports all sample, pre- and post-policy means and standard deviations using employer-side data. Standard deviations are shown in square brackets.

**Table 2: Summary Statistics: Applicant Sample**

|                                          |           | Female    |            |           | Male      |           |
|------------------------------------------|-----------|-----------|------------|-----------|-----------|-----------|
|                                          | All       | Pre       | Post       | All       | Pre       | Post      |
|                                          | (1)       | (2)       | (3)        | (4)       | (5)       | (6)       |
| <u>Applicant Characteristics:</u>        |           |           |            |           |           |           |
| Age                                      | 27.73     | 28.06     | 27.34      | 28.48     | 28.64     | 28.30     |
|                                          | [5.16]    | [5.16]    | [5.13]     | [5.35]    | [5.26]    | [5.44]    |
| High Education Level                     | 0.57      | 0.59      | 0.56       | 0.47      | 0.49      | 0.44      |
|                                          | [0.49]    | [0.49]    | [0.50]     | [0.50]    | [0.50]    | [0.50]    |
| High Work Experience                     | 0.62      | 0.65      | 0.59       | 0.69      | 0.70      | 0.68      |
|                                          | [0.49]    | [0.48]    | [0.49]     | [0.46]    | [0.46]    | [0.47]    |
| <u>Characteristics of Applied Job:</u>   |           |           |            |           |           |           |
| Wages                                    | 9299.63   | 9739.56   | 9007.62    | 11317.13  | 11629.00  | 11109.55  |
|                                          | [9820.94] | [6790.33] | [11386.53] | [9523.91] | [8916.48] | [9902.20] |
| With Time Amenity                        | 0.33      | 0.31      | 0.34       | 0.27      | 0.25      | 0.29      |
|                                          | [0.47]    | [0.46]    | [0.47]     | [0.45]    | [0.43]    | [0.45]    |
| With Social Insurance                    | 0.71      | 0.76      | 0.68       | 0.71      | 0.75      | 0.68      |
|                                          | [0.45]    | [0.43]    | [0.47]     | [0.45]    | [0.43]    | [0.47]    |
| <u>Application Intensity / Duration:</u> |           |           |            |           |           |           |
| Weekly Apply ( $Y = 1$ )                 | 0.38      | 0.38      | 0.38       | 0.38      | 0.38      | 0.38      |
|                                          | [0.49]    | [0.49]    | [0.49]     | [0.49]    | [0.48]    | [0.49]    |
| Weekly Application Number                | 2.23      | 2.01      | 2.41       | 2.13      | 1.92      | 2.29      |
|                                          | [5.91]    | [5.10]    | [6.47]     | [5.92]    | [5.48]    | [6.24]    |
| Total Application Number                 | 25.03     | 21.50     | 28.38      | 23.63     | 20.99     | 26.02     |
|                                          | [36.27]   | [32.61]   | [39.15]    | [35.49]   | [33.51]   | [37.04]   |
| Search Duration                          | 11.30     | 10.98     | 11.61      | 11.30     | 11.35     | 11.24     |
|                                          | [13.52]   | [13.60]   | [13.45]    | [13.96]   | [14.20]   | [13.74]   |

*Notes:* This table reports all sample, pre- and post-policy means and standard deviations by gender using employer-side data. Standard deviations are shown in square brackets.

**Table 3: Effects of Maternity Leave Extension on Callback Rates**

|                                                                       | All Applications |          |          | By Applicant Gender |          |
|-----------------------------------------------------------------------|------------------|----------|----------|---------------------|----------|
|                                                                       |                  |          |          | Female              | Male     |
|                                                                       | (1)              | (2)      | (3)      | (4)                 | (5)      |
| <b>Dependent Variable: Give a Positive Reply (<math>Y = 1</math>)</b> |                  |          |          |                     |          |
| $D_{ct} \times \Delta\%ML_c \times \text{Female}$                     | -0.242*          | -0.172** | -0.169** |                     |          |
|                                                                       | (0.132)          | (0.080)  | (0.079)  |                     |          |
| $D_{ct} \times \Delta\%ML_c$                                          |                  |          |          | -0.077***           | 0.054*** |
|                                                                       |                  |          |          | (0.015)             | (0.009)  |
| Female $\times$ Time FE                                               | ✓                | ✓        | ✓        |                     |          |
| Female $\times$ Job City FE                                           | ✓                | ✓        | ✓        |                     |          |
| Job City $\times$ Time FE                                             | ✓                | ✓        | ✓        |                     |          |
| Job Characteristics                                                   | ✓                |          |          |                     |          |
| Job FE                                                                |                  | ✓        | ✓        | ✓                   | ✓        |
| Applicant Characteristics                                             |                  |          | ✓        | ✓                   | ✓        |
| Workday Indicator                                                     | ✓                | ✓        | ✓        | ✓                   | ✓        |
| Time FE                                                               |                  |          |          | ✓                   | ✓        |
| Obs.                                                                  | 328,758          | 331,275  | 331,219  | 164,552             | 167,396  |
| Adjusted $R^2$                                                        | 0.158            | 0.430    | 0.433    | 0.439               | 0.438    |
| Pre-policy Mean                                                       | 0.219            | 0.219    | 0.219    | 0.219               | 0.216    |

*Notes:* All regressions use the applicant-side sample. Job characteristics include the number of openings, industry, firm size, and ownership type. Applicant characteristics include education, work experience, and age. Standard errors, clustered at the city of employment level, are reported in parentheses. The pre-policy means for the DDD estimates correspond to applications from female. \*\*\*  $p < 0.01$ , \*\*  $p < 0.05$ , \*  $p < 0.1$ .

