The Shadow Mommy Effect: Maternity Costs and Statistical Discrimination in Hiring*

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Abstract

This paper investigates statistical discrimination against women of prime childbearing age in an online labor market where family status is unobserved. Using a correspondence experiment with 35,713 fictitious applications across China's four first-tier cities, we document a sharp hiring penalty for women at age 29. Specifically, we find that the gender callback gap widens by 1.1 percentage points at age 29 relative to age 24. To identify the mechanism, we conducted an incentivized vignette experiment with 1,800 participants that holds productivity constant while varying the salience of maternity costs. We find that explicit maternity risk drives the female hiring share down from 0.57 to 0.15. Heterogeneity analysis supports this cost-based channel: the field penalty disappears in state-owned enterprises and diminishes in cities with lower labor costs and stronger childcare support. The results demonstrate that employers actively price the expected costs of maternity leave into hiring, even when applicants disclose no family information.

Keywords: Childbearing age, Perceived maternity risk, Correspondence study, Vignette experiment, Labor market discrimination

JEL Classification: C93, J13, J16, J71, M51

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1 Introduction

Despite progress in gender equality, pronounced gender gaps persist in modern labor markets and reinforce stereotypes (Barbulescu and Bidwell, 2013; Bertrand et al., 2010; Blau and Kahn, 2017; Gibson and Lawrence, 2010; Si, 2022). While extensive literature attributes these disparities to the *child penalty* borne by mothers (Budig and England, 2001; Correll et al., 2007; Cortés and Pan, 2023; Goldin, 2021; Juhn and McCue, 2017; Kleven et al., 2019a,b; Yu and Kuo, 2017; Zhang et al., 2024), the market pricing of fertility costs extends beyond actual parenthood. Applying the lens of statistical discrimination (Aigner and Cain, 1977), we argue that employers discount female labor based on risk rather than reality. We term this the *shadow mommy effect*, a phenomenon where the intersection of age and gender levies a penalty on women of prime childbearing age independent of their actual maternal status.

China presents a compelling laboratory to investigate this phenomenon. Despite its economic dynamism, the labor market remains marked by persistent structural barriers characterized by childcare burdens and gender inequality (Brussevich et al., 2021; Zhang et al., 2024). A 2025 survey highlights this disparity, finding that 62.5% of female respondents faced inquiries about their marital or parental status during interviews compared to only 18.5% of men (Zhaopin, 2025). This targeted screening corroborates recent findings that employers treat family status as a decisive cost factor, assigning significant negative weight to potential fertility liabilities, such as maternity leave, when evaluating female employees (Agarwal et al., 2024; Chen and Tian, 2025; Du, 2023; He et al., 2023; Huang and Fan, 2025; Li and Xiao, 2025; Wang and Chen, 2023).

While recent literature has begun to explore these dynamics, significant gaps remain regarding the precise mechanisms of discrimination on modern hiring platforms. Notably, He et al. (2023) exploit the exogenous shock of China's fertility policy relaxation to identify discrimination against women. Our work departs from this focus on policy shocks to examine a fundamental information friction inherent in the "blind" screening process. Since Chinese law prohibits gender discrimination in hiring, online job boards typically standardize resumes to omit sensitive details about marital and parental status. Unlike studies that depend on policy changes or explicit status disclosure, we analyze how employers price risk in an informational void. This setting facilitates statistical discrimination where employers, lacking explicit data, rely on age and gender as imperfect signals of perceived fertility risk.

In this study, we examine the existence and mechanisms of the shadow mommy effect in the Chinese labor market. We adopt a dual empirical strategy designed to overcome the identification challenges common in standard correspondence studies. First, we conduct an

extensive field experiment to quantify the magnitude of the penalty. We then introduce a controlled vignette experiment to isolate the causal mechanism. This combined design advances the analysis from merely documenting unequal treatment to pinpointing the specific economic parameters, namely productivity versus maternity costs, that drive it.

We first measure the behavioral magnitude of this effect through a large-scale correspondence test. We address a previously understudied form of discrimination that targets perceived maternity rather than actual maternal status (Bertrand and Duflo, 2017). Accordingly, we submitted 35,713 fabricated CVs to genuine job advertisements in the IT, accounting, and HR sectors across Beijing, Shanghai, Guangzhou, and Shenzhen. By systematically varying the age and gender of applicants while holding qualifications constant, we identify a significant causal penalty for female applicants at age 29, an age widely viewed as the prime period for childbearing.

Crucially, we overcome the identification challenge of distinguishing whether this penalty arises from maternity risk or unobserved productivity differences. To isolate the mechanism, we conducted a supplementary vignette experiment with 1,800 participants. Although the field experiment reveals clear discrimination, observational data alone cannot disentangle whether employers penalize women of childbearing age due to perceived lower productivity or anticipated financial costs. The vignette experiment separates these channels by presenting employers with candidates who possess identical productivity profiles but differ in their expected costs associated with maternity. This design allows us to examine how hiring intentions change when the salience of maternity costs varies while holding productivity constant. The resulting pattern is inconsistent with statistical discrimination based on productivity and provides direct evidence that the mechanism is driven by anticipated costs.

Our findings provide a unified account of the shadow mommy effect. The field experiment demonstrates that women of prime childbearing age face distinct disadvantages, particularly in the male-dominated IT sector and the gender-mixed HR sector. The vignette experiment subsequently clarifies the mechanism. When productivity is held constant without family information, respondents display a modest penalty based on age and gender, suggesting that employers treat the interaction of these traits as a proxy for fertility risk. Once the potential cost of maternity becomes explicit, the hiring rate for women aged 29 drops sharply as the anticipated maternity leave generates the strongest penalty. The pattern across conditions confirms that discrimination is driven by anticipated labor costs rather than perceptions of productivity. This mechanism further aligns with the heterogeneity observed in the field experiment. The shadow mommy effect is minimal in state-owned enterprises because they

are less sensitive to labor costs in the short run. Additionally, the effect is largely absent in Guangzhou and Shenzhen where lower labor costs and stronger grandparental childcare support mitigate the maternity burdens anticipated by employers.

This paper contributes to three strands of research. First, we extend the literature on the child penalty and fertility discrimination by shifting the focus from realized motherhood to probabilistic maternity risk. Prior studies leveraging explicit disclosures of family status (Li and Xiao, 2025; Wang and Chen, 2023) or variation induced by policy in fertility expectations (He et al., 2023) have provided important evidence on discrimination linked to family responsibilities. We complement this work by isolating the "signal extraction" problem employers face during standardized recruitment. We document that statistical discrimination operates even in the absence of explicit family signals, effectively pricing the "option value" of future maternity leave into current hiring decisions.

Second, we contribute to the identification of discriminatory mechanisms by integrating an extensive field experiment with a controlled vignette experiment. Whereas existing studies often infer mechanisms from observational patterns, our design holds productivity constant and varies only the salience of costs associated with maternity, thereby distinguishing employer concerns about anticipated maternity costs from beliefs about general productivity. The vignette results demonstrate that the penalty is driven primarily by expected financial and operational costs of maternity leave rather than perceived productivity differences.

Third, we add to research on the institutional determinants of gender inequality, including evidence that maternity cost sharing affects labor market outcomes (Jessen et al., 2019). Our heterogeneity analysis shows that the hiring penalty is most pronounced in cost-sensitive private firms and in high-wage cities with limited childcare support. In aggregate, these findings situate the shadow mommy effect within the broader institutional and childcare context and clarify the mechanism through which perceived maternity risk influences initial hiring decisions.

The remainder of the paper is organized as follows. Section 2 reviews the relevant literature and provides the institutional background. Section 3 describes the design of the field experiment, including the pre-experiment surveys and the implementation of the correspondence test. Section 4 presents the field experiment data, outlines the empirical models, and reports the main results. Section 5 introduces the vignette experiment and identifies the causal mechanism. Section 6 examines heterogeneity in the field data to assess consistency with this mechanism. The final section concludes.

2 Related Literature and Institutional Background

2.1 Child Penalty and Gender Disparity in the Workforce

Gender inequality in the workplace is a global phenomenon, with a noticeable disparity persisting in the workforce, even in the most gender-equal societies (Kleven et al., 2019a,b). The child penalty is one of the primary issues contributing to the enduring gender disparities in the labor market (Andresen and Nix, 2022; Cortés and Pan, 2023; Goldin, 2021; Kleven et al., 2019a,b; Zhang et al., 2024). Notably, Kleven et al. (2019a) illustrate that women face an average long-term earnings reduction of 20% due to children, a trend observed across six countries with varying policies and norms.

China serves as a representative example of a large emerging economy. Although the labor force participation rate among women in China is relatively high compared to other Asian countries, it has declined from 73% in 1990 to 59% in 2020 following market-oriented economic reforms (Brussevich et al., 2021; Hare, 2016; Liu et al., 2014). The ratio of women to men in the labor force has also fallen over recent decades. This trend is particularly striking given that women have surpassed men in higher education enrollment.[1] Several studies highlight how childcare responsibilities hinder female engagement in the labor force, particularly among those with preschool-aged children (Connelly et al., 2018; Du and Dong, 2013; Liu et al., 2014; Maurer-Fazio et al., 2011; Zhang et al., 2024). Recent evidence reveals that fertility policies intended to motivate families to have more children might inadvertently deepen gender inequality. Studies by Du (2023), Agarwal et al. (2024), Chen and Tian (2025), and Huang and Fan (2025) indicate that the relaxation of China's one-child policy has adversely impacted female labor force participation and exacerbated the gender wage gap. He et al. (2023) found that the transition from the one-child to the two-child policy adversely affected the job prospects of women more than men. Furthermore, Li and Xiao (2025) demonstrated fertility discrimination against married women following the implementation of the three-child policy.

2.2 Perceived Fertility and the Shadow Mommy Effect

While most studies have explored the child penalty based on realized fertility, few acknowledge that its impact extends beyond actual mothers. Empirical evidence reveals workplace biases against married women without children who are suspected of imminent pregnancy (Becker et al., 2019; Gloor et al., 2018, 2022; Li and Xiao, 2025; Petit, 2007; Wang and Chen,

[1] According to Education Statistics for 2020, the proportion of female students in undergraduate programs was 50.96%, whereas it was 52.53% in master's programs. The data were retrieved from the Ministry of Education of the People's Republic of China at http://www.moe.gov.cn/jyb_sjzl/moe_560/2020/quanguo/202108/t20210831_556360.html.

2023). We conceptualize this broader phenomenon as the *shadow mommy effect*, a distinctive penalty imposed on women of childbearing age based on perceived rather than realized fertility risk. This bias is readily triggered by minimal information, with the interaction of age and gender serving as a decisive demographic determinant (Delacruz and Speer, 2023; Gloor et al., 2022; Zamberlan et al., 2024).

Our study advances existing research by pinpointing the shadow mommy effect on labor demand in the Chinese job market through simulations of the recruitment process. Online labor marketplaces have become the predominant channel for hiring in China. Since 2019, legal regulations have prohibited employers from inquiring about a female applicant's marital or parental status, leading online job boards to adopt standardized resume templates that omit these details (Kuhn and Shen, 2023). However, this information suppression may unintentionally incentivize broad discrimination against women perceived as prospective mothers. Unable to verify family status directly, employers may view women of prime childbearing age as high-risk candidates likely to incur fertility costs. This informational void fosters statistical discrimination against the entire demographic as firms anticipate higher liabilities arising from maternity leave, childcare needs, and potential workforce interruptions (Cortés and Pan, 2023; Gloor et al., 2022; He et al., 2023; Jessen et al., 2019; Li and Xiao, 2025).

The financial structure of maternity leave further entrenches this bias. During our study period, paid maternity leave in China ranged from 128 to 178 days depending on the province. Employers often view this as a financial burden because the public social security system does not fully cover salaries, requiring firms to supplement the difference (Li and Xiao, 2025). Beyond direct payments, firms incur indirect costs to arrange temporary replacements. Consequently, employers in high-wage cities or cost-sensitive sectors may avoid hiring women of prime childbearing age. These economic concerns are compounded by gendered asymmetries in parental responsibilities (Zhang et al., 2024). In contrast to maternity leave, paternity leave is voluntary and brief, typically lasting only 10 to 30 days. Reinforced by traditional norms, women bear the primary responsibility for childcare while men contribute significantly less (Connelly et al., 2018; Du and Dong, 2013; Maurer-Fazio et al., 2011). This disparity fuels employer concerns regarding potential productivity losses among women balancing work with caregiving. Ultimately, the stark divergence in how parental status impacts women versus men exacerbates the risk of discrimination against women of childbearing age.

3 Field Experimental Design

3.1 Cities Included in the Field Experiment

We conducted the experiment in four prominent metropolises collectively known as China's "first-tier" cities: Beijing, Shanghai, Guangzhou, and Shenzhen. Marked by rapid urbanization, technological innovation, and vibrant business ecosystems, these cities represent the vanguard of China's urban economy. With their comparable levels of economic development, they provide a rich array of employment opportunities across diverse industries, serving as critical hubs for the country's workforce.[2]

Maternity leave policies vary slightly by location: Beijing and Shanghai mandate 128 to 158 days, whereas Guangzhou and Shenzhen offer 178 days. In contrast, paternity leave is limited to 10 days in Shanghai and 15 days in the remaining three cities. Despite this short duration, the take-up rate for paternity leave is low. A recent survey by the Beijing Federation of Trade Unions found that 41.78% of employees had never utilized paternity leave, and 39% were uncertain about its availability within their organizations. Even among those aware of the policy, 64.53% declined to take it, citing fears of negative career repercussions.[3]

3.2 Pre-experimental Survey

To empirically determine the critical experimental parameters for our correspondence test, most notably the socially perceived prime childbearing age in the focal cities, we conducted a pre-experimental online survey targeting full-time workers in each of the four metropolises between December 2020 and January 2021. The 73-item questionnaire assessed societal attitudes toward gender discrimination in the workplace alongside relevant demographic characteristics.[4] As shown in Table B.1, our final sample comprises 572 valid responses, stratified evenly across genders and cities.

3.2.1 Age Categories

Since marital and parental status are typically omitted from CVs in the Chinese job market, being of prime childbearing age signals a perceived likelihood of parenthood. To empirically determine the socially perceived prime childbearing age, survey participants were asked to

[2]We restricted the study to four cities rather than conducting a nationwide analysis to control for regional heterogeneity in development and social norms. As the country's most progressive regions, these four cities offer women the widest array of career opportunities, allowing us to isolate labor demand discrimination without the complicating influence of regional labor supply constraints.

