Job Characteristics, Gender Sorting, and Gender Pay Gap: Evidence from Online Job Postings *

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May 5, 2022

Abstract

Researchers have extensively studied gender differences in employment outcomes, yet little is known about the degree that such differences are formed before employment. Using data on millions of job ads in China and applicants' gender composition, we document a persistently negative correlation between the share of female applicants and posted wages, both across and within firms and occupations. To understand why women shy away from high-wage positions, we analyze textual data of the job ads by defining a set of theory-founded job characteristics, including skill requirements, gender-typical tasks, willingness to compete, preference for job flexibility and business trip, and attitude towards wage uncertainty and age discrimination. We find that women tend to apply for jobs with characteristics signaling lower wages and avoid characteristics linked to higher wages. Decomposition analysis shows that nontraditional job characteristics jointly contribute to nearly half of the observed correlation between the share of female applicants and posted wage within narrowly defined occupations and labor markets.

*We thank Leah Boustan, Henry Farber, Gong Jie, Ilyana Kuziemko, Alexandre Mas, and Jessica Pan for their helpful comments. Mingyu Chen benefited from generous financial support from the Industrial Relations Section at Princeton University. Any errors are our own.

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1 Introduction

Over the last century, even though gender convergence has occurred in education attainment, labor force participation, work experience, and income, there are still persistent and substantial gender differences in earnings and job types in most labor markets (Blau & Kahn, 2017; Cortés & Pan, 2018). Research studying these gender gaps has primarily focused on the employment stage. Employers often provide a rich set of job characteristics in vacancy postings in today's job market, ranging from wage level, skill requirements to job amenities. Hence, as job seekers have idiosyncratic preferences for job characteristics, gender differences in jobs can start to form during the job search process and translate to differences in employment outcomes.

In this paper, we study gender differences in preferences for various job characteristics when applying for jobs and draw implications for potential gender gaps in earnings. First, we investigate the correlation between the gender composition of the applicants and posted wage and document a persistently negative association even controlling for detailed occupations and firms. We then ask, relative to men, why do women shy away from high-wage positions, in addition to consideration of occupation and firm? Utilizing rich data of job ads in China, we characterize skill requirements, gender-typical tasks, the extent of competition, preference for job flexibility and business travel, attitude towards wage uncertainty and age discrimination, and time pressure at the job level and study how those job characteristics help us understand mechanisms. Recent literature has tried to unpack the sources of gender differences and job applications (Flory, Leibbrandt, & List, 2015; Helleseter, Kuhn, & Shen, 2020; Kuhn, Shen, & Zhang, 2020; Jensen, 2020; Arceo-Gómez et al., 2020; He, Neumark, & Weng, 2021; Chaturvedi, Mahajan, Siddique, et al., 2021; Cortes, Jaimovich, & Siu, 2021). However, in general, studies tend to either document the negative relationship between the female share of applicants and posted wages but not be able to see what generates it or explore the mechanisms but focus on subsets of explanations and not test the relative importance of them together.

By scraping vacancy data from one of China's largest online job boards for a year, we constructed a data set containing rich information on job characteristics and applicant composition for over 16 million job ads. Specifically, we collect all information that employers provide on the job ad page, including job characteristics such as posted wage, requirements on education and experience, job amenities, occupation, industry, location, full job description, and firm characteristics such as firm name, structure, and size. In addition, because the job board requires each applicant to indicate their gender when submitting a job application, we collected information on the applicant composition by gender for each job ad through a paid service. Our data enables us to examine whether there exists gender difference in the valuation of job characteristics within narrowly defined occupations and firms. Although the vacancies in our data are concentrated in the private sector and focus on young and well-educated job seekers, overall, it is broadly representative of the Chinese labor market as a whole.

We categorize keywords and phrases from ad texts into a set of job characteristics. To do that, we start by using a word segmentation tool[1] based on the mechanical word segmentation method to cut Chinese texts into word sequences. Then, we manually winnow down the 3000 words and phrases with the highest frequency as well as keywords and benefits recorded by employers into a set of ad characteristics. We first follow Deming and Kahn (2018) to code 10 commonly observed and recognizable job skills in our data. Next, motivated by Gelblum (2020), we categorize six female-typical tasks and four male-typical tasks. Then, we apply Deming and Kahn (2018)'s method to define a set of job attributes comprising the extent of aspiration, pressure, competition, flexibility, business travel, wage uncertainty and age discrimination. Finally, we categorize ads into different groups regarding different day offs per month and different working hours per day, separately. The selection of these ad characteristics and corresponding keywords and phrases is motivated by literature exploring the gender difference in willingness to pay for job characteristics in explaining the residual gender wage gap.