**Table 4: Heterogeneous Effects by Government Coverage of Extension**

| VARIABLES                                  | Govt Cover<br>(1) | No Govt Cover<br>(2) |
|--------------------------------------------|-------------------|----------------------|
| $D_{ct} \times \Delta\%ML_c \times Female$ | -0.139<br>(0.090) | -0.251*<br>(0.128)   |
| Female $\times$ Time FE                    | ✓                 | ✓                    |
| Female $\times$ City of Employment FE      | ✓                 | ✓                    |
| City of Employment $\times$ Time FE        | ✓                 | ✓                    |
| Job FE                                     | ✓                 | ✓                    |
| Applicant Characteristics                  | ✓                 | ✓                    |
| Workday Indicator                          | ✓                 | ✓                    |
| Obs.                                       | 132,942           | 198,192              |
| Adjusted $R^2$                             | 0.434             | 0.430                |
| Pre-policy Mean                            | 0.247             | 0.202                |

*Notes:* This table reports subgroup analyses of the impact of maternity leave extensions on the gender gap in callback rates, defined as the difference between female and male applicants (Female – Male). Column (1) presents estimates for regions where the additional cost of extended leave is covered by local city governments (Zhejiang, Jiangsu, and Shanghai) like national maternity leave, while Column (2) shows results for regions without such coverage (Chongqing, Tianjin, Beijing, Jiangxi, Hubei, Jilin, and Guangxi). The analysis is based on the employer-side sample. Standard errors, clustered at the city of employment level, are reported in parentheses. The pre-policy means for the DDD estimates correspond to applications from female. \*\*\*  $p < 0.01$ , \*\*  $p < 0.05$ , \*  $p < 0.1$ .

**Table 5: Effects of Policy on Job Characteristics and Received Application Counts**

| <b>Panel A: Job Characteristics</b>  |                     |                   |                       |                          |                     |
|--------------------------------------|---------------------|-------------------|-----------------------|--------------------------|---------------------|
| VARIABLES                            | # Positions<br>(1)  | Log Wage<br>(2)   | Time Amenities<br>(3) | Social Insurance<br>(4)  | Edu Req High<br>(5) |
| $D_{ct} \times \Delta\%ML_c$         | -25.096<br>(16.373) | -0.036<br>(0.088) | 0.028<br>(0.090)      | -0.029<br>(0.082)        | -0.038<br>(0.079)   |
| Obs.                                 | 11,248              | 11,248            | 11,248                | 11,248                   | 11,248              |
| Adjusted $R^2$                       | 0.002               | 0.104             | 0.009                 | 0.016                    | 0.037               |
| Pre-policy Mean                      | 9.177               | 9.084             | 0.283                 | 0.708                    | 0.326               |
| <b>Panel B: Application Received</b> |                     |                   |                       |                          |                     |
| VARIABLES                            | Total Num<br>(1)    | Female Num<br>(2) | Weekly Num<br>(3)     | Weekly Female Num<br>(4) |                     |
| $D_{ct} \times \Delta\%ML_c$         | 7.820<br>(9.836)    | -4.071<br>(6.791) | -0.214<br>(0.630)     | -0.167<br>(0.220)        |                     |
| Obs.                                 | 11,248              | 11,248            | 219,614               | 219,614                  |                     |
| Adjusted $R^2$                       | 0.018               | 0.009             | 0.327                 | 0.295                    |                     |
| Pre-policy Mean                      | 22.770              | 11.310            | 1.480                 | 0.728                    |                     |

Notes: Each column reports estimates for a separate dependent variable. All regressions use the employer-side sample. Panel A examines the effects on posted job characteristics, including wages, benefits, and qualification requirements. Panel B presents results on application volumes, including female-specific counts. For regressions in Panel A and the total application counts in Panel B, the unit of observation is the job posting. These regressions include city of employment and calendar-week fixed effects. For regressions on weekly application volumes, the unit of observation is a job-week, and the specification includes job and calendar-week fixed effects. Standard errors, clustered at the city of employment level, are reported in parentheses. \*\*\* $p < 0.01$ , \*\* $p < 0.05$ , \* $p < 0.1$ .

**Table 6: Effects of Extension on Characteristics of Applied Job**

| <b>Panel A: All Applicants</b>                    |                      |                   |                   |                  |                  |                  |
|---------------------------------------------------|----------------------|-------------------|-------------------|------------------|------------------|------------------|
| VARIABLES                                         | Log(Wage)            | Time Amenities    | Social Insurance  |                  |                  |                  |
|                                                   | (1)                  | (2)               | (3)               |                  |                  |                  |
| $D_{ct} \times \Delta\%ML_c \times \text{Female}$ | -0.234***<br>(0.074) | 0.170*<br>(0.089) | -0.050<br>(0.100) |                  |                  |                  |
| Obs.                                              | 293,221              | 293,222           | 293,222           |                  |                  |                  |
| Adjusted $R^2$                                    | 0.613                | 0.052             | 0.090             |                  |                  |                  |
| Pre-policy Mean                                   | 9.033                | 0.309             | 0.755             |                  |                  |                  |
| <b>Panel B: By Applicant Gender</b>               |                      |                   |                   |                  |                  |                  |
| VARIABLES                                         | Female               |                   |                   | Male             |                  |                  |
|                                                   | Log(Wage)            | Time Amenities    | Social Insurance  | Log(Wage)        | Time Amenities   | Social Insurance |
|                                                   | (1)                  | (2)               | (3)               | (4)              | (5)              | (6)              |
| $D_{ct} \times \Delta\%ML_c$                      | -0.126**<br>(0.055)  | 0.103*<br>(0.059) | -0.016<br>(0.075) | 0.008<br>(0.065) | 0.025<br>(0.047) | 0.083<br>(0.054) |
| Obs.                                              | 149,885              | 149,885           | 149,885           | 143,838          | 143,839          | 143,839          |
| Adjusted $R^2$                                    | 0.604                | 0.038             | 0.089             | 0.589            | 0.066            | 0.090            |
| Pre-policy Mean                                   | 9.033                | 0.309             | 0.755             | 9.197            | 0.252            | 0.754            |

