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

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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. In response, female job seekers submitted 4.4 more job applications, shifted toward jobs with 5.4% lower wages, and experienced 0.9 weeks longer job search duration than male applicants. We also find that subsidies to firms help alleviate the adverse impact of maternity leave extensions on gender disparities in hiring and earnings. Our findings reveal that gender-specific family policies can unintentionally weaken female job prospects and widen gender gaps in the labor market, while cost sharing between firms and the government plays a positive role.

Keywords: Maternity leave; Family policies; gender inequality; Labor market; Job applications; Search duration; Callback rates.

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

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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. Therefore, it is unclear whether observed labor market patterns affected by maternity policy–such as lower female labor force participation–stem from supply-side choices (e.g., reduced willingness to work) or demand-side constraints (e.g., hiring discrimination), making 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 come from `Zhaopin.com`, one of China's largest online job boards. 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, ten 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 maternity leave duration reduces callback rates to female applicants by 1.7 percentage points relative to comparable male applicants; this estimate implies that, at the observed average policy shock intensity, i.e., a 22% increase in maternity leave duration, female job seekers of child-bearing age experienced an average decline of 3.7 percentage points in callbacks, which represents a 17% reduction of the baseline 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 is mainly driven by a decline in women's callback rates, while those for men remain largely unchanged. Event-study estimates reveal no evidence of pre-existing 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 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, government subsidies for extended leave wages can partially mitigate employers' discriminatory responses toward female applicants, highlighting the importance of shifting the financial burden from firms to the public sector. Similarly, jobs that offer social insurance—which entails greater government contribution—are associated with smaller reductions in female callback rates. 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 lower time demands, such as those offering time-related amenities like "weekends off" or "no overtime," also show milder effects on gender gap, likely due to reduced expected costs of leave. Fourth, firms and industries with higher search frictions, as 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. Fifth, the greatest negative effects occur among women of peak fertility age, aligning with employers' perceived higher risk of leave-taking. 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. Likewise, 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 applications received.

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 and extend their job search by 0.9 weeks, calculated at the average intensity of the policy shock, whereas men show no comparable 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; Zveglich 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).[1] 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).[2] 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 analyses that provide deeper insight into the mechanisms underlying the decline in callback

[1] 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.

[2] 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.

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), particularly discrimination driven by family-related responsibilities (He et al., 2023).[3] While He et al. (2023) examine the effects of lifting of 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. This suggests 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.

[3] 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.

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.[4] As shown in Figure 1(a), most provinces provide a total of 158 days.[5] 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.[6] 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%.[7]

[Insert Figure 1 about here]

2.2 Costs Faced by Firms for Paid Leave

Compared to other countries, the maternity leave in China is characterized by full pay and long paid duration, which can place a greater financial burden on employers.[8] Firms face two primary costs associated with maternity leave. The first is the wages for employees

[4] 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.

[5] 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.

[6] 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.

[7] 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.

[8] 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.

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.[9] Firms that do not participate in the maternity insurance scheme must fully cover the employee's salary during leave.[10]

For province-level maternity leave extensions ranging from 30 to 90 days, wage payment policies vary across local governments. Before January 1, 2021, provinces such as Fujian, Guangdong, Guangxi, Heilongjiang, Shanxi, Shaanxi, Sichuan, and Inner Mongolia had not issued any official documents specifying that the government would cover wage payments during the province-level leave period. In such cases, the cost was typically assumed to be borne by employers. In contrast, other provinces stated that the government would assume responsibility for these payments under the same conditions as for national maternity leave. Between 2021 and 2022, among the regions that extended province-level maternity leave , only Shanghai, Zhejiang, and Jiangsu issued official documents confirming that the additional wage costs during the extended period would be covered by the maternity insurance fund, similar to the national leave. Other regions that extended leave during this period did not announce any such subsidy.

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 co-workers, 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 to female applicants, particularly those of prime childbearing age, in order to mitigate the financial risks associated with extended maternity leave.

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 announce-

[9] If an employee's pre-leave salary is below this average, she will receive the average wage.

[10] As we show in Section 3, about 66% of the firms in our sample provide social insurance benefits that include maternity insurance.

ment and were specified in official policy documents, which often included other family and fertility support measures. The announcements were usually sudden and unanticipated.[11]

All changes were implemented at the provincial level, each of which issued its own policy.[12] 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.[13] 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.[14] That is, the 10 regions shown in Figure 1(b).

Given the variation in both the baseline leave duration and the length of extensions across provinces, we use the ratio of additional days (ΔML_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 alternative measures of policy intensity in Section 5.3, including binary indicators

[11]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.

[12]For expositional simplicity, we also refer to the four provincial-level municipalities, Beijing, Shanghai, Tianjin and Chongqing, as provinces.

[13]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.

[14]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.

and 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 `Zhaopin.com`, one of the largest online recruitment platforms in China, covering the period from January 1, 2021, to December 31, 2022. `Zhaopin` represents approximately 30% of the China online recruitment market, with over 230 million active individual users and around 6 million registered firms. The platform has been widely used in academic research, including by Kuhn and Shen (2013) and Fang et al. (2020). It spans nearly all industries, a broad range of regional economic conditions, and job seekers with diverse levels of human capital, allowing for rich heterogeneity analyses. Nonetheless, as noted by Kuhn and Shen (2013), online job postings tend to attract young, 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 indicators, 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, linking information on 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 reply 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 `Zhaopin.com` data, 80% of 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 20,000 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 most likely to be affected by maternity leave policies, and also accounts for 90% of all job seekers on the platform.[15] 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.[16]

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. Notably, as 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

[15] This statistic is obtained from the applicant-side sample.