We start by documenting a key fact that there exists a negative correlation between the gender composition of the applicants and posted wages, even controlling for education and experience requirements, occupations and firms. In detail, we regress log wage on the share of female applicants and find a raw coefficient -0.6, suggesting that a 10% increase in the share of female applicants for a particular position will, on average, signal 6% lower wage. After adding detailed controls, including education and experience requirements, industry,

[1] We use jiebaR, see https://github.com/qinwf/jiebaR.

firm, occupation, and location, we still obtain an unexplained correlation of -0.36.

To explore potential channels through which women tend to shy away from high-wage jobs, our analysis first links ad characteristics and the share of female applicants. We regress the share of female applicants on a full set of ad characteristic measures and show that the prevalence of these job characteristics is correlated with gender difference in application behavior even within narrowly defined occupations and controlling for education and experience requirements. Next, we examine whether variation in ad characteristics is related to the ad's posted wage. We show that ad characteristics that are positively correlated with the share of female applicants tend to be negatively associated with the ad posted wage. Finally, we examine how gender differences in job choice based on these job characteristics translate into the gender wage gap in jobs applied. In detail, we use the share of female applicants to proxy for female share of employment and test how the correlation between log wage and female share change when adding ad characteristics measures.

In terms of job skill requirements, we first find that ads asking for skills with high returns, such as cognitive and project management skills discourage women from applying. Our results are in accordance with the literature showing the underrepresentation of women in STEM jobs as cognitive skills are explicitly coded by keywords such as "math" and "statistics" and project management skills are highly demanded in STEM fields.[2] Second, while the literature documents women's preference for positions interacting and communicating with people[3], we find that women are more likely to choose occupations or firms emphasizing social and interpersonal skills but within occupation and firm, they tend to sort into positions requiring service skills (customer service skill) but shy away from those demanding management skills (people management skill). Finally, we find that women are consistently inclined to apply for jobs requiring character, writing, and general computer skills, both across and within firms and occupations. However, even though those skills themselves may be valuable in jobs, specifying those skills might be a signal of lower-paying jobs where require obedience and tasks with low promotability.

[2]Studies such as Carrell, Page, and West (2010), Zafar (2013), Stinebrickner and Stinebrickner (2014) and Mouganie and Wang (2020) try to explain the underrepresentation of women in STEM fields.

[3]Studies show that women tend to prefer jobs that require empathy and interacting with people (see Fortin (2008), Grove, Hussey, and Jetter (2011), Folbre (2012) and Lordan and Pischke (2016).).

We also document evidence that jobs involving female-typical tasks such as helping and caring for others, documenting and recording information, following direction of leaders or supervisors and doing chores attract women to apply for.[4] More importantly, those job tasks have negative returns in the labor market and women need to pay for their favored work activities. Instead, male-typical tasks including operating and repairing machine, problem solving, decision making and work covering high-tech are highly rewarded by firms. However, female applicants tend to not select those positions.

As for job attributes, the share of female applicants is consistently low when job ads list "aspiration", "pressure", or "competition". This pattern is in line with the literature suggesting that women have less aspiration for high-wage and promotion[5] and women disproportionately shy away from competition[6]. Importantly, we find a positive correlation between listing "aspiration", "pressure", or "competition" and posted wage, implying that firms compensate those job attributes associated with high work intensity for higher salaries.

Considering alternative work arrangements, we find that women are less likely to sort into jobs with time or location flexibility although flexible jobs are highly rewarded in our data. The reason is that work flexibility does not typically imply more family-friendly outcomes but might lead to some less family-friendly characteristics like work overtime and irregular work schedules[7]. Hence, employers compensate the potential less family-friendly attributes for higher wages, but it is hard to attract women with greater family responsibilities. Similarly, women tend to avoid positions demanding business travel frequently or at short notice, both across and within firms and occupations. While firms reward employee's greater commitment to work and regular business travel for higher wage, women expected to devote more time in family choose to spend less time on commuting time and business

[4] Our findings are consistent with Gelblum (2020), who shows women's willingness to pay for job content like helping people, caring for others, and documenting and recording information is significantly higher than men. We also reach similar conclusion as Babcock et al. (2017), who find that women are more likely to volunteer or accept requests for tasks with low promotability.

[5] Azmat, Cuñat, and Henry (2021) records that more than 50% of the gender promotion gap is attributed to the gender differences in aspirations to be promoted.

[6] Studies show that women prefer to avoiding high-stakes competition and women underperform relative to men under competition. See Jurajda and Münich (2011), Ors, Palomino, and Peyrache (2013), Morin (2015), Azmat, Calsamiglia, and Iriberri (2016) and Cai et al. (2019).