[3]Source: http://www.news.cn/legal/2022-04/25/c_1128592428.htm.

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

identify the typical age at which parents have their first child. As depicted in Figure 1, the age group most strongly associated with first-time parenthood is 27–29, a range commonly regarded as the onset of childbearing by respondents. We triangulated these data with findings from the 2020 National Census, which reports that the average age of first marriage is 28 for women and 29 for men.[5] Consequently, we selected 29 as the representative age for the onset of motherhood. Moreover, census fertility rates indicate an average number of births per woman of 0.8 in Beijing, 0.7 in Shanghai, and 1.2 in Guangdong Province (which includes Guangzhou and Shenzhen), suggesting that the one-child norm persists despite the policy relaxation.

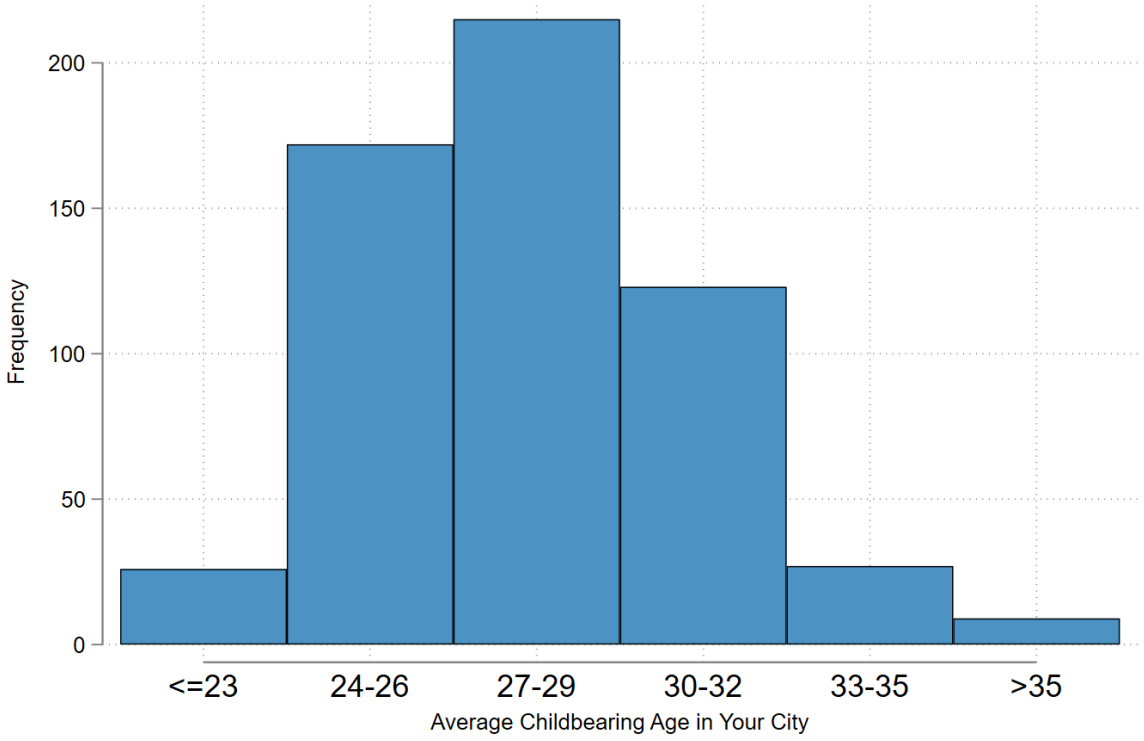


Figure 1: The conventional age for first-time parenthood

Note: Data obtained from the preexperiment survey conducted by the authors. The related question is as follows: "Please estimate the average age at which people have their first child in your city".

All fictitious applicants held a bachelor's degree. Given that university graduation typically occurs at age 22 in China, we established 24 as the pre-childbearing age. This accounts for individuals entering the job market after gaining two years of work experience. Conversely, we selected 34 as the post-prime age, as it is widely assumed that individuals have completed their transition to parenthood by this stage, as shown in Figure 1. Additionally, age discrimination in the Chinese labor market often manifests by age 35, a barrier referred to as the "age-35

[5]Nonmarital births are uncommon in China, where most couples choose parenthood only after marriage.

phenomenon" (Huang and Zhang, 2021; Leng and He, 2021). Hence, we limited our experiment to individuals younger than 35 to eliminate the potential confounding effect of general age discrimination.[6]

3.2.2 Occupation Categories

The magnitude and direction of gender discrimination often vary across occupations due to gender stereotyping (Booth and Leigh, 2010; Carlsson, 2011; Citci et al., 2026; Riach and Rich, 2006; Weichselbaumer, 2004; Zamberlan et al., 2024). Consequently, the current experiment stratified sectors to include a female-dominated field, a male-dominated field, and a mixed-gender profession. We drew upon our survey data to assess gender stereotyping in various occupations commonly recruited through online job postings, as shown in Table B.2. Based on these findings, we selected accounting (ACC) as the female-dominated field, information technology (IT) as the male-dominated field, and human resources (HR) as the mixed field. We prioritized these professions because they feature a substantial volume of job openings, ensuring sufficient liquidity for the correspondence test.

3.2.3 Perspectives on Child Penalty by City

Beyond calibrating the experimental parameters, the pre-experimental survey offered valuable insights into societal perceptions of the child penalty. Respondents rated the extent to which parenthood negatively impacts careers for women versus men on a scale from 0 (strongly disagree) to 10 (strongly agree). As shown in Figure 2, participants across all cities acknowledged that motherhood harms female careers, with average scores consistently exceeding the neutral midpoint of 5 (pink circles). In contrast, perceptions regarding fatherhood consistently fell below this midpoint (blue squares), suggesting that paternity is not viewed as professionally detrimental. The difference between these scores (gray triangles) quantifies the perceived "child penalty," defined here as the asymmetric career cost attributed to motherhood relative to fatherhood. Notably, Beijing exhibited the highest perceived penalty, followed by Shanghai, Guangzhou, and Shenzhen.

[6] We selected discrete age categories over a continuous range to differentiate between the pre-childbearing, prime, and post-prime phases. This decision was necessitated by strict real-name registration requirements in China, which constrained the number of feasible fictitious identities. Since each account required a distinct mobile number linked to a unique citizen identification number, we maximized statistical power by randomizing job applications at the employer level rather than creating a vast number of applicant profiles. The detailed experimental procedures are provided below.

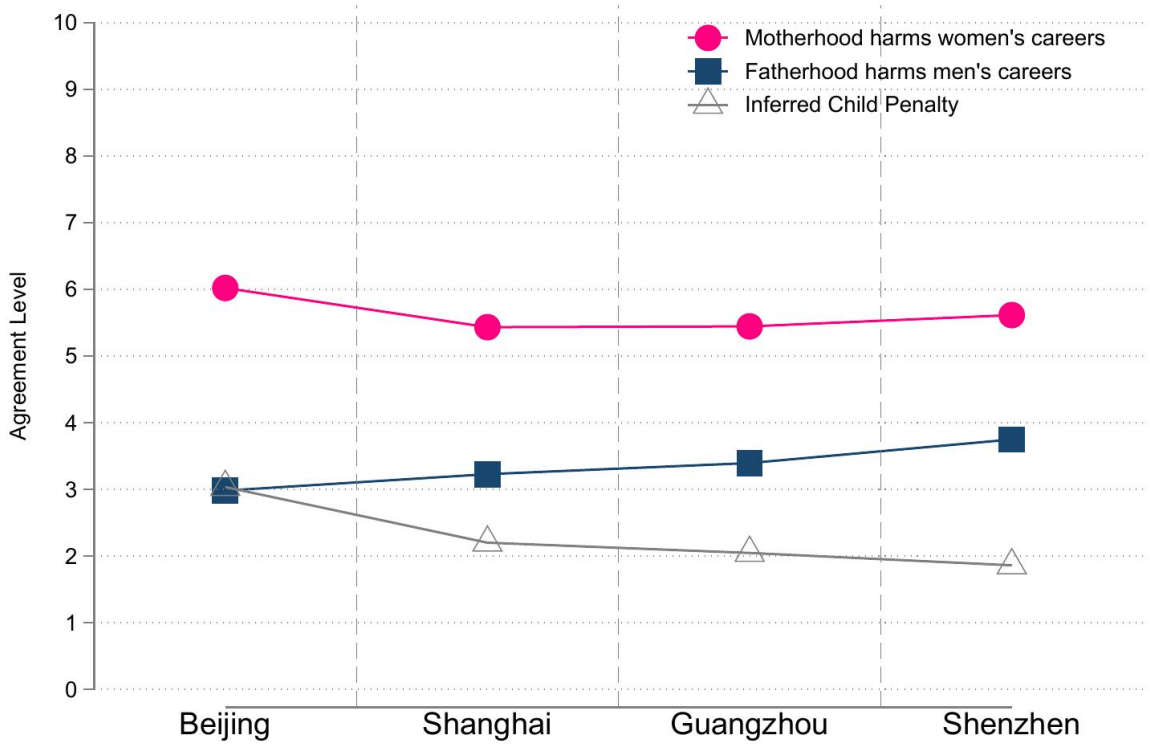


Figure 2: Respondents' perspectives on parental impact in organizations

Note: Data obtained from the preexperiment survey conducted by the authors. The related questions are as follows: "Do you agree with the statement that having a child negatively affects a woman's/man's career?" The responses were collected via a scale ranging from 0 (strongly disagree) to 10 (strongly agree).

3.3 Correspondence Testing

We executed the correspondence test on 51job.com, a dominant online recruitment platform in China. To initiate applications, users must register using a mobile number bound to their national identity card, a requirement that enforces real-name verification. The platform mandates a standardized resume format containing fields for name, gender, age, date of birth, education, work experience, career objectives, salary expectations, skills, certifications, and contact details. Within each of the three target sectors, we constructed resumes for female and male candidates across three age cohorts (24, 29, and 34). This yielded a total of 18 distinct applicant profiles.

3.3.1 Signaling Potential Maternal Status: Women of Prime Childbearing Age

Our primary analysis centers on female applicants aged 29, a demographic associated with imminent childbearing, and those aged 34, representing the early stages of motherhood. We compare these groups against 24-year-old women and men across all three age cohorts. Because

standard resume templates require gender disclosure, we explicitly indicated the sex of each candidate. We reinforced this signal by assigning distinctively feminine and masculine given names validated in our preliminary surveys, pairing them with common Chinese surnames. These names were randomly allocated to applicants consistent with their gender.

3.3.2 Other Characteristics of Fictitious Resumes

We standardized education by assigning all applicants a bachelor's degree from Chang'an University in a major aligned with their target profession. Situated in Xi'an, Chang'an University is a recognized key national university geographically distant from our four experimental sites. We selected this institution to signal reputable academic quality while neutralizing potential alumni bias or regional preferences associated with local universities. We meticulously constructed work histories to commensurate with each candidate's age and specialization. Competencies, project portfolios, certifications, and salary expectations were calibrated to match their tenure and seniority. Reflecting standard market norms, all applicants were presented as currently employed professionals seeking new opportunities. To avoid location bias, candidates reported current residency in Wuhan, a major central hub roughly equidistant from all four target metropolises. All resumes explicitly stated a willingness to relocate for interviews and employment.

We assigned unique mobile numbers and email addresses to each applicant. We excluded photographs since they remain optional in Chinese recruitment and introduce potential confounds related to facial attractiveness (Deng et al., 2020; Maurer-Fazio and Lei, 2015). Appendix C provides a sample resume.

3.3.3 Experimental Procedure

We conducted the experiment and data collection between March and June 2021, coinciding with the peak hiring season for experienced professionals. Using a web-scraping algorithm, we collected all job vacancy advertisements for IT, accounting, and HR positions posted on 51job.com within the preceding 30 days. We restricted the sample to full-time positions requiring a bachelor's degree in Beijing, Shanghai, Guangzhou, and Shenzhen. To exclude outliers associated with executive-level roles, we omitted positions with a posted monthly salary exceeding 40,000 CNY. We then applied a balanced randomization strategy in which vacancies within each field (IT, accounting, and HR) were divided into six groups statistically matched on observable characteristics such as firm details, job requirements, and expected salary. Each group was assigned one of the six resume profiles defined by the interaction of gender and the

three age categories (24, 29, and 34). Crucially, we submitted exactly one application per vacancy corresponding to the specific profile assigned to that group. This approach ensured that each vacancy received only one application from our experiment while uniformly distributing the six profiles across vacancies within each field. In total, we successfully submitted 35,713 job applications. Figure B.1 presents a schematic diagram of the job application process used in our correspondence tests across occupational fields.

We defined positive responses from employers as callbacks, which were monitored via mobile phones, text messages, emails, and platform notifications. Since rejection is typically silent, a callback represents a specific intent to interview. In our experiment, the majority of callbacks occurred within a week. A team of six research assistants, balanced by gender to represent the applicant profiles, managed the correspondence. Upon receiving a callback, the assistants promptly declined the invitation by stating that the applicant was no longer available, thereby minimizing any disruption to the hiring process.

3.4 Design Rationale: Between-Subjects Randomization

We employed a randomized between-subjects design, submitting strictly one application per job vacancy. While matched-pair designs (sending multiple fictitious CVs to the same firm) remain standard in discrimination literature (e.g., Bertrand and Mullainathan, 2004), we adopted a singleton design to ensure the internal validity of our estimates in a high-frequency digital labor market. This choice is driven by three methodological imperatives.

First, and most critically, the singleton design eliminates the estimation bias arising from violations of the Stable Unit Treatment Value Assumption (SUTVA). As Phillips (2019) demonstrates, matched-pair designs inevitably introduce spillover effects because an employer's evaluation of one candidate is endogenously determined by the presence of the other. In a competitive hiring market, receiving a "competitor" CV can mechanically alter the callback probability for the primary CV through contrast effects or capacity constraints. By strictly isolating each application, we ensure that every observation is independent, thereby satisfying SUTVA and yielding a clean, unbiased estimator of the treatment effect.