[16] 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 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 $ML_{c,2021}$:

$$\Delta\%ML_c = \frac{\Delta ML_c}{ML_{c,2021}}. \tag{2}$$

The coefficient β 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: δ_{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., 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 δ_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.[17] 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 job-city level to account for within-city correlation in policy enforcement and employer responses.

[17] 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.

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 $g \in \{female, male\}$:

$$Y^g_{ijct} = \alpha^g + \gamma^g D_{ct} \times \Delta\%ML_c + \delta^g_t + \delta^g_j + X^g_i + Workday^g_t + \varepsilon^g_{ijct}, \tag{3}$$

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

We include time fixed effects δ^g_t to absorb time-varying shocks, and job fixed effects δ^g_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. Similarly to Equation 1 we control for applicant-level characteristics X^g_i and $Workday^g_t$. Standard errors are also clustered at the job-city 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:

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

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 θ_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 to Equation 1 settings.[18] Standard errors are, again, clustered at the job-city level.

[18] The $\delta_{female*t}$ in Equation 4 is female-by-calendar year fixed effect.

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:

$$Y_{ijct} = \alpha + \kappa D_{ct} \times \Delta\% ML_c \times \mathit{Female}_i + \delta_{c*t} + \delta_{\mathit{female}*t} + \delta_i + \varepsilon_{ijct}, \tag{5}$$

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 here is the residence city of the applicant. The key coefficient of interest, κ, 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 (δ_{c*t}), gender-by-week fixed effects ($\delta_{\mathit{female}*t}$), and individual fixed effects (δ_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 the applicant's city of residence.

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

$$Y^g_{ijct} = \alpha^g + \kappa^g D_{ct} \times \Delta\% ML_c + \delta^g_t + \delta^g_i + \varepsilon^g_{ijct}, \tag{6}$$

where the coefficient κ^g captures the treatment effect on the application behavior for applicants of gender g.

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 application is approximately 6 weeks. 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:

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

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 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 additionally control for job characteristics, including the number of openings, industry, firm size, and ownership type, allowing comparisons across similar types of jobs. Column (2) includes job fixed effects, which absorb unobserved, time-invariant job-level heterogeneity, such as the HR response speed. 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 callbacks is primarily driven by a decrease in callback rates to females, while callback rates to males remain largely unaffected.

[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 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 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 province 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 from national fertility policy, we account for the implementation of China's "three-child policy."[19] 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 in time-related fixed effects. This adjustment helps mitigate confounding from holiday effects, especially around the Spring Festival, which may influence employer behavior. As reported in Table A4, our key results remain stable across 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.[20] In all alternative specifications, the estimated effects remain consistent, reinforcing the credibility 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 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.

[19] This policy is officially announced on May 31, 2021. This policy permits each couple to have up to three children and was uniformly adopted nationwide.

[20] 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.

Anticipation Effects. To test for policy anticipation, we examine public search behavior around the policy period, which is measured by the Baidu Search Index.[21] 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 no single province drives the main results.

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 whether the government's financial responsibility for extended maternity leave influences employer behavior. 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 Subsidy for Extended Leave Wages. As stated in Section 2.2, among the ten regions that extended maternity leave, only Shanghai, Zhejiang, and Jiangsu issued official document stating that the additional wage costs during the extended leave period would be covered by maternity insurance fund like national maternity leave. In contrast, the other regions did not announce any such subsidy. This institutional variation enables us to test whether shifting the financial burden of maternity leave from firms to the public sector alters employers' hiring responses. Specifically, we divide the sample into "cover" and "no-cover" groups based on whether the local government subsidizes the wage costs for the extension. Using the same specification as in Equation 1, we estimate the model separately for each group. As shown in Table 4, regions without government subsidy exhibit nearly twice the increase in gender gaps in callback rates compared to subsidized regions. The effect is statistically significant in the "no-cover" group but not in the "cover" group. These

[21] Baidu is the largest search engine in China. The Baidu Search Index, similar to Google Trends, captures time series data on search frequencies for different terms.

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 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 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. 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. As shown in Panel (c) of Figure 3, women in the peak fertility age group experience the largest relative decrease in the probability of receiving callbacks compared to men of the same age, likely reflecting employers' perceived higher risk of imminent maternity leave by female job seekers in this group.

Highly educated women, by contrast, 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.

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 attractive to and suitable for women.

Second, callback rates may decline if the total number of applications per job increases, particularly from female applicants, while the number of available positions remains fixed. 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 first posted after the policy implementation. These regressions control for city and calendar week 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 if the corresponding week occurs 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 witnessed a 5.4% reduction in the wage level of the jobs applied compared to their male counterparts. 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.[22] A third possible explanation is that extended

[22]Table A6 shows the relationship between the duration of the search 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

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 the duration of the job search and the characteristics of the job, specifically the presence of time-related amenities and social insurance, in Appendix Table A5. The estimated coefficients change negligibly under these alternative specifications, suggesting that neither changes in preferences nor longer search durations can fully 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 A5).

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 do not exhibit significant shifts in job search behavior in any dimension.

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]

search. 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 and calendar week fixed effects, as well as (education by age by experience fixed effects). Given that our sample consists of randomly selected applicants for each calendar year, some individuals may have initiated a job search in the previous year or continued into the next. In such cases, the calculated duration of the job search may be censored. To address this issue, we drop applicants who submitted any application before week 9 or after week 44 of the calendar year. The choice of week 9 is based on the 90th percentile of within-applicant search gaps, indicating that 90% of the job seekers in our selected sample begin their search within the calendar year.