[7] Our results are similar to that of Mas and Pallais (2020).

travel.[8]

Nearly half of ads in our sample demand workers with certain range of ages and exhibit some extent of age discrimination. From our analysis, women are more willing to obey firm's age requirements and also more likely to apply for positions aiming at young workers. Meanwhile, ads specifying age requirements, especially targeting young applicants, on average pay lower salaries. This pattern is probably the consequence of equilibrium effects. Studies indicate that age discrimination is gender-biased — female-targeted ads tend to set young age range and older women receive significantly lower callback rates and job offers(Kuhn & Shen, 2013; Neumark, Burn, & Button, 2019; Carlsson & Eriksson, 2019; Helleseter, Kuhn, & Shen, 2020). Hence, to improve the probability of interview and response to the gender-biased age discrimination, women choose ads with explicit age requirements and those searching for young workers. We also find that wage uncertainty, or the share of floating wage, signal a higher average wage but attract fewer female applicants. Hence, women's preference to avoid uncertainty and risk may hurt them more in the labor market and lead to larger gender pay gap at the application stage. Finally, we show that women tend to avoid jobs not guaranteeing weekends and positions with long working hours per day.

In the sequential decomposition analysis, we find that adding industry, firm, occupation and city fixed effects translates the raw coefficient of share of female applicants on posted wage from -0.6 to -0.5, roughly 17.7%. When further controlling for traditional explanatory variables in the labor market, education and experience requirements, the correlation between the gender application composition and wage reduces another 27.2%. Lastly, the full set of nontraditional ad characteristics jointly can explain an extra 21.1% fall in the correlation between the share of female applicants and log wage. To examine the relative importance of each group of ad characteristics in explaining the gender wage gap conditional on other ad characteristics, we conduct a full decomposition following Gelbach (2016). Adding the full set of ad characteristics changes the coefficients on the share of female applicants from -0.50 to -0.28, roughly 43%. Education and experience requirements explain about half of the change while other nontraditional ad characteristics contribute to nearly another

[8] Our findings are consistent with studies documenting gender differences in commuting behavior and business travel(White, 1986; Bøler, Javorcik, & Ulltveit-Moe, 2018; Petrongolo & Ronchi, 2020; Le Barbanchon, Rathelot, & Roulet, 2021).

half. Specifically, job skills and job tasks account of more than 30% of the gap explained by the full set of covariates. Variation in "aspiration", "pressure" and "competition" together and variation wage uncertainty both lead to about 3% change. Variation in flexibility and working time plays essentially zero role in explaining the gender wage gap in jobs applied, probably due to the small sample specifying that information.

We directly contribute to a small but growing strand of literature utilizing online job ad data to study gender disparities at the job searching process. Kuhn and Shen (2013) first examine explicit gender discrimination in the online labor market in China, focusing on ads where firms state explicit gender requests. They find that ads directed towards females are more likely to state young age, height and beauty requirements, compared with male-targeted ads. Following Kuhn and Shen (2013), Helleseter, Kuhn, and Shen (2020) and Kuhn, Shen, and Zhang (2020) document "age twist"[9] phenomenon and study how applicants response to firm's explicit gender preferences, respectively. Recent papers further predict firm's implicit gender preference or firm's gender stereotype from texts of non-targeted ads and explore corresponding applicant behavior (Arceo-Gómez et al., 2020; Chaturvedi, Mahajan, Siddique, et al., 2021). Simultaneously, rich information regarding job descriptions and job requirements from internet job board enables studies on task-specific skills performed in work by gender (Cortes, Jaimovich, & Siu, 2021), the gender gap in returns to skills (Jensen, 2020), gender difference in willingness to compete (Flory, Leibbrandt, & List, 2015) and gender difference in preference for flexibility (He, Neumark, & Weng, 2021). While we also highlight the importance of words in job ads, our work is not confined to one typical dimension such as gender discrimination or gender differences in skills. In contrast, we utilize the text specified in job ads to categorize a set of job characteristics based on several hypotheses in explaining gender sorting in jobs and the gender wage gap and test the relative importance of those hypotheses.