Second, this approach ensures ecological validity in the era of algorithmic screening. Modern recruitment platforms like 51job.com utilize aggressive fraud-detection algorithms to filter resume spam. Submitting multiple methodologically similar resumes to a single vacancy, often from related IP addresses or device fingerprints, dramatically increases the probability of being flagged as bot activity. Such flagging would introduce non-random measurement error, compromising the internal validity of the experiment. By limiting our interaction to a single,

organic application per firm, we mimic the behavior of genuine job seekers and avoid triggering algorithmic suppression, ensuring that our experimental footprint remains negligible.

Third, the statistical power of our extensive sample renders the efficiency gains of paired designs unnecessary. Although between-subjects designs typically require larger samples to match the statistical power of paired designs, our study is exceptionally well-powered with a total sample of $N = 35,713$. This robust sample size guarantees that randomization effectively balances unobservable applicant characteristics across firm and job attributes, enabling the precise estimation of treatment effects without the confounding risks inherent in paired testing.

4 Field Experiment: Data, Models, and Main Effect

4.1 Summary Statistics for the Experimental Sample

4.1.1 Application Characteristics

Table 1 presents summary statistics for the experimental sample and the variables used in the analysis. Our sample is balanced across gender, age cohorts, and occupational sectors. On average, each job advertisement attracted approximately 150 applications, indicating intense competition from the labor supply side. As illustrated in the upper panel of Figure A.2, accounting emerged as the most competitive sector, followed by HR and IT.

Regarding applicant qualifications, approximately 33% of our candidates possessed work experience perfectly aligned with the position requirements. We defined a dummy variable to identify these well-matched applications. Similarly, approximately 44% of applicants held salary expectations matching the offered compensation, captured by a corresponding dummy variable indicating a salary match.

4.1.2 City and Firm Characteristics

As shown in Table 1, the geographic distribution of applications was 12% in Beijing, 38% in Shanghai, 22% in Guangzhou, and 28% in Shenzhen. The distribution of jobs across IT, accounting, and HR within each city remained remarkably consistent, as depicted in the lower panel of Figure A.2. Our sample covers a diverse array of firm ownership structures and sizes, including state-owned enterprises, foreign-invested firms, and private entities (both listed and non-listed).

Given that randomization occurred at the employer level, we conducted a balancing test on firm attributes observed in job postings. As illustrated in Figure A.3, the estimated coefficients are small and statistically indistinguishable from zero, indicating no systematic sorting of

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
Information Technology (IT)	0.35	0.48	0	1
Accounting (ACC)	0.35	0.48	0	1
Human Resources (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. The data were collected by the authors between March and June 2021.

female applicants or those of prime childbearing age into specific types of job postings. This confirms the validity of our randomization and rules out selection bias regarding our key variables of interest.

4.2 Empirical Models and Variables

4.2.1 Baseline Analysis: Group-Specific Interactions

To characterize callback patterns and quantify the hiring penalty or premium for each demographic profile, we estimate a series of linear probability models. Instead of imposing a unified interaction structure across all groups at once, we isolate the deviation of each gender-age group k (e.g., 29-year-old women) from the baseline additive effects of gender and age. The estimation equation is specified as follows:

$$Callback_{ij} = \alpha + \tau_k D_{k,i} + \gamma Female_i + \delta_1 Age29_i + \delta_2 Age34_i + X'i\Gamma + \epsilon_{ij}, \quad (1)$$

where the dependent variable $Callback_{ij}$ is an indicator for applicant i receiving a callback for a job vacancy in city j. $D_{k,i}$ is a binary indicator that equals 1 if applicant i belongs to the specific target group k (e.g., $Female \times Age29$) and 0 otherwise. We estimate this equation separately for each of the six demographic combinations.

Our primary coefficient of interest, τ_k, captures the interaction effect. It measures the extent to which the callback rate for group k deviates from the level predicted exclusively by the additive main effects of gender (γ) and age (δ_1, δ_2). For example, if τ_k is negative for 29-year-old women, it indicates a "penalty" for this specific intersection beyond the general age and gender gaps. We plot these τ_k estimates in Figure 3 to visualize the penalty or premium associated with each demographic profile.

The control vector X includes indicators for work experience and salary matches, the logarithm of the number of applications received, required work experience, and the occupational field (IT, accounting, or HR). Additionally, we control for firm characteristics, such as ownership type, size, and industry. We also include fixed effects for the month of job posting and the month of application submission. City fixed effects α_j capture time-invariant city heterogeneity. Standard errors are clustered at the applicant level to account for any arbitrary correlation in the error term ϵ_{ij}.

4.2.2 Main Specification: Identifying the Shadow Mommy Penalty

To formally test the hypothesis that women of prime childbearing age face a distinct penalty relative to men of the same age, we employ a unified difference-in-differences specification. In contrast to Equation (1), which estimates group deviations individually, Equation (2) integrates interaction terms for both age groups to isolate the causal impact of perceived maternity risk. The specification is as follows:

$$\begin{aligned} Callback_{ij} = \alpha_j + \beta_1(Female \times Age29)_i + \beta_2(Female \times Age34)_i + \beta_3 Female_i \\ + \beta_4 Age29_i + \beta_5 Age34_i + X_i'\gamma + \epsilon_{ij}, \end{aligned} \tag{2}$$

Here, $Female_i$ indicates whether applicant i is a woman. $Age29_i$ identifies whether applicant i is 29 years old, the demographic proxy for peak childbearing. Similarly, $Age34_i$ indicates whether applicant i is 34 years old, an age often perceived as marking the early stages of motherhood.

Equation (2) serves as our principal empirical model for examining the impact of prime childbearing age on job opportunities. Our primary coefficient of interest, β_1, corresponds to the interaction term $Female \times Age29$. It measures the *additional* penalty women face at age 29 relative to men of the same age, benchmarked against the baseline gender difference observed at age 24. Specifically, β_1 tests whether the gender gap significantly widens during the prime childbearing window. Additionally, the interaction term $Female \times Age34$, with its coefficient β_2, quantifies whether the gender gap changes at age 34 relative to the baseline. β_3 captures the baseline gender gap for 24-year-olds, while β_4 and β_5 capture the general age trends for men. The control variables in Equation (2) remain consistent with those described in Equation (1).

4.3 Results

4.3.1 Descriptive Evidence and Visual Patterns

Table 2 summarizes the descriptive statistics for callback rates and application volume. In aggregate, the unconditional callback probability for female applicants (1.60%) is slightly higher than that for males (1.34%). However, these aggregate figures mask a critical reversal driven by the intersection of age and gender. While female applicants enjoy a distinct callback premium at ages 24 (2.26% vs. 1.60%) and 34 (1.06% vs. 0.61%), this advantage evaporates and reverses specifically at age 29. At this prime childbearing age, the female callback rate drops to 1.48%, falling below the male rate of 1.80%. This distinct decline at age 29 provides the initial descriptive evidence of a *shadow mommy effect*, indicating that women face a relative penalty

specifically during the window of peak perceived fertility risk.

Heterogeneity across occupations and regions further contextualizes these patterns. The overall female advantage is largely driven by the accounting and HR sectors, where women receive significantly more callbacks than men (1.40% vs. 0.83% and 2.47% vs. 1.47%, respectively). In contrast, in the male-dominated IT sector, women face a substantial penalty (1.06% vs. 1.74%). Geographically, the raw gender gap is negative for women in Beijing (1.12% vs. 1.43%) but positive in Shanghai, Guangzhou, and Shenzhen. Given that the average vacancy attracted 150 applicants, the generally low callback rates (under 2%) reflect intense competition on the supply side.

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 is invited to an interview during the experiment.

To rigorously isolate the interaction effects from baseline trends, we estimate Equation (1) using OLS and visualize the specific group deviations (τ_k) in Figure 3. The plot reveals a distinct divergence at the prime childbearing age. As illustrated by the gap between the female series (pink triangles) and the male series (gray circles), the transition to age 29 triggers opposite labor market responses. Male applicants benefit from a premium associated with prime age, as indicated by the positive interaction coefficients. In contrast, female applicants face a significant callback penalty. This negative impact is statistically significant and originates primarily from the IT and HR sectors. We also observe notable heterogeneity across fields. For instance, men aged 34 face disadvantages in IT, whereas women aged 24 are favored in HR. However, the shadow mommy pattern characterizing a relative decline for women at age 29 remains consistent across all fields. In the accounting sector where women dominate, the penalty at age 29 is statistically indistinguishable from zero, but the qualitative drop relative to the baseline at age 24 persists.

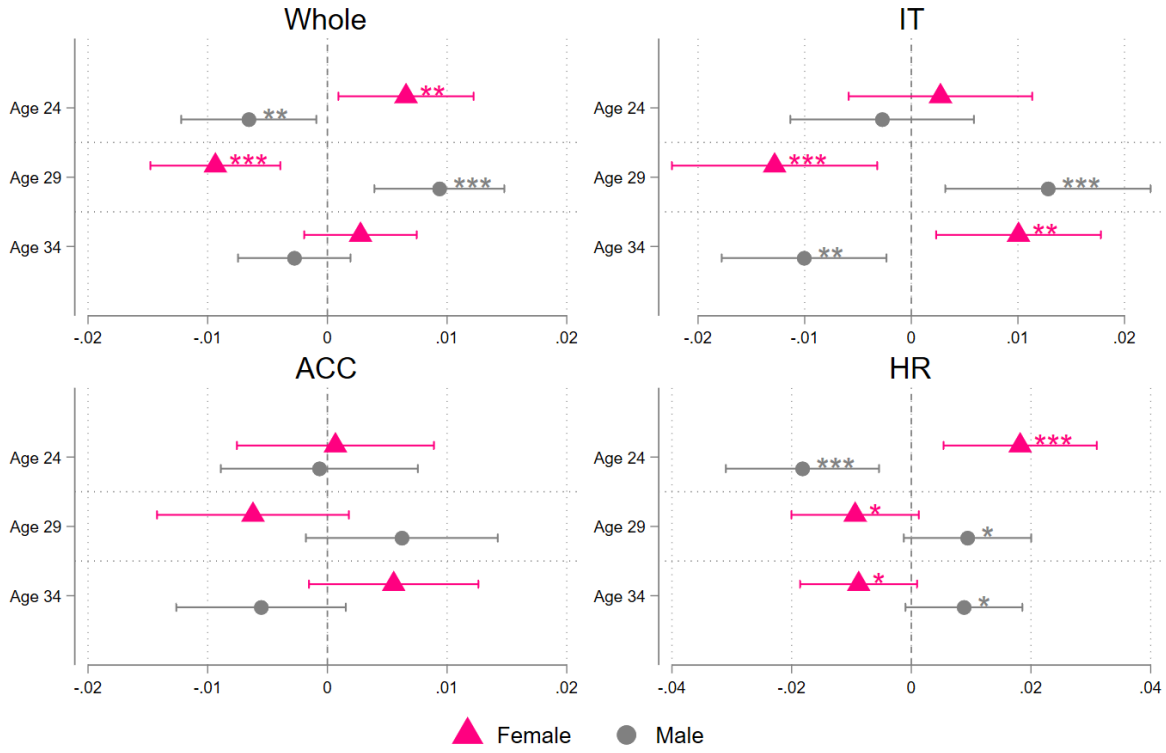


Figure 3: Callback Rates by Gender

Note: The graph displays the results of a baseline analysis on the callback rates for different age groups in each gender. The dependent variable is an indicator variable for whether the applicant is invited to an interview. The plots depict the estimated coefficients of the key variable of interest, namely, the interaction term between gender and age dummies in each regression. The pink triangle markers represent the estimated coefficients of the female dummy interacting with each age category, whereas the gray round markers represent the estimated coefficients of the male dummy interacting with each age category. The 95% confidence intervals are illustrated by the horizontal bars and their caps. The size of the p value is labeled $^{*}p < 0.1$; $^{**}p < 0.05$; and $^{***}p < 0.01$.

4.3.2 The Magnitude of the Shadow Mommy Effect

To quantify the causal magnitude of this penalty, we estimate Equation (2) using OLS. The results are presented in Table 3, with the full sample in Column (1) and subsamples by occupational field in Columns (2) through (4).[7]

Table 3: Impact of Childbearing Age on Callback Probability 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 indicates whether the applicant is invited to participate in 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 their work experience matches the requirements of the advertised position, whether their 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 firm's characteristics, 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. $^{*}p < 0.1$; $^{**}p < 0.05$; $^{***}p < 0.01$.

Column (1) corroborates our primary finding: women of prime childbearing age face a statistically significant hiring penalty. The coefficient for the interaction term between female and age 29 is negative and statistically significant at the 1% level. In this specification, the reference group is male applicants aged 24; thus, the coefficient on $Female$ (0.007) represents the female-minus-male callback gap at age 24. The interaction coefficient $Female \times Age29$

[7] The results remain robust to the Heckman-Siegelman critique (Heckman and Siegelman, 1993). We have applied the method proposed by Neumark (2012) to conduct a robustness check, with the detailed analysis presented in Appendix D.

(-0.011) captures how that female-minus-male gap changes at age 29 relative to age 24.

Economically, this implies that the gender gap widens by 1.1 percentage points at age 29 compared to age 24. Combining the main and interaction terms, the implied gender gap at age 29 is $0.007 - 0.011 = -0.004$, meaning that 29-year-old women have a callback probability approximately 0.4 percentage points lower than otherwise identical 29-year-old men, holding observed job and firm characteristics constant.

To contextualize this magnitude, a 0.4 percentage point gap corresponds to approximately 4 fewer callbacks per 1,000 applications for 29-year-old women relative to comparable 29-year-old men. For comparison, at age 24, the estimate implies a female advantage of 0.7 percentage points, or roughly 7 more callbacks per 1,000 applications relative to comparable 24-year-old men. This sharp reversal from an early advantage to a significant penalty captures the core "shadow mommy" pattern captured by the interaction term. In contrast, the interaction term for female candidates at age 34 is negative but statistically indistinguishable from zero, suggesting that the penalty is most acute during the years associated with peak fertility risk.

The magnitude of the penalty varies significantly across occupational fields. In the male-dominated IT industry (Column 2), female applicants aged 29 face a 1.0 percentage point decrease in callback probability, a result statistically significant at the 10% level. Notably, male applicants in this sector enjoy a "prime age" premium as they are 1.1 percentage points more likely to receive a callback than their younger counterparts. In the accounting field (Column 3), the coefficient for 29-year-old females is negative at 0.5 percentage points but statistically insignificant.