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 policyy intensity of 22%, women submit approximately 4.4 additional applications and extend their search by 0.9 weeks. 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 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 should 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.

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Tables

Table 1: Summary Statistics: Employer Sample

	All (1)	Pre (2)	Post (3)
Job Characteristics:			
Required Number of Employees	12.47	9.18	14.88
	[72.70]	[56.48]	[82.52]
Wage	10075.90	9898.45	10206.20
	[5250.09]	[5180.68]	[5297.08]
With Time Amenity	0.29	0.28	0.29
	[0.45]	[0.45]	[0.45]
With Social Insurance	0.66	0.71	0.63
	[0.47]	[0.46]	[0.48]
High Education Requirement	0.30	0.33	0.28
	[0.46]	[0.47]	[0.45]
Give a positive reply ($Y = 1$):			
All Sample	0.26	0.22	0.28
	[0.44]	[0.41]	[0.45]
Female	0.26	0.22	0.28
	[0.44]	[0.41]	[0.45]
Male	0.26	0.22	0.29
	[0.44]	[0.41]	[0.45]
Number of Applications Received:			
Weekly Number	1.67	1.48	1.79
	[6.76]	[5.23]	[7.57]
Weekly Number from Female	0.83	0.73	0.89
	[4.55]	[3.48]	[5.11]
Total Number	29.65	22.77	34.71
	[88.25]	[62.95]	[102.65]
Total Number from Female	14.69	11.31	17.17
	[59.63]	[38.90]	[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)
Applicant Characteristics:						
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]
Characteristics of Applied Job:						
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]
Application Intensity / Duration:						
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	By Applicant Gender: Male
	(1)	(2)	(3)	(4)	(5)
Dependent Variable: Give a Positive Reply ($Y = 1$)					
$D_{ct} \times \Delta\%\text{ML}_c \times$ Female	-0.242*	-0.172**	-0.169**		
	(0.132)	(0.080)	(0.079)		
$D_{ct} \times \Delta\%\text{ML}_c$				-0.095*	-0.003
				(0.056)	(0.082)
Female × Time FE	✓	✓	✓		
Female × Job City FE	✓	✓	✓		
Job City × Time FE	✓	✓	✓		
Job Characteristics	✓				
Job FE		✓	✓	✓	✓
Applicant Characteristics			✓	✓	✓
Workday Indicator	✓	✓	✓	✓	✓
Time FE				✓	✓
Obs.	328,758	331,275	331,219	163,097	166,318
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: Each column reports estimates from a separate regression. The regression uses the employer-side sample. The pre-policy means for the DDD estimates correspond to applications from female, which applies to all subsequent employer-side results tables unless explicitly stated. 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 level are reported in parentheses. *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$.

Table 4: Heterogeneous Effects by Government Coverage of Extension

VARIABLES	Govt Cover (1)	No Govt Cover (2)
$D_{ct} \times \Delta\%ML_c \times Female$	-0.139	-0.251*
	(0.090)	(0.128)
Female × Time FE	✓	✓
Female × Job City FE	✓	✓
Job City × Time FE	✓	✓
Job FE	✓	✓
Applicant Characteristics	✓	✓
Workday Indicator	✓	✓
Observations	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 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 are clustered at the job-city level and reported in parentheses. *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$.

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

Panel A: Job Characteristics					
VARIABLES	# Positions	Log Wage	Time Amenities	Social Insurance	Edu Req High
	(1)	(2)	(3)	(4)	(5)
$D_{ct} \times \Delta\%\text{ML}_c$	-25.096	-0.036	0.028	-0.029	-0.038
	(16.373)	(0.088)	(0.090)	(0.082)	(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
Panel B: Application Received					
VARIABLES	Total Num	Female Num	Weekly Num	Weekly Female Num	
	(1)	(2)	(3)	(4)	
$D_{ct} \times \Delta\%\text{ML}_c$	7.820	-4.071	-0.214	-0.167	
	(9.836)	(6.791)	(0.630)	(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	0.752	

Notes: Each column reports estimates from a separate regression. The regression uses 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 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. Robust standard errors clustered at the city level are reported in parentheses. $^{***}p < 0.01$, $^{**}p < 0.05$, $^{*}p < 0.1$.

Table 6: Effects of Extension on Characteristics of Applied Job

Panel A: All Applicants

VARIABLES	Log(Wage)	Time Amenities	Social Insurance
	(1)	(2)	(3)
$D_{ct} \times \Delta\%\mathrm{ML}_c \times$ Female	-0.234***	0.170*	-0.050
	(0.074)	(0.089)	(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

Panel B: By Applicant Gender

	Female			Male		
VARIABLES	Log(Wage)	Time Amenities	Social Insurance	Log(Wage)	Time Amenities	Social Insurance
	(1)	(2)	(3)	(4)	(5)	(6)
$D_{ct} \times \Delta\%\mathrm{ML}_c$	-0.126**	0.103*	-0.016	0.008	0.025	0.083
	(0.055)	(0.059)	(0.075)	(0.065)	(0.047)	(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

