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# Childbearing Age and Gender Discrimination in Hiring Decisions: A Large-Scale Field Experiment[☆]

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**Abstract**

We conduct a large-scale field experiment in China to investigate the effect of being of childbearing age on gender discrimination in the labor market. We send 35,713 fictitious resumes to real job postings on a major Chinese online recruitment platform for jobs in four leading cities, Beijing, Shanghai, Guangzhou, and Shenzhen, which vary in the length of maternity leave. We send applications for positions advertised in the *male-dominated* field of information technology (IT), the *female-dominated* field of accounting (ACC), and the *mixed-gender* field of human resources (HR). We systematically vary the age and gender of the job applicants and record callbacks for interviews. To accurately mimic the job application process in the Chinese labor market, we do not disclose the applicants' family status. We find that women of childbearing age are subject to discrimination in the field of IT, a problem that also exists in HR and ACC, particularly in Beijing and Shanghai. There is no obvious discrimination against women of childbearing age in Guangzhou or Shenzhen, where maternity leave is longer. In the aggregate, the evidence indicates that women of childbearing age face statistical discrimination that prevents them from obtaining equal employment opportunities.

**Keywords:** Correspondence Study, Discrimination, Fertility, Labor Market, Maternity Leave

**JEL Classification:** C93, J71, J16, M51

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# 1 Introduction

Women's economic empowerment is crucial for social and economic development in both developed and developing countries (Duflo, 2012). Despite improvements in gender equality, gender gaps remain pronounced in modern societies, especially in the labor market (Blau and Kahn, 2017; Jayachandran, 2021). Securing gender parity at work is central to the 2030 Agenda for Sustainable Development.[1] The recent COVID-19 pandemic has disproportionately affected women's employment outcomes and made this objective increasingly challenging (Alon et al., 2020; Dang and Nguyen, 2021). Evidence has shown that unequal parental responsibilities contribute to the persistent gender disparities in the labor market (Kleven et al., 2019a,b; Cortés and Pan, forthcoming). Therefore, policies regarding fertility and family care may influence not only a family's desire to have children but also gender parity within the workplace.

China has gradually relaxed its birth control mandate to allow two children beginning in 2011, eventually resulting in the "universal two-child policy" in 2016. The "universal three-child policy" was recently announced in late 2021. Family policies, including maternity leave policies, have been reformed to align with these latest fertility policies. Women of childbearing age, as the majority of mothers and a significant percentage of the labor force, are directly affected by policies pertaining to fertility and family care. Recent studies have indicated that increased labor market barriers associated with childcare burdens and gender discrimination impede women's participation in the labor market and their ability to fulfill their egalitarian potential (Zhang and Huang, 2020; Brussevich et al., 2021; Si, 2022).

In this paper, we conduct a large-scale field experiment in China to investigate the effect of being of childbearing age on gender discrimination in the labor market. Specifically, we examine whether being of childbearing age affects women's employment opportunities during the initial stages of the hiring process using a correspondence test. We also investigate whether differences in the length of the maternity leave offered across cities may influence gender inequality in the labor market. Analyzing these issues is essential for understanding the obstacles associated with the labor market demand for women of fertile age. It is also relevant to the current policy debate regarding parental leave reforms in China.

Correspondence testing is a well-established method for investigating discrimination in the labor market (Bertrand and Duflo, 2017; Gaddis, 2018; Neumark, 2018). A correspondence experiment consists of creating fictitious applicants with well-designed but realistic resumes, which are then used in response to real job advertisements. Resumes in the treatment group

[1] The UN Secretary General's High Level Panel on Women's Economic Empowerment, *Leave No One Behind: A Call to Action for Gender Equality and Women's Economic Empowerment*. Available at: https://www.empowerwomen.org/-/media/files/un%20women/empowerwomen/resources/hlp%20briefs/unhlp%20full%20report.pdf?la=en.

have the perceived minority trait, while the other elements are equivalent to those in the control group. By comparing the callback rates between the treatment and control groups, discrimination against the perceived minority trait can be identified. Due to its randomized controlled nature, correspondence testing can address many of the endogeneity issues that arise in nonexperimental data when identifying discrimination. Such testing has been used to examine discrimination against various perceived characteristics that can be randomized on a resume, such as race and ethnicity, gender, caste and religion, as well as unemployment spells in the labor markets of different countries (*e.g.*, Bertrand and Mullainathan, 2004; Carlsson, 2011; Banerjee et al., 2009; Eriksson and Rooth, 2014). Bertrand and Duflo (2017) propose that future correspondence studies could be conducted to inspect discrimination against women who have or are likely to have children.

To investigate whether being of childbearing age affects women's labor market opportunities, we conduct a large-scale correspondence experiment in four megacities in China: Beijing, Shanghai, Guangzhou, and Shenzhen. We conducted preexperiment surveys in the focal cities between December 2020 and January 2021 to collect background information for the experimental design, such as what ages are generally recognized as childbearing age. From March to June 2021, we submitted more than 35,000 fictitious applications to job openings on a large online job board. We sent applications for available positions advertised on the website during the experimental period in a *male-dominated* field, that is, information technology (IT), in a *female-dominated* field, that is, accounting (ACC), and in a *mixed-gender* field, that is, human resources (HR). There are six key variants within each occupation: pre-fertile age females, fertile age females, post-fertile age female, pre-fertile age males, fertile age males, and post-fertile age males. We recorded the callbacks from employers, which are positive feedback inviting the candidate to the next step, such as an interview. With the randomization of gender, age, and the related work experience of applications received by the various employers, we can assess whether employers differentiate between female applicants of fertile age and otherwise equivalent job applicants. Moreover, we explore whether the longer maternity leave periods in Guangzhou and Shenzhen than in Beijing and Shanghai exacerbate the labor market barriers for women of childbearing age since firms in cities with longer maternity leave periods are more likely to encounter higher hiring costs.

Our study is novel in three aspects. First, we examine employment discrimination against women of childbearing age in systematically varying fields—male-dominated, female-dominated, and mixed-gender—to determine whether the unique nature of the field makes a difference. To the best of our knowledge, this is the first study to investigate potential maternity discrimination in the labor market, taking into account the impact of the field. Second, we prepare resumes that reflect real and common job applications in the Chinese labor market without disclosing family-related statuses such as marital status, number of children, and number of potential children. This is in contrast to most studies that *explicitly* disclose such information (Petit, 2007; Correll et al., 2007; Becker et al., 2019; Albert et al., 2011; Bygren et al., 2017; Horváth, 2020; Kim et al., 2020; He et al., forthcoming). Providing these details not only differentiates the resumes from those encountered in the actual Chinese job market but may also introduce confounding factors. Therefore, our experimental design ensures external validity; it also enables us to investigate whether there is *implicit* discrimination against women of childbearing age when their marital and maternal status is *not disclosed*. Third, we explore the potential policy impact of the length of maternity leave by comparing the discrimination experienced by women of childbearing age in Beijing and Shanghai with that in Guangzhou and Shenzhen, where maternity leave is longer.

Our study contributes to two lines of literature. First, it adds to the literature that uses correspondence testing to examine maternal and marital status discrimination in the labor market against people of specific genders and ages, an area that has not been adequately explored (Bertrand and Duflo, 2017; Becker et al., 2019). A review by Baert (2018) of almost all correspondence studies conducted between 2005 and 2018 reveals that most of the available evidence comes from Europe and the United States. Petit (2007) reports hiring discrimination against young and childless female applicants for high-skilled administrative jobs in France due to their high likelihood of maternity. Correll et al. (2007) use both laboratory and correspondence experiments to find that mothers in the US labor market face discrimination but fathers do not. Becker et al. (2019) examine evidence from German-speaking countries and discover discrimination against married but childless women seeking part-time employment. However, Albert et al. (2011) and Bygren et al. (2017) examine the Spanish and Swedish labor markets, respectively, and find no evidence of discrimination based on gender or parental status.

Studies focusing on the Chinese labor market have been limited and inconclusive. Horváth (2020) examines the impacts of marital status on job-finding in accounting and finance in China (Shanghai and Xi'an) and finds no evidence of significant effects for either gender. In contrast, Kim et al. (2020) find discrimination in the accountant job market (Beijing and Shanghai) against married women without children and married women who expect to have another child. Recent research by He et al. (forthcoming) into three fields, sales, administrative assistance, and customer service, also suggests that women, rather than men, are subject to discrimination in the job market due to expectations of family responsibilities.[2] Our study provides the latest evidence on discrimination against women with potential maternal status in the Chinese labor market. More importantly, our study distinguishes itself from previous

[2]The focus of He et al. (forthcoming) differs from ours in that they examine the impact of the change from the one-child policy to the two-child policy (two children are allowed for families in which one parent was an only child) on expectations of family responsibilities. In their experiment, He et al. (forthcoming) disclose whether the job applicant is the only child in his or her family. This disclosure, however, may introduce confounders (e.g., only children may be perceived as less trusting, less trustworthy, and less conscientious (Cameron et al., 2013)).

studies through the three contributions that we mentioned above: the examination of fields with varying gender dominance, the nondisclosure of family-related status, and the length of maternity leave.

Second, our study contributes to the growing literature that explores the impact of motherhood and family policies on gender inequality in the labor market (Ruhm, 1998; Maurer-Fazio et al., 2011; Olivetti and Petrongolo, 2017; Kleven et al., 2019a,b, 2021; Chen et al., 2021; Cortés and Pan, forthcoming; He et al., forthcoming). The impact of parenthood on the labor market outcomes of women relative to their male counterparts is known as the child penalty, which contributes to the gender gap in work in many countries (Kleven et al., 2019a). Our results indicate that the child penalty can be imposed during the hiring stage not only on actual mothers but also on women of childbearing age who do not even disclose their maternal status. Furthermore, the findings of our study may have implications for the current reform of parental leave policies at the provincial level, which attempts to accommodate the relaxation of fertility policies in China.

We find that women of childbearing age are discriminated against in the field of IT, a problem that also exists in HR and accounting, particularly in Beijing and Shanghai. There is no evident discrimination against women of childbearing age in Guangzhou and Shenzhen, where maternity leave is longer. The results suggest heterogeneity in discrimination against women of childbearing age across occupational fields and cities. The results of this study remain robust to several robustness tests, including applying the method proposed by Neumark (2012) to address the Heckman-Siegelman critique (Heckman and Siegelman, 1993). In general, it appears that women of childbearing age face demand-side barriers that negatively impact their employment opportunities. The evidence implies that it is the statistical discrimination against women who are likely to be in the early stages of motherhood that hinders them from obtaining equal employment.[3] In contrast to popular belief, employment costs associated with the length of maternity leave do not necessarily account for the discrimination against women of childbearing age.

The rest of this paper is organized as follows. The next section provides an overview of the institutional background on female labor force participation, as well as fertility and family policies in China during the period when we conducted our experiment. In Section 3, the experimental design, including the implementation of the preexperiment surveys and correspondence testing, is outlined in detail. Section 4 describes the data collected and presents the results. The final section discusses the findings and concludes the paper.

[3] Statistical discrimination occurs when employers make hiring decisions based on a calculation of a group's average or other statistical characteristics, rather than the applicant's actual quality (Aigner and Cain, 1977).

# 2 Institutional Background and Related Studies

## 2.1 Female Labor Market Participation

The labor force participation rate among women in China is relatively high compared with that in other countries in Asia and around the world. However, since China's market-oriented economic reform, the proportion of women participating in the labor force has been declining (Liu et al., 2014; Brussevich et al., 2021). Women's labor force participation in China decreased from 73% in 1990 to 62% in 2020. The ratio of women to men in the labor force has also declined over recent decades.[4]

Several studies have provided insight from the perspective of labor supply and have indicated that childcare obligations inhibit the participation of women in the labor force, especially those with preschool children (Maurer-Fazio et al., 2011; Du and Dong, 2013; Liu et al., 2014; Connelly et al., 2018). Analyses from the labor demand side usually incorporate correspondence testing in the hiring market. China's hiring market is composed of two types of recruitment: campus and social. Campus recruitment targets university graduates in their senior year from September to November in the fall and from March to April in the spring. Social recruitment usually targets people with work experience and occurs throughout the year but most frequently in March and April. Zhou et al. (2013) conducted the first correspondence study to investigate gender discrimination in social recruitment. They found that the hiring markets for professionals generally favor women over men. However, the study of campus recruitment by Zhang et al. (2021) shows that female college graduates are less likely to receive interview calls than their male counterparts.

Online job boards have become the primary channel for job seeking in China. Kuhn and Shen (2013) examine explicit gender discrimination in job advertisements using evidence obtained from an online job board during a period when it was legal to express gender preferences in job advertisements. Their results do not reveal systematic discrimination against a particular gender. The use of explicit gender preferences in job advertisements is no longer permitted since new regulations were enacted in 2019 to protect the rights of women.[5] Moreover, employers are prohibited from asking a female applicant about her marital and parental status and making hiring decisions based on these factors. However, the enforcement of this provision is difficult, especially when employers are able to discriminate implicitly, such as by not inviting women with high fertility chances to interviews. Our study examines whether such implicit discrimination occurs against fertile-aged female job applicants who do not indicate their maternity status when applying for jobs.