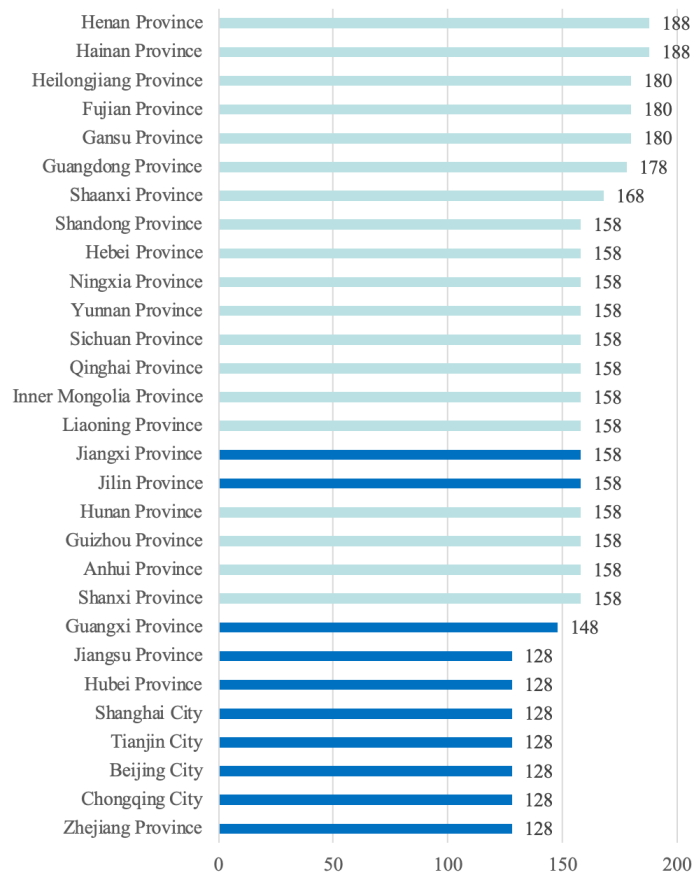
*Notes:* This table reports regression results on characteristics of applied jobs using applicant-side data. The dependent variables are the log wage of applied jobs, and binary indicators for whether the applied job offers time amenity or social insurance benefits. Panel A is estimated by Equation 5, controlling for individual fixed effects, female-by-calendar week fixed effects, and city-by-calendar week fixed effects. Panel B presents separate regressions for female and male applicants, controlling for individual and calendar week fixed effects. Standard errors, clustered at the city of residence level, are reported in parentheses. The pre-policy means for the DDD estimates correspond to female applicants. \*\*\* $p < 0.01$ , \*\* $p < 0.05$ , \* $p < 0.1$ .

**Table 7: Effects of Extension on Applicant Job Search Behavior**

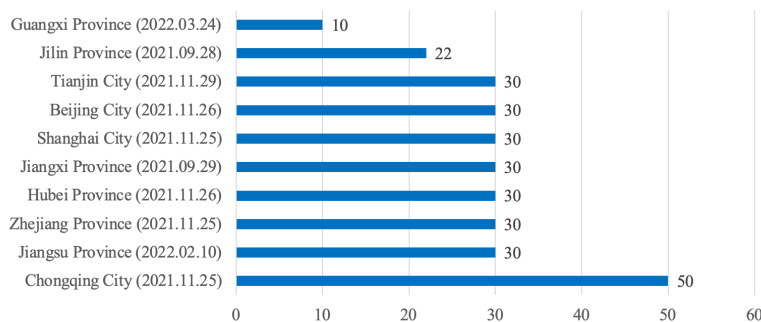
| VARIABLES                    | Weekly Apply ( $Y = 1$ ) |                   | # Weekly Application |                   | # Total Application  |                  | Search Duration     |                  |
|------------------------------|--------------------------|-------------------|----------------------|-------------------|----------------------|------------------|---------------------|------------------|
|                              | Female                   | Male              | Female               | Male              | Female               | Male             | Female              | Male             |
|                              | (1)                      | (2)               | (3)                  | (4)               | (5)                  | (6)              | (7)                 | (8)              |
| $D_{ct} \times \Delta\%ML_c$ | -0.025<br>(0.086)        | -0.022<br>(0.084) | -0.376<br>(0.726)    | -0.376<br>(0.726) | 20.016***<br>(6.262) | 8.417<br>(8.281) | 9.566***<br>(3.123) | 5.536<br>(3.439) |
| Obs.                         | 67,745                   | 68,312            | 68,312               | 68,312            | 5,892                | 6,031            | 5,892               | 6,031            |
| Adjusted $R^2$               | 0.051                    | 0.050             | 0.096                | 0.096             | 0.072                | 0.077            | 0.252               | 0.257            |
| Pre-policy Mean              | 0.380                    | 0.376             | 2.005                | 1.915             | 21.500               | 20.990           | 10.976              | 11.351           |

*Notes:* This table presents the effects on applicant job search behavior using applicant-side data. Outcome variables include: (1) the weekly probability of submitting an application; (2) the number of applications submitted per week; (3) the total number of applications submitted; and (4) total search duration, measured in weeks. For regressions on weekly application behavior, the unit of observation is a applicant-week, and we include individual fixed effects and calendar week fixed effects. For regressions on total applications and search duration, the unit of observation is the applicant. We include city and calendar week fixed effects, and control for applicant characteristics using education-by-age-by-experience fixed effects. Standard errors, clustered at the city of residence level, are reported in parentheses. \*\*\* $p < 0.01$ , \*\* $p < 0.05$ , \* $p < 0.1$ .