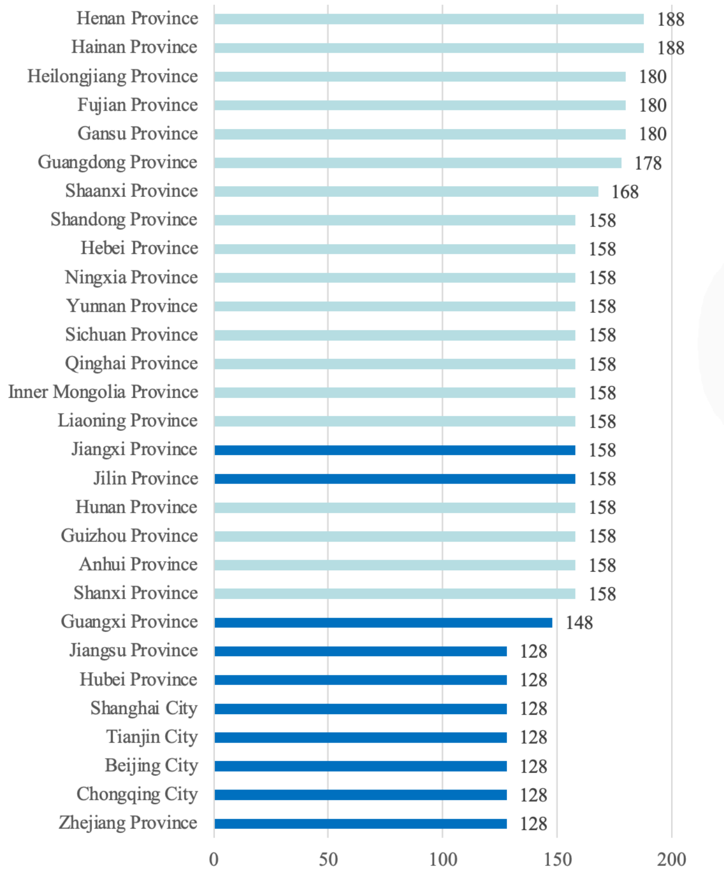
Notes: This table reports estimates from regressions using applicant-side data. The dependent variables are the log wage of applied jobs, and binary indicators for whether the applied job offers time amenity or social insurance benefits. The pre-policy means for the DDD estimates correspond to female applicants, which applies to all subsequent applicant-side results tables unless explicitly stated. 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. All regressions cluster standard errors at the city level. $^{***}p < 0.01$, $^{**}p < 0.05$, $^{*}p < 0.1$.

Table 7: Effects of Extension on Applicant Job Search Behavior

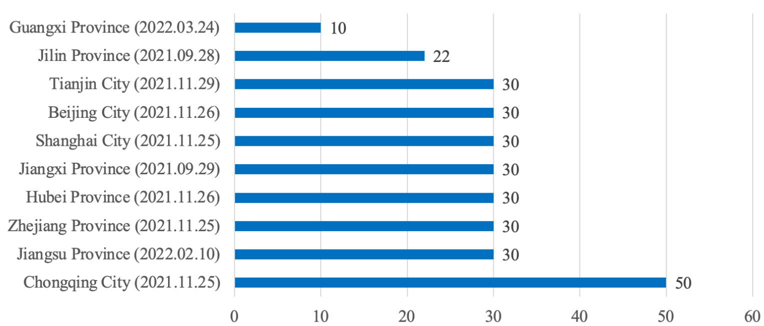
	Weekly Apply ($Y=1$)		# Weekly Application		# Total Application		Search Duration	
VARIABLES	Female	Male	Female	Male	Female	Male	Female	Male
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
$D_{ct} \times \Delta\%\mathrm{ML}_c$	-0.025	-0.022	-0.376	-0.376	20.016***	8.417	3.850**	-0.889
	(0.086)	(0.084)	(0.726)	(0.726)	(6.262)	(8.281)	(1.763)	(1.489)
Obs.	67,745	68,312	68,312	68,312	5,892	6,031	2,956	3,121
Adjusted R^2	0.051	0.050	0.096	0.096	0.072	0.077	0.142	0.122
Pre-policy Mean	0.380	0.376	1.915	1.915	21.500	20.990	5.036	5.037

Notes: Each column presents estimates from a separate regression 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 during the job search period; and (4) total search duration, measured in weeks. For regressions on weekly application behavior, we construct an applicant-week panel by aggregating applications by calendar week and imputing zeros for weeks with no observed submissions. These specifications 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. To ensure accurate measurement of search duration, Column 7-8 exclude applicants who submitted any application before week 9 or after week 44 of the calendar year. Robust standard errors clustered at the city 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.