[4]Statistics from the International Labour Organization, ILOSTAT database. Data retrieved from the World Bank at https://data.worldbank.org/indicator/SL.TLF.CACT.FE.ZS?locations=CN and https://data.worldbank.org/indicator/SL.TLF.CACT.FM.ZS?locations=CN.

[5]Source: http://www.mohrss.gov.cn/SYrlzyhshbzb/jiuye/zcwj/201902/t20190221_310707.html.

## 2.2 Fertility and Family Policies

The family policies in China usually complement the fertility policies.[6] From 1980 to 2011, China implemented a policy of one child per family. During that period, maternity leave was usually 90 days in length. Since 2012, the one-child policy has been relaxed, and since 2016, all families have been permitted to have two children. Consequently, maternity leave was extended to 98 days in 2012. Moreover, in 2016, each province extended its maternity leave beyond the national minimum and introduced paternity leave. At the time of our experiment, Beijing and Shanghai offered 128 days of maternity leave, while Guangzhou and Shenzhen offered 178 days. Compared to these lengths, the length of paternity leave is rather short, at 15 days in Beijing, Guangzhou and Shenzhen and 10 days in Shanghai. In line with traditional gender norms, the majority of childcare responsibilities are usually held by females, while males contribute less, as evidenced by the difference in the length of the parental leaves taken by women and men. The relaxation of the fertility policy had a limited effect on encouraging fertility. The total number of births per woman in China increased from 1.6 in 2011 to 1.7 in 2020.[7] In a continued attempt to rectify the declining birth rate, a universal three-child policy was announced in late 2021.[8] Subsequently, further reforms regarding family policies are on the horizon along with heated debates. On the one hand, extended maternity leave may alleviate some of the burdens placed on working mothers. A lengthy maternity leave, on the other hand, is perceived as negatively impacting women's career opportunities and development, thereby aggravating gender inequalities in the labor market. For instance, employers may find it more costly to hire female employees who will take extended maternity leave. There are two main costs involved. First, there is the portion of the employee's salary during her maternity leave that is not covered by Social Security. Then, there is the additional expense associated with finding someone to temporarily fulfill the duties of the employee on maternity leave.

# 3 Experimental Design

## 3.1 Preexperiment Survey

The experiment was conducted in Beijing, Shanghai, Guanzhou, and Shenzhen, four of the most modern cities in China. These four megacities have similar levels of economic development and are a good source of job openings across a multitude of fields. In terms

[6] A detailed review of the evolution of China's family policies over the past 70 years is provided by Liu et al. (2020).

[7] Statistics from the World Bank database. Data retrieved from https://data.worldbank.org/indicator/SP.DYN.TFRT.IN?locations=CN.

[8] Our experiment was completed before the announcement of this new policy.

of maternity leave provisions, Beijing and Shanghai offer shorter leaves of 128 days, and Guangzhou and Shenzhen offer longer leaves of 178 days. To gain more insight into the key experimental elements relevant to the correspondance testing, specifically, the conventional childbearing age for women in each place, we conducted preexperimental online surveys in each of the four megacities between December 2020 and January 2021. There were 73 questions on the questionnaire, which explored the viewpoints of people regarding gender discrimination in the workplace and certain demographics.[9] As shown in Table B.1, 572 questionnaires were retrieved, with an even distribution across genders and cities.

Given that a woman's marital and maternal status, as well as the number of children that she has, are not commonly included on a CV in the Chinese job market, being of childbearing age serves as an indicator for maternal status, which can be used to examine the expected effect of fertility on hiring decisions. Three age levels are defined for job applicants: prefertile, fertile, and postfertile. Survey participants are asked what they believe is the typical age at which parents have their first child. Based on the information collected in the surveys, shown in Table B.2, the age at which a person is most likely to have her/his first child is 29 years old, which is considered the beginning of childbearing age.[10] All job applicants in our experiment possess a bachelor's degree. It is common in China for people to graduate from a university with a bachelor's degree at the age of 22. The prefertility age is set to 24 years old, not only because most people do not have their first child before the age of 24 but also because it is likely that people begin to enter the social recruitment market after having two years of work experience following graduation. The postfertility age is set at 34 years old since most people have already given birth to their first child at this age, as shown in Table B.2. Additionally, in China, ageism at work can begin as early as 35 years old, which is sometimes referred to as the "age 35 phenomenon" (Leng and He, 2021; Huang and Zhang, 2021).

The level and direction of gender discrimination can vary across occupations due to gender stereotyping (Riach and Rich, 2006). The experiment therefore focuses on a female-dominated field, a male-dominated field, and a mixed-gender field. Our survey collected information on gender stereotyping in several occupations that recruit through online job postings, as shown in Table B.3. In light of the information provided, we target accounting as the female-dominated field, IT as the male-dominated field, and HR as the mixed field. There are also a large number of job openings in the market for these three professions.

[9]The full set of survey questions is available in Appendix B.1.

[10]Based on the latest national census in 2020, the fertility rates in Beijing, Shanghai, and Guangdong Province (where Guangzhou and Shenzhen are located) are 0.8, 0.7, and 1.2, respectively (Statistics from China Population Census Yearbook 2020. Data retrieved from `http://www.stats.gov.cn/tjsj/pcsj/rkpc/7rp/zk/html/B0604a.jpg`). Thus, we focus on the potential effects of having a first child.

## 3.2 Generating Resumes

The correspondence test was conducted on one of the largest, leading recruitment websites in China, 51job.com. The website provides a standard resume template that includes information such as name, gender, age, date of birth, educational background, work experience, job intentions, salary expectations, skills, professional certificates, and contact information. In each of the three fields we target, we generate resumes for female and male candidates aged 24, 29, and 34. Thus, 18 modules of fictitious resumes are generated.

### 3.2.1 Signaling Potential Maternal Status: Childbearing-aged Women

Our treatment group comprises 29-year-old women to represent female job applicants who are of childbearing age. The control group includes women aged 24 and 34, as well as men aged 24, 29, and 34. Gender information is generally included on resumes. Additionally, we developed different feminine and masculine given names whose gender identities were verified in the preexperiment surveys, combining them with the most common Chinese surnames. These names were randomly assigned to applicants according to their gender.

### 3.2.2 Other Characteristics of the Fictitious Resumes

All applicants hold a bachelor's degree from Chang'an University in a field relevant to their intended profession. Chang'an University is a national key university located in Xi'an, the capital of Shaanxi Province, which is far from the four experimental cities. We selected this university because most employers consider it a mediocre school, as well as to avoid any preference of local employers for local universities. The previous work experience of applicants was carefully fabricated to match their age and specialty. The applicant's skills, project experience, professional certifications, and salary expectations for the next job are also aligned with their previous work experience and seniority. As is common in social recruitment, all applicants are currently employed and looking for new opportunities. They currently reside and work in Wuhan, the capital city of Hubei Province, which is approximately the same distance from each of the four experimental cities. All applicants claim to be able to move to the new city for interviews and their next job.

We created a user account for each job applicant on 51job.com. Therefore, each applicant's contact information is unique, including her or his mobile number and email address. A photograph of the applicant was not included on the resume due to its customarily optional nature, as well as the fact that facial attractiveness may influence interview callbacks (Maurer-Fazio et al., 2011).

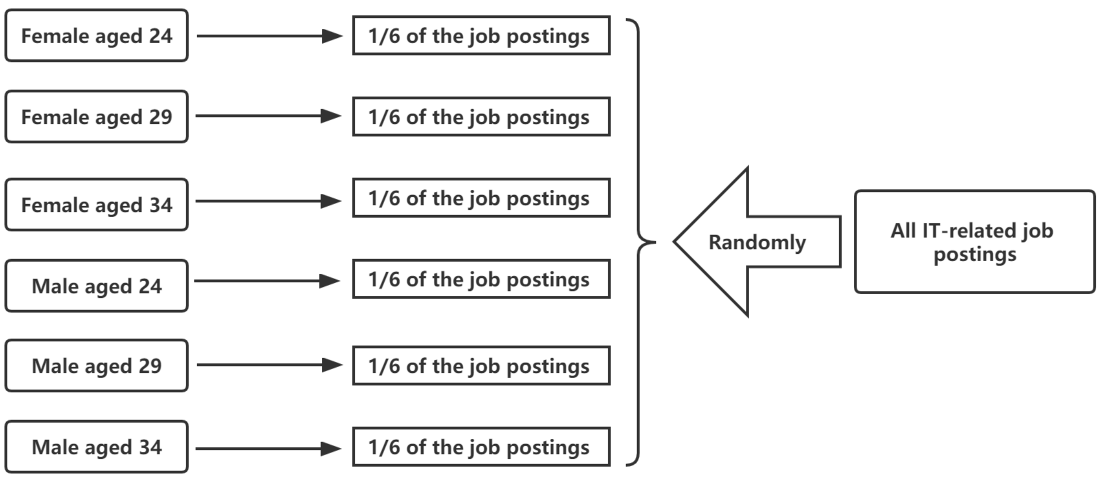


**Figure 1:** Schematic Diagram of the Job Application Process in IT

*Note:* This diagram shows the job application process in IT.

## 3.3 Procedure

The experiment and data collection took place between March and June 2021, the peak period for social recruitment. In place of sending both treated and control resumes to each employer, we submitted one job application to each employer. This reduces the likelihood of the fictitious applicants being detected by the employers. Moreover, the stable unit treatment value assumption is likely to be violated in paired designs, which would lead to biased results (Phillips, 2019).

Specifically, we gathered all job vacancy advertisements on 51job.com for accounting, HR, and IT posted within the past 30 days using a web scraping program. We kept full-time positions in Beijing, Shanghai, Guangzhou, and Shenzhen that required at least a bachelor's degree. We also excluded positions with a posted monthly salary exceeding 40 thousand RMB to exclude high-end positions. We then randomly divided all positions within each field (accounting, HR, and IT) into six categories based on firm information, job requirements, and expected salary. Finally, we submitted one application to each vacancy posting within one of the six job posting categories corresponding to the six resume modules (females and males of prefertile, fertile, and postfertile ages) within each field of accounting, HR, and IT. Figure 1 shows a schematic diagram of the job application process in IT. The same process was applied to HR and accounting. Therefore, each candidate applied for job positions at a variety of firms with different characteristics. Each firm received only one application from our experiment. In total, 35,713 job applications were successfully submitted.

Table 1 presents summary statistics for the experimental sample and the variables used in the analysis. There is an equal distribution across genders, age levels, and occupations

**Table 1:** Summary Statistics

| Variables | Mean | Standard Deviation | Min | Max |
|---|---|---|---|---|
| ***Application Characteristics:*** | | | | |
| Female Applicant | 0.50 | 0.50 | 0 | 1 |
| Male Applicant | 0.50 | 0.50 | 0 | 1 |
| Applicant Age: 24 | 0.34 | 0.47 | 0 | 1 |
| Applicant Age: 29 | 0.33 | 0.47 | 0 | 1 |
| Applicant Age: 34 | 0.33 | 0.47 | 0 | 1 |
| Applicant's experience: Good match | 0.33 | 0.47 | 0 | 1 |
| Applicant's expected salary matched | 0.44 | 0.50 | 0 | 1 |
| IT | 0.35 | 0.48 | 0 | 1 |
| Accounting (ACC) | 0.35 | 0.48 | 0 | 1 |
| HR | 0.30 | 0.46 | 0 | 1 |
| No. of applicants per advertised position | 150.68 | 198.68 | 1 | 2449 |
| ***City Dummies:*** | | | | |
| Beijing | 0.12 | 0.33 | 0 | 1 |
| Shanghai | 0.38 | 0.49 | 0 | 1 |
| Guangzhou | 0.22 | 0.41 | 0 | 1 |
| Shenzhen | 0.28 | 0.45 | 0 | 1 |
| ***Firm Characteristics:*** | | | | |
| Listed company | 0.08 | 0.27 | 0 | 1 |
| State-owned enterprise | 0.07 | 0.26 | 0 | 1 |
| Foreign company | 0.19 | 0.39 | 0 | 1 |
| Private enterprise | 0.64 | 0.48 | 0 | 1 |
| Non-listed company | 0.02 | 0.12 | 0 | 1 |
| Type unknown | 0.00 | 0.02 | 0 | 1 |
| Large-size (No.of employees>1000) | 0.19 | 0.39 | 0 | 1 |
| Medium-size (150<No.of employees<1000) | 0.39 | 0.49 | 0 | 1 |
| Small-size (No.of employees<150) | 0.40 | 0.49 | 0 | 1 |
| Size unknown | 0.02 | 0.13 | 0 | 1 |

*Notes:* Total number of observations: $N$ = 35713. Data collected by the authors between March and June 2021.

in the sample. Each job advertisement that we responded to received approximately 150 applications on average, indicating intense labor supply-side competition. Approximately 33% of our applicants have work experience that perfectly meets the expectations for the positions.[11] A dummy variable is defined for those applications with well-matched experience. Approximately 44% of our applicants have salaries expectations that are in line with the proposed salaries for the positions. A dummy variable is used to indicate a salary match. The percentage of jobs applied for in Beijing, Shanghai, Guangzhou, and Shenzhen are 12%, 38%, 22%, and 28%, respectively. Our job applications were submitted to a variety of firms with different characteristics, such as varying ownership structures and sizes. To check for randomness and to ensure that there was no selection effect, we perform a balance test of the characteristics relevant to the job postings on our key variables of interest. As shown in Table A.1, there is no indication of a selection effect such that female candidates or women of childbearing age are related to any characteristics of the job postings.