# Figures



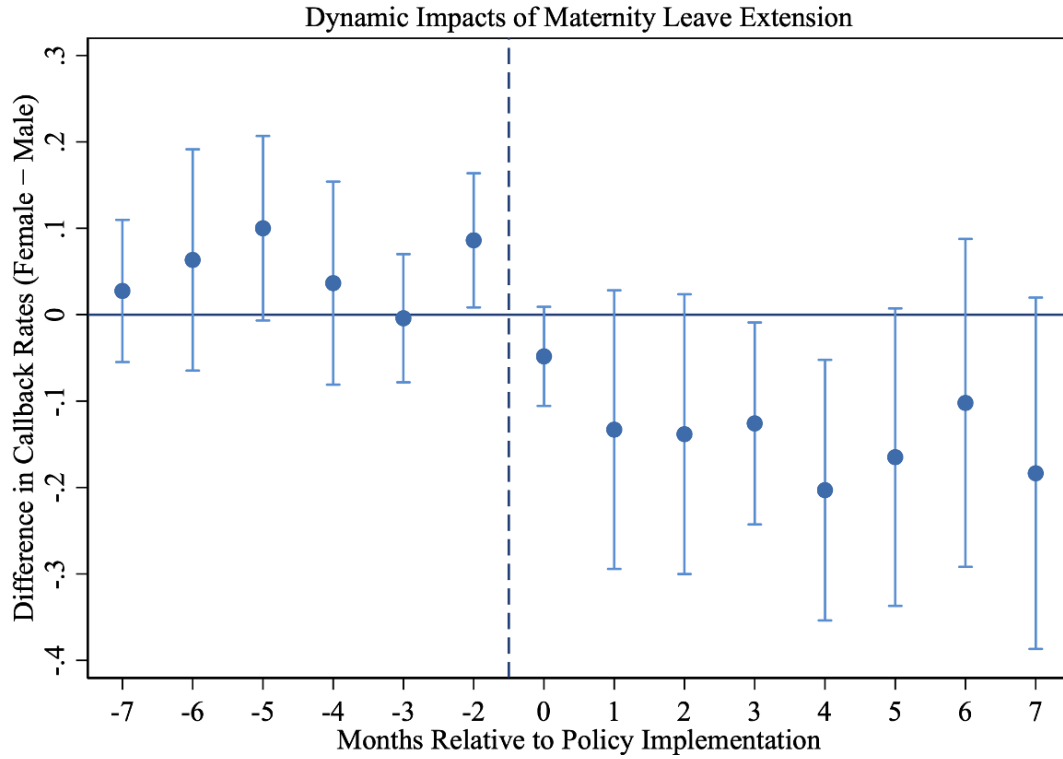
(a) Maternity leave days on 2021/01/01



(b) Extended maternity leave days during 2021-2022

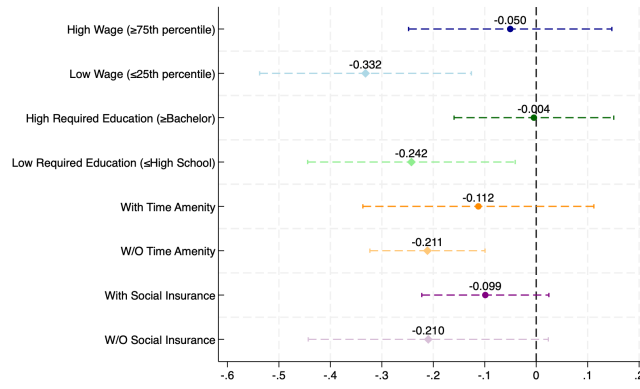
**Figure 1: Maternity Leave Days in China**

*Notes:* The figures refer to the maximum duration of maternity leave for a first birth. Panel (a) presents maternity leave entitlements across provinces and municipalities as of January 1, 2021. Panel (b) displays the number of additional leave days granted during 2021–2023. Dates in parentheses indicate when the extensions were implemented.

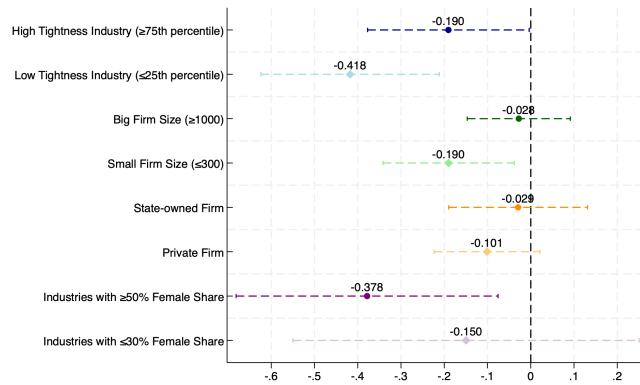


**Figure 2: Dynamic Impact of Extension on Gender Gap in Callback Rates**

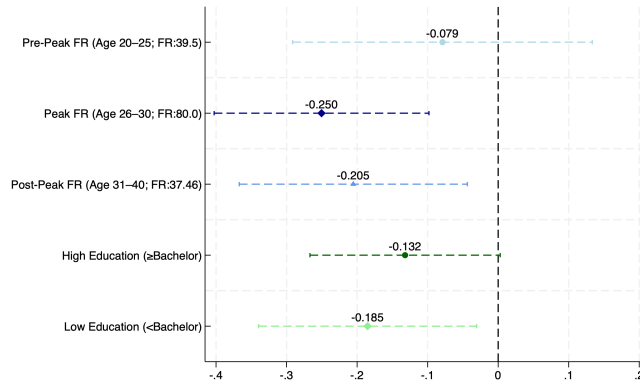
*Notes:* This event-study plot illustrates the dynamic effects of maternity leave extensions on the gender gap in job callbacks (Female – Male), estimated using Equation 4. Estimates are based on employer-side data, and all coefficients are relative to the month before implementation. The vertical line indicates one month before the policy took effect. The regression controls for city-by-calendar week, gender-by-calendar week, gender-by-city, and job fixed effects, as well as applicant characteristics and workday status. Standard errors, clustered at the city of employment level. Shaded bands represent 90% confidence intervals.