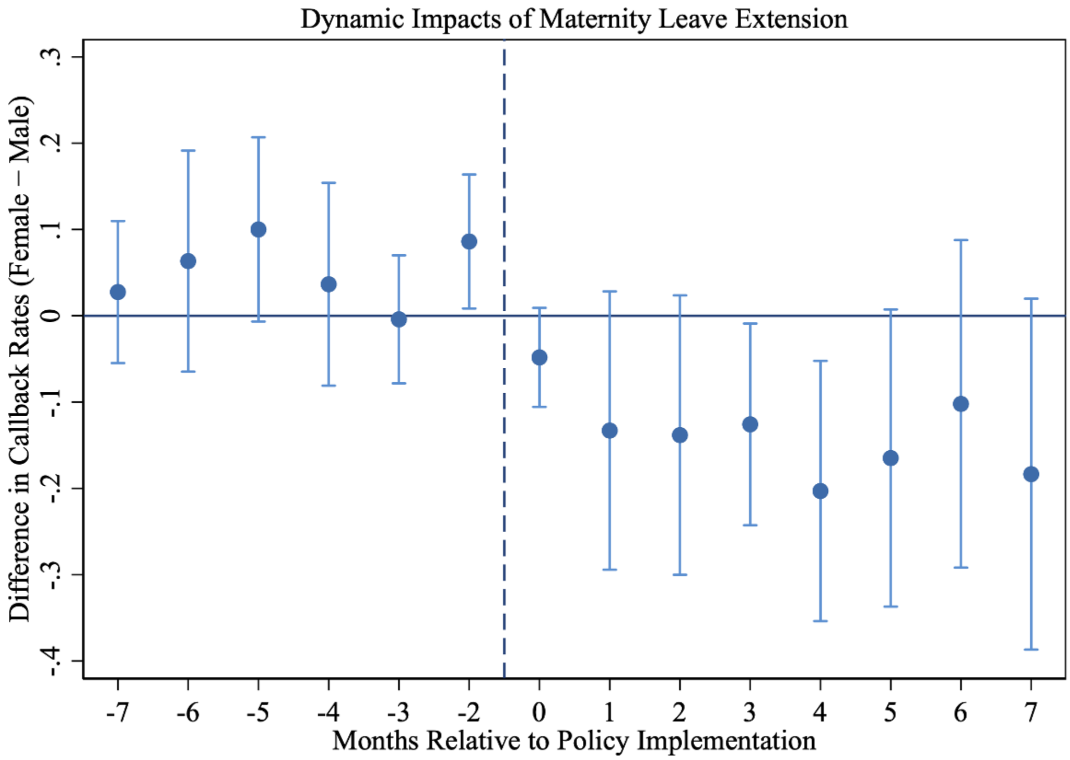
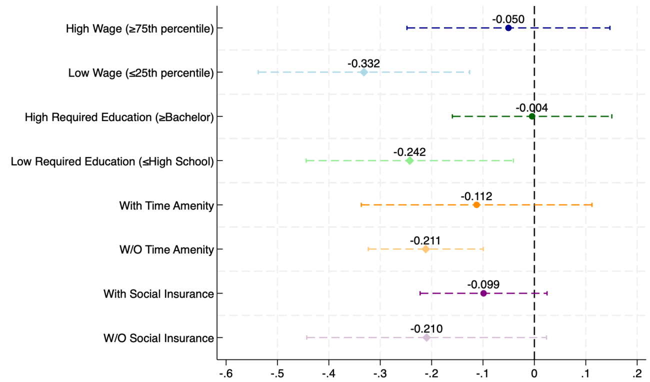
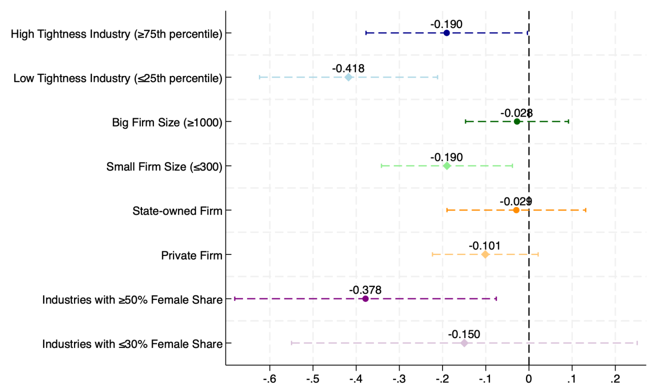


Figure 2: Dynamic Impact of Extension on Gender Gap in Callback Rates

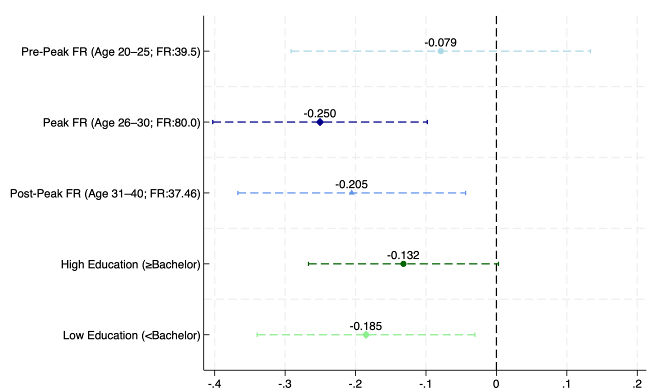
Notes: This event-study plot illustrates the dynamic effects of maternity leave extensions on the gender gap in job callbacks (Female − Male), estimated using equation 4. Estimates are based on job-level data, and all coefficients are relative to the month before implementation. The vertical line indicates 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 are clustered at the city 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. All estimates are accompanied by 90% confidence intervals. 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 level.