Positive responses from employers are captured as callbacks in our experiment, which are carefully tracked via mobile phones, text messages, emails, and messages from 51job.com's inbox. Contacts are normally not made if the employer is not interested. An interview is usually the next step after a callback. In our experiment, the majority of callbacks occurred within a week. Six research assistants, three males and three females who mimicked the six applicants in each occupation, assisted with responding to and recording the callbacks. In response to a callback, our research assistants replied promptly to inform the employer that the applicant was no longer available for the position, thus enabling them to move on to a different job candidate.

# 4 Results

## 4.1 Baseline Results

Table 2 summarizes the means of the raw callback rates and the number of job applications by gender. The unconditional probability of receiving a callback among females is 1.60%, and that among males is 1.34%. During the COVID-19 pandemic, callback rates were low, indicating a loose labor market. Considering that the average number of applications received for a single position was 150, competition from the labor supply side appears to have been fierce. The fact that we submitted a large number of applications may also contribute to the low callback rate, as a percentage of them did not perfectly match the requirements for the positions. The callback rate for female applicants in the 24 and 34 age groups is higher than that for male applicants, whereas among applicants in the 29 years old age group, female

[11] Approximately 2% of the advertised positions in the sample do not specify the level of experience needed.

**Table 2:** Raw Callback Rates

| | Female Applicants | | Male Applicants | |
|---|---|---|---|---|
| | Callback Rate (in %) | No. of Observations | Callback Rate (in %) | No. of Observations |
| All | 1.60 | 17916 | 1.34 | 17797 |
| Age 24 | 2.26 | 6016 | 1.60 | 5991 |
| Age 29 | 1.48 | 5942 | 1.80 | 5941 |
| Age 34 | 1.06 | 5958 | 0.61 | 5865 |
| IT | 1.06 | 6324 | 1.74 | 6315 |
| ACC | 1.40 | 6214 | 0.83 | 6170 |
| HR | 2.47 | 5378 | 1.47 | 5312 |
| Beijing | 1.12 | 2148 | 1.43 | 2168 |
| Shanghai | 1.58 | 6843 | 1.33 | 6825 |
| Guangzhou | 1.56 | 3917 | 1.29 | 3797 |
| Shenzhen | 1.88 | 5008 | 1.36 | 5007 |

*Notes:* The variable "callback" indicates whether an applicant was invited to an interview during the experiment.

applicants have a lower callback rate. This is the first indication that women of childbearing age are comparatively disadvantaged in the hiring market. Compared with their male counterparts, female applicants receive fewer callbacks in IT but receive more in accounting and HR. Female applicants are less likely to receive callbacks for jobs in Beijing than male applicants. They have a higher callback rate in Shanghai, Guangzhou, and Shenzhen.

The raw callback rates are also examined by plotting four different groups of applicants: females of childbearing age (CF), females of other ages (OF), males of childbearing age (CM), and males of other ages (OM), using applicants with matched work experiences. As illustrated in Figure 2, the experience-matched sample has higher callback rates, and the patterns reflect the same as those observed in the full sample.[12] The mean callback rate of females in accounting and HR is higher than that of males. However, there were distinct differences between the CF and OF groups. In the IT industry, female candidates tend to receive fewer callbacks than men.

To control for potential confounding factors, we use OLS regressions in the following analysis. We begin with a baseline analysis to estimate whether gender has an impact on the likelihood of receiving a callback from an employer. The baseline specification is as follows:

$$Callback_{ij} = \alpha_j + \beta_1 Female_i + \beta_2 Age29_i + \beta_3 Age34_i + X_i'\gamma + \epsilon_{ij} \tag{1}$$

where the dependent variable is an indicator for applicant $i$ receiving a callback for a job vacancy in city $j$. $Female_i$ indicates whether applicant $i$ is a woman. $Age29_i$ indicates whether

[12] We conduct all the following analyses using the full sample. The results are similar and robust when using only the sample with matched experience and are available upon request.

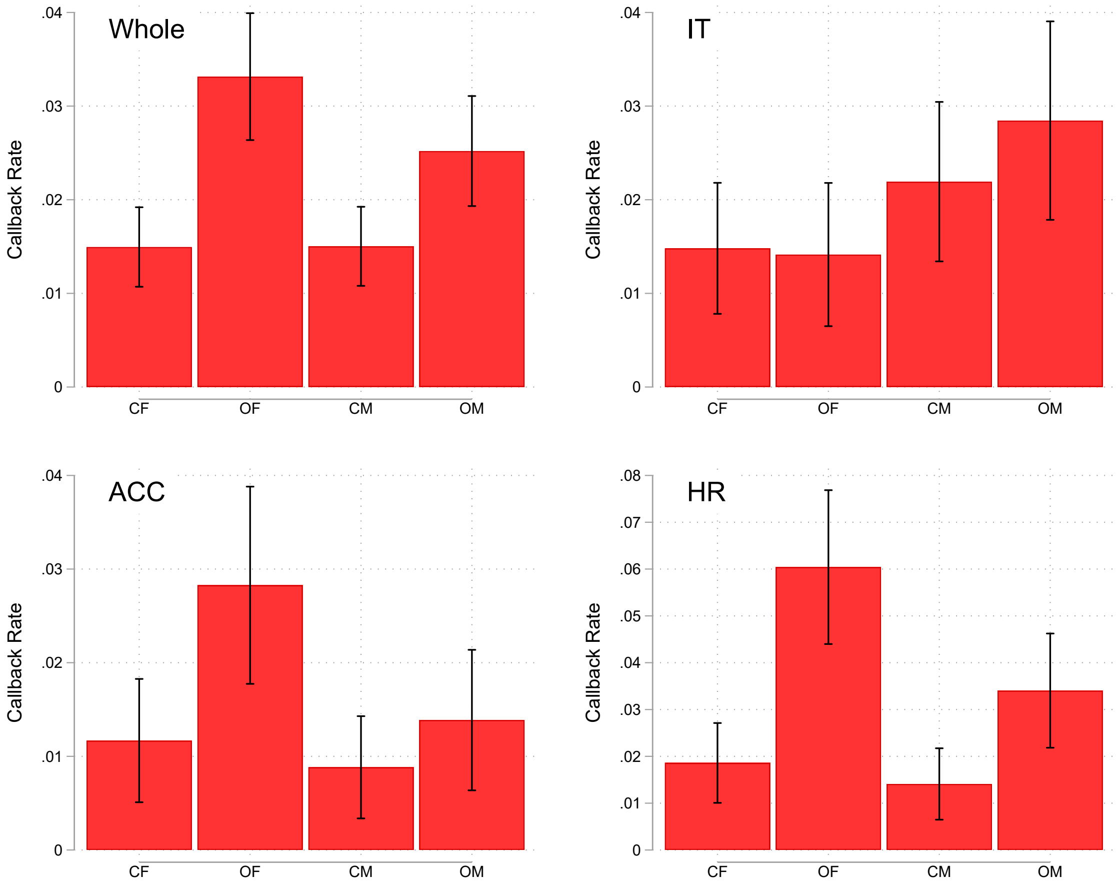


**Figure 2:** Mean Callback Rates for Different Applicants with Matched Working Experience

*Note:* These figures display the mean callback rate for applicants with work experience well aligned with the requirements for the advertised position. The applicants are categorized as follows: childbearing-aged (29-year-old) females (CF), other-aged (24- or 34-year-old) females (OF), childbearing-aged (29-year-old) males (CM), other-aged (24- or 34-year-old) males (OM). The black lines indicate 95% confidence intervals.

**Table 3:** Impact of Gender on the Probability of a Callback for Job Applicants

| *Dependent Variable:* | Callback (yes=1; no=0) | | | |
|---|---|---|---|---|
| | Whole | IT | ACC | HR |
| | (1) | (2) | (3) | (4) |
| Female | 0.003** | −0.007*** | 0.006*** | 0.010*** |
| | (0.001) | (0.002) | (0.002) | (0.003) |
| Age 29 | −0.004** | 0.006* | −0.004 | −0.019*** |
| | (0.002) | (0.003) | (0.003) | (0.005) |
| Age 34 | −0.008*** | −0.004 | −0.007** | −0.018*** |
| | (0.002) | (0.003) | (0.003) | (0.005) |
| Working Experience Matched | 0.008*** | 0.005* | 0.006** | 0.015*** |
| | (0.002) | (0.003) | (0.002) | (0.004) |
| Expected Salary Matched | −0.000 | −0.001 | −0.002 | −0.001 |
| | (0.002) | (0.003) | (0.003) | (0.005) |
| Shanghai | 0.004* | −0.001 | 0.005* | 0.009** |
| | (0.002) | (0.004) | (0.003) | (0.004) |
| Guangzhou | 0.000 | −0.003 | −0.001 | 0.006 |
| | (0.002) | (0.004) | (0.003) | (0.005) |
| Shenzhen | 0.003 | −0.003 | 0.006** | 0.009* |
| | (0.002) | (0.004) | (0.003) | (0.005) |
| Log No. Applicants | −0.004*** | −0.003* | −0.002** | −0.005*** |
| | (0.001) | (0.001) | (0.001) | (0.001) |
| Mean of Dep. Variable | 0.015 | 0.014 | 0.011 | 0.020 |
| Firm Characteristics | Yes | Yes | Yes | Yes |
| Observations | 35713 | 12639 | 12384 | 10690 |

*Notes:* The dependent variable is an indicator variable for whether the applicant was invited to an interview. The key variable of interest is whether the applicant is female. The set of covariates includes dummies for the applicant's age, whether her/his work experience matches the advertised position, whether her/his expected salary matches the advertised salary, the cities where the position is advertised, the logarithm of the number of applications received for the advertised position, and work experience expected for the advertised position. The characteristics of the firm, including type, size, and industry, are controlled for. Fixed effects for the month of the job posting and the of the application submission are also included. The model in Column (1) also controls for the field (IT, ACC, or HR). Robust standard errors in parentheses are clustered at the applicant level. $^{*}p < 0.1$; $^{**}p < 0.05$; $^{***}p < 0.01$.

applicant $i$ is 29 years old, which is considered childbearing age. $Age34_i$ indicates whether applicant $i$ is 34 years old. Applicants aged 24 years compose the reference group. The vector of application characteristics $X$ includes indicators for whether the applicant's work experience matches the requirements for the advertised position, whether the applicant's expected salary matches that of the advertised salary, the logarithm of the number of applications received for the advertised position, the work experience expected for the position, and the field of the position (IT, ACC, or HR). In addition, we control for the characteristics of the company posting the position, such as its type, size, and industry. Fixed effects for the month of the job posting and the month of the application submission are also included. The set of city fixed effects $\alpha_j$ absorbs time-invariant city characteristics. Standard errors are clustered at the applicant level to account for any arbitrary correlation in the error term, $\epsilon_{ij}$.

Based on the baseline linear probability model Eq. (1), Table 3 presents the results for the whole sample in Column (1) and for each field in Columns (2)-(4). In the whole sample, female applicants are significantly more likely to receive a positive response from employers by 0.3 percentage points. This positive effect is attributed to the sample of accounting and HR applications, where female applicants are significantly more likely than male applicants to receive a callback, by 0.6 and 1.0 percentage points, respectively. In contrast, female candidates who apply for IT jobs are significantly less likely by 0.7 percentage points to receive a favorable response from employers. The results suggest that females are favored in the female-dominated field of accounting and the mixed-gender field of HR but disadvantaged in the male-dominated field of IT. The gender differences in the callback rates for the different fields are consistent with findings from previous research, such as Riach and Rich (2006) and Becker et al. (2019), which suggest that gender stereotyping can be at play in the hiring process (Weichselbaumer, 2004; Booth and Leigh, 2010).

## 4.2 The Impact of Being of Childbearing Age on Female Applicants

To investigate the impact of being of childbearing age on female applicants, we use the following linear probability model Eq. (2) and estimate the probability of receiving a callback for job applicant $i$ applying for a job in city $j$. The specification is as follows:

$$Callback_{ij} = \alpha_j + \theta_1(Female \times Age29)_i + \theta_2 Female_i + \theta_3 Age29_i + \theta_4 Age34_i + X_i'\gamma + \epsilon_{ij}. \quad (2)$$

The variables in Eq. (2) have the same meaning as in Eq. (1). The coefficient of interest, $\theta_1$, captures the additional impact of a female applicant being of childbearing age on the callback rate.

The results are presented in Table 4 for the full sample in Column (1) and for each field in Columns (2)-(4). The probability of a woman receiving a callback decreases by 0.9 percentage points when she is of fertile age, statistically significant at the 1% level. In the IT industry, a woman's fertile age is associated with a reduction in her chances of receiving a positive response by 1.3 percentage points, statistically significant at the 1% level. By comparison, men in the same age group are 1.2 percentage points more likely to be contacted than men in the younger age group. Women of other ages have a negative but insignificant chance of receiving a callback. Combining these results with the results in Table 3 Column (2), it is evident that women of fertile age are the most likely to be victims of gender discrimination in the IT sector. Moreover, being a woman of fertile age is negatively correlated with the chance of receiving a callback in HR (statistically significant at the 10% level) and in accounting (statistically insignificant).