The results for the HR sector are particularly salient (Column 4). Here, female applicants face a substantial penalty at both age 29 and age 34. The estimates indicate a decrease of 1.8 percentage points in callback probability for both age groups, statistically significant at the 5

Collectively, these regression results confirm the existence of a *shadow mommy effect*: women of prime childbearing age face diminished employment prospects even when their maternal status remains undisclosed. The fact that the penalty is large at age 29 but insignificant at age 24 supports a mechanism of statistical discrimination based on anticipated costs. Employers appear to be pricing in the expected costs of maternity leave, a behavior often described as "maybe baby" bias (Gloor et al., 2018, 2022; Jessen et al., 2019; Li and Xiao, 2025; Wang and Chen, 2023).

Furthermore, the positive premium for 24-year-old women suggests that employers may be engaging in a tenure-adjusted cost calculation. The preference for younger women over 29-year-olds implies that firms may view the former as "safe" investments likely to turnover before

entering their prime childbearing years. This behavior is rationalized by the high turnover rates characterizing the Chinese labor market. Empirical data indicate that the average tenure of Chinese employees is approximately 22 months, with workers under 23 often remaining with an employer for as few as seven months (Dani, 2020; Hiller, 2018). This dynamic contrasts sharply with Western labor markets, where tenures often exceed a decade (Hiller, 2018). Given that tenure increases with age, rising from seven months for those under 23 to approximately 3.5 years for those aged 29 to 38 (Liu, 2018), employers appear to engage in myopic optimization. They prioritize younger women for immediate labor without the risk of maternity costs while avoiding 29-year-olds who are statistically more likely to require maternity leave during their tenure.

5 Identifying the Mechanism: A Vignette Experiment

While the field experiment establishes a robust behavioral bias against women of prime childbearing age, a fundamental identification challenge persists. Observational data alone cannot distinguish whether this penalty stems from concerns regarding general productivity or the specific financial liabilities associated with maternity. To isolate these mechanisms, we designed a controlled vignette experiment that separates the causal impact of anticipated maternity costs from productivity signals.

5.1 Experimental Design

We conducted an online experiment with 1,800 participants recruited from Beijing, Shanghai, Guangzhou, and Shenzhen via the Credamo platform. The study employed a mixed factorial design combining a between-subjects assignment of age and occupation with a within-subjects manipulation of family information.

Participants were first stratified into nine distinct treatment cells defined by the interaction of three age groups (24, 29, and 34) and three occupational sectors. We recruited 200 participants for each cell ($3 \times 3 \times 200 = 1,800$). Within their assigned age-occupation profile, participants then evaluated a randomized sequence of hiring scenarios. Specifically, participants assigned to the age 24 and 29 cohorts completed four decision tasks (Conditions C1–C4), while those in the age 34 cohort completed five (Conditions C1–C5). The presentation order of these vignettes was randomized at the individual level to mitigate order effects.

In each scenario, participants assumed the role of an employer choosing between a male and a female candidate. To isolate the effect of family status from baseline productivity con-

cerns, the vignette explicitly stated: "the two candidates are identical in age, education, work experience, and other aspects." Throughout the sequence, the candidates' age and occupation remained fixed consistent with the participant's assigned treatment. Consequently, all observable productivity factors were held constant, ensuring that the only varying attributes were gender and the marital or parental information specified in the condition.

Participants received a base monetary payment for participation supplemented by a performance-based bonus. To measure second-order beliefs, we included an incentivized elicitation task where participants earned a bonus for accurately predicting the share of other participants who chose the female candidate in each condition. We also collected standard demographic information. The complete experimental instructions for a representative treatment are provided in Appendix E.1.

The key experimental conditions are summarized in Table 4. Conditions C1, C2, C4, and C5 are symmetric, presenting female and male candidates with identical marital and parental statuses. In contrast, Condition C3 introduces a deliberate asymmetry where only the female candidate faces potential maternity-related costs, a design choice that mirrors the gendered reality of labor market policies.

Table 4: Vignette Experiment Conditions

Condition	Female Candidate	Male Candidate	Mechanism Tested
C1	Age 24/29/34	Same as female candidate	Implicit fertility risk inferred solely from age × gender
C2	Age 24/29/34; married; no child mentioned	Same as female candidate	Marital status as an implicit fertility signal
C3	Age 24/29/34; married and may soon become pregnant, implying about 150 days of maternity leave	Age 24/29/34; married	Explicit anticipated maternity-leave cost
C4	Age 24/29/34; married; one child aged about 1 year	Same as female candidate	Short-term childcare responsibility
C5	Age 34; married; one child aged about 6 years	Same as female candidate	Reduced maternity/childcare costs (lower perceived burden)

*Note:*Each participant completed a sequence of randomized vignettes within their assigned ageâoccupation treatment. Participants in the age 24 and age 29 groups completed four vignettes (Conditions C1–C4). Participants in the age 34 group completed five vignettes (Conditions C1–C5).

5.2 Hypotheses

This vignette experiment allows us to test four key hypotheses about the behavioral foundations of the shadow mommy effect, focusing on how employers interpret signals of potential and realized maternity-related costs. We denote the proportion of subjects hiring the female candidate in a given condition as p.

- **H1 (Implicit Fertility Bias Replication):** Replicating the core finding of our field experiment, we test whether employers use age as an implicit proxy for fertility risk even when no family information is provided. We predict that, in the baseline condition (C1), 29-year-old women (peak fertility age) will have a lower hiring rate than 24-year-old women: $p_{29,C1} < p_{24,C1}$.

- **H2 (Signaling Gradient):** We hypothesize that employers interpret marital and family information as increasingly strong signals of potential maternity-related costs. As the fertility signal becomes more explicit, the hiring rate for the female candidate should decline: $p_{C1} > p_{C2} > p_{C3}$. Marriage alone (C2) may signal the possibility of pregnancy, while explicit mention of maternity leave (C3) represents the strongest cost signal.

- **H3 (Anticipated vs. Realized Costs):** We test whether the "maybe-baby" penalty, driven by anticipated maternity leave, differs from the motherhood penalty arising from ongoing childcare demands. Because the possibility of a forthcoming 150-day maternity leave in C3 imposes a large, immediate, and one-sided cost on employers, it should trigger a stronger hiring penalty than the more routine childcare responsibilities implied when both candidates have a one-year-old child in C4. We therefore expect the lowest hiring rate in the "maybe-baby" condition ($p_{C3} < p_{C4}$).

- **H4 (Cost Duration):** We hypothesize that the motherhood penalty observed in C4 is temporary and linked to the intensive-care stage of early childhood. When the child is school-aged (C5), the expected time and flexibility costs for employers are much lower, and the hiring penalty should weaken. Accordingly, we predict that the hiring rate for women with a school-aged child will be significantly higher than for those with an infant ($p_{C5} > p_{C4}$).

5.3 Experimental Results

The vignette experiment provides clear evidence that discrimination against women arises not from concerns about productivity but from expectations of maternity-related costs. Because the vignette holds constant all observable productivity attributes, any variation in hiring behavior must result from how employers interpret gender, age, marital status, and parental status. The empirical patterns align with the findings from the field experiment and allow us to identify the mechanism underlying the shadow mommy effect.

Table 5 reports the proportion of respondents who selected the female candidate in each condition. In the baseline (C1), where no marital or parental information is provided, the female

hiring rate is relatively high (0.57). This condition is most comparable to the field experiment, in which resumes omitted family information. Consistent with **H1**, even in this neutral setting, respondents use age as an implicit signal of fertility risk. The hiring rate for 29-year-old women is significantly lower than for 24-year-old women (0.54 versus 0.60; $p = 0.03$) and also lower than for 34-year-old women, although this latter difference is not statistically significant. This result reproduces the field experiment's finding that women at the peak fertility age face the strongest hiring penalty despite being observationally identical to male applicants.

Table 5: Share of Respondents Choosing the Female Candidate

Group	C1	C2	C3	C4	C5
Pooled sample	0.57	0.50	0.15	0.38	0.54
By age					
Age 24	0.60	0.50	0.16	0.41	–
Age 29	0.54	0.48	0.15	0.38	–
Age 34	0.58	0.52	0.16	0.34	0.54

Notes: Entries show the proportion of respondents selecting the female candidate under each experimental condition. C1: Baseline (no marital or parental information); C2: Married; C3: May soon become pregnant (possible maternity leave); C4: Parent of a one-year-old child; C5: Parent of a six-year-old child (only included for age 34). All vignette profiles hold constant education, experience, and all productivity characteristics.

Introducing marital information in C2 lowers the hiring rate of women to 0.50. This decline is consistent with **H2**. Marriage appears to serve as an implicit signal of impending pregnancy even in the absence of explicit parental information. When anticipated maternity costs are made explicit in C3 by stating that the female candidate may soon take approximately 150 days of maternity leave, the hiring rate drops sharply to only 0.15. The observed pattern ($p_{C1} > p_{C2} > p_{C3}$) is monotonic, large in magnitude, and statistically significant at the 1% level. This demonstrates that discrimination against women escalates as the potential cost of maternity becomes more salient.

Crucially, the contrast between the 42 percentage point drop in the vignette and the 1.1 percentage point penalty in the field clarifies the nature of the discrimination. Condition C3 presents a scenario where maternity risk is explicit and immediate, eliciting a severe negative response from employers. In contrast, the field setting involves significant uncertainty regarding whether a specific 29-year-old will actually take leave. Consequently, the modest penalty observed in the field acts as an attenuated reflection of this underlying aversion. The vignette reveals the potential magnitude of the penalty when risk is salient, while the field results demonstrate how employers weigh this risk probabilistically under uncertainty.

The comparison between C3 and C4 isolates anticipated maternity leave from realized childcare responsibilities. In C4, both candidates are described as married and having a one-year-old

child. The hiring rate for women rises to 0.38. This is more than double the rate observed in C3. The result supports **H3**. Employers penalize the possibility of imminent maternity leave substantially more than the day-to-day childcare responsibilities that are assumed to be shared by both male and female candidates.

H4 concerns the duration of the motherhood penalty. When the child is of school age, as in C5, the hiring rate for women increases to 0.54. This level is close to the baseline rate in C1. This indicates that the penalty observed in C4 is temporary and concentrated in the early stages of intensive childcare. Once children are older and require less parental time and flexibility, hiring discrimination against mothers largely disappears.

Table 6 shows that these patterns are consistent across the three occupational contexts: Accounting, IT, and HR. Although the overall hiring rates differ slightly by occupation (female candidates are hired more frequently in Accounting and HR than in IT), the ordering of conditions remains the same. Within each occupation, the age-29 penalty in C1 becomes negligible once information about marital or parental status is disclosed (conditions C2 through C5), reinforcing the finding that age penalties operate through fertility inference rather than general productivity concerns.

Table 6: Share of Respondents Choosing the Female Candidate, by Occupation

Occupation (by age)	C1	C2	C3	C4	C5
Accounting					
Age 24	0.71	0.59	0.16	0.43	–
Age 29	0.64	0.56	0.16	0.46	–
Age 34	0.75	0.71	0.18	0.42	0.69
Information Technology					
Age 24	0.44	0.40	0.14	0.31	–
Age 29	0.41	0.36	0.13	0.33	–
Age 34	0.35	0.32	0.14	0.22	0.35
Human Resources					
Age 24	0.65	0.51	0.19	0.49	–
Age 29	0.58	0.52	0.16	0.37	–
Age 34	0.63	0.55	0.16	0.39	0.58

Notes: Entries show the proportion of respondents selecting the female job candidate under each experimental condition, stratified by occupational context (Accounting, IT, Human Resources) and age of the candidate profile. C1: Baseline (no marital or parental information); C2: Married; C3: May soon become pregnant (possible maternity leave); C4: Parent of a one-year-old child; C5: Parent of a six-year-old child (only included for age 34). All vignette profiles hold constant education, work experience, and productivity characteristics.

Table 7 reports the share of respondents selecting the female job candidate, stratified by the gender of the respondent. It reveals a consistent pattern in which a lower proportion of male respondents chose to hire females across all conditions. Male selection rates were significantly lower than 0.5 (random choice) at the 1% level. In contrast, female respondents

were significantly more likely to hire females in C1 and C2 but switched to preferring males when maternity costs became salient in C3. Combined with the field experiment results, this suggests that male employers exhibit a stronger baseline preference for male candidates, whereas female employers penalize female candidates primarily when maternity costs are made explicit. In addition, participants' incentivized guesses about others' hiring decisions follow the same pattern as actual choices, indicating that the maternity-related penalty is commonly expected rather than idiosyncratic; these results are reported in Appendix E.2.

Table 7: Share of Respondents Choosing the Female Candidate, by Employer Gender

Condition	Male employer	Female employer	Difference	*p-value*
C1	0.38	0.69	−0.30	0.000***
C2	0.32	0.61	−0.28	0.000***
C3	0.06	0.21	−0.14	0.000***
C4	0.26	0.46	−0.22	0.000***
C5	0.33	0.65	−0.32	0.000***

Notes: Entries display the proportion of participants selecting the female candidate in each condition, separately by participant gender. The "Difference" column reports the proportion for Male respondents minus that for Female respondents (so positive values indicate a higher female selection rate among male participants). Reported p values test the null hypothesis that the male and female proportions are equal within condition using a two sided test of difference in proportions. Significance stars denote *** $p < 0.01$, ** $p < 0.05$, * $p < 0.10$.

Taken together, the vignette experiment complements the field experiment by demonstrating that discrimination against women is causally driven by expectations of maternity-related labor costs rather than by perceived productivity differences. Age-related penalties emerge only when employers infer fertility risk from age. Once family information is revealed, the penalty shifts to the magnitude and timing of expected maternity-related costs. The sequence of Conditions C1 through C5 therefore isolates the mechanism behind the shadow mommy effect.

6 Heterogeneity Analysis

In this section, we examine whether the treatment effects in the field exhibit heterogeneity consistent with the cost-based mechanism identified in the vignette study. While firm types and locations are not randomized, disaggregating the results by these dimensions offers suggestive evidence regarding the underlying economic drivers of the shadow mommy effect.

6.1 Heterogeneity by Firm Ownership: The Role of Cost Sensitivity

Firm ownership structure engenders distinct organizational characteristics and practices that shape hiring preferences. As Zhou et al. (2013) demonstrate, different ownership types

manifest divergent gender preferences during recruitment. Accordingly, we conduct a subsample analysis based on ownership categories to explore the mediating and moderating effects of institutional factors on the shadow mommy effect.