(a) By Job Type



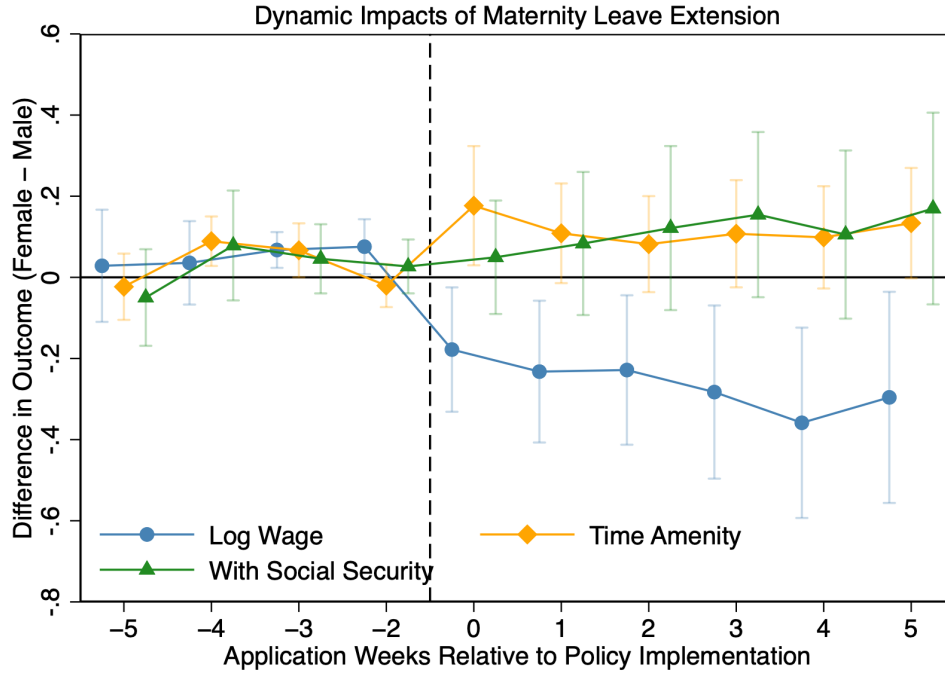
(b) By Firm/Industry Type



(c) By Applicant Type

### Figure 3: Heterogeneous Effects of Maternity Leave Extension

*Notes:* This figure presents subgroup analyses of the effects of maternity leave extensions on the gender gap in job callbacks (Female – Male). Panel (a) reports heterogeneous effects by job type; Panel (b) examines heterogeneity by firm and industry characteristics; and Panel (c) explores differences across applicant characteristics. Regressions control for city-by-week, gender-by-week, gender-by-city, and job fixed effects, as well as applicant-level characteristics and workday status. Standard errors, clustered at the city of employment level. All estimates are accompanied by 90% confidence intervals.



**Figure 4: Dynamic Effects of Extension on Job Characteristics of Applied Positions**

*Notes:* This figure presents dynamic estimates of the gender gap (Female – Male) in the characteristics of jobs applied. Estimates are based on Equation 7, using applicant-side data. The regression includes individual fixed effects, female-by-calendar week fixed effects, and city-by-calendar week fixed effects. The vertical line marks the the last week of application activity prior to the policy. The horizontal axis represents event time, defined as the number of application weeks relative to policy. Coefficients represent effects relative to the last application week before policy. Shaded areas indicate 90% confidence intervals. Standard errors, clustered at the city of residence level.

# Appendix

**Table A1: Robustness: Control for Concurrent Policies and COVID-19**

| VARIABLES                                         | Other Leave Controls<br>(1) | COVID Controls<br>(2) | Post-Three Child<br>(3) |
|---------------------------------------------------|-----------------------------|-----------------------|-------------------------|
| $D_{ct} \times \Delta\%ML_c \times \text{Female}$ | -0.236***<br>(0.053)        | -0.132**<br>(0.061)   | -0.176**<br>(0.084)     |
| $\text{Paternal}_{ct}/100 \times \text{Female}$   | -0.088<br>(0.155)           |                       |                         |
| $\text{Childcare}_{ct}/100 \times \text{Female}$  | 0.307<br>(0.190)            |                       |                         |
| # Cases (k) $\times$ Female                       |                             | -0.002<br>(0.002)     |                         |
| # New Infections (k) $\times$ Female              |                             | 0.000<br>(0.000)      |                         |
| Obs.                                              | 331,219                     | 304,497               | 283,377                 |
| Adjusted $R^2$                                    | 0.433                       | 0.433                 | 0.440                   |
| Pre-policy Mean                                   | 0.219                       | 0.219                 | 0.240                   |

*Notes:* Column (1) controls for changes in paternity and childcare leave, interacted with a female dummy. Column (2) includes province-week-level COVID-19 measures—newly confirmed and active cases at the province-week level—interacted with the female dummy. Column (3) restricts the sample to the post-2021.05.31 period to account for the potential influence of the nationwide Three-Child Policy. All specifications include city-by-calendar week, gender-by-calendar week, gender-by-city, and job fixed effects, as well as applicant characteristics and workday status. Standard errors, clustered at the city of employment level, are reported in parentheses. \*\*\* $p < 0.01$ , \*\* $p < 0.05$ , \* $p < 0.1$ .

**Table A2: Effects of Paternal and Childcare Leave Extensions on Callback Rates**

| VARIABLES                                                              | Paternal Leave Extension<br>(1) | Childcare Leave Extension<br>(2) |
|------------------------------------------------------------------------|---------------------------------|----------------------------------|
| $D_{ct} \times (\Delta \text{Paternal}_c / 100) \times \text{Female}$  | -0.022<br>(0.220)               |                                  |
| $D_{ct} \times (\Delta \text{Childcare}_c / 100) \times \text{Female}$ |                                 | 0.031<br>(0.076)                 |
| Obs.                                                                   | 107,840                         | 507,371                          |
| Adjusted $R^2$                                                         | 0.427                           | 0.428                            |
| Pre-policy Mean                                                        | 0.315                           | 0.291                            |

*Notes:* This table examines whether extensions of paternal or childcare leave have differential effects on female applicants' callback rates relative to those of male applicants. Column (1) restricts the sample to provinces that extended paternity leave during 2021–2022 but did not implement maternity leave extensions. Column (2) includes provinces that only implemented childcare leave extensions. All specifications include city-by-calendar week, gender-by-calendar week, gender-by-city, and job fixed effects, as well as applicant characteristics and workday status. Standard errors, clustered at the city of employment level, are reported in parentheses. \*\*\* $p < 0.01$ , \*\* $p < 0.05$ , \* $p < 0.1$ .

**Table A3: Robustness: Alternative Sample Restrictions**

| VARIABLES                                         | No Extension<br>Provinces<br>(1)       | Jobs Restriction<br>(2)                                                | Age 45+ Female<br>(3)    | Age 45+ Male<br>(4)    |
|---------------------------------------------------|----------------------------------------|------------------------------------------------------------------------|--------------------------|------------------------|
| $D_{ct} \times \Delta\%ML_c \times \text{Female}$ | -0.067**<br>(0.027)                    | -0.177**<br>(0.086)                                                    |                          |                        |
| $D_{ct} \times \Delta\%ML_c$                      |                                        |                                                                        | 0.137<br>(0.115)         | -0.073<br>(0.059)      |
| Sample Restriction                                | Treated +<br>No Extension<br>Provinces | Jobs with<br>>10 Applications<br>and <30 Vacancies<br>in Treated Prov. | 45+ Female<br>in Treated | 45+ Male<br>in Treated |
| Obs.                                              | 838,654                                | 304,903                                                                | 5,339                    | 18,510                 |
| Adjusted $R^2$                                    | 0.431                                  | 0.422                                                                  | 0.531                    | 0.462                  |
| Pre-policy Mean                                   | 0.294                                  | 0.205                                                                  | 0.089                    | 0.126                  |