To further explore the effect of being of fertile age on women in the hiring market, we perform a subgroup analysis that separately compares applicants aged 29 and 24 and applicants aged 29 and 34. Table A.2 provides the results for the subgroup of applicants

**Table 4:** Impact of Being of Childbearing Age on the Probability of a Callback for Female Applicants

| *Dependent Variable:* | Callback (yes=1; no=0) | | | |
|---|---|---|---|---|
| | Whole | IT | ACC | HR |
| | (1) | (2) | (3) | (4) |
| Female × Age 29 | −0.009*** | −0.013*** | −0.006 | −0.009* |
| | (0.003) | (0.005) | (0.004) | (0.005) |
| Female | 0.006*** | −0.003 | 0.008*** | 0.013*** |
| | (0.002) | (0.002) | (0.002) | (0.003) |
| Age 29 | 0.000 | 0.012*** | −0.001 | −0.014** |
| | (0.003) | (0.005) | (0.004) | (0.005) |
| Age 34 | −0.008*** | −0.004 | −0.007** | −0.018*** |
| | (0.002) | (0.003) | (0.003) | (0.005) |
| Working Experience Matched | 0.008*** | 0.005* | 0.006** | 0.015*** |
| | (0.002) | (0.003) | (0.002) | (0.004) |
| Expected Salary Matched | −0.000 | −0.001 | −0.002 | −0.001 |
| | (0.002) | (0.003) | (0.003) | (0.005) |
| Shanghai | 0.004* | −0.001 | 0.005* | 0.009** |
| | (0.002) | (0.004) | (0.003) | (0.004) |
| Guangzhou | 0.000 | −0.003 | −0.001 | 0.006 |
| | (0.002) | (0.004) | (0.003) | (0.005) |
| Shenzhen | 0.003 | −0.003 | 0.006** | 0.009* |
| | (0.002) | (0.004) | (0.003) | (0.005) |
| Log No. Applicants | −0.004*** | −0.003* | −0.002** | −0.005*** |
| | (0.001) | (0.001) | (0.001) | (0.001) |
| Mean of Dep. Variable | 0.015 | 0.014 | 0.011 | 0.020 |
| Firm Characteristics | Yes | Yes | Yes | Yes |
| Observations | 35713 | 12639 | 12384 | 10690 |

*Notes:* The dependent variable is an indicator variable for whether the applicant was invited to an interview. The key variable of interest is whether the applicant is a woman of childbearing age (29 years of age). The set of covariates includes dummies for the applicant's age, whether her/his work experience matches the requirements of the advertised position, whether her/his expected salary matches the advertised salary, and the cities where the position is advertised; the logarithm of the number of applications received for the advertised position; and work experience expected for the advertised position. The characteristics of the firm, including type, size, and industry, are controlled for. Fixed effects for the month of the job posting and the month of the application submission are also included. The model in Column (1) also controls for field (IT, ACC, or HR). Robust standard errors in parentheses are clustered at the applicant level. $^{*}p < 0.1$; $^{**}p < 0.05$; $^{***}p < 0.01$.

aged 29 and 24, which provides a comparison of fertile- and pre-fertile-aged applicants. The results demonstrate that there is a negative association of 1.1 percentage points across the sample between being a woman of fertile age and receiving a callback. The trend is particularly strong among fertile-aged female applicants for positions in HR and IT, where the negative effect is 1.9 percentage points and 1.0 percentage point, respectively. The results for the subgroup of applicants who are 29 and 34 years of age are presented in Table A.3 to illustrate the difference between fertile- and post-fertile-aged applicants. In line with the main findings in Table 4, being of fertile age significantly reduces the likelihood of female applicants receiving a callback by 0.8 percentage points. In contrast, male applicants who are 29 years of age have a significantly higher probability of being called back than those who are 34 years of age by 1.3 percentage points. These results are largely driven by candidates in the IT field. Men aged 29 are 2.3 percentage points more likely to receive a callback than men aged 34. However, being 29 reduces the chances of female applicants receiving a callback by 1.5 percentage points. Additionally, there is a statistically significant negative effect on being a fertile-aged woman in accounting.

Moreover, on the basis of Eq. (2), we further explore the impact of potential maternity by including an additional variable, $Female \times Age34$. Table A.4 presents the results. Female candidates who are 29 years old are less likely to receive a callback for the entire sample. The effect is particularly evident in the area of IT. For jobs in HR, both women aged 29 and women aged 34 are less likely to receive a callback than women aged 24, although women are generally more likely to receive callbacks than men. Overall, the results in Tables 4 and A.2-A.4 are consistent, which demonstrates that being of fertile age reduces women's chances of receiving a positive response from an employer in the hiring process. These findings suggest that there may be statistical discrimination against women of fertile age.

**Result 1**: *As a whole, women of childbearing age face discrimination. There is heterogeneity in the discrimination across fields. Comparatively, discrimination is more prevalent in the field of IT, with a majority of male workers, than in the field of HR, with a balanced gender mix, or the field of accounting, with a majority of female workers.*

## 4.3 The Impact of the Length of Maternity Leave on Female Applicants

Employers may view employees in the early stages of motherhood as more costly, which could be a major reason why women of childbearing age are discriminated against in the work force. A longer maternity leave could potentially increase these costs and adversely impact the employment prospects of women of fertile age. To examine whether the length of maternity leave plays a role in the gender discrimination in hiring decisions, we employ the following linear probability model Eq. (3) to estimate the probability of job applicant $i$, applying for a job in a city $j$, receiving a callback. The specification is as follows:

$$\begin{aligned} Callback_{ij} = \alpha_j + \rho_1(Female \times Age29)_i \times LL_j + \rho_2(Female \times Age29)_i + \rho_3 Female_i \times LL_j \\ + \rho_4 Age29_i \times LL_j + \rho_5 Female_i + \rho_6 Age29_i + \rho_7 Age34_i + X_i'\gamma + \epsilon_{ij}. \end{aligned} \tag{3}$$

where $LL_j$ is an indicator for whether city $j$ offers maternity leave with a longer duration, which is the case in Guangzhou and Shenzhen in our experiment. The other variables have the same interpretation as in Eq. (1) and Eq. (2). The coefficient of interest is $\rho_1$, which measures the specific impact of a female applicant of childbearing age seeking employment in a city with longer maternity leave on her chances of receiving a positive employer response.

Table 5 presents the results for the whole sample in Column (1) and for each field in Columns (2)-(4). In the entire sample, the estimate for the variable $Female \times Age29$ shows that being of fertile age significantly reduces a woman's callback rate by 1.4 percentage points if the job is located in Beijing or Shanghai. This effect is quite consistent across the different fields. However, there is no additional discrimination against women of fertile age in Guangzhou and Shenzhen, where maternity leaves are longer, as indicated by the estimate for the variable $Female \times Age29 \times LL$. It appears that female job applicants of fertile age are not more disadvantaged in cities with longer maternity leaves, such as Guangzhou and Shenzhen, than in cities with shorter maternity leaves, such as Beijing and Shanghai. Despite our results showing no additional discrimination in Guangzhou or Shenzhen relative to Beijing and Shanghai, it cannot be concluded that the length of maternity leave has no bearing on discrimination against women of childbearing age in the labor market. Other factors may be at play in cities such as Beijing and Shanghai that increase the barriers to employment for women in their reproductive years.

**Result 2**: *There is no additional discrimination based on being of childbearing age in Guangzhou or Shenzhen (cities with longer maternity leaves) relative to Beijing and Shanghai (cities with shorter maternity leaves).*

## 4.4 Subsample Analysis

### 4.4.1 Subsample Analysis by City

To further explore the situation in different cities, we conduct a subsample analysis by city. Table 6, Panels I to IV, present estimates of Eq. (2) for the whole subsample and each occupation in Beijing, Shanghai, Guangzhou, and Shenzhen, respectively. For jobs in Beijing, being of fertile age significantly reduces the callback rate for women by 1.7 percentage points. The impact is evident, with a 2.8-percentage point reduction for jobs in IT and a 2.1-percentage point reduction for jobs in accounting. In Shanghai, being of fertile age significantly lowers

**Table 5:** Impact of the Length of Maternity Leave on Female Applicants

| *Dependent Variable:* | Callback (yes=1; no=0) | | | |
|---|---|---|---|---|
| | Whole | IT | ACC | HR |
| | (1) | (2) | (3) | (4) |
| Female × Age 29× Longer PML Cities | 0.009 | −0.001 | 0.013 | 0.016 |
| | (0.006) | (0.010) | (0.008) | (0.011) |
| Female × Age 29 | −0.014*** | −0.012* | −0.013** | −0.018** |
| | (0.004) | (0.007) | (0.005) | (0.007) |
| Female × Longer PML Cities | 0.001 | 0.001 | −0.002 | 0.002 |
| | (0.003) | (0.005) | (0.004) | (0.007) |
| Age 29 × Longer PML Cities | −0.004 | −0.005 | −0.005 | −0.003 |
| | (0.004) | (0.008) | (0.005) | (0.007) |
| Female | 0.005*** | −0.003 | 0.009*** | 0.012** |
| | (0.002) | (0.003) | (0.003) | (0.005) |
| Age 29 | 0.002 | 0.014** | 0.002 | −0.013* |
| | (0.003) | (0.006) | (0.005) | (0.007) |
| Age 34 | −0.008*** | −0.004 | −0.007** | −0.018*** |
| | (0.002) | (0.003) | (0.003) | (0.005) |
| Working Experience Matched | 0.008*** | 0.005* | 0.006** | 0.015*** |
| | (0.002) | (0.003) | (0.002) | (0.004) |
| Expected Salary Matched | −0.000 | −0.001 | −0.002 | −0.001 |
| | (0.002) | (0.003) | (0.003) | (0.005) |
| Shanghai | 0.004* | −0.001 | 0.005* | 0.009** |
| | (0.002) | (0.004) | (0.003) | (0.004) |
| Guangzhou | −0.000 | −0.001 | −0.001 | 0.003 |
| | (0.003) | (0.005) | (0.004) | (0.006) |
| Shenzhen | 0.003 | −0.002 | 0.006* | 0.006 |
| | (0.003) | (0.004) | (0.003) | (0.006) |
| Log No. Applicants | −0.004*** | −0.002* | −0.002** | −0.005*** |
| | (0.001) | (0.001) | (0.001) | (0.001) |
| Mean of Dep. Variable | 0.015 | 0.014 | 0.011 | 0.020 |
| Firm Characteristics | Yes | Yes | Yes | Yes |
| Observations | 35713 | 12639 | 12384 | 10690 |

*Notes:* The dependent variable is an indicator variable for whether the applicant was invited to an interview. The key variable of interest is whether the applicant is a woman of childbearing age (29 years of age) who is applying to jobs in cities with longer paid maternity leave policies (Guangzhou and Shenzhen). The set of covariates includes dummies for the applicant's age, whether her/his work experience matches the requirements of the advertised position, whether her/his expected salary matches the advertised salary, and the cities where the position is advertised; the logarithm of the number of applications received for the advertised position; and work experience expected for the advertised position. The characteristics of the firm, including type, size, and industry, are controlled for. Fixed effects for the month of the job posting and the month of the application submission are also included. The model in Column (1) also controls for the field (IT, ACC, or HR). Robust standard errors in parentheses are clustered at the applicant level. $^{*}p < 0.1$; $^{**}p < 0.05$; $^{***}p < 0.01$.

women's callback rates by 1.2 percentage points, and jobs in accounting and HR contribute 1.1 and 2.3 percentage points of this decrease, respectively. In Guangzhou, there is no evidence of discrimination against women of childbearing age, since the estimates for the key variable of interest, $Female \times Age29$, are small and insignificant. In Shenzhen, being of fertile age significantly decreases the callback rate for female applicants in the IT sector by 1.6 percentage points.