First, we stratify the total sample into state-owned enterprises (SOEs) and non-state-owned enterprises (NSOEs). SOEs constitute a significant segment of the Chinese economy. According to World Bank estimates, the share of SOEs in China's GDP ranges from 23% to 28%, and their portion of total employment spans from 5% to 16% (Zhang, 2019). We estimate Equation (2) and plot $\widehat{\beta_1}$ and $\widehat{\beta_2}$, which correspond to the coefficients of the key interaction terms $Female \times Age29$ and $Female \times Age34$, in Figure 4. The blue triangle markers represent estimates for the full sample, while orange squares, green diamonds, and red circles represent the IT, accounting, and HR fields, respectively. The upper-left plot in Figure 4 displays the estimates for SOEs, whereas the upper-right plot shows the results for NSOEs.

As shown, for jobs in SOEs, there is no statistically significant negative association between being a woman of prime childbearing age and callback rates. However, among NSOE jobs, being 29 years old reduces women's callback rate by 1.0 percentage point, a result statistically significant at the 1% level. For IT positions, being 29 years old significantly decreases a woman's callback rate by 1.1 percentage points; similarly, for HR positions, being 29 and 34 years old significantly lowers a woman's callback rate by 1.6 and 1.7 percentage points, respectively. A comparison of these estimates with the main results in Table 3 reveals that the magnitude of the coefficients is quantitatively similar, indicating that the main results are driven primarily by jobs in NSOEs.

This divergence aligns with fundamental differences in the objective functions of state and private entities. NSOEs operate under hard budget constraints, a financial reality that forces them to be highly sensitive to marginal labor costs and the potential liabilities of maternity leave. In contrast, SOEs are often characterized by "soft budget constraints" and are mandated to prioritize policy compliance and social stability over strict profit maximization (Lin et al., 2020). Consequently, the absence of a penalty in the state sector suggests that SOEs are less sensitive to the potential cost of maternity leave rather than holding different beliefs about female productivity.

Next, we divide the sample into foreign-invested enterprises (FIEs) and non-foreign-invested enterprises (NFIEs) and estimate Equation (2) for each subsample by field. The lower plots in Figure 4 display coefficient plots for these groups. As shown by the lower-left plot, we find no statistically significant evidence of discrimination against female applicants of prime childbearing age in FIEs across all three fields. However, the lower-right plot indicates that for

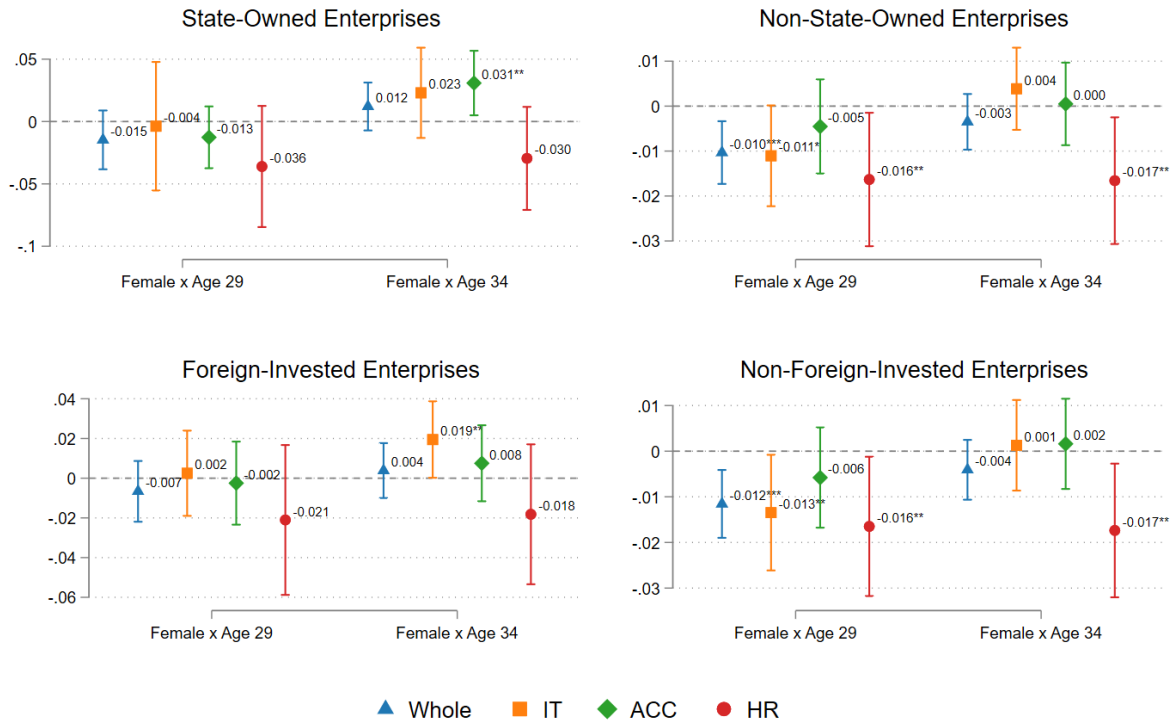


Figure 4: Impact of Prime Childbearing Age on Female Applicants by Firm Ownership

Note: The graph presents the results of a subsample analysis in which the positions advertised were with SOEs, NSOEs, FIEs, and NFIEs. The dependent variable is an indicator variable for whether the applicant is invited to an interview. The plots show the estimated coefficients of the key variables of interest: whether the applicant is a woman of prime childbearing age (29 years of age) and whether the applicant is a woman of late childbearing age (34 years of age). The corresponding regression estimates are labeled. The blue triangle markers represent estimated coefficients for the full sample, the orange square markers represent estimated coefficients for the IT field, the green diamond markers represent estimated coefficients for the accounting field, and the red circle markers represent estimated coefficients for the HR field. The 95% confidence intervals are illustrated by the vertical bars and their caps. The size of the p value is labeled $^{*}p < 0.1$; $^{**}p < 0.05$; and $^{***}p < 0.01$.

positions within NFIEs, being 29 years old reduces the callback rate for female applicants by 1.2 percentage points. This reduction is significantly influenced by employment in the IT and HR sectors. Furthermore, being 34 years old correlates with a lower callback rate for female applicants in HR roles. Once more, the magnitudes of the estimated coefficients closely align with the point estimates in the main results from Table 3, underscoring that positions in NFIEs shape the primary effects.

This heterogeneity likely stems from distinct organizational norms and resource constraints. FIEs often transplant management practices and corporate cultures from their home countries, which frequently mandate stricter adherence to equal opportunity standards. Tang and Zhang (2021) document that foreign affiliates from nations with strong gender equality norms employ significantly more women in China. Furthermore, as multinational entities, FIEs typically possess greater financial resources and organizational slack than domestic private firms, rendering them less sensitive to the marginal cost of potential maternity leave. Consequently, the combination of imported institutional norms and reduced cost sensitivity likely insulates FIEs from the shadow mommy effect.

6.2 Heterogeneity by City: The Role of Labor Costs and Childcare Support

To explore regional heterogeneity, we disaggregate our analysis by city. We estimate Equation (2) for each city and by field. The estimated coefficients for the key interaction terms, $Female \times Age29$ and $Female \times Age34$, are depicted in Figure 5. For jobs in Beijing, being 29 years old significantly decreases the callback rate for women by 1.9 percentage points. This penalty is particularly acute in specific sectors, with a 3.5 percentage point reduction in IT and a 2.2 percentage point reduction in accounting. In Shanghai, being aged 29 significantly lowers women's callback rates by 1.5 percentage points. The adverse impact is concentrated in HR positions, where being aged 29 reduces female applicants' callback rates by 4.1 percentage points. Additionally, women at age 34 experience similar negative effects. However, in Guangzhou, we find no evidence of discrimination against women of prime childbearing age, as the estimates for the key variables of interest are small and statistically indistinguishable from zero. Similarly, there is no statistically significant evidence in Shenzhen that being of prime childbearing age decreases the callback rate for female applicants. In summary, the shadow mommy effect is strictly concentrated in Beijing and Shanghai, while remaining absent in Guangzhou and Shenzhen.

Several structural factors likely explain this geographic heterogeneity. One likely driver is the variation in labor costs. Because maternity leave necessitates temporary labor substitution,

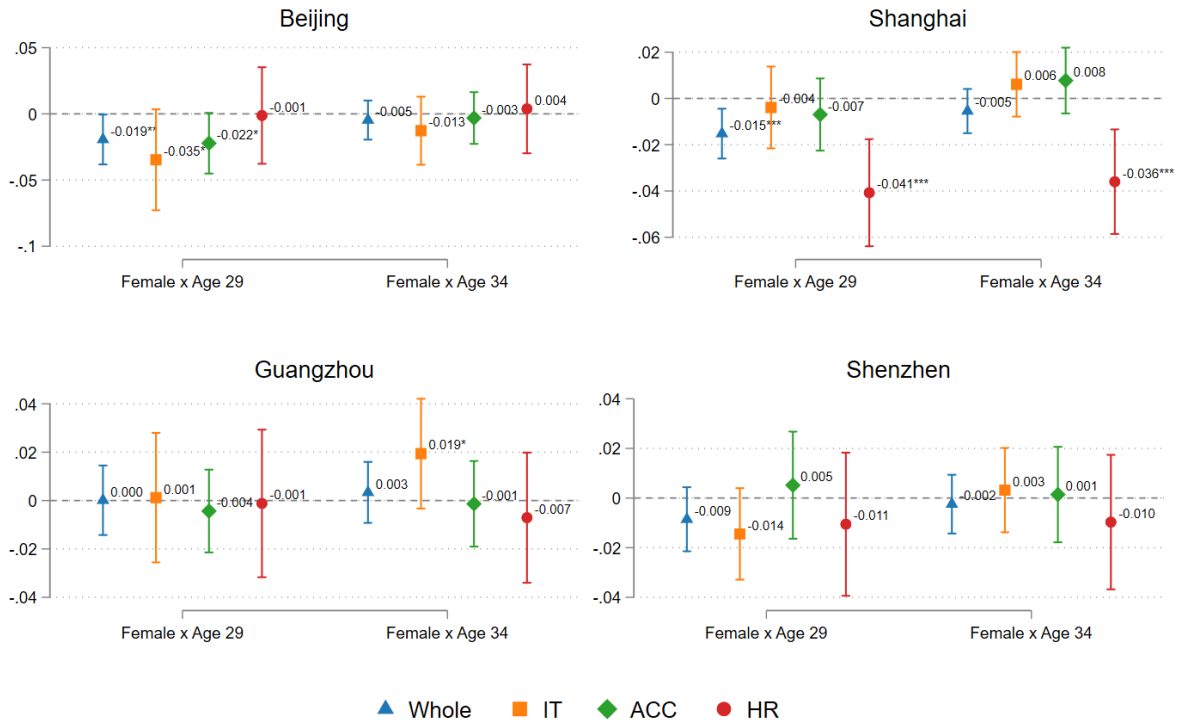


Figure 5: Impact of Prime Childbearing Age on Female Applicants by City

Note: The graph presents the results of a subsample analysis in which the advertised positions are located in Beijing, Shanghai, Guangzhou, and Shenzhen. The dependent variable is an indicator variable for whether the applicant is invited to an interview. The plots show the estimated coefficients of the key variables of interest: whether the applicant is a woman of prime childbearing age (29 years of age) and whether the applicant is a woman of late childbearing age (34 years of age). The corresponding regression estimates are labeled. The blue triangle markers represent estimated coefficients for the full sample, the orange square markers represent estimated coefficients for the IT field, the green diamond markers represent estimated coefficients for the accounting field, and the red circle markers represent estimated coefficients for the HR field. The 95% confidence intervals are illustrated by the vertical bars and their caps. The size of the p value is labeled $^{*}p < 0.1$; $^{**}p < 0.05$; and $^{***}p < 0.01$.

high-wage cities impose a steeper replacement cost on employers. Figure A.4 depicts the average annual salaries in Beijing, Shanghai, Guangzhou, and Shenzhen from 2017 to 2021. As observed, Beijing has the highest average salary, closely followed by Shanghai, with both surpassing the average salaries in Guangzhou and Shenzhen. This indicates that labor costs in Beijing and Shanghai are notably higher than in Guangzhou and Shenzhen. Therefore, employers in Beijing and Shanghai might be less inclined to hire women in their prime childbearing years because of the elevated financial liabilities, especially given their higher cost sensitivity. This aligns with Jessen et al. (2019)'s findings in Germany, which suggest that monetary costs play a significant role in driving discrimination against women with potential maternal status.

Additionally, differences in parental responsibilities related to the traditional homemaker-breadwinner norm may interact with the level of the child penalty in different cities (Andresen and Nix, 2022; Doepke et al., 2023; Kleven et al., 2019a; Zhang et al., 2024). As demonstrated by the pre-experimental survey, respondents generally agree more strongly that motherhood negatively impacts a woman's career than they do that fatherhood affects a man's career. As depicted in Figure 2, the agreement that motherhood harms women's careers is most pronounced in Beijing. Conversely, the consensus that fatherhood has a detrimental effect on men's careers diminishes from Shenzhen, Guangzhou, and 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, a finding consistent with the 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. Collectively, discrimination against perceived maternity status could be reinforced by the substantial disparity in how parental status impacts the careers of women and men. This discrepancy likely arises from traditional differences in parental responsibilities rooted in gendered social norms.

Moreover, given recent research emphasizing the vital role of childcare in female labor force participation in China (Zhou et al., 2022), we explore potential differences in childcare support among these four cities. Because of the scarcity of public childcare facilities and limited market-based services, it is common in China for grandparents to play a significant role in raising children, especially those younger than three (Ji et al., 2020; Meng et al., 2023; Wang et al., 2021).[8] Deng et al. (2023) and Meng et al. (2023) find that the accessibility of grandparental childcare could mitigate discrimination by companies against women with children and decrease the motherhood penalty in China. Therefore, we examine differences in the

[8] In China, the minimum age for kindergarten enrollment is typically three years.

availability of grandparental childcare among the four cities using data from the China Health and Retirement Longitudinal Study (CHARLS).[9] According to the CHARLS data from 2018, grandparents in Beijing spend 673.6 annual hours caring for their grandchildren, whereas in Shanghai, this figure is 1,102.6 hours. In contrast, grandparents in Guangzhou provide 2,320.1 hours, and those in Shenzhen provide 2,072.8 hours. These data demonstrate that grandparents in Guangzhou and Shenzhen invest significantly more time caring for their grandchildren than do their counterparts in Beijing and Shanghai. This regional variation aligns with differences in childcare availability. In Guangzhou and Shenzhen, where grandparental childcare involvement is more extensive and labor costs are lower, the anticipated burden of maternity leave on employers may be mitigated. While we cannot causally isolate this factor, the correlation between lower penalties and higher childcare support reinforces the hypothesis that the shadow mommy effect is driven by the employer's expected cost burden.