*Notes:* This table presents robustness checks under alternative sample definitions. Column (1) uses provinces without maternity leave extensions during 2021–2022 as control. Column (2) restricts to jobs that receive more than 10 applications and advertise fewer than 30 vacancies to mitigate extreme callback rate outliers. Columns (3)–(4) restrict the sample to individuals aged 45 or older. Column (3) is limited to females, and Column (4) to males. All specifications include city-by-calendar week, gender-by-calendar week, gender-by-city, and job fixed effects, as well as applicant characteristics and workday status. Standard errors, clustered at the city of employment level, are reported in parentheses. \*\*\* $p < 0.01$ , \*\* $p < 0.05$ , \* $p < 0.1$ .

**Table A4: Robustness: Alternative Policy Intensity and Time Controls**

| VARIABLES                                                | Use Extension Days<br>(1) | Use Lunar Date FE<br>(2) |
|----------------------------------------------------------|---------------------------|--------------------------|
| $D_{ct} \times (\Delta ML_c / 100) \times \text{Female}$ | -0.130**<br>(0.062)       |                          |
| $D_{ct} \times \Delta \% ML_c \times \text{Female}$      |                           | -0.165**<br>(0.079)      |
| Obs.                                                     | 331,219                   | 331,197                  |
| Adjusted $R^2$                                           | 0.433                     | 0.433                    |
| Pre-policy Mean                                          | 0.219                     | 0.219                    |

*Notes:* This table reports robustness checks under alternative regression specifications. Column (1) replaces the baseline policy intensity variable with the number of extended maternity leave days (in hundreds). Column (2) replaces the calendar week with lunar calendar week in time-related fixed effects. All specifications include city-by-week, gender-by-week, gender-by-city, and job fixed effects, as well as applicant characteristics and workday status. Standard errors, clustered at the city of employment level, are reported in parentheses.

\*\*\* $p < 0.01$ , \*\* $p < 0.05$ , \* $p < 0.1$ .

**Table A5: Heterogenous: Interaction with Fertility Probability**

| VARIABLES                                  | Interaction Model<br>(1) |
|--------------------------------------------|--------------------------|
| $D_{ct} \times \Delta \% ML_c \times FP_i$ | -0.565*<br>(0.329)       |
| $D_{ct} \times \Delta \% ML_c$             | 0.117<br>(0.158)         |
| Obs.                                       | 21,757                   |
| Adjusted $R^2$                             | 0.473                    |
| Pre-policy Mean                            | 0.190                    |

*Notes:* This table reports estimates from an interaction specification examining whether the effect of maternity leave extensions on callback rates varies with fertility probability ( $FP_i$ ). The fertility probability is constructed at the city–education–age level and represents the predicted probability of childbirth within the next three years. The regression sample includes only applications from female applicants with a bachelor’s degree and less than one year of work experience. All regressions control for fertility probability, time fixed effects, job fixed effects, applicant-level characteristics, and workday status. Standard errors, clustered at the city of employment level, are reported in parentheses. \*\*\* $p < 0.01$ , \*\* $p < 0.05$ , \* $p < 0.1$ .

**Table A6: Effects of Extension on Characteristics of Applied Job: Alternative Controls**

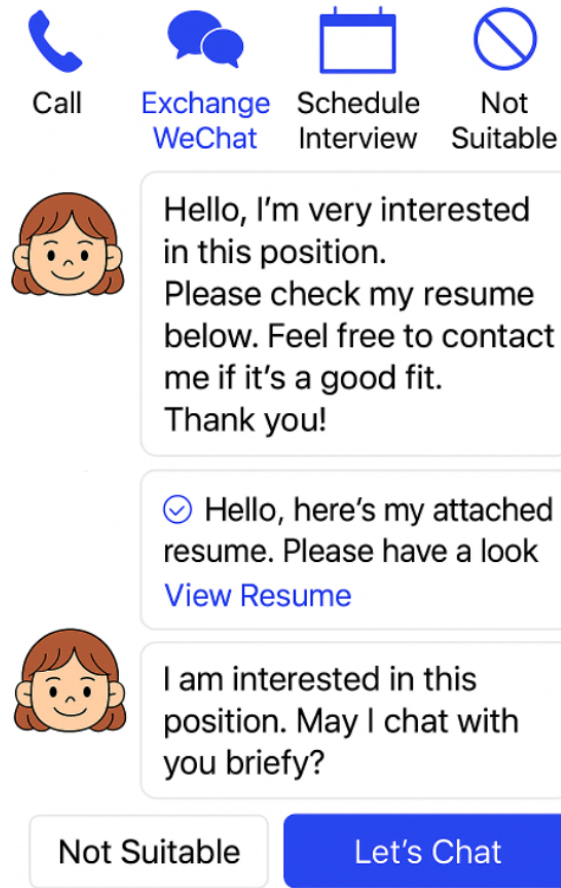
| VARIABLES                                            | Log Wage             |                      |                      |                      | Time Amenity         |
|------------------------------------------------------|----------------------|----------------------|----------------------|----------------------|----------------------|
|                                                      | (1)                  | (2)                  | (3)                  | (4)                  | (5)                  |
| $D_{ct} \times \Delta\%ML_{ct} \times \text{Female}$ | -0.234***<br>(0.074) | -0.242***<br>(0.074) | -0.228***<br>(0.072) | -0.236***<br>(0.071) | 0.163*<br>(0.089)    |
| Time Amenity                                         |                      |                      | -0.020***<br>(0.002) | -0.020***<br>(0.002) |                      |
| Social Insurance                                     |                      |                      | 0.043***<br>(0.005)  | 0.043***<br>(0.005)  |                      |
| Log Wage                                             |                      |                      |                      |                      | -0.027***<br>(0.003) |
| Search Day FE                                        | No                   | Yes                  | No                   | Yes                  | No                   |
| Obs.                                                 | 293,221              | 293,207              | 293,221              | 293,207              | 293,221              |
| Adjusted $R^2$                                       | 0.613                | 0.613                | 0.614                | 0.614                | 0.053                |
| Pre-policy Mean                                      | 9.033                | 9.033                | 9.033                | 9.033                | 0.309                |

*Notes:* This table reports regression results based on applicant-side data. The dependent variables include the log wage and whether the applied jobs offer time amenity. Search day is the length of time (in days) since the applicant began their first job search. All regressions control for individual fixed effects, female-by-calendar week fixed effects, and city-by-calendar week fixed effects. Standard errors, clustered at the city of residence level, are reported in parentheses. \*\*\* $p < 0.01$ , \*\* $p < 0.05$ , \* $p < 0.1$ .