**Table 6:** Impact of Being of Childbearing Age on Female Applicants by City

| *Dependent Variable:* | Callback (yes=1; no=0) | | | |
|---|---|---|---|---|
| | Whole | IT | ACC | HR |
| | (1) | (2) | (3) | (4) |
| *Panel I: Beijing* | | | | |
| Female × Age 29 | -0.017** | -0.028* | -0.021** | -0.003 |
| | (0.008) | (0.017) | (0.009) | (0.013) |
| Female | 0.003 | 0.002 | 0.010* | -0.002 |
| | (0.004) | (0.006) | (0.006) | (0.009) |
| Age 29 | 0.007 | 0.022 | 0.002 | -0.006 |
| | (0.008) | (0.015) | (0.009) | (0.015) |
| Age 34 | -0.007 | -0.010 | -0.005 | -0.010 |
| | (0.006) | (0.010) | (0.007) | (0.013) |
| Mean of Dep. Variable | 0.013 | 0.018 | 0.007 | 0.013 |
| Observations | 4316 | 1706 | 1491 | 1119 |
| *Panel II: Shanghai* | | | | |
| Female × Age 29 | -0.012*** | -0.007 | -0.011* | -0.023*** |
| | (0.004) | (0.008) | (0.006) | (0.009) |
| Female | 0.006*** | -0.005 | 0.009** | 0.017*** |
| | (0.002) | (0.004) | (0.004) | (0.006) |
| Age 29 | 0.001 | 0.010 | 0.001 | -0.009 |
| | (0.004) | (0.008) | (0.006) | (0.009) |
| Age 34 | -0.008*** | -0.005 | -0.009* | -0.011 |
| | (0.003) | (0.004) | (0.005) | (0.008) |
| Mean of Dep. Variable | 0.015 | 0.013 | 0.011 | 0.020 |
| Observations | 13668 | 4743 | 4894 | 4031 |
| *Panel III: Guangzhou* | | | | |
| Female × Age 29 | -0.002 | -0.009 | -0.004 | 0.002 |
| | (0.006) | (0.011) | (0.007) | (0.012) |

Continued on next page

**Table 6:** Impact of Being of Childbearing Age on Female Applicants by City

| *Dependent Variable:* | Callback (yes=1; no=0) | | | |
|---|---|---|---|---|
| | Whole | IT | ACC | HR |
| | (1) | (2) | (3) | (4) |
| Female | 0.004 | -0.006 | 0.002 | 0.016** |
| | (0.003) | (0.006) | (0.004) | (0.007) |
| Age 29 | -0.003 | 0.011 | -0.002 | -0.018 |
| | (0.005) | (0.011) | (0.007) | (0.012) |
| Age 34 | -0.010** | -0.007 | -0.005 | -0.025** |
| | (0.004) | (0.008) | (0.006) | (0.011) |
| Mean of Dep. Variable | 0.014 | 0.014 | 0.009 | 0.020 |
| Observations | 7714 | 2420 | 2742 | 2552 |
| *Panel IV: Shenzhen* | | | | |
| Female × Age 29 | -0.007 | -0.016* | 0.004 | -0.006 |
| | (0.005) | (0.008) | (0.009) | (0.011) |
| Female | 0.008** | 0.000 | 0.010** | 0.013* |
| | (0.003) | (0.004) | (0.005) | (0.007) |
| Age 29 | -0.001 | 0.013* | -0.006 | -0.018* |
| | (0.005) | (0.008) | (0.007) | (0.011) |
| Age 34 | -0.009** | 0.001 | -0.010 | -0.026*** |
| | (0.004) | (0.006) | (0.008) | (0.009) |
| Mean of Dep. Variable | 0.016 | 0.013 | 0.015 | 0.021 |
| Observations | 10015 | 3770 | 3257 | 2988 |
| Firm Characteristics | Yes | Yes | Yes | Yes |

*Notes:* Panels I, II, III, and IV present the results of a subsample analysis in which the positions advertised were located in Beijing, Shanghai, Guangzhou, and Shenzhen, respectively. The dependent variable is an indicator variable for whether the applicant was invited to an interview. The key variable of interest is whether the applicant is a woman of childbearing age (29 years of age). The set of covariates includes dummies for the applicant's age, whether her/his work experience matches the requirements of the advertised position, whether her/his expected salary matches the advertised salary, and the cities where the position is advertised; the logarithm of the number of applications received for the advertised position; and work experience expected for the advertised position. The characteristics of the firm, including type, size, and industry, are controlled for. Fixed effects for the month of the job posting and the month of the application submission are also included. The model in Column (1) also controls for the field (IT, ACC, or HR). Robust standard errors in parentheses are clustered at the applicant level. $^{*}p < 0.1$; $^{**}p < 0.05$; $^{***}p < 0.01$.

Taken together, these results show that women of childbearing age are likely to face discrimination in the hiring market, especially when seeking employment in the field of IT. The situation is particularly serious in Beijing and Shanghai, where signs of discrimination are also evident in the fields of accounting and HR. In line with the findings in Table 5, the results of the subsample analysis suggest that discrimination against women of fertile age does not increase with the length of local maternity leave but in a direction contrary to expectations.

### 4.4.2 Subsample Analysis by Firm Ownership

The study by Zhou et al. (2013) shows that different types of companies tend to have different gender preferences when hiring new employees. Thus, we conduct a subsample analysis based on the different types of firms ownership. The ownership information is provided by 51job.com when job advertisements are published. First, we divide the total sample into state-owned enterprises (SOEs) and non-state-owned enterprises (NSOEs). Panels I and II of Table 7 present estimates of Eq. (2) for each subsample and field. For jobs in SOEs, there is a negative association of 2.1 percentage points between being a woman of fertile age and callback rates. This effect is significantly influenced by employment in accounting, which accounts for 2.8 percentage points of this decline. Among NSOE jobs, being of fertile age reduces women's callback rate by 0.9 percentage points. For IT jobs, being of fertile age significantly reduces a woman's callback rate by 1.3 percentage points. Overall, it appears that women's employment opportunities are negatively affected by their potential maternity, regardless of whether the employment is with an SOE.

**Table 7:** Impact of Being of Childbearing Age on Female Applicants by Firm Ownership

| *Dependent Variable:* | Callback (yes=1; no=0) | | | |
|---|---|---|---|---|
| | Whole | IT | ACC | HR |
| | (1) | (2) | (3) | (4) |
| *Panel I: SOEs* | | | | |
| Female × Age 29 | -0.021* | -0.014 | -0.028** | -0.022 |
| | (0.011) | (0.025) | (0.013) | (0.020) |
| Female | 0.002 | -0.008 | 0.014* | 0.006 |
| | (0.005) | (0.009) | (0.008) | (0.010) |
| Age 29 | 0.025** | 0.040 | 0.022* | 0.007 |
| | (0.011) | (0.024) | (0.013) | (0.018) |
| Age 34 | 0.006 | 0.000 | 0.020* | -0.015 |
| | (0.007) | (0.013) | (0.011) | (0.013) |
| Mean of Dep. Variable | 0.014 | 0.020 | 0.008 | 0.014 |
| Observations | 2612 | 886 | 1023 | 703 |
| *Panel II: NSOEs* | | | | |
| Female × Age 29 | -0.009*** | -0.013*** | -0.005 | -0.008 |
| | (0.003) | (0.005) | (0.004) | (0.006) |

Continued on next page

**Table 7:** Impact of Being of Childbearing Age on Female Applicants by Firm Ownership

| *Dependent Variable:* | Callback (yes=1; no=0) | | | |
|---|---|---|---|---|
| | Whole | IT | ACC | HR |
| | (1) | (2) | (3) | (4) |
| Female | 0.006*** | -0.002 | 0.008*** | 0.014*** |
| | (0.002) | (0.002) | (0.002) | (0.004) |
| Age 29 | -0.002 | 0.011** | -0.002 | -0.016*** |
| | (0.003) | (0.005) | (0.004) | (0.006) |
| Age 34 | -0.009*** | -0.004 | -0.009*** | -0.019*** |
| | (0.002) | (0.003) | (0.003) | (0.005) |
| Mean of Dep. Variable | 0.015 | 0.014 | 0.011 | 0.020 |
| Observations | 33101 | 11753 | 11361 | 9987 |
| *Panel III: FIEs* | | | | |
| Female × Age 29 | -0.009 | -0.007 | -0.006 | -0.012 |
| | (0.006) | (0.009) | (0.009) | (0.014) |
| Female | 0.003 | -0.005 | 0.004 | 0.008 |
| | (0.003) | (0.005) | (0.005) | (0.009) |
| Age 29 | -0.002 | -0.002 | 0.005 | -0.009 |
| | (0.006) | (0.009) | (0.008) | (0.015) |
| Age 34 | -0.010** | -0.010 | -0.004 | -0.019* |
| | (0.004) | (0.006) | (0.006) | (0.011) |
| Mean of Dep. Variable | 0.014 | 0.010 | 0.010 | 0.024 |
| Observations | 6757 | 2285 | 2503 | 1969 |
| *Panel IV: NFIEs* | | | | |
| Female × Age 29 | -0.010*** | -0.014** | -0.007 | -0.008 |
| | (0.003) | (0.006) | (0.005) | (0.006) |
| Female | 0.006*** | -0.002 | 0.009*** | 0.014*** |
| | (0.002) | (0.003) | (0.002) | (0.004) |
| Age 29 | 0.001 | 0.015*** | -0.001 | -0.015** |
| | (0.003) | (0.005) | (0.004) | (0.006) |
| Age 34 | -0.008*** | -0.003 | -0.007** | -0.018*** |
| | (0.002) | (0.003) | (0.004) | (0.006) |
| Mean of Dep. Variable | 0.015 | 0.015 | 0.011 | 0.019 |
| Observations | 28956 | 10354 | 9881 | 8721 |
| Firm Characteristics | Yes | Yes | Yes | Yes |

*Notes:* Panels I, II, III, and IV present the results of a subsample analysis in which the positions advertised were with SOEs, NSOEs, foreign companies, and local companies. The dependent variable is an indicator variable for whether the applicant was invited to an interview. The key variable of interest is whether the applicant is a woman of childbearing age (29 years of age). The set of covariates includes dummies for the applicant's age, whether her/his work experience matches the requirements of the advertised position, whether her/his expected salary matches the advertised salary, and the cities where the position is advertised; the logarithm of the number of applications received for the advertised position; and work experience expected for the advertised position. The characteristics of the firm, including type, size, and industry, are controlled for. Fixed effects for the month of the job posting and the month of the application submission are also included. The model in Column (1) also controls for the field (IT, ACC, or HR). Robust standard errors in parentheses are clustered at the applicant level. $^{*}p < 0.1$; $^{**}p < 0.05$; $^{***}p < 0.01$.

In addition, we divide the total sample into foreign-invested enterprises (FIEs) and non-foreign-invested enterprises (NFIEs). Table 7 Panels III and IV present estimates of Eq. (2) for each subsample and field. The estimates in Panel III indicate that there is no evidence of discrimination against female applicants of childbearing age who apply for positions in FIEs across all three fields. However, for positions in NFIEs, being a woman of fertile age reduces the callback rate by 1.0 percentage points. This reduction is significantly driven by employment in IT, which accounts for 1.4 percentage points of the negative effect, as shown in Panel IV.

### 4.4.3 Subsample Analysis by Salary Level Advertised

Considering that gender discrimination may differ based on salaries, we examine whether there is a difference in discrimination between jobs with different advertised salaries. Figure 3 displays quantile-box plots of salaries for positions posted on 51job.com in HR, accounting, and IT. The mean monthly salaries for HR jobs, accounting jobs, and IT jobs are 11458 RMB, 11534 RMB, and 14393 RMB, respectively. The average monthly salary for the entire sample is 12520 RMB. Based on the mean salary for each group, we conduct a subsample analysis and present estimates of Eq. (2) in Table 8. Panel I provides the results for the subgroup with salaries above the average, and Panel II contains the results for the subgroup with salaries below the average. It appears that being of fertile age significantly reduces women's callback rate by 0.9 to 1.0 percentage points regardless of whether they apply for jobs with salaries above or below the average. In accounting, the likelihood of a female applicant of fertile age receiving a positive response decreases by 1.1 percentage points when applying for a position with a salary that is above the average. The chances of female candidates of fertile age receiving a callback from a position with a salary that is below average are reduced by 1.7 percentage points when applying for IT jobs.

**Result 3**: *There is no childbearing age-based discrimination in foreign-invested enterprises, while it is observed in other types of enterprises. Childbearing age-based discrimination is observed in both positions with posted salaries below the average and those with posted salaries above the average.*

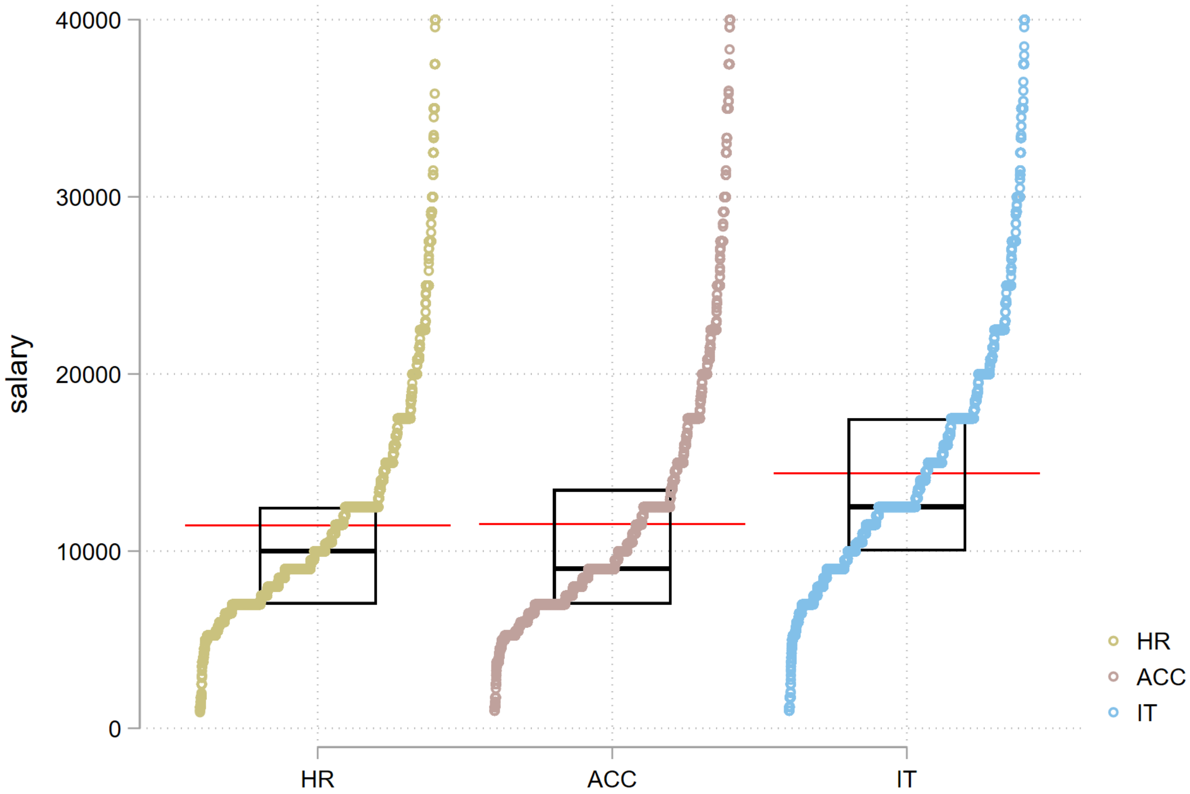


**Figure 3:** Quantile-Box Plot of Advertised Salaries by Field

*Note:* The red lines represent the mean monthly salaries (IT: 14393, HR: 11458, ACC: 11534) for the advertised positions in RMB. The mean monthly salary for the whole sample is 12520 RMB.