7 Discussion and Conclusion

In this study, we investigate the impact of prime childbearing age on women's employment opportunities using a two-pronged experimental design that combines a large-scale correspondence test with a mechanism-oriented vignette study. Our field experiment simulates real-world job-seeking conditions by sending fictitious CVs to 35,713 active job advertisements across four major Chinese cities: Beijing, Shanghai, Guangzhou, and Shenzhen. We target three distinct sectors to capture varying gender norms: the male-dominated field of IT, the female-dominated field of accounting, and the mixed-gender field of HR.

Our findings document substantial labor market discrimination against women of prime childbearing age. Biased decisions emerge specifically at the intersection of gender and age, giving rise to what we term the *shadow mommy effect*, a phenomenon where discrimination persists even when maternity and marital status are unobserved. This penalty is particularly pronounced in the IT and HR sectors. Notably, we observe a distinct reversal in hiring preferences: while 24-year-old women enjoy a hiring premium over men, this advantage is completely eliminated and reversed by age 29. This pattern suggests that employers engage in myopic optimization or a tenure-adjusted cost calculation.

To causally identify the mechanism driving this effect, we conducted a follow-up vignette experiment with 1,800 participants. This study allows us to disentangle general productivity concerns from specific maternity-related costs. The results demonstrate that discrimination

[9] The CHARLS is a nationally representative sample of Chinese residents aged 45 and above and is designed to support scientific research on elderly individuals (Zhao et al., 2014).

escalates sharply when the probability of future maternity leave becomes salient, even among candidates with identical education and experience. This pattern suggests that unobserved productivity differences are unlikely to be the primary driver of the penalty. Instead, the combined evidence indicates that the shadow mommy effect is driven by employer concerns over anticipated maternity leave costs.

Comparing the field and vignette results clarifies the nature of the shadow mommy effect. The vignette reveals a severe latent aversion to maternity costs when they are certain. In contrast, the field results reflect an environment of uncertainty where employers must infer fertility risk based on age. Consequently, the observed field penalty operates as a probability-weighted price: employers discount the value of 29-year-old female candidates by the expected cost of future leave, applying a significantly attenuated version of the severe sanction they would impose if maternity were certain.

Heterogeneity analysis from the field experiment further validates this cost-based mechanism. We find that the shadow mommy effect is primarily concentrated in Non-State-Owned Enterprises and Non-Foreign-Invested Enterprises, which are typically more sensitive to labor costs. In contrast, the penalty vanishes in State-Owned Enterprises, which face softer budget constraints and stricter anti-discrimination mandates. Furthermore, the penalty is mitigated in cities with stronger public childcare support, suggesting that externalizing the costs of child-rearing can reduce the burden on individual firms. Geographically, we observe significant regional variation, with the shadow mommy effect being most pronounced in Beijing and Shanghai, cities characterized by higher labor costs and less grandparental childcare relative to Guangzhou and Shenzhen.

This study contributes to the literature on gender disparities by examining the often-overlooked discrimination against women of prime childbearing age based on potential rather than actual motherhood. We demonstrate how the intersection of gender and age intensifies employment disadvantages. This dynamic perpetuates a vicious cycle that impedes gender equity and potentially suppresses fertility rates, as women face a trade-off between career progression and family planning. Our findings suggest that policy interventions must move beyond simple non-discrimination mandates to address the underlying cost structure. Effective measures should include expanding public childcare support to reduce the private cost of motherhood, implementing strong ESG policies to incentivize long-term workforce stability, and encouraging paternity leave to redistribute the perceived risk between male and female employees.

Our study is subject to several limitations. First, our experimental design captures discrimi-

nation only at the initial callback stage, leaving subsequent stages such as interviews and wage bargaining unexplored. Second, our experiment focused on a single general job recruitment platform, excluding specialized platforms and headhunters. Finally, while we identify the mechanism through experimental variation, future research could leverage exogenous policy shocks to further establish the causal link between fertility policies and hiring discrimination in different regulatory environments.

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Appendix A Supplementary Figures and Tables

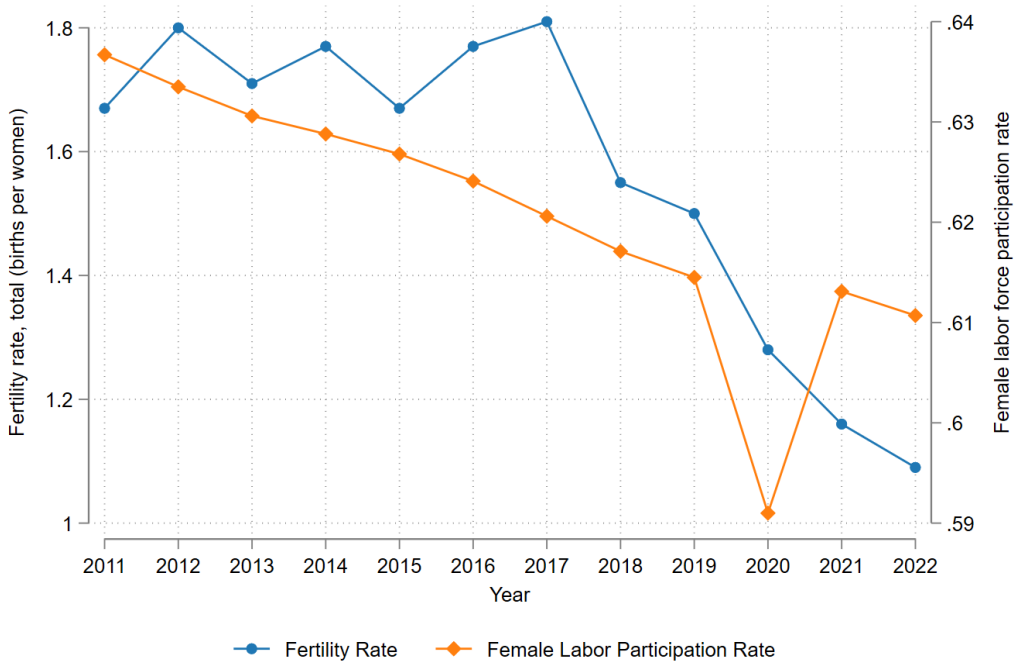


Figure A.1: Fertility trends and female labor participation in China (2011–2022)

Note: The blue circle line illustrates China's total fertility rate, measured as children per woman, from 2011–2022. The orange diamond line represents the labor force participation rate among females aged 15 and above in China during the same period. Data source: The World Bank.

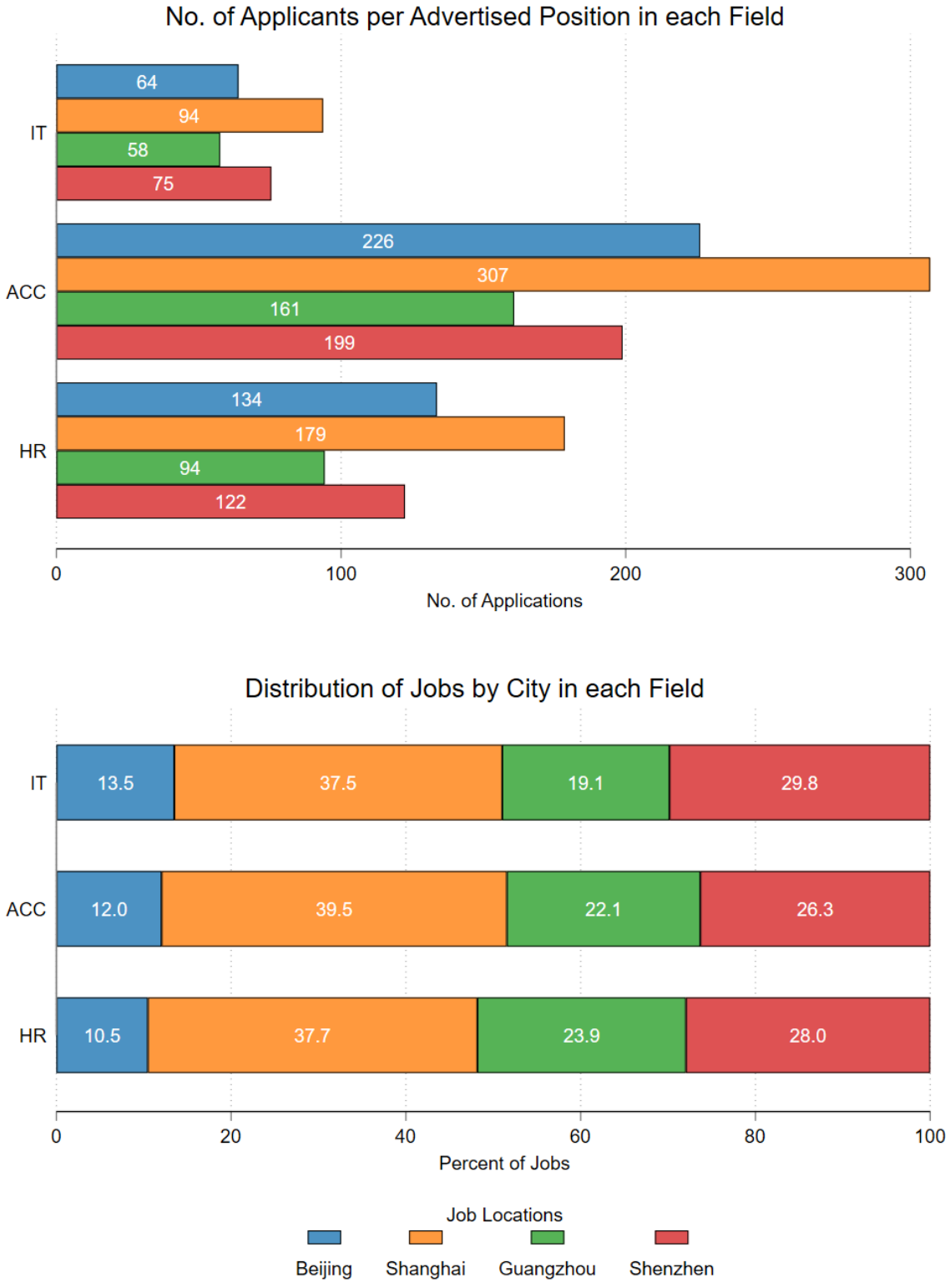


Figure A.2: Job Posting Characteristics across Fields and Cities

Note: The data were collected by the authors between March and June 2021.

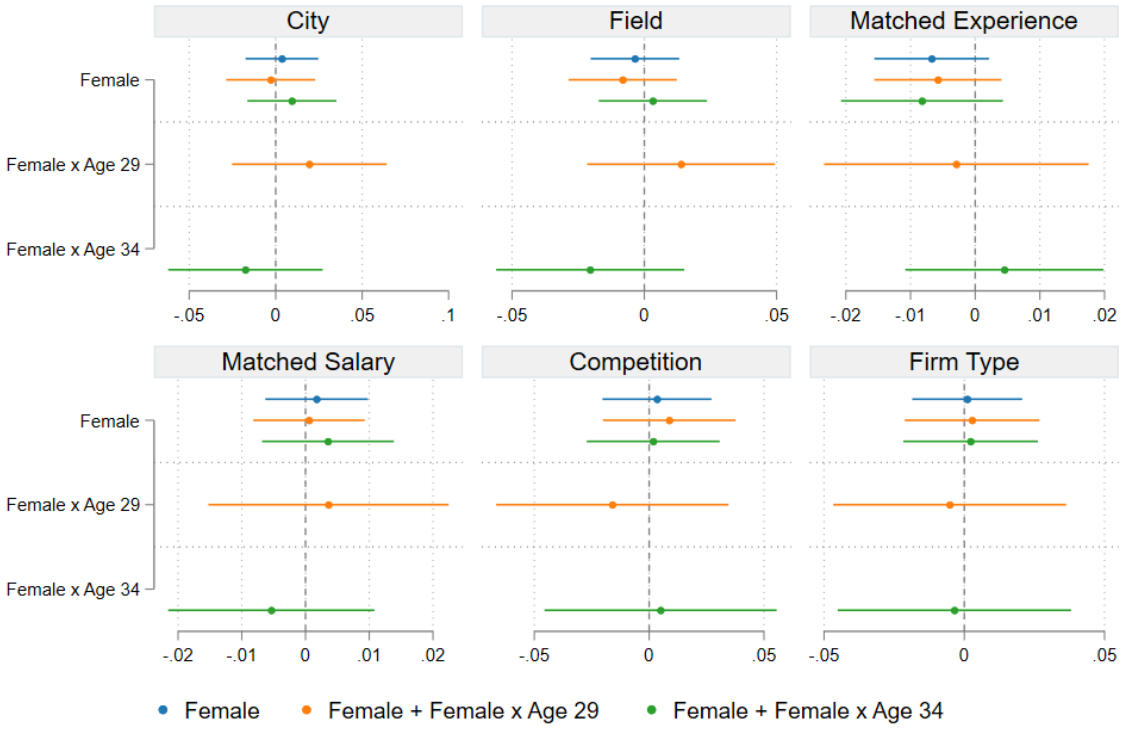


Figure A.3: Balancing Test

Note: The graph illustrates the estimated coefficients of the balancing tests. The blue markers plot the estimated coefficients of each characteristic of the job postings (the city in which the position is advertised, the field of the advertised positions, whether the applicant's working experience is a good match for the requirements of the advertised position, whether the applicant's expected salary is in line with the advertised salary, the logarithm of the number of applications received for the advertised position, and the type of firm that advertised the position) on the female dummy. The orange markers plot the estimated coefficients of each job posting characteristic on both the female dummy variable and the interaction term of the female and age 29 dummies. The green markers plot the estimated coefficients of each job posting characteristic on both the female dummy variable and the interaction term of the female and age 34 dummies. The horizontal spikes represent the 95% CIs.