Beyond the gender disparities, rich and large-scale data from online job postings has increasingly been utilized to understand a variety of issues in the labor market. For instance, the correlation between job skill requirements and average regional pay measures and firm performance (Deming & Kahn, 2018), how firm adjust skill requirements facing technological

[9] Female-targeted ads tend to ask for young applicants and male-targeted ads tend to require middle-aged men. Details see Helleseter, Kuhn, and Shen (2020).

change and the Great Recession (Hershbein & Kahn, 2018), whether job applicants respond to the posted wage and job title (Banfi & Villena-Roldan, 2019; Marinescu & Wolthoff, 2020), and how firm's distress affect the applicant pool that it attracts (Brown & Matsa, 2016). We join the literature with detailed job vacancy data in China — we have direct wage measure at job level rather than average wage at the location-occupation level. Besides job ad data, we study gender difference in job search behavior using the share of female applicants at job level rather than inferred gender of applicants from names with the access to the application data. In contrast to job ads focusing on one typical city or limiting to professional jobs, 51job data is a more representative sample of the online labor market in China by almost covering all cities and including more than 900 detailed occupations.

More broadly, a large literature makes efforts to explain the persistent gender wag gap beyond gender differences in education attachments and working experience, such as comparative advantages in job skills and tasks by gender (Bacolod & Blum, 2010; Rendall, 2018; Stinebrickner, Stinebrickner, & Sullivan, 2020; Gelblum, 2020; Cortes, Jaimovich, & Siu, 2021), the gender gap in willingness to compete (Buser, Niederle, & Oosterbeek, 2014; Flory, Leibbrandt, & List, 2015; Reuben, Sapienza, & Zingales, 2015; Zhang, 2019; Samek, 2019; Cai et al., 2019), gender difference in preference for flexibility (Flabbi & Moro, 2012; Goldin, 2014; Mas & Pallais, 2017; Wiswall & Zafar, 2018; He, Neumark, & Weng, 2021), the gender difference in commuting and travelling patterns (White, 1986; Bøler, Javorcik, & Ulltveit-Moe, 2018; Petrongolo & Ronchi, 2020; Le Barbanchon, Rathelot, & Roulet, 2021), gender difference in risk and uncertainty taking (Dohmen & Falk, 2011; Charness & Gneezy, 2012; Ertac & Gurdal, 2012; Iriberri & Rey-Biel, 2021), gender-biased age discrimination in the labor market (Kuhn & Shen, 2013; Neumark, Burn, & Button, 2019; Carlsson & Eriksson, 2019; Kuhn, Shen, & Zhang, 2020; Helleseter, Kuhn, & Shen, 2020) and differential average working time by gender (Hotchkiss & Pitts, 2007; Cha & Weeden, 2014; Cortés & Pan, 2017, 2019). We contribute to the literature by presenting new evidence on the quantitative relevance of hypothetical factors for observed gender differences in occupational choice and wages. To our knowledge, we are one of the first studies to test all those hypotheses simultaneously in the real-world setting. Before the availability of job ad data, job skills and work activities are usually measured at occupation level relying on DOT and O*NET databases. With detailed and rich information of 51job vacancy data, we can characterize job attributes and determine the quantitative importance of theories for gender sorting and gender wage gap even within firms and occupations.

While isolating hiring decisions of employers, the results enrich our understanding of gender difference in job seekers' preference in real world setting. Much of the evidence on gender differences in psychological attributes/noncognitive skills has been gleaned from laboratory experiments, there may be questions about how well the experiment represents what would occur in a real-world setting(Harrison & List, 2004; Pager, 2007; Blau & Kahn, 2017). While filed experiments (Flory, Leibbrandt, & List, 2015; Mas & Pallais, 2017; Wiswall & Zafar, 2018; Samek, 2019; He, Neumark, & Weng, 2021) take advantage of randomization, but due to the constraint of time and resources, they are conducted to limited and usually a specific group of applicants. Using millions of online postings, we are able to explore the quantitative relevance of factors for a larger scale and more diverse sample.

The rest of the paper is structured as follows. In Section 2, we describe the data sets and key variables. Section 3 covers the method to define a set of ad characteristics from thousands of keywords and phrases in the job ads. Section 4 documents gender differences in application behavior and pay differentials across a range of ad characteristics. Section 5 concludes.

2 Data

Our primary data source is the universe of job advertisements posted on 51job.com, the largest comprehensive online job board in China[10]. Specializing in professional, high-education and private sector jobs, 51job posts more than 10 million of job openings and services over 100 million job seekers per year.