**Table 8:** Impact of Being of Childbearing Age on Female Applicants by Salary Level

| *Dependent Variable:* | Callback (yes=1; no=0) | | | |
|---|---|---|---|---|
| | Whole | IT | ACC | HR |
| | (1) | (2) | (3) | (4) |
| *Panel I: Posted Salary of the Positions above the Average* | | | | |
| Female × Age 29 | −0.010** | −0.007 | −0.011** | −0.009 |
| | (0.004) | (0.007) | (0.006) | (0.007) |
| Female | 0.004* | −0.001 | 0.006* | 0.010*** |
| | (0.002) | (0.003) | (0.003) | (0.004) |
| Age 29 | 0.010** | 0.015** | 0.003 | 0.003 |
| | (0.004) | (0.007) | (0.006) | (0.007) |
| Age 34 | −0.000 | −0.002 | 0.000 | −0.009* |
| | (0.002) | (0.004) | (0.004) | (0.005) |
| Shanghai | −0.004 | −0.007 | −0.006 | 0.003 |
| | (0.004) | (0.006) | (0.005) | (0.005) |
| Guangzhou | −0.003 | −0.007 | −0.008 | 0.009 |
| | (0.004) | (0.007) | (0.006) | (0.006) |
| Shenzhen | −0.005 | −0.008 | −0.006 | 0.011* |
| | (0.004) | (0.006) | (0.006) | (0.006) |
| Log No. Applicants | 0.001 | 0.001 | −0.003 | 0.000 |
| | (0.001) | (0.002) | (0.002) | (0.002) |
| Mean of Dep. Variable | 0.010 | 0.012 | 0.008 | 0.012 |
| Observations | 11432 | 5226 | 4585 | 4491 |
| *Panel II: Posted Salary of the Positions below the Average* | | | | |
| Female × Age 29 | −0.009** | −0.017** | −0.003 | −0.007 |
| | (0.004) | (0.007) | (0.006) | (0.008) |
| Female | 0.007*** | −0.004 | 0.009*** | 0.016*** |
| | (0.002) | (0.003) | (0.003) | (0.005) |
| Age 29 | −0.007 | 0.018** | −0.007 | −0.029** |
| | (0.005) | (0.008) | (0.006) | (0.012) |
| Age 34 | −0.016*** | −0.001 | −0.016** | −0.033*** |
| | (0.005) | (0.008) | (0.006) | (0.012) |
| Shanghai | 0.007*** | 0.004 | 0.012*** | 0.011* |
| | (0.003) | (0.005) | (0.003) | (0.006) |
| Guangzhou | 0.002 | 0.001 | 0.004 | 0.002 |
| | (0.003) | (0.005) | (0.003) | (0.007) |
| Shenzhen | 0.007** | 0.000 | 0.014*** | 0.005 |
| | (0.003) | (0.005) | (0.004) | (0.007) |
| Log No. Applicants | −0.004*** | −0.004** | −0.002 | −0.008*** |
| | (0.001) | (0.002) | (0.002) | (0.002) |
| Mean of Dep. Variable | 0.017 | 0.016 | 0.013 | 0.025 |
| Observations | 23725 | 7180 | 7613 | 6062 |
| Firm Characteristics | Yes | Yes | Yes | Yes |

*Notes:* Panels I and II present the results for the subsamples whose posted salaries are above/below the median for each occupation. The dependent variable is an indicator variable for whether the applicant was invited to an interview. The key variable of interest is whether the applicant is a woman of childbearing age (29 years of age). The set of covariates includes dummies for the applicant's age, whether her/his work experience matches the requirements of the advertised position, whether her/his expected salary matches the advertised salary, and the cities where the position is advertised; the logarithm of the number of applications received for the advertised position; and work experience expected for the advertised position. The characteristics of the firm, including type, size, and industry, are controlled for. Fixed effects for the month of the job posting and the month of the application submission are also included. The model in Column (1) also controls for the field (IT, ACC, or HR). Robust standard errors in parentheses are clustered at the applicant level. $^{*}p < 0.1$; $^{**}p < 0.05$; $^{***}p < 0.01$.

## 4.5 Robustness Checks

### 4.5.1 Probit Models with Marginal Effects

To check whether the main results are robust to different specifications, we use a probit model to estimate the marginal effect of being a fertile-aged female applicant on the probability of receiving a positive employer response. Table 9 presents probit estimates of the marginal effect (at the mean) for the whole sample and for each field. The results demonstrate that female applicants of fertile age have a 0.8 percentage point lower likelihood of being contacted. The evidence for this effect is statistically significant for IT and accounting jobs. Overall, the estimated marginal effects from the probit models provide results similar to those obtained from the linear probability model in Table 4, suggesting that the findings are robust to the choice of specifications.[13]

### 4.5.2 Impact of the Variance of the Unobservable Determinants of Productivity

Correspondence tests can identify discrimination by employers and overcome the issue of endogeneity due to unobserved individual-level heterogeneity. A caveat with this method, however, is that the variance of the unobservables can bias the measurement of discrimination; this issue is referred to as the Heckman-Siegelman critique (Heckman and Siegelman, 1993). Specifically, the variance of the unobservables may influence the degree of discrimination when employers perceive a group-level difference in the variance of unobserved productivity. The reason is that if the variance varies between groups of applicants, its effect on the callback rate may be incorrectly attributed to discrimination (Heckman, 1998; Carlsson et al., 2014). Neumark (2012) proposes a method for distinguishing between the unbiased estimate of discrimination and the variance of the unobservables. We use the Neumark method to determine whether our estimates of discrimination are robust to the Heckman-Siegelman critique. The method involves two steps. The first step is to estimate a heteroskedastic probit model. The second step is to decompose the marginal effect from the heteroskedastic probit model into two parts: the effect through the level of discrimination, which represents the unbiased estimate of discrimination, and the effect through the variance of the unobservables. Considering that the focus of our research is on fertile-aged women, we compare fertile-aged women with other-aged women, as well as fertile-aged women with men.

Column (1) of Table 10 presents the results for fertile-aged women versus women of other ages. Panel I provides the estimate from the standard probit model for comparison with Panel II, which provides the marginal effect estimate from the heteroskedastic probit model. Both

[13] Additionally available upon request are probit estimations for the results in the other tables, which support the same conclusions.

**Table 9:** Impact of Being of Childbearing Age on Female Applicants: Probit Models

| *Dependent Variable:* | Callback (yes=1; no=0) | | | |
|---|---|---|---|---|
| | Whole | IT | ACC | HR |
| | (1) | (2) | (3) | (4) |
| Female × Age 29 | −0.008*** | −0.008** | −0.006* | −0.007 |
| | (0.002) | (0.004) | (0.003) | (0.004) |
| Female | 0.005*** | −0.003 | 0.007*** | 0.010*** |
| | (0.001) | (0.003) | (0.002) | (0.002) |
| Age 29 | 0.003 | 0.009*** | 0.002 | −0.006 |
| | (0.002) | (0.003) | (0.003) | (0.004) |
| Age 34 | −0.007*** | −0.004 | −0.005** | −0.013*** |
| | (0.002) | (0.003) | (0.003) | (0.004) |
| Working Experience Matched | 0.005*** | 0.005** | 0.004** | 0.008*** |
| | (0.001) | (0.002) | (0.002) | (0.002) |
| Expected Salary Matched | −0.000 | −0.001 | −0.002 | −0.000 |
| | (0.001) | (0.003) | (0.002) | (0.003) |
| Shanghai | 0.003 | −0.001 | 0.004 | 0.007 |
| | (0.002) | (0.003) | (0.003) | (0.004) |
| Guangzhou | 0.000 | −0.002 | 0.000 | 0.005 |
| | (0.002) | (0.003) | (0.003) | (0.004) |
| Shenzhen | 0.002 | −0.003 | 0.006* | 0.007* |
| | (0.002) | (0.003) | (0.003) | (0.004) |
| Log No. Applicants | −0.003*** | −0.002** | −0.002* | −0.004*** |
| | (0.001) | (0.001) | (0.001) | (0.001) |
| Mean of Dep. Variable | 0.015 | 0.014 | 0.011 | 0.020 |
| Firm Characteristics | Yes | Yes | Yes | Yes |
| Observations | 35396 | 11035 | 11206 | 10084 |

*Notes:* Probit models with marginal effects (at the mean). The dependent variable is an indicator variable for whether the applicant was invited to an interview. The key variable of interest is whether the applicant is a woman of childbearing age (29 years of age). The set of covariates includes dummies for the applicant's age, whether her/his work experience matches the requirements of the advertised position, whether her/his expected salary matches the advertised salary, and the cities where the position is advertised; the logarithm of the number of applications received for the advertised position; and work experience expected for the advertised position. The characteristics of the firm, including type, size, and industry, are controlled for. Fixed effects for the month of the job posting and the month of the application submission are also included. The model in Column (1) also controls for the field (IT, ACC, or HR). Robust standard errors in parentheses are clustered at the applicant level. $^{*}p < 0.1$; $^{**}p < 0.05$; $^{***}p < 0.01$.

**Table 10:** The Neumark Method for Testing the Heckman-Siegelman Critique

| *Treatment group:* | Fertile-Aged Women | |
|---|---|---|
| *Comparison group:* | Other-Aged Women | Men |
| | (1) | (2) |
| I. Basic probit model (marginal effects) | −0.006*** | −0.003 |
| | (0.002) | (0.002) |
| II. Heteroskedastic probit model (marginal effects) | −0.005*** | −0.008*** |
| | (0.002) | (0.003) |
| III. Decomposition | | |
| Marginal effect through level (unbiased effects) | −0.050*** | −0.053*** |
| | (0.005) | (0.004) |
| Marginal effect through variance | 0.045*** | 0.045*** |
| | (0.004) | (0.005) |
| Ralative standard deviation of unobserved variables (treatment/comparison) | 2.507 | 2.766 |
| Wald test statistics: null hypothesis that ratio of standard deviations = 1 ($p$-value) | 0.122 | 0.358 |
| Wald test statistics: null hypothesis that ratio of coefficients are equal ($p$-value) | 0.126 | 0.579 |
| Number of Observations | 17916 | 23739 |

*Notes:* The dependent variable is an indicator variable for whether the applicant was invited to an interview. The set of covariates includes the applicant's gender, age, whether her/his work experience matches the advertised position, whether her/his expected salary matches the advertised salary, the cities in which the position is advertised, the logarithm of the number of applications received for the advertised position, and dummies for the field (IT, ACC, or HR). Fixed effects for the month of the job posting and the month of the application submission are also included. Standard errors are in parentheses. $^{*}p < 0.1$; $^{**}p < 0.05$; $^{***}p < 0.01$.

estimates suggest that fertile-aged women are significantly less likely than women of other ages to receive a positive employer response. Moreover, the Neumark decomposition in Panel III reveals that this adverse effect is largely underestimated. The marginal effect through the level of discrimination is much greater in magnitude and statistically significant. The effect through the variance of the unobserved variables is positive and significant. This result indicates that the relatively low quality of the experimental applicants has led to a relative advantage for the applicants from the higher variance group, leading to an underestimate of the extent of discrimination against female applicants of fertile age.

Table 10, Column (2), provides a comparison of fertile-aged women and men. In Panel II, the marginal effect from the heteroskedastic probit model shows that fertile-aged women are significantly less likely to receive a callback than men. There is a large difference in the estimates obtained from the standard probit in Panel I and the heteroskedastic probit model in Panel II, suggesting a perceived difference in the variance of unobservables between groups. Similar to Column (1), the Neumark decomposition of Panel III indicates that the negative impact on fertile-aged women is statistically significant but is also greatly underestimated.

Overall, based on the Neumark method, we confirm that women of childbearing age are discriminated against in the job market. Due to the limitations of our experimental design, it is likely that we have underestimated the extent of the discrimination to which they are subjected in the real world.

# 5 Discussion and Conclusion

In this paper, we perform a large-scale correspondence test to investigate the impact of being of childbearing age on women's employment opportunities. Our experiment is conducted in four major Chinese cities, namely, Beijing, Shanghai, Guangzhou, and Shenzhen, using one of the largest online job boards. The target professions are the male-dominated field of IT, the female-dominated field of accounting, and the mixed-gender field of HR. The age and gender of the applicants are systematically varied, and we track interview callbacks. Our study differs from the literature on potential maternity discrimination by systematically investigating the effects of different types of fields (male-dominated, female-dominated, and gender-mixed), using a design with nondisclosure of marital status, and examining the effect of differences in maternity leave duration.