**Table A7: Relationship Between Job Search Length and Log Wage**

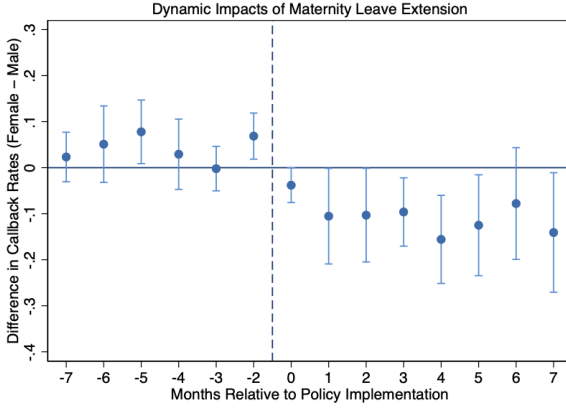
| VARIABLES                            | Log Wage              |                   |                      |
|--------------------------------------|-----------------------|-------------------|----------------------|
|                                      | All Applicants<br>(1) | Female<br>(2)     | Male<br>(3)          |
| Search Length (10 days)              | -0.011**<br>(0.004)   | -0.008<br>(0.008) | -0.014***<br>(0.005) |
| Search Length (10 days) <sup>2</sup> | 0.004***<br>(0.001)   | 0.002<br>(0.002)  | 0.005***<br>(0.001)  |
| Obs.                                 | 293,709               | 149,876           | 143,833              |
| Adjusted $R^2$                       | 0.609                 | 0.603             | 0.588                |
| Pre-policy Mean                      | 9.081                 | 9.081             | 9.081                |

*Notes:* This table reports the relationship between applicants' search length (in tens) and the wage of applied jobs, based on applicant-side data. Search length is the length of time (in days) since the applicant began their first job search. All regressions include individual fixed effects. Standard errors, clustered at the city of residence level, are reported in parentheses. \*\*\* $p < 0.01$ , \*\* $p < 0.05$ , \* $p < 0.1$ .

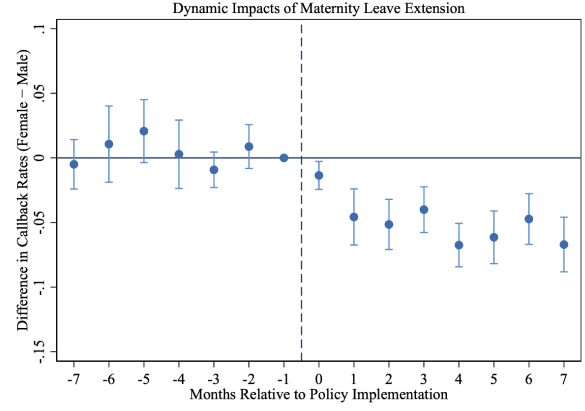


**Figure A1: Example of Employer-side Chat Interface on Platform**

*Note:* This figure displays the employer-side chat interface on the job platform (translated into English). A response is classified as positive if the employer takes any of the following actions: (1) initiates a phone call; (2) exchanges WeChat accounts (a widely used messaging app in China); (3) schedules an interview; or (4) replies “Let’s chat” in response to an applicant’s message expressing interest in the position.



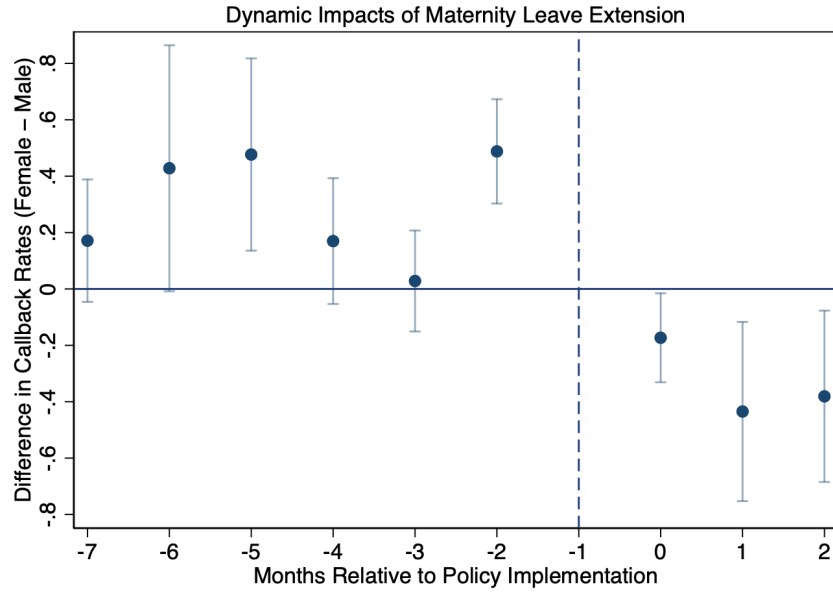
(a) Interact with the additional days



(b) W/O intensity

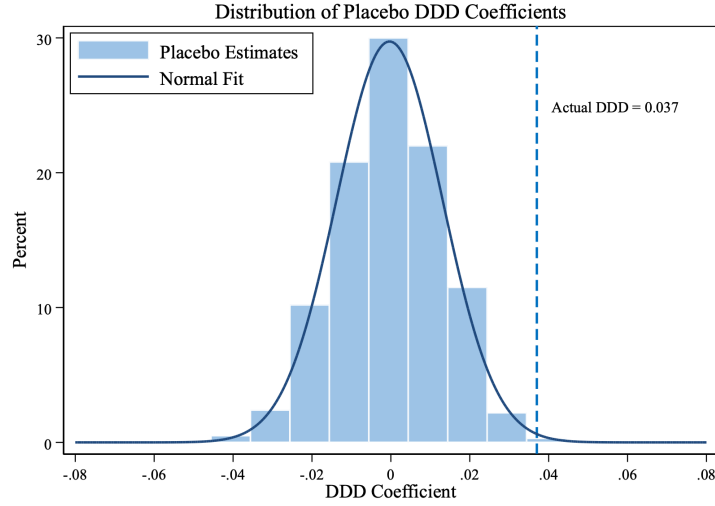
**Figure A2: Robustness: Alternative Definitions of Policy Intensity**