The data comprises two parts, job description and applicant distribution of several dimensions, both at ad-level. Specifically, job description, posted by the employer, specify a set of ad characteristics including wage range, education, experience, major, language and age requirements, industry, occupation, benefits, the location, number of openings, the date

[10]Established in 1999, 51.job is the first public-traded enterprise in the human resource service industry in China.

the ad was posted, firm name, firm characteristics (firm type, firm size, and brief introduction of firm) and detailed textual description of the position. Particularly, 51job.com classify occupations at three levels: major group, minor group and detailed occupation. There are 11 major groups, 65 minor groups and total of 952 detailed occupations. Besides, there are 11 major industries and 60 minor industries in 51job.com system. Each employer will select one detailed occupation and one minor industry when posting ads. Later, we will focus our baseline analysis on minor groups of occupation and industry and control for detailed occupations in robustness checks. Procedures for parsing the ad-level actual text and extracting keywords and phrases are discussed in the Appendix. In the next subsection, we show how we follow Deming and Kahn (2018) to define job skills in our data, follow Gelblum (2020) to categorize male-typical and female-typical tasks and how we further distill more than 3,000 keywords and phrases and code additional ad characteristics including the extent of aspiration, pressure, competition, flexibility, business travel, wage uncertainty, age discrimination and working time for each ad.

For a typical job seeker, she needs to first construct an online standardized resume, encompassing demographic information (gender and age), education level, working experience, and current yearly salary range. Then, she can search for jobs based on the desired location, expected wage range, education and experience requirements and firm characteristics. After reading a full-page description of a given ad, she can apply for the job by sending her online resume to the employer. The second part of our data consists of the distribution of applicants' gender, age, education level, working experience and current salary wage for each ad.

We collected job description as well as applicant's information from November 1, 2018 to October 31, 2019, resulting in a sample with over 16 million million ads. Several sample restrictions are performed for better estimation: (1) we focus on ads in the mainland China; (2) we remove observation missing key information (posted wage, occupation, industry, and location at the city-level); (3) we drop ads containing other languages except Chinese and English and ads are fully consisted of English; (4) we do not consider ads with top 99.9% and bottom 0.1% wage and ads with top 99% and bottom 1% length of detailed textual description; (5) finally we focus our attention on ads with at least two applicants. These restrictions help to avoid the extreme value of wage, length of description and female share of applicants. The resulting database covers the remaining 93% sample with over 8.1 million ads.

As the time series in our data is quite short, we aggregate all job postings, taking an unweighted average across different months. Hence, our analysis of gender sorting and gender wage gap relying on a cross-sectional relationship, controlling for time of collection or ad posted date. According to Deming and Kahn (2018), this aggregation helps to clean out time noise in skill requirements and job characteristics driven by factors beyond our analysis, such as seasonality of labor market conditions.

Descriptive statistics of ad characteristics (panel A), firm characteristics (panel B) and application information (panel C) are provided in the Table 1. For our sample encompassing a total of 8,136,758 job ads, 24% of which do not specify education requirements, 17% of which require a high school degree or less, 40% of which require some postsecondary education, and 18% of which require at least a bachelor's degree. Nearly half of ads indicate none or less than 1 year of working experience requirements. Conditional on explicit requirements, job ads on average demand 2.7 years of experience. As for age requirements, about 48% of job ads display age restrictions with a conditional mean 28.8. One advantage of our data is the rich information of posted wage—almost all job ads[11] specify posted wage with the mean yearly wage 98,993.6 RMB. The final job characteristics is the number of openings: about 75% of ads show the number of positions advertised and the conditional mean is 5.6. 51job also exhibits some standardized measure of firm characteristics. A large share (68.9%) of the ads is posted by firms of small and medium size, with less than 500 employees and an overwhelming fraction (95.6%) of the ads is placed by domestic and foreign[12] firms of private sector firms. Finally, firms post an average of 680 ads, although there is a wide range. Considering application information, about 96% of the ads attract more than 1 applicant. Focusing on the sample with at least 2 applicants, on average, total of 52 applicants with 20 female applicants send their resume to the employer.

According to Kuhn and Shen (2013), compared with a broader sample of occupied jobs, job postings on Internet job board are expected to display some differences for several

[11]Only 1,121 of 8,792,670 (0.01%) raw ads do not specify posted wage.

[12]We follow Kuhn and Shen (2013) to define "foreign-owned" category as sum of foreign direct investment [FDI], joint ventures, and foreign representative offices.

reasons. First, job vacancies overrepresents entry-level jobs and underrepresents positions with managerial roles and requiring rich working experience, relative to a sample of employed workers. Second, jobs in emerging, expanding, and high-turnover occupations and industries also account for a larger proportion in a sample of job ads than in a population of occupied jobs. Finally, job postings on an online job portal ask for a significantly higher education and professional skill level than the median position. To assess the representativeness of job ads posted in 51job relative to the overall Chinese labor market, we compare the distribution of job vacancies across a set of job characteristics to a representative sample of employees in urban China, taken from the 2018 China Labour Statistical Yearbook[13].