In general, female candidates receive fewer callbacks in IT, while male candidates receive fewer callbacks in HR and accounting. However, we find that women of childbearing age face discrimination in the labor market, although their maternity status is unknown to employers. This is most evident in the IT field but also occurs in HR and accounting, especially in Beijing and Shanghai. This suggests that discrimination against women of childbearing age can occur even in the absence of a disclosure of maternity status. The intuition is that employers make inferences regarding the likelihood of female candidates giving birth based on their age.

We find that discrimination against women of fertile age is widespread across SOEs, NSOEs, local businesses, and both in positions with salaries above the average and those with salaries below the average. The results indicate that statistical discrimination against women who are likely to be in the early stages of motherhood prevents them from receiving equal employment opportunities. The conclusion that women of fertile age are subject to discrimination in the hiring process is robust to the Heckman-Seigelman critique. However, based on a Neumark decomposition, we find that it is likely that we have underestimated the extent to which they are subject to discrimination in the real world.

We also examine whether differences in maternity leave duration affect women's employment prospects in different cities. Contrary to expectations, in Beijing and Shanghai, where maternity leaves are shorter, women are more likely to face discrimination than in Guangzhou and Shenzhen, where maternity leaves are longer. In this regard, it appears that the employment costs associated with the length of maternity leave do not necessarily reflect discrimination against women of childbearing age.

Furthermore, other factors that increase barriers to employment for women who are at the peak of their reproductive potential may be at play in cities such as Beijing and Shanghai. Labor costs might be one such factor. It is common for women to take maternity and childcare leaves during the early stages of motherhood. For employers, this entails finding temporary employees to perform their duties during such absences. Thus, the higher the labor costs in a city, the more expensive it is for employers to hire temporary workers. Figure 4 illustrates the average annual salaries in Beijing, Shanghai, Guangzhou, and Shenzhen for the period 2017 to 2020. As shown, Beijing has the highest average salary, closely followed by Shanghai, both of which have higher salaries than Guangzhou or Shenzhen. As a result, it is possible for employers in Beijing and Shanghai to be less inclined to hire women in their fertile years due to the additional higher costs they may potentially incur.

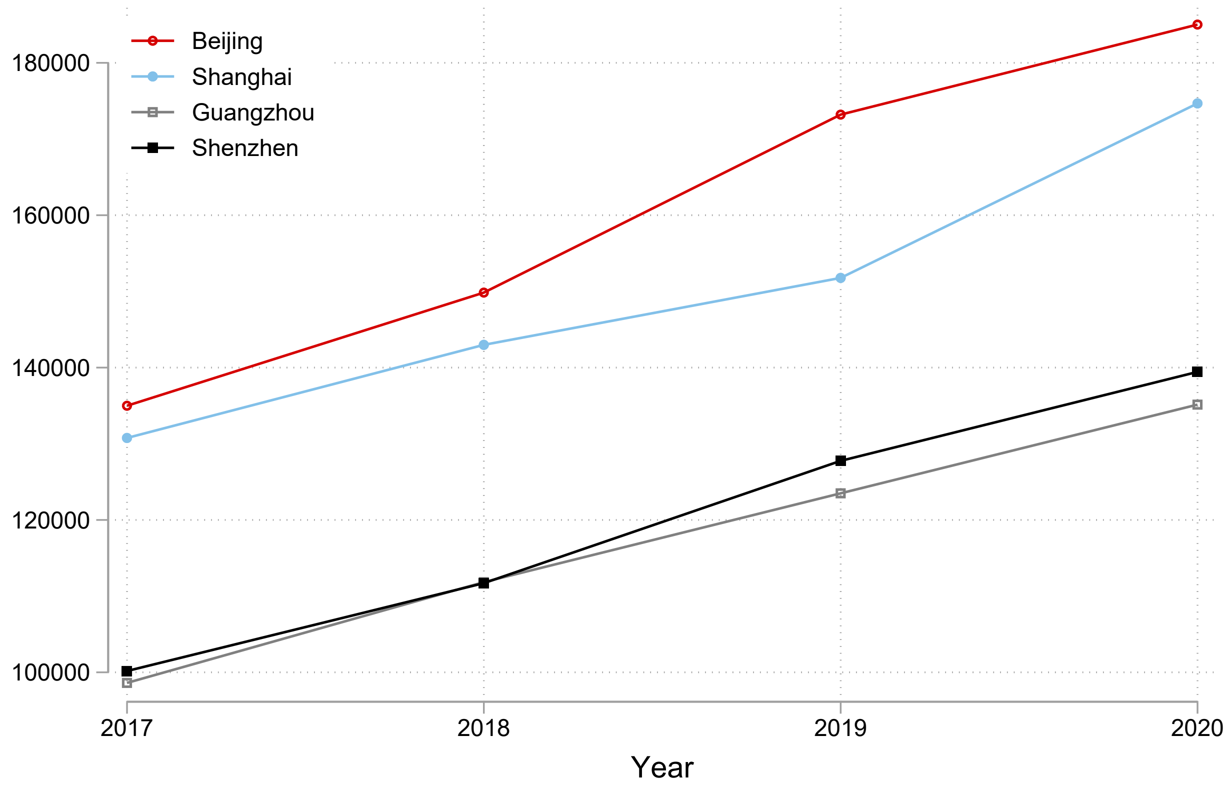


**Figure 4:** Average Annual Salary of Employees

*Note:* Salary averages for employees in each city for the period 2017-2020 in RMB. Data from the National Bureau of Statistics of China.

Additionally, differences in gender norms related to the traditional homemaker-breadwinner norm may work in concert with the level of the child penalty in different cities (Kleven, 2022). In the preexperimental surveys, we asked respondents the extent to which they believe that motherhood or fatherhood can negatively affect a woman's or man's career. As illustrated in Figure 5, the extent to which people agree that motherhood hurts a woman's career is much greater than the extent to which they agree that fatherhood hurts a man's career. The degree of agreement that motherhood harms women's careers is highest in Beijing. In contrast, the degree of agreement that fatherhood harms men's careers declines from Shenzhen, Guangzhou, Shanghai, to Beijing. Since the child penalty reflects the effects of parenthood on women relative to men, this pattern implies that the child penalty is more severe in Beijing and Shanghai than in Guangzhou and Shenzhen, which is consistent with our main results from the correspondence test. Furthermore, this may imply that the gendered institution of the homemaker-breadwinner norm is stronger in cities with a larger child penalty.

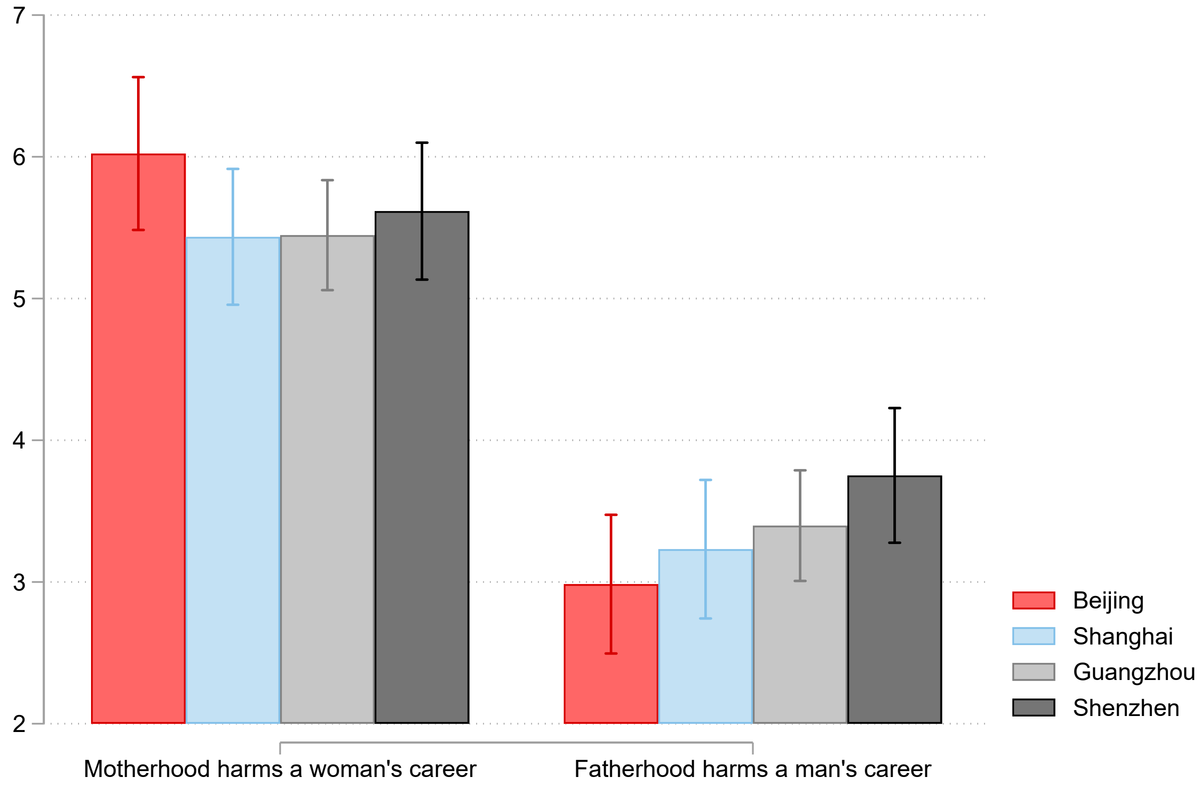


**Figure 5:** Perspectives on Parenthood's Impact on Careers

*Note:* Data from a survey conducted by the authors. Measures of attitudes toward parenthood's impact on careers: Do you agree that motherhood/fatherhood can negatively affect a woman/man's career? Response range from 0=strongly disagree to 10=strongly agree. Mean values by city and their 95 percent confidence intervals are plotted.

Overall, our correspondence study reveals that women of childbearing age are discriminated against during the hiring stage in the labor market, while there is heterogeneity across fields and cities. As a result, women may incur a potential child penalty even when they begin to seek employment and even if they are not currently mothers. Recent studies have established the importance of gender norms in driving gender convergence (Kleven et al., 2021; Kleven, 2022). This is also true in China, where traditional gender norms remain in place (Chen and Ge, 2018; Ye and Zhao, 2018; Si, 2022). It is therefore necessary for public policies to create incentives to change gendered institutions and conservative norms. For instance, current debates on reforms to family policies are largely centered on whether it is beneficial to further extend maternity leaves. However, our findings suggest that it is more crucial to address the disproportionate distribution of parental leaves between mothers and fathers. With a more equitable share of childcare responsibilities between women and men, women of fertile age will be less likely to suffer from a potential child penalty, granting them more equal opportunities in the job market.

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# Appendix A Supplementary Figures and Tables

**Table A.1:** Balancing Regressions

| *Dependent Variable:* | City | | Field | | Matched Experience | | Matched Salary | | Competition | | Firm Type | | Firm Size | |
|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|
| | (1) | (2) | (3) | (4) | (5) | (6) | (7) | (8) | (9) | (10) | (11) | (12) | (13) | (14) |
| Female | 0.004 | −0.003 | −0.004 | −0.008 | −0.007 | −0.006 | 0.002 | 0.001 | 0.003 | 0.009 | 0.001 | 0.003 | −0.002 | 0.006 |
| | (0.011) | (0.013) | (0.009) | (0.010) | (0.005) | (0.005) | (0.004) | (0.004) | (0.012) | (0.015) | (0.010) | (0.012) | (0.008) | (0.010) |
| Female × Age 29 | | 0.019 | | 0.014 | | −0.003 | | 0.004 | | −0.016 | | −0.005 | | −0.025 |
| | | (0.023) | | (0.018) | | (0.010) | | (0.010) | | (0.026) | | (0.021) | | (0.017) |
| Observations | 35713 | 35713 | 35713 | 35713 | 35713 | 35713 | 35713 | 35713 | 35713 | 35713 | 35713 | 35713 | 35713 | 35713 |

*Notes:* The dependent variable in Columns (1)-(2) is the city in which the position is advertised. The dependent variable in Columns (3)-(4) is the field of the advertised positions. The dependent variable in Columns (5)-(6) is whether the applicant's working experience is a good match for the requirements of the advertised position. The dependent variable in Columns (7)-(8) is whether the applicant's expected salary is in line with the advertised salary. The dependent variable in Columns (9)-(10) is the logarithm of the number of applications received for the advertised position. The dependent variable in Columns (11)-(12) is the type of firm that advertised the position. The dependent variable in Columns (13)-(14) is the size of the firm that advertised the position. Robust standard errors in parentheses are clustered at the applicant level. $^{*}p < 0.1$; $^{**}p < 0.05$; $^{***}p < 0.01$.