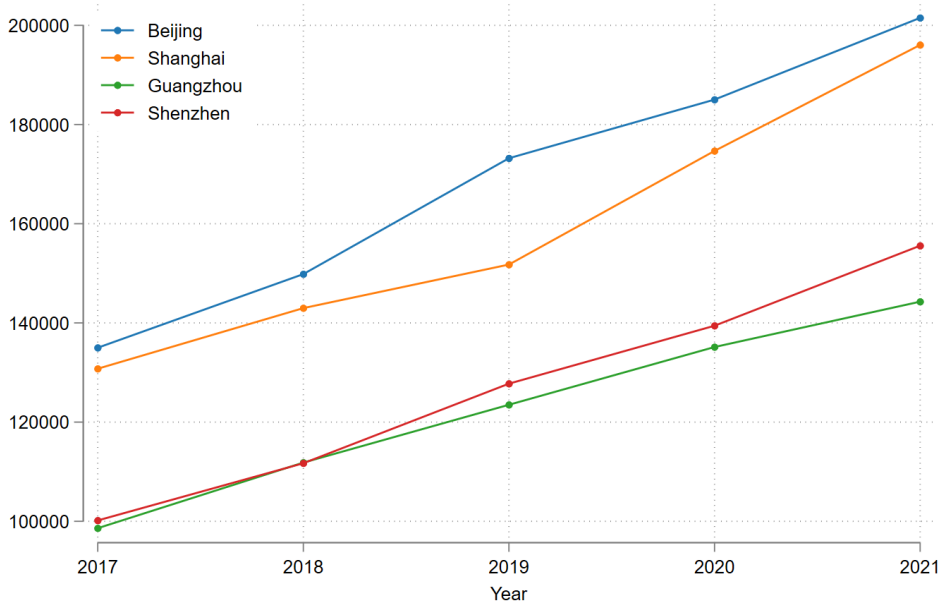


Figure A.4: Average annual salaries of urban employees

Note: Salary averages for employees in each city for the 2017–2021 period measured in Chinese yuan. The data were obtained from the National Bureau of Statistics of China.

Appendix B Preexperiment Survey

B.1 Survey Questions

Please note that the original survey is in Chinese; 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 receive 3 CNY. It takes approximately 10 minutes to complete the questionnaire. The choices that you make and the personal information that you disclose in this study are both anonymous and absolutely confidential.

Please note that the questionnaire includes numerous attention test questions. If you answer any of the attention tests incorrectly, you will be asked to stop 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 0–10, 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:
(on a scale of 0–10, where 0 represents no discrimination and 10 represents severe discrimination)

(a) Programmer (computer/internet/communication/electronics)
(b) Sales and customer service
(c) Accounting/finance (finance/audit/tax, accounting/finance/banking/insurance)
(d) Chemical engineering (biotech/pharmaceutical/chemical/medical)
(e) Public relations/media (advertising/marketing/media/art)

(f) Human resources/administration/senior management
(g) Consulting/law (consulting/law/education/research)
(h) Training (consulting/law/education/research)
(i) Research (consulting/law/education/research)
(j) Civil servant (government agencies/translation/other)

35 – 44. Please estimate the level of discrimination against male applicants in the following occupations:
(on a scale of 0–10, where 0 represents no discrimination and 10 represents severe discrimination)

(a) Programmer (computer/internet/communication/electronics)
(b) Sales and customer service
(c) Accounting/finance (finance/audit/tax, accounting/finance/banking/insurance)
(d) Chemical engineering (biotech/pharmaceutical/chemical/medical)
(e) Public relations/media (advertising/marketing/media/art)
(f) Human resources/administration/senior management
(g) Consulting/law (consulting/law/education/research)
(h) Training (consulting/law/education/research)
(i) Research (consulting/law/education/research)
(j) Civil servant (government agencies/translation/other)

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?
(on a scale of 0–10, where 0 represents "completely unconcerned" and 10 represents "very concerned")

49. To what extent do you think that listed companies will not hire female job seekers of childbearing age?
(on a scale of 0–10, where 0 represents "completely unconcerned" and 10 represents "very concerned")

50. To what extent do you think unlisted companies will not hire female job seekers of childbearing age?
(on a scale of 0–10, where 0 represents "completely unconcerned" and 10 represents "very concerned")

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?
(on a scale of 0–10, where 0 represents "completely unconcerned" and 10 represents "very concerned")

(a) Up to 5000 CNY
(b) 5001 to 10,000 CNY
(c) 10,001 to 30,000 CNY
(d) 30,001 to 50,000 CNY
(e) Above 50,000 CNY

56. According to your own reproductive intentions (without considering the family planning policy), please select the most suitable reproductive plan for you between the ages of 20 and 35:

(a) Do not wish to have children
(b) Wish to have a daughter
(c) Wish to have a son
(d) Wish to have a child, gender does not matter
(e) Wish to have two daughters
(f) Wish to have two sons
(g) Wish to have a daughter and a son
(h) Wish to have two children, gender does not matter
(i) Wish to have three or more children, at least two of whom are daughters
(j) Wish to have three or more children, at least two of whom are sons
(k) Wish to have three or more children, gender does not matter
(l) Uncertain/difficult to answer

57. Please indicate your level of agreement with the statement that "Having a child negatively affects a woman's career"
(on a scale of 0–10, where 0 represents strongly disagree and 10 represents strongly agree).

58. Please indicate your level of agreement with the statement that "Having a child negatively affects a man's career"
(on a scale of 0–10, where 0 represents strongly disagree and 10 represents strongly agree).

59. Please indicate your level of agreement with the statement that "It is better for a mother to go to work after her child begins school"
(on a scale of 0–10, where 0 represents strongly disagree and 10 represents strongly agree).

60. Please indicate your level of agreement with the statement that "During an economic recession, female employees need to be fired first"
(on a scale of 0–10, where 0 represents strongly disagree and 10 represents strongly agree).

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 been employed full time?

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

(a) Up to 1000 CNY
(b) 1001–3000 CNY
(c) 3001–5000 CNY
(d) 5001–7000 CNY
(e) 7001–10,000 CNY
(f) 10,001–15,000 CNY
(g) 15,001–20,000 CNY
(h) 20,001–30,000 CNY
(i) 30,001–50,000 CNY
(j) 50,001–100,000 CNY
(k) Above 100,000 CNY

66. Please select your marital and parental status:

(a) Unmarried
(b) Married without children
(c) Married with children
(d) Divorced without children

(e) Divorced with children
(f) Widowed without children
(g) Widowed with children

67. Please select the number of daughters that you now have: (0/1/2/3 or more)

68. Please select the number of sons that you now have: (0/1/2/3 or more)

69. Please select the average number of children that your colleagues have: (0/1/2/3 or more)

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

(a) Government institution
(b) Public institution
(c) Married with children
(d) State-owned enterprise
(e) Foreign-invested enterprise
(f) Joint venture enterprise
(g) Private enterprise
(h) Self-employed
(i) Student
(j) Homemaker
(k) Retiree
(l) Others

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

(a) Computer/internet/communication/electronics
(b) Sales/customer service
(c) Accounting/finance/banking/insurance
(d) Production/operation/procurement/logistics
(e) Biology/pharmaceutical/chemical/medical
(f) Advertising/marketing/media/art
(g) Construction/real estate
(h) Human resources/administration/senior management
(i) Consulting/law
(j) Education
(k) Research
(l) Service industry
(m) Government institution
(n) Translation
(o) Others

72. Please score the level of gender discrimination that you have experienced during recruitment:
(on a scale of 0–10, where 0 indicates no experience of discrimination and 10 indicates experiencing severe discrimination)

73. Please score the level of gender discrimination that you have experienced at work:
(on a scale of 0–10, where 0 indicates no experience of discrimination and 10 indicates experiencing severe discrimination)

B.2 Supplementary Tables Derived from the Preexperiment Survey

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 obtained from the preexperiment survey conducted by the authors.

Table B.2: 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: The data were obtained from the preexperiment survey conducted by the authors. On a scale of 0 to 10, the smaller the value is, the more female-dominated the field is; the greater the value is, the more male-dominated the field is.

B.3 Supplementary Figure: Overview of Experimental Procedure

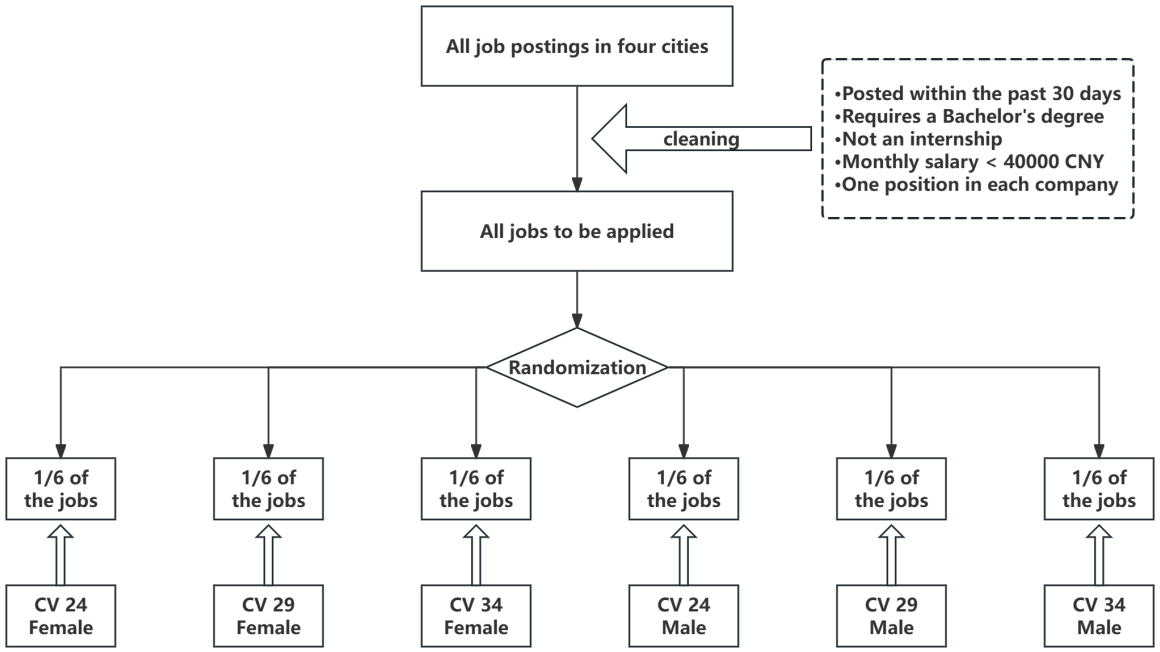


Figure B.1: Schematic Diagram of Job Application Procedures in Each Field

Note: This diagram illustrates the job application process for each field in the correspondence testing experiment.

Appendix C Example of a Fictitious Resume

Here is an original fictitious resume that was used in the experiment. The resume is in Chinese, and an English translation is provided below.



2021/3/14 人才招聘求职网-前程无忧 | 51job 简历分析

www.51job.com 前程无忧 打印 导出

张芷兰 ID:417659856

13316027434 zhangzlicu@126.com

女 | 29 岁 (1992/03/03) | 现居住武汉 | 7年工作经验

最近工作

职位: 中级前端开发工程师
公司: 九恒星（武汉）信息技术有限公司
行业: 计算机软件

最高学历/学位

专业: 计算机科学与技术
学校: 长安大学
学历/学位: 本科

求职意向

期望薪资: 20-30万 元/年 地点: 广州
职能: Web前端开发
工作类型: 全职

期望薪资: 20-30万 元/年 地点: 上海
职能: Web前端开发
工作类型: 全职

期望薪资: 20-30万 元/年 地点: 北京
职能: Web前端开发
工作类型: 全职

求职状态: 目前正在找工作 到岗时间: 1个月内

工作经验

2018/12-至今 **中级前端开发工程师** | 开发部
九恒星（武汉）信息技术有限公司 [2年3个月]
计算机软件 | 上市公司
工作描述: 1、负责前端日常维护工作;
2、负责Web端功能模块开发及维护工作;
3、负责移动端产品（微信、Android、IOS）的H5开发及维护工作。

2017/3-2018/12 **中级前端开发工程师** | IT部
武汉中科通达高新技术股份有限公司 [1年9个月]
计算机服务(系统、数据服务、维修) | 民营公司
工作描述: 1、负责PC 端与移动产品的HTML 与CSS 页面编写，解决web 端与移动端的适配问题，同时进行代码优化;
2、实现产品UI 和交互方面开发需求，确保产品具有优质的用户体验;
3、了解项目各项要求，配合后台开发人员实现产品前端界面效果与功能。

2014/7-2017/3 **前端开发工程师** | IT部
武汉中科通达高新技术股份有限公司 [2年8个月]
计算机服务(系统、数据服务、维修) | 民营公司
工作描述: 1. 协助项目负责人进行项目的需求分析、技术选型;
2. 基于用户的需求，配合项目负责人制定项目开发计划;
3. 与产品经理和UI 设计师讨论产品设计，根据详细设计进行程序开发、单元测试、开发手册编写，及缺陷修复工作;
4. 负责web 前端页面、移动端内嵌H5 页面开发及前端交 互以及前端性能提升优化.

项目经验

https://i.51job.com/resume/resume_preview.php?lang=c&resumeid=417659856&3877112907 1/2

2018/12-2021/1 **流量云平台（移动端）**

所属公司： 九恒星（武汉）信息技术有限公司

项目描述： 流量云平台是一款集供应商管理、产品管理、订单管理，合作伙伴管理，客户管理，账单/报表统计、财务管理，系统权限管理于一体的供应链管理订单平台。

责任描述： 1）使用Vue2.0 全家桶和ElementUI 实现项目的开发；

2）使用lib-flexible实现前端页面能够在不同尺寸屏之间适配。

2017/3-2018/12 **交通管理综合应用平台**

所属公司： 武汉中科通达高新技术股份有限公司

项目描述： 交通管理系统是一款数据可视化的智能化管理的系统。

责任描述： 1. 使用地图对车辆行驶轨迹、行驶位置以及对应终点，实现定位可视化功能；

2. 使用Echarts 对车辆数据数据进行监控统计功能.