Suggested by Appendix Table A1, ads on 51job generally target younger workers, require higher education level and are posted by firms in private sector, compared to the overall Chinese labor force. Specifically, while less than one quarter of the workforce in urban China is under 30 years old, nearly 60% of 51job potions pursue applicants with an average age under 30. In terms of education requirements, while about 67% of employees at most finished their high school in 2017, only less than 42% of 51job ads do not explicitly request education of college or above. Over 36% of employees working in SOEs and collectives while less than 5% of ads published by firms in those sectors. Overall, the comparison reflects that while covering a large amount and a wide variety of jobs, 51job disproportionately serves firms focusing on young, well-educated applicants in the private sector.

To shed light on the association between 51job ads and the overall Chinese labor market, we also compare the distribution of general employment and that of ads on 51job across broad occupation and industry categories. While the 51job industry and occupation categories do not match with yearbook categories neatly, several conclusions regarding industry and occupation mix can be drawn from the comparison. First, cs/internet/communication/electronics industries are highly overrepresented on 51job, totally accounting for over 27% of all vacancies posted on 51job compared with about 2% of overall workforce. Second, the most underrepresented industries on 51job are trade/consumption/manufacturing/operation and service, relative to the total working population. Third, considering occupation categories, ads aiming at professional and

[13]Issued by the National Bureau of Statistics, the 2018 China Labour Statistical Yearbook contains information and summary statistics related to the Chinese labor market in 2017.

technical workers are overrepresented on 51job while postings recruiting public servants are clearly underrepresented. To sum up, the distribution of vacancies across occupations and industries on 51job is similar to that of the nationally representative sample (both correlation of more than 0.7[14]). Therefore, job ads on 51job are broadly representative of the Chinese economy as a whole, and they account for a substantial slide of the labor market.

3 Method

We first follow Deming and Kahn (2018) to define 10 categories of job skills in our data. As their classification and coding are quietly useful across a wide range of jobs, we borrow the same keywords and phrases to label skills of each category. Panel A of Table 2 lists the 10 skills as well as the corresponding words and phrases. Following their definition, for each skill, we create a dummy variable with value 1 if a particular ad contains at least one of the keywords or phrases listed, while it could cover many.

Beyond the job skills, we further examine several conceptual categories of tasks from the gender-related angle. Following Gelblum (2020), we start by categorizing four female-typical tasks and three male-typical tasks. Specifically, while Gelblum (2020) define the first female-typical task as "helping and caring for others" and estimate worker's willingness to pay using a hypothetical choice experiment, it is harder to define "help" and "care for" as a whole in job ads data as only brief keywords and phrases are identified to signal a job task. Thus, we characterize those two female-typical tasks separately and extract corresponding keywords and phrases from Gelblum (2020)'s definition, respectively. The third job task "document" is described by verbs "document" and "record" listed in the task "documenting and recording information" of Gelblum (2020). We isolate "cooperate" from "working and communicating with others and displaying a cooperative attitude" in Gelblum (2020) as keywords such as communication and collaboration have been considered when Deming and Kahn (2018) define social skills. Considering male-typical tasks, we borrow

[14]Marinescu (2017), Marinescu and Rathelot (2018) and Marinescu and Wolthoff (2020) conclude that the vacancies and job applicants on CareerBuilder.com are representative of the US labor market by showing that the distribution of vacancies across occupations is similar to that of CPS (correlation of over 0.7).

keywords “operate”, “repair” and “maintain” to categorize the “operate” task related to equipment, machine and device. We also split “making decisions and solving problems” in Gelblum (2020) into two tasks and can their relative power in explaining the gender sorting and the gender wage gap. We further include two female-typical tasks, “follow the leader” and “do chores”, to approximate tasks with low promotability introduced by Babcock et al. (2017).[15] The final male-typical task is “cover high-technology” as the share of male workers is relative high in fields such as artificial intelligence, energy and electronic.

One contribution of this paper is applying the method of Deming and Kahn (2018) in coding broader job characteristics from the open text of ads. The criteria for selecting these job characteristics are that they are potentially significant in explaining gender segregation and gender pay differentials and are generally applicable to a wide range of jobs. Specifically, we start by manually picking out relevant words from the top 3000 words and phrases with high frequency. Then, keywords and words describing job benefits are considered as they are recorded by the employer and could represent key information of the ad. Using standard Chinese dictionary, we further include synonyms to cover various writing styles of different employers. Finally, we create 9 categories of job characteristics, involving the extent of aspiration, pressure, competition, flexibility, business travel, wage uncertainty, age discrimination as well as working time of each job position, shown in the panel C and panel D of Table 2.