**Table A.2:** Impact of Being of Childbearing Age on the Probability of Receiving a Callback: Age 29 vs Age 24

| *Dependent Variable:* | Callback (yes=1; no=0) | | | |
|---|---|---|---|---|
| | Whole | IT | ACC | HR |
| | (1) | (2) | (3) | (4) |
| Female × Age 29 | −0.011*** | −0.010* | −0.005 | −0.019** |
| | (0.003) | (0.006) | (0.005) | (0.007) |
| Female | 0.007*** | −0.005 | 0.006* | 0.023*** |
| | (0.003) | (0.004) | (0.004) | (0.006) |
| Age 29 | 0.001 | 0.011** | −0.001 | −0.009 |
| | (0.003) | (0.005) | (0.004) | (0.006) |
| Working Experience Matched | 0.009*** | 0.005* | 0.006** | 0.018*** |
| | (0.002) | (0.003) | (0.003) | (0.004) |
| Expected Salary Matched | 0.000 | −0.000 | −0.003 | 0.001 |
| | (0.003) | (0.004) | (0.004) | (0.006) |
| Shanghai | 0.004 | −0.004 | 0.005 | 0.011** |
| | (0.003) | (0.005) | (0.004) | (0.006) |
| Guangzhou | −0.000 | −0.004 | −0.002 | 0.008 |
| | (0.003) | (0.006) | (0.004) | (0.006) |
| Shenzhen | 0.002 | −0.007 | 0.007 | 0.012* |
| | (0.003) | (0.005) | (0.004) | (0.006) |
| Log No. Applicants | −0.004*** | −0.001 | −0.002 | −0.006*** |
| | (0.001) | (0.002) | (0.001) | (0.002) |
| Mean of Dep. Variable | 0.018 | 0.017 | 0.013 | 0.024 |
| Firm Characteristics | Yes | Yes | Yes | Yes |
| Observations | 23890 | 8460 | 8284 | 7146 |

*Notes:* Samples of 29- and 24-year-olds are included in the analysis. The dependent variable is an indicator variable for whether the applicant was invited to an interview. The key variable of interest is whether the applicant is a woman of childbearing age (29 years of age). The set of covariates includes dummies for the applicant's age, whether her/his work experience matches the requirements of the advertised position, whether her/his expected salary matches the advertised salary, and the cities where the position is advertised; the logarithm of the number of applications received for the advertised position; and work experience expected for the advertised position. The characteristics of the firm, including type, size, and industry, are controlled for. Fixed effects for the month of the job posting and the month of the application submission are also included. The model in Column (1) also controls for the field (IT, ACC, or HR). Robust standard errors in parentheses are clustered at the applicant level. $^{*}p < 0.1$; $^{**}p < 0.05$; $^{***}p < 0.01$.

**Table A.3:** Impact of Being of Childbearing Age on the Probability of Receiving a Callback: Age 29 vs Age 34

| *Dependent Variable:* | Callback (yes=1; no=0) | | | |
|---|---|---|---|---|
| | Whole | IT | ACC | HR |
| | (1) | (2) | (3) | (4) |
| Female × Age 29 | −0.008*** | −0.015*** | −0.007* | −0.000 |
| | (0.003) | (0.005) | (0.004) | (0.005) |
| Female | 0.004*** | −0.000 | 0.009*** | 0.004 |
| | (0.002) | (0.003) | (0.003) | (0.003) |
| Age 29 | 0.013*** | 0.023*** | 0.011*** | 0.007* |
| | (0.002) | (0.005) | (0.003) | (0.004) |
| Working Experience Matched | −0.003 | −0.005 | −0.004 | −0.003 |
| | (0.002) | (0.005) | (0.003) | (0.004) |
| Expected Salary Matched | 0.000 | −0.002 | −0.002 | 0.004 |
| | (0.002) | (0.004) | (0.003) | (0.004) |
| Shanghai | 0.003 | 0.001 | 0.005* | 0.005 |
| | (0.002) | (0.005) | (0.003) | (0.004) |
| Guangzhou | 0.002 | −0.003 | 0.002 | 0.007 |
| | (0.002) | (0.005) | (0.003) | (0.005) |
| Shenzhen | 0.004 | −0.002 | 0.009** | 0.006 |
| | (0.002) | (0.005) | (0.004) | (0.004) |
| Log No. Applicants | −0.002** | −0.002 | −0.001 | −0.003** |
| | (0.001) | (0.002) | (0.001) | (0.002) |
| Mean of Dep. Variable | 0.012 | 0.014 | 0.010 | 0.013 |
| Firm Characteristics | Yes | Yes | Yes | Yes |
| Observations | 23706 | 8360 | 8221 | 7125 |

*Notes:* Samples of 29- and 34-year-olds are included in the analysis. The dependent variable is an indicator variable for whether the applicant was invited to an interview. The key variable of interest is whether the applicant is a woman of childbearing age (29 years of age). The set of covariates includes dummies for the applicant's age, whether her/his work experience matches the requirements of the advertised position, whether her/his expected salary matches the advertised salary, and the cities where the position is advertised; the logarithm of the number of applications received for the advertised position; and work experience expected for the advertised position. The characteristics of the firm, including type, size, and industry, are controlled for. Fixed effects for the month of the job posting and the month of the application submission are also included. The model in Column (1) also controls for the field (IT, ACC, or HR). Robust standard errors in parentheses are clustered at the applicant level. $^{*}p < 0.1$; $^{**}p < 0.05$; $^{***}p < 0.01$.

**Table A.4:** Impact of Being of Childbearing Age on the Probability of Receiving a Callback for Female Applicants

| *Dependent Variable:* | Callback (yes=1; no=0) | | | |
|---|---|---|---|---|
| | Whole | IT | ACC | HR |
| | (1) | (2) | (3) | (4) |
| Female × Age 29 | −0.011*** | −0.010* | −0.005 | −0.018** |
| | (0.003) | (0.006) | (0.005) | (0.007) |
| Female × Age 34 | −0.003 | 0.005 | 0.003 | −0.018*** |
| | (0.003) | (0.005) | (0.004) | (0.007) |
| Female | 0.007*** | −0.005 | 0.006* | 0.022*** |
| | (0.002) | (0.004) | (0.004) | (0.006) |
| Age 29 | 0.001 | 0.011** | −0.001 | −0.010* |
| | (0.003) | (0.005) | (0.004) | (0.006) |
| Age 34 | −0.007*** | −0.006* | −0.009** | −0.009* |
| | (0.002) | (0.004) | (0.003) | (0.006) |
| Working Experience Matched | 0.008*** | 0.005* | 0.006** | 0.015*** |
| | (0.002) | (0.003) | (0.002) | (0.004) |
| Expected Salary Matched | −0.000 | −0.001 | −0.002 | −0.001 |
| | (0.002) | (0.003) | (0.003) | (0.005) |
| Shanghai | 0.004* | −0.001 | 0.005* | 0.009** |
| | (0.002) | (0.004) | (0.003) | (0.004) |
| Guangzhou | 0.000 | −0.003 | −0.001 | 0.006 |
| | (0.002) | (0.004) | (0.003) | (0.005) |
| Shenzhen | 0.003 | −0.003 | 0.006** | 0.009* |
| | (0.002) | (0.004) | (0.003) | (0.005) |
| Log No. Applicants | −0.004*** | −0.003* | −0.002** | −0.005*** |
| | (0.001) | (0.001) | (0.001) | (0.001) |
| Mean of Dep. Variable | 0.015 | 0.014 | 0.011 | 0.020 |
| Firm Characteristics | Yes | Yes | Yes | Yes |
| Observations | 35713 | 12639 | 12384 | 10690 |

*Notes:* The dependent variable is an indicator variable for whether the applicant was invited to an interview. The key variable of interest is whether the applicant is a woman of childbearing age (29 years of age). The set of covariates includes dummies for the applicant's age, whether her/his work experience matches the requirements of the advertised position, whether her/his expected salary matches the advertised salary, and the cities where the position is advertised; the logarithm of the number of applications received for the advertised position; and work experience expected for the advertised position. The characteristics of the firm, including type, size, and industry, are controlled for. Fixed effects for the month of the job posting and the month of the application submission are also included. The model in Column (1) also controls for the field (IT, ACC, or HR). Robust standard errors in parentheses are clustered at the applicant level. $^{*}p < 0.1$; $^{**}p < 0.05$; $^{***}p < 0.01$.

# Appendix B Preexperiment Survey

## B.1 Survey Questions

Note that the original survey was in Chinese, and what follows is an English translation.

Welcome to this social research questionnaire. The questionnaire contains some subjective judgment questions. After completing the questionnaire, you will be paid 3 yuan. It takes approximately 10 minutes to answer the questionnaire. The choices that you make and the personal information that you disclose in this study are both anonymous and absolutely confidential.

Note that the questionnaire includes a number of attention test questions. If you get any of the attention tests wrong, you will leave the questionnaire and will not be paid.

1. Please indicate your age: (less than 18/ 18/ 19/.../60/ over 60)
2. Please select your city of residence: (Beijing/Shanghai/Guangzhou/Shenzhen)
3. Are you currently working full-time now?: (Yes/No)
4. Please estimate the average age at which people have their first child in your city: (Less than 22/ 22/ 23/.../ 34/ 35/ More than 35)
5. Please estimate the average number of children per couple in your city: (0/ 1/ 2/ 3 or more)

6 –13. Please estimate the masculinity or femininity of the following names (on a scale of 0 to 10, where 0 means must be female and 10 means must be male): Zhou Hengyu; Zhou Mengmeng; Zhou Feiman; Zhou Pengcheng; Zhou Zhilan; Zhou Zhihao; Zhou Junwei; Zhou Jingshu

14 – 23. Please estimate the gender ratios of the following occupations (on a scale of 0 to 10, where 0 means a high percentage of female employees and 10 means a high percentage of male employees):

(a) Information technology
(b) Sales and customer service
(c) Accounting and finance
(d) Chemicals and pharmaceuticals
(e) Media and advertising
(f) Human resources
(g) Consulting and legal services
(h) Training and education
(i) Research
(j) Government

24. This is an attention test question; please select option E.

25 – 34. Please estimate the level of discrimination against female applicants in the following occupations:

35 – 44. Please estimate the level of discrimination against male applicants in the following occupations:

45. This is an attention test question; please select option B.

46 – 48. To what extent do you think the following types of units will not hire female applicants of childbearing age?

49. To what extent do you think that listed companies will not hire female job seekers of childbearing age?

50. To what extent do you think unlisted companies will not hire female job seekers of childbearing age?

51 – 55. For jobs with the indicated salary level, to what extent do you think that employers tend not to hire a female applicant of childbearing age?:

56. Consider only your personal desire to bear children (ignoring the fertility policy); please select the following plan that best matches your own:

57. Do you agree with the statement that "Having a child negatively affects a woman's career"?

58. Do you agree with the statement that "Having a child negatively affects a man's career"?

59. Do you agree with the statement that "It is better for a mother to go to work after her child begins school"?

60. Do you agree with the statement that "During an economic recession, female employees need to be fired first":

61. This is an attention test question; please select option D.

62. Please select your gender: (female; male; do not want to answer)

63. Please select your highest degree:
(Junior high school; High School; Bachelor's degree; Master's degree)

64. How many years have you had full-time employment?

65. Please estimate your average monthly income during the past year (including wages, subsidies, investments, part-time jobs, etc. ):

66. Please select your marital status:

67. Please select the number of daughters that you now have:

68. Please select the number of sons that you now have:

69. Please select the average number of children that your colleagues have:

70. Please select the type that best describes your current work unit:

71. Please select the category that best describes your current occupation:

72. Please score the level of gender discrimination that you have experienced during recruitment:

73. Please score the level of gender discrimination that you have experienced at work:

## B.2 Tables

**Table B.1:** Number of Retrieved Surveys across Cities and Genders

| City | Gender | | | Total |
|---|---|---|---|---|
| | Female | Male | Prefer not to say | |
| Beijing | 69 | 62 | 0 | 131 |
| Shanghai | 76 | 71 | 0 | 147 |
| Guangzhou | 94 | 65 | 2 | 161 |
| Shenzhen | 71 | 60 | 2 | 133 |
| Total | 310 | 258 | 4 | 572 |

*Notes:* Data from the preexperiment survey conducted by the authors.

**Table B.2:** Age When Having First Child

| Age levels | Freq. | Percent |
|---|---|---|
| Younger than 24 | 26 | 4.55 |
| Between 24 and 26 | 172 | 30.07 |
| Between 27 and 29 | 215 | 37.59 |
| Between 30 and 32 | 123 | 21.5 |
| Older than 32 | 36 | 6.29 |
| Total | 572 | 100 |

*Notes:* Data from the preexperiment survey conducted by the authors.

**Table B.3:** Gender Stereotyping in Various Fields

| Field | Mean | S.D. | Median | N |
|---|---|---|---|---|
| Accounting | 2.65 | 2.65 | 2 | 572 |
| Sales and customer service | 3.01 | 2.73 | 3 | 572 |
| Media and advertising | 3.1 | 2.62 | 3 | 572 |
| Training and education | 3.19 | 2.63 | 3 | 572 |
| Human resources (HR) | 3.49 | 2.76 | 3 | 572 |
| Government | 3.82 | 2.86 | 5 | 572 |
| Consulting and legal services | 3.9 | 2.83 | 4 | 572 |
| Research | 4.64 | 2.95 | 5 | 572 |
| Information technology (IT) | 5.16 | 2.83 | 6 | 572 |
| Chemicals and pharmaceuticals | 5.62 | 2.79 | 6 | 572 |

*Notes:* Data from the preexperiment survey conducted by the authors. The smaller the value, the more female-dominated the field is; the greater the value, the more male-dominated the field is.