*Notes:* This figure compares dynamic treatment effects using two definitions of policy strength: (a) an interaction with the number of extended leave days, and (b) a binary indicator for any extension (without intensity). In figure (b), we restrict the sample to provinces that initially offered 128 days of leave and later extended it uniformly by 30 days, ensuring a consistent policy shock intensity across regions. All specifications include city-by-calendar week, gender-by-calendar week, gender-by-city, and job fixed effects, as well as applicant characteristics and workday status. Standard errors clustered at the city of employment level. All estimates are derived from employer-level data with 90% confidence intervals shown.



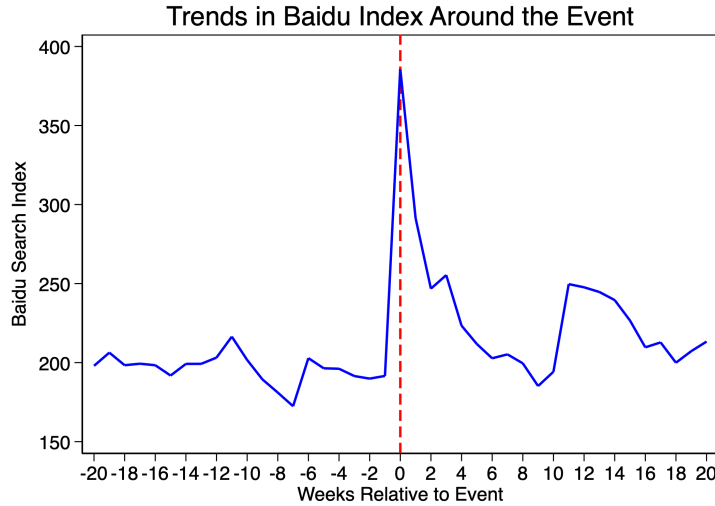
**Figure A3: Event-Study Estimates Using Sun & Abraham (2020) Estimator**

*Notes:* This plot shows dynamic treatment effects estimated using the Sun & Abraham (2020) method. Specifically, we restrict the sample to observations before February 2022 and designate Jiangsu (policy implemented on February 10, 2022) and Guangxi (March 24, 2022) as the never-treated control group. Regressions include city-by-calendar week, gender-by-calendar week, gender-by-city, and job fixed effects, as well as applicant characteristics and workday status. Standard errors clustered at the city of employment level. All estimates are accompanied by 90% confidence intervals.



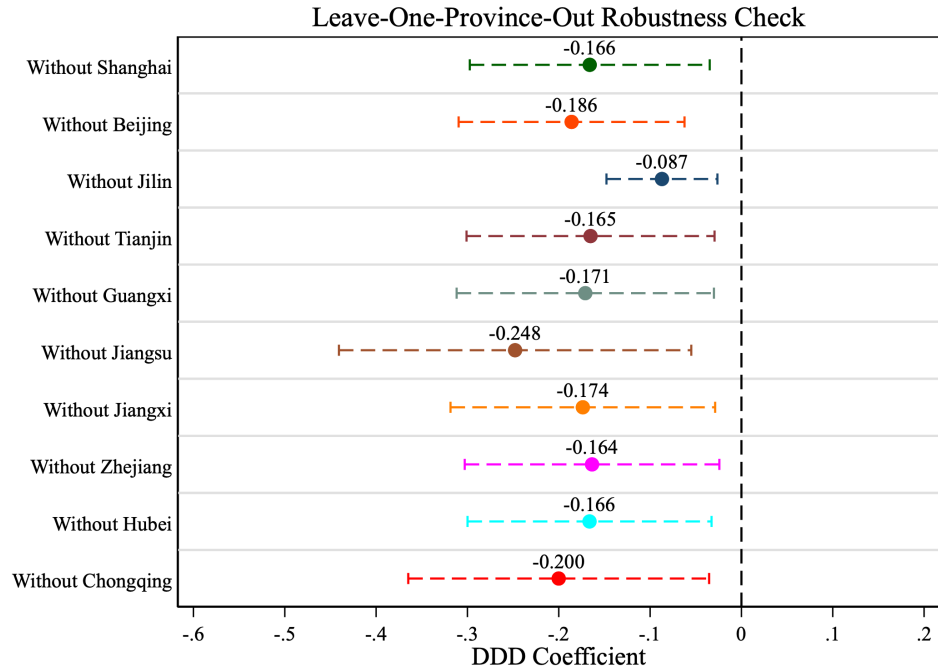
**Figure A4: Placebo Test via Randomized Policy Time Simulation**

*Notes:* This histogram shows the distribution of estimated policy effects from 1,000 placebo tests. In each simulation, a randomly selected untreated province is assigned a pseudo-treatment month, and dynamic coefficients are re-estimated by Equation 1.



**Figure A5: Baidu Search Index for “Maternity Leave” Around Policy Shock**

*Notes:* This figure plots the average Baidu Search Index for the term “maternity leave” across treated provinces from 20 weeks before to 20 weeks after the policy announcement. The vertical line represents the week of official policy issuance.



**Figure A6: Leave-One-Out Robustness of Dynamic Policy Effects**

*Notes:* This plot presents dynamic estimates where one treated province is excluded at a time. Regressions control for city-by-week, gender-by-week, gender-by-city, and job fixed effects, as well as applicant-level characteristics and workday status. Standard errors are clustered at the city of employment level. Shaded areas represent 90% confidence intervals. All estimates are accompanied by 90% confidence intervals.