技术架构：vue 全家桶+antV

2015/12-2017/3 **运输后台管理系统Vue开发**

所属公司： 武汉中科通达高新技术股份有限公司

项目描述： 本项是为某物流公司开发运输管理平台，实现交易配送提供实时信息数据支撑。主要功能包括了配送车辆管理，承运司机个人信息管理，司机-商户对接管理，配送区域信息管理等。

责任描述： 1. 负责配送车辆管理、司机-商户对接管理等模块的迭代开发与维护；

2. 按质按量完成项目组长分配的开发任务；

3. 将学习到的新技术分享汇报给组员。

技术架构：vue 全家桶+antV

2014/11-2015/8 **公司内部应用平台开发**

所属公司： 武汉中科通达高新技术股份有限公司

项目描述： 该平台具有权限等级区分功能。平台具备用户行为分析功能，并且连通公司财务系统，可自主通过算法计算盈收。

责任描述： 1. 搭建结构框架；

2. 使用vue实现需求功能.

教育经历

2010/9-2014/7 **长安大学**

本科 | 计算机科学与技术

技能特长 （包含IT技能、语言能力、证书、成绩、培训经历）

技能/语言

Web前端 精通

HTML5 熟练

JavaScript 熟练

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CV Translation - Female 29

Zhang Zhilan

- Mobile: 13316027434
- Email: zhangzlicu@126.com
- Gender: Female | Age: 29 (1992/03/03) | Current Residence: Wuhan | Work Experience: 7 years

Most Recent Employment

- Position: Intermediate Front-End Developer
- Company: Jiuhengxing (Wuhan) Information Technology Co., Ltd.
- Industry: Computer Software

Highest Degree/Major

- Major: Computer Science and Technology
- School: Chang'an University
- Degree: Bachelor's Degree

Career Objective

- Expected Salary: 200,000 - 300,000 RMB/year
- Function: Web Front-End Development
- Job Type: Full-time
- Location: Guangzhou, Shanghai, Beijing
- Job Seeking Status: Currently looking for a job
- Availability: Within one month

Work Experience

- Dec 2018-Present **Intermediate Front-End Developer** | Development Department
  - Jiuhengxing (Wuhan) Information Technology Co., Ltd. [2 years 3 months]
  - Computer Software | Public Company
  - Job Description:
    1. Responsible for routine front-end maintenance;
    2. In charge of developing and maintaining web-end functional modules;
    3. Accountable for H5 development and maintenance of mobile products (WeChat, Android, iOS).
- Mar 2017 - Dec 2018 **Intermediate Front-End Developer** | IT Department
  - Wuhan Zhongke Tongda High-Tech Co., Ltd. [1 year 9 months]

    - Computer Services (System, Data Services, Maintenance) | Private Company
    - Job Description:
        1. Tasked with writing HTML and CSS pages for PC and mobile products, addressing web and mobile compatibility issues, and optimizing code;
        2. Implemented UI and interaction development requirements to ensure high-quality user experience;
        3. Understood project requirements and collaborated with backend developers to achieve front-end interface effects and functionalities.
- Jul 2014 - Mar 2017 **Front-End Developer** | IT Department
    - Wuhan Zhongke Tongda High-Tech Co., Ltd. [2 years 8 months]
    - Computer Services (System, Data Services, Maintenance) | Private Company
    - Job Description:
        1. Assisted in project requirement analysis and technical selection;
        2. Based on user requirements, worked with project leaders to formulate development plans;
        3. Discussed product design with product managers and UI designers, developed programs, conducted unit testing, wrote development manuals, and fixed defects;
        4. Responsible for web front-end page development, mobile embedded H5 page development, front-end interaction, and performance optimization.

Project Experience

- Dec 2018 - Jan 2021 **Traffic Cloud Platform (Mobile End) Company**
    - Company: Jiuhengxing (Wuhan) Information Technology Co., Ltd.
    - Project Description: A supply chain management order platform integrating supplier management, product management, order management, partner management, customer management, billing/report statistics, financial management, and system permission management.
    - Responsibility Description:
        1. Utilized Vue 2.0 ecosystem and ElementUI for project development;
        2. Employed lib-flexible for front-end page adaptation across different screen sizes.
- Mar 2017 - Dec 2018 **Comprehensive Application Platform for Traffic Management Company**
    - Company: Wuhan Zhongke Tongda High-Tech Co., Ltd.
    - Project Description: An intelligent management system with data visualization for traffic management.
    - Responsibility Description:
        1. Used maps to visualize vehicle trajectories, positions, and corresponding endpoints;
        2. Applied Echarts for vehicle data monitoring and statistical functions.
    - Technical Architecture: Vue ecosystem + antV
- Dec 2015 - Mar 2017 **Transportation Backend Management System Vue Development Company**

    - Company: Wuhan Zhongke Tongda High-Tech Co., Ltd.
    - Project Description: Developed a transportation management platform for a logistics company, providing real-time data support for transaction delivery. Main functions included vehicle management, carrier driver information management, driver-merchant interface management, and delivery area information management.
    - Responsibility Description:
        1. Responsible for iterative development and maintenance of modules such as vehicle management and driver-merchant interface management;
        2. Completed development tasks assigned by the project leader on time and with quality;
        3. Shared and reported newly learned technologies with team members.
    - Technical Architecture: Vue ecosystem + antV
- Nov 2014 - Aug 2015 **Internal Application Platform Development Company**
    - Company: Wuhan Zhongke Tongda High-Tech Co., Ltd.
    - Project Description: The platform featured permission level differentiation, user behavior analysis, and integration with the company's financial system, capable of autonomously calculating revenue through algorithms.
    - Responsibility Description:
        1. Built the structural framework;
        2. Implemented required functionalities using Vue.

Education

- Sep 2010 - Jul 2014 **Chang'an University**
- Degree: Bachelor's in Computer Science and Technology

Skills and Strengths

- Web Front-End - Proficient
- HTML5 - Skilled
- JavaScript - Skilled

Appendix D 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) proposed 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 estimates a heteroskedastic probit model. The second step decomposes 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 childbearing-aged women, we compare childbearing-aged women with other-aged women and with men.

Column (1) of Table D.1 presents the results for childbearing-aged women versus women of other ages. Panel I provides estimates from the standard probit model for comparison with the information shown in Panel II, which provides the marginal effect estimate from the heteroskedastic probit model. Both estimates suggest that childbearing-aged women are significantly less likely than women of other ages to receive a positive employer response. Moreover, the Neumark decomposition shown in Panel III reveals that this adverse effect is largely underestimated. The marginal effect of the level of discrimination is much greater in magnitude and statistically significant. The effect of the variance of the unobserved variables is positive and significant. These results indicate that the relatively low quality of the experimental applicants led to a relative advantage for the applicants from the higher variance group, which in turn led to an underestimate of the extent of discrimination against female applicants of childbearing age.

Table D.1, Column (2), provides a comparison of childbearing-aged women and men. In Panel II, the marginal effect from the heteroskedastic probit model shows that childbearing-aged women are significantly less likely to receive a callback than men are. There is a large

Table D.1: The Neumark Method for Testing the Heckman-Siegelman Critique

Treatment group:	Childbearing-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)
Relative 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 is 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. $^{*}p < 0.1$; $^{**}p < 0.05$; $^{***}p < 0.01$.

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 childbearing-aged women is statistically significant but is also greatly underestimated.

Overall, according to the Neumark method, we confirm that women of prime childbearing age are discriminated against in the job market. Furthermore, due to the limitations of our experimental design, it is likely that we have underestimated the extent of the discrimination they were subjected to in the real-world conditions.

Appendix E Vignette Experiment

E.1 Online Vignette Experiment Instruction

The following is an English translation of the experimental instructions and questionnaire used in the vignette experiment. The original experiment was conducted in Chinese. The example below corresponds to the **Information Technology (IT)** occupation treatment for the **Age 34** candidate group.

E.1-1 Informed Consent and Introduction

Welcome to this study on decision-making. In addition to the fixed payment for the questionnaire, you have the opportunity to earn an extra cash bonus. We will randomly select 10% of participants; if you are selected, we will randomly extract one of your estimation tasks and calculate your bonus based on the accuracy of your decision in that task. Your decisions and personal data in this study are anonymous and strictly confidential.

E.1-2 Hiring Scenarios (Randomized Order)

Condition C1 (Baseline) Suppose you are an employer recruiting an employee for an **IT (Information Technology)** position in your company. There are two candidates, one female and one male. The two candidates are identical in age, education, work experience, and other aspects.

- Candidate 1: Female, 34 years old
- Candidate 2: Male, 34 years old

Which candidate would you hire?

□ Candidate 1: Female, 34 years old

□ Candidate 2: Male, 34 years old

Condition C2 (Married) Suppose you are an employer recruiting an employee for an **IT (Information Technology)** position in your company. There are two candidates, one female and one male. The two candidates are identical in age, education, work experience, and other aspects.

- Candidate 1: Female, 34 years old, married
- Candidate 2: Male, 34 years old, married

Which candidate would you hire?

□ Candidate 1: Female, 34 years old, married

□ Candidate 2: Male, 34 years old, married

Condition C3 (Maternity Cost Salience) Suppose you are an employer recruiting an employee for an **IT (Information Technology)** position in your company. There are two candidates, one female and one male. Apart from the difference in the possibility of maternity leave, the two candidates are identical in age, education, work experience, and other aspects. The female candidate just got married and may soon become pregnant, meaning your company would need to provide approximately 150 days of maternity leave.

- Candidate 1: Female, 34 years old, married, with the possibility of enjoying about 150 days of maternity leave
- Candidate 2: Male, 34 years old, married

Which candidate would you hire?

□ Candidate 1

□ Candidate 2

Condition C4 (One-Year-Old Child) Suppose you are an employer recruiting an employee for an **IT (Information Technology)** position in your company. There are two candidates, one female and one male. The two candidates are identical in age, education, work experience, and other aspects. The female candidate is married and has a child around 1 year old. The male candidate is married and has a child around 1 year old.

- Candidate 1: Female, 34 years old, married, has a 1-year-old child
- Candidate 2: Male, 34 years old, married, has a 1-year-old child

Which candidate would you hire?

□ Candidate 1

□ Candidate 2

Condition C5 (Six-Year-Old Child) Suppose you are an employer recruiting an employee for an **IT (Information Technology)** position in your company. There are two candidates, one female and one male. The two candidates are identical in age, education, work experience, and other aspects. The female candidate is married and has a child around 6 years old. The male candidate is married and has a child around 6 years old.

- Candidate 1: Female, 34 years old, married, has a 6-year-old child
- Candidate 2: Male, 34 years old, married, has a 6-year-old child

Which candidate would you hire?

□ Candidate 1

□ Candidate 2

E.1-3 Incentivized Belief Elicitation

Please estimate the percentage of other participants who chose to hire Candidate 1 (the Female Candidate) in the question above. If your guess is within 5% of the actual percentage, you will receive 2 RMB.

- **Your Estimate (0-100%): _____**

E.1-4 Demographic Questionnaire

1. **What is your gender?**
    - Male / Female
2. **What is your age?**
    - Under 18 / 18–24 / 25–34 / 35–44 / 45–54 / 55–64 / 65–74 / 75+
3. **What was your average monthly income in the past year?**
    - Below 1,000 RMB ... [Options continue up to] ... Above 100,000 RMB
4. **What is your highest level of education?**
    - Junior high or below / High school / Associate degree / Bachelor's degree / Master's degree / Doctoral degree or above
5. **What is your current employment status?**

- Employed / Self-employed / Unemployed (looking) / Unemployed (not looking) / Homemaker / Student / Military / Retired / Unable to work

6. **Location:** [Participants selected their city/province]

E.2 Guess Results

After completing the hiring task, participants were asked to guess the percentage of others who would choose the female candidate under the same condition. The guessing task was incentivized: one percent of participants were randomly selected for payment, and those whose guess fell within five percentage points of the true proportion received a monetary bonus. The aggregate patterns, reported in Table E.1 and Table E.2, reveal that participants' beliefs closely tracked the actual hiring behavior. The average guesses display the same across-condition pattern across conditions as the realized hiring rates, with the lowest perceived female selection rate in condition C3 and higher perceived rates in C1 and C5.

Participants tended to underestimate hiring of women when no family related information was provided (C1) and when only marital status was disclosed (C2). Participants also tended to underestimate hiring of women when parenthood was described symmetrically for both candidates (C4 and C5). In contrast, participants overestimated hiring of women in condition C3, in which maternity leave costs applied only to the female candidate. This pattern suggests that participants believe that explicit maternity leave risk substantially reduces the likelihood that the female candidate is selected, consistent with the interpretation that hiring penalties for women of prime childbearing age are related to anticipated maternity related costs rather than solely to general productivity concerns. Overall, the belief elicitation results indicate that these expectations about maternity related costs are common among participants and not limited to their own realized choices.

Table E.1: Average Percentage Guess of Others Hiring the Female Candidate (Pooled Sample)

Age of candidate	C1	C2	C3	C4	C5
Age 24	48.47	45.15	25.74	39.77	—
Age 29	46.52	42.17	24.57	39.66	—
Age 34	48.13	46.21	24.85	35.57	46.98

Notes: Table reports subjects' incentivized guesses, expressed as percentages, of the share of other participants in the same condition who would hire the female candidate. C1: Baseline (no family related information provided). C2: Married (for both candidates). C3: Married and may soon become pregnant with possible maternity leave (applies only to the female candidate). C4: Parent of a one year old child (for both candidates). C5: Parent of a six year old child (for both candidates; shown only for the age 34 profile). The guessing task was incentivized: 1 percent of participants were randomly selected for payment, and those whose guess fell within five percentage points of the true proportion received a monetary bonus.

Table E.2: Average Percentage Guess of Others Hiring the Female Candidate, by Occupation

Occupation (by age)	C1	C2	C3	C4	C5
Accounting (ACC)					
Age 24	51.74	49.40	28.62	42.82	—
Age 29	52.30	46.42	25.84	44.56	—
Age 34	54.03	51.04	26.49	37.96	51.58
Information Technology (IT)					
Age 24	44.60	41.99	24.65	35.51	—
Age 29	40.78	37.04	23.20	36.41	—
Age 34	41.15	40.41	24.38	30.39	40.35
Human Resources (HR)					
Age 24	49.06	44.08	23.93	40.97	—
Age 29	46.49	43.06	24.65	37.99	—
Age 34	49.23	47.18	23.67	38.36	49.02

Notes: Entries report incentivized guesses of the share of others selecting the female candidate in each condition, disaggregated by occupational context. All candidate qualifications were held constant. Conditions were presented within participant in randomized order within each assigned ageâoccupation treatment. Only condition C5 applies to the age thirty four profile.