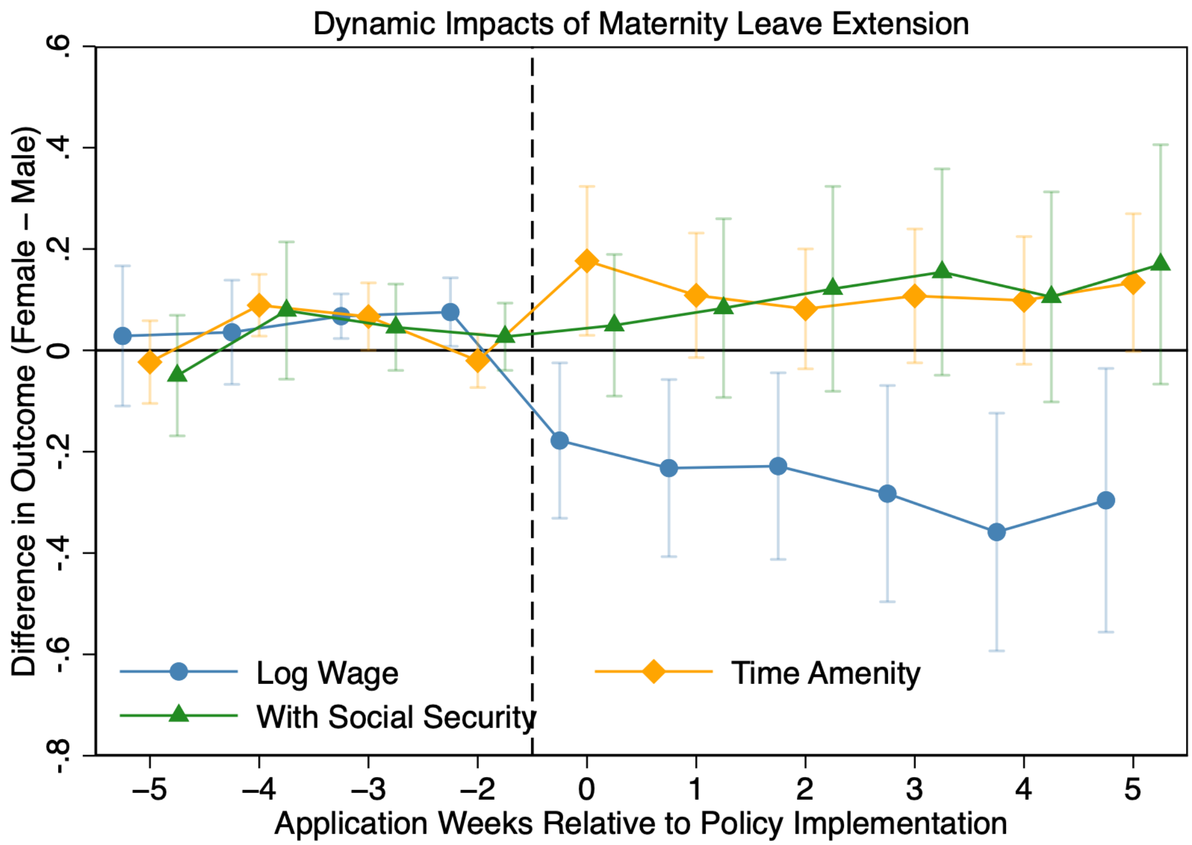


Figure 4: Dynamic Effects of Extension on Job Characteristics of Applied Positions

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.

Appendix

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

VARIABLES	Other Leave Controls (1)	COVID Controls (2)	Post-Three Child (3)
$D_{ct} \times \Delta\%\text{ML}_c \times$ Female	-0.236***	-0.132**	-0.176**
	(0.053)	(0.061)	(0.084)
Paternal$_{ct}$/100 $\times$ Female	-0.088		
	(0.155)		
Childcare$_{ct}$/100 $\times$ Female	0.307		
	(0.190)		
# Cases (k) $\times$ Female		-0.002	
		(0.002)	
# New Infections (k) $\times$ Female		0.000	
		(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 city-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 are clustered at the city level and 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	Childcare Leave Extension
	(1)	(2)
$D_{ct} \times (\Delta \text{Paternal}_c/100) \times \text{Female}$	-0.022	
	(0.220)	
$D_{ct} \times (\Delta \text{Childcare}_c/100) \times \text{Female}$		0.031
		(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 in paternal leave or childcare leave have differential effects on female applicants' callback rates. 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 only have childcare leave extensions. The interaction terms capture whether gender-specific effects exist for non-maternity leave reforms. 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 level are reported in parentheses. $^{***}p < 0.01$, $^{**}p < 0.05$, $^{*}p < 0.1$.

Table A3: Robustness: Alternative Sample Restrictions

VARIABLES	No Extension Provinces (1)	Jobs Restriction (2)	Age 45+ All (3)	Age 45+ Female (4)	Age 45+ Male (5)
$D_{ct} \times \Delta\%\mathrm{ML}_c \times$ Female	-0.067**	-0.177**	-0.188		
	(0.027)	(0.086)	(0.118)		
$D_{ct} \times \Delta\%\mathrm{ML}_c$				-0.073	0.137
				(0.059)	(0.115)
Sample Restriction	Treated + No Extension Provinces	Jobs with >10 apps	Age 45+ in Treated Prov.	45+ Female in Treated	45+ Male in Treated
Obs.	838,654	304,903	24,058	18,510	5,339
Adjusted R^2	0.431	0.422	0.480	0.462	0.531
Pre-policy Mean	0.294	0.205	0.118	0.126	0.089

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)–(5) restrict the sample to individuals aged 45 or older. Column (4) is limited to females, and Column (5) 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 level are shown in parentheses. $^{***}p < 0.01$, $^{**}p < 0.05$, $^{*}p < 0.1$.

Table A4: Robustness: Alternative Policy Intensity and Time Controls

VARIABLES	Use Extension Days	Use Lunar Date FE
	(1)	(2)
$D_{ct} \times (\Delta\text{ML}_c/100) \times$ Female	-0.130**	
	(0.062)	
$D_{ct} \times \Delta\%\text{ML}_c \times$ Female		-0.165**
		(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-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 level are reported in parentheses. $^{***}p < 0.01$, $^{**}p < 0.05$, $^{*}p < 0.1$.

Table A5: Effects of Extension on Characteristics of Applied Job: Alternative Controls

	Log Wage				Time Amenity
VARIABLES	(1)	(2)	(3)	(4)	(5)
$D_{ct} \times \Delta\%\mathrm{ML}_{ct} \times$ Female	-0.234***	-0.242***	-0.228***	-0.236***	0.163*
	(0.074)	(0.074)	(0.072)	(0.071)	(0.089)
Time Amenity			-0.020***	-0.020***	
			(0.002)	(0.002)	
Social Insurance			0.043***	0.043***	
			(0.005)	(0.005)	
Log Wage					-0.027***
					(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. 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 level are in parentheses. $^{***}p < 0.01$, $^{**}p < 0.05$, $^{*}p < 0.1$.