The first job attributes listed is “aspiration”, described by keywords chosen to match “aspiration to be promoted and well-paid” in the context of job ads. To explain the gender differences in earnings and promotions, several studies explore gender differences in career aspiration as a potential mechanism.[16] Extending to the entire labor market in China, we explore whether women systematically apply for jobs with lower extent of career aspiration expected by the employers than men. For instance, “unlimited” suggests unlimited career path and remuneration and “challenging” refer to the challenging tasks. Alternatively,

[15] They find that relative to men, women are more likely to volunteer, be asked to volunteer or accept requests to volunteer for a task with slight effect on their evaluation and career advancement.

[16] Analyzing the performance of young lawyers, Azmat and Ferrer (2017) find that male lawyers’ better performance, billing more hours and generating more new client revenue, is largely attributed to their high career aspirations. Focusing on the same sample, Azmat, Cuñat, and Henry (2021) record that more than 50% of the gender promotion gap is attributed to the gender differences in aspirations to be promoted.

motivated, goal-based, and ambitious employees are desired.

As for the intensity of "competition" of positions, we choose keywords and phrases such as "performance-based pay", "assessment", and "tournament". Gender differences in response to competitive pressure have been found in the laboratory experiments. The key findings are that women prefer to avoiding high-stakes competition and women underperform relative to men under competition (Details of these studies see excellent surveys by Marianne (2011).). Moreover, recent literature shows that gender differences in competitiveness may further lead to behavior and choice differences by gender. [17] We select these words deliberately to measure competitive workplace where wage is tightly linked to self-performance, employees face regular (weekly, monthly, or quarterly) assessment, or tournaments are held among teams.

Job vacancies that require ability to deal with "pressure" are categorized by keywords and phrases such as "stress tolerance", "psychological adjustment", and "face difficulty". Specifically, jobs under high pressure explicitly ask for capacity to face stress and difficulty or good mindset and self-adjustment ability. Here we follow the literature on gender and competition, which discusses gender difference in willingness to compete and gender performance gap under high-stakes competition or pressure.

We define the fourth job attribute, "flexibility" as either "work from home" or "flexible working time", following closely the definition used in Mas and Pallais (2017). A large literature has studied how men and women value alternative work arrangements differentially and how these differences help to explain the residual gender wage gap (See Goldin and Katz (2011), Goldin and Katz (2016), Flabbi and Moro (2012), Goldin (2014), Wiswall and Zafar (2018), Mas and Pallais (2017) and Cortés and Pan (2019).).[18] While the former is

[17] For example, Buser, Niederle, and Oosterbeek (2014) documents the high predictive power of a standard laboratory measure of competitiveness on the later choice of academic tracks and finds that gender gap in competitiveness accounts for about 20% of the gender gap in track choice. Focusing on the job search process, two papers implement field experiments on job-entry decisions and find that the competitive compensation package disproportionately deter women's application decision (Flory, Leibbrandt, & List, 2015; Samek, 2019).

[18] For instance, recent work by Wiswall and Zafar (2018) and Mas and Pallais (2017) seek to quantify the gender differences in willingness to pay for flexibility. Wiswall and Zafar (2018) find that women have higher willingness to pay for jobs with the option of working part-time – women are willing to pay 7.3 percent of

described by phrases “work from home” and “flexible workplace”, “flexible working time” is an umbrella term for phrases such as “floating working time” and “no attendance required”.

The fifth job attribute we explore is “travel”, specified by keyword “travel” and phrases “on business” and “business trip”. In detail, it illustrate the situation where workers are expected to travel or go on a business trip frequently and at short notice. Due to heavier caring responsibilities in the household, women may hold stronger distaste for commuting time or business travel. Indeed, the literature has documented a consistently shorter commuting time of female workers, compared with that of males. [19] Gender differences in willingness to commute and travel have also been put forward to account for the persistence of the gender wage gap (White, 1986; Bøler, Javorcik, & Ulltveit-Moe, 2018; Petrongolo & Ronchi, 2020; Le Barbanchon, Rathelot, & Roulet, 2021).

Utilizing the wage range posted by firms for each ad, we defined “wage uncertainty” as the ratio of the difference between wage maximum and wage minimum to wage maximum, which takes value from 0 to 1. In other words, the difference between wage maximum and wage minimum can be regarded as floating part of the posted wage. Hence, “wage uncertainty” refers to the proportion of fluctuating wage in the expected wage. The construction of this job attribute is motivated by the larger literature recording the gender differences in risk and uncertainty taking. Both the evidences in the lab[20] and the field experiment[21] suggest that women are less likely to guess, take risk or make risky decisions. Relying on the application composition data, we are able to test whether female and male applicants respond differently to wage uncertainty in the real world.