Table A6: Relationship Between Job Search Length and Log Wage

	Log Wage		
VARIABLES	All Applicants	Female	Male
	(1)	(2)	(3)
Search Length (10 days)	-0.011**	-0.008	-0.014***
	(0.004)	(0.008)	(0.005)
Search Length^2	0.004***	0.002	0.005***
	(0.001)	(0.002)	(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 duration length and the wage of applied jobs, based on applicant-side data. All regressions include individual fixed effects. Standard errors clustered at the city level are reported in parentheses. $^{***}p < 0.01$, $^{**}p < 0.05$, $^{*}p < 0.1$.

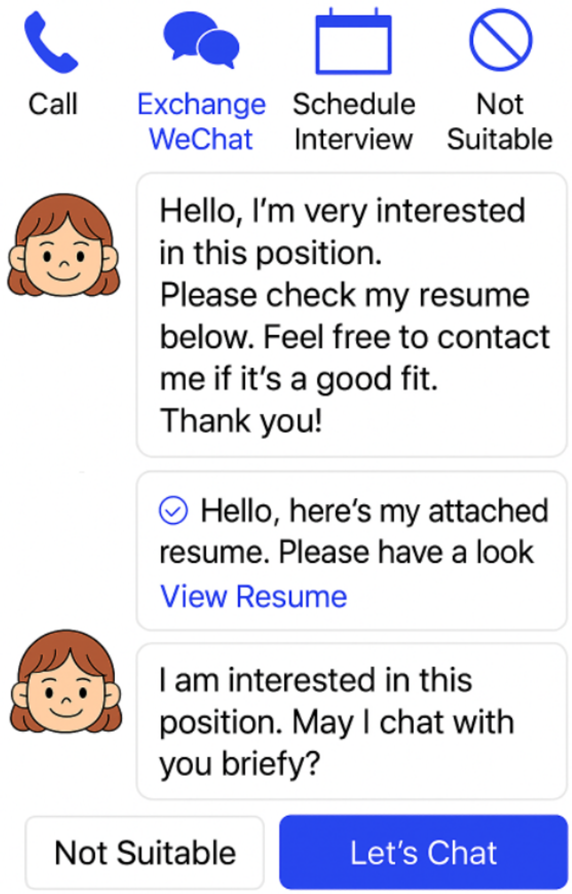
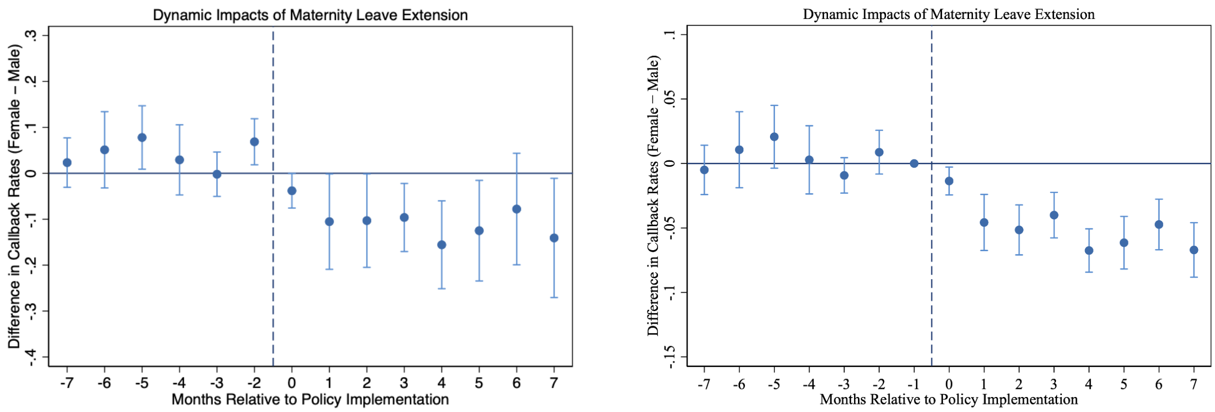


Figure A1: Example of Employer-side Chat Interface on Platform

Note: This figure displays the employer-side chat interface on the Zhilian 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 treatment 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 level. All estimates are derived from job-level data with 90% confidence intervals shown.

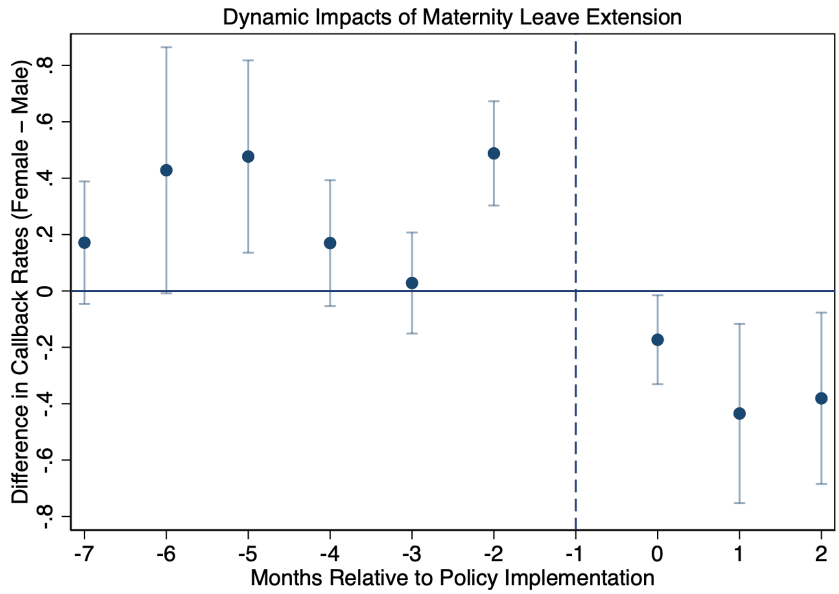


Figure A3: Event-Study Estimates Using Sun & Abraham (2020) Estimator

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 level. All estimates are accompanied by 90% confidence intervals.

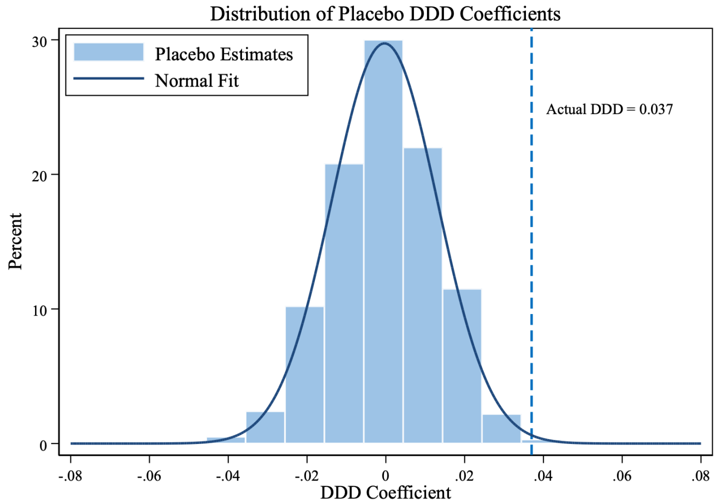


Figure A4: Placebo Test via Randomized Policy Time Simulation

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.

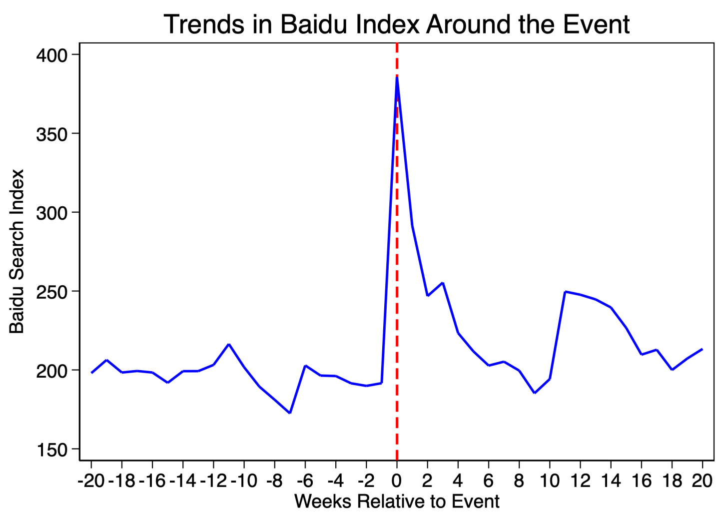


Figure A5: Baidu Search Index for "Maternity Leave" Around Policy Announcement

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.

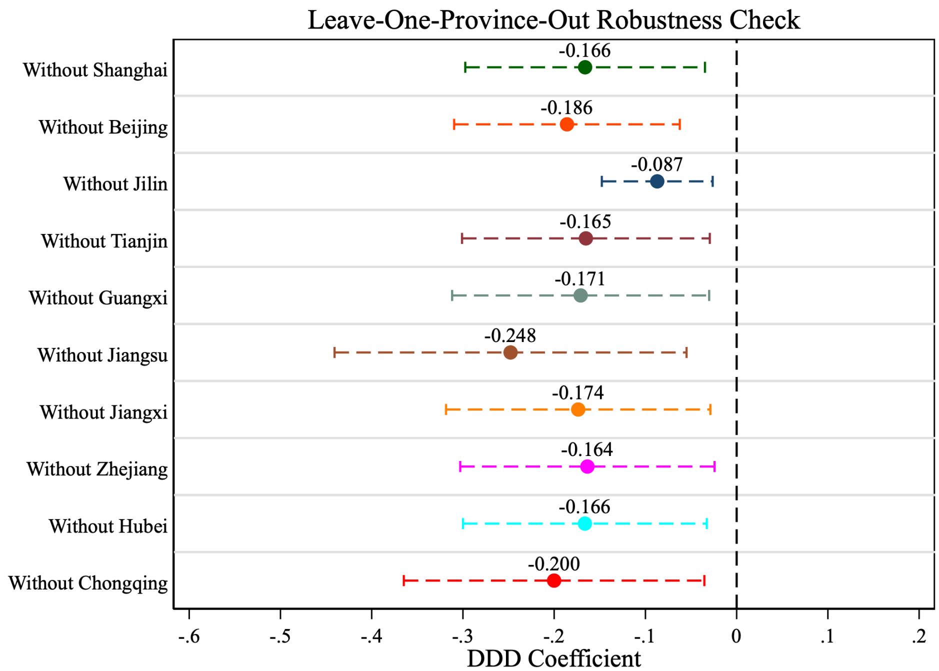


Figure A6: Leave-One-Out Robustness of Dynamic Policy Effects

Notes: This plot presents dynamic estimates where one treated province is excluded at a time. All estimates are accompanied by 90% confidence intervals. 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 level. Shaded areas represent 90% confidence intervals.