In addition to job attributes, a large fraction of ads (47.8% of job ads in our sample)

annual salary for the part-time option, compared with 1 percent of annual salary that men are willing to give up. While Mas and Pallais (2017) document that women place a higher value on work from home, they also show that the differences in observed work arrangements by gender are not large enough to account for a significant part of gender pay gap.

[19] Women in OECD countries on average spend 22 minutes for daily commuting while men spend 33 minutes.

[20] Dohmen and Falk (2011) show that women tend to avoid the variable payment scheme than men when the alternative is a fixed payment in a controlled laboratory experiment.

[21] For instance, Charness and Gneezy (2012) find that women invest less and are more financially risk averse than men. Ertac and Gurdal (2012) document a much lower proportion of women willing to be a group leader and make risky decisions, relative to men.

explicitly state age requirements and demonstrate some extent of age discrimination. According to studies investigating age discrimination in the labor market, women suffer more from age bias than men (Kuhn & Shen, 2013; Neumark, Burn, & Button, 2019; Carlsson & Eriksson, 2019; Helleseter, Kuhn, & Shen, 2020). While it is well-documented that older women receive significantly fewer callbacks relative to men in the resume correspondence study (Neumark, Burn, & Button, 2019; Carlsson & Eriksson, 2019), less is known about whether female and male applicants react differently to explicit age requirements in job ads. We examine the existence of gender difference in the response to age discrimination by defining whether the ad denotes any age requirement, the upper and lower bound of expected age.

Several categories regarding working time are characterized based on working time per day and day offs per month. A growing number of papers have investigated how working time requirements affect women's decisions on entry in labor market and job application choices. As women, especially women with children, typically take greater family responsibilities, they are more likely to place a higher valuation on regular or even short working hours (Cha, 2013; Cortés & Pan, 2017). More importantly, how occupations compensate for long working hours may lead to the gender wage gap. Goldin (2014) records that gender wage gap is larger in occupations with a higher degree of convexity in the association between pay and working hours as women who prefer to short working hours will sort into those occupations. [22] In particular, we classify ads into four groups in terms of day offs per month and working hours per day separately. Specifically, "day off" groups include "No specify day off", "less than 6 day offs per month", "6-8 day offs per month", and "at least 8 day offs per month". "Working hour" groups include "No specify hour", "less than 8 hours per day", "8-9 hours per day" and "more than 9 hours per day".

Figure 1 plots the share of ads listing each ad characteristics. As can be seen, skill

[22] Recent literature documents fruitful evidence on the role of working time in shaping the gender segregation and gender pay gap. For example,Cha and Weeden (2014) find that the stagnant convergence of the gender wage gap since 1979 can be partially explained by the increasing returns to overwork and gender differences in the propensity to work overtime. Using Danish data, Kleven, Landais, and Søgaard (2019) show that earnings penalty after childbirth is partially due to reducing working hours. Finally, Cortés and Pan (2019) document that exogenous shocks in the possibility of supplying long hours, via the flows of low-skilled immigration, reduce the gender earnings gap for high-skilled women.

demand is fairly high for cognitive and social skills – 57% of job ads specify a cognitive skill requirement and almost 79% list a social skill requirement. Considering the full sample, the share of ads expecting other job skills ranges from one-seventh (writing) to more than a half (customer service). The high frequency of appearance for social skills and customer service skills is not surprising as more than one quarter of ads in 51job data are under the sales and customer service occupation category. Regarding female-typical tasks, about 35% of ads describe the job content involving help or provide personal assistance to a co-worker or a customer. Nearly 16% of jobs request workers to care for and support people in workplace. 15% of jobs containing tasks like documenting, recording or maintaining information in written or electronic form. Owing to the highly demanded social skills, more than 45% of jobs comprise of cooperation with others. A substantial proportion of ads asking worker to follow leader's instruction (21%) or do chores like printing and copying files (28%). In general, the shares of ads specifying male-typical are lower than those listing female-typical tasks. The pattern is not overwhelming as more than half of jobs on 51job website are entry-level jobs, which are more likely to follow instruction or do chores in daily work. About 18% of jobs include operating and repairing equipment and mechanized devices. 7% of ads ask for solving problems and 23% of jobs related to making decisions. Finally, 6% of jobs cover high-technology and demand specific knowledge.

As for job attributes, 20% to 30% of job ads indicate some extent of working pressure, competitive environment, and aspiration requirements. Approximately 24% of job positions adopt flexible work arrangement. 7% of jobs require greater commitment to work and involve business travel frequently or at short notice. More than 47% of postings explicitly state preferred age range for applicants. Regarding the wage uncertainty, the average proportion of floating wage is about one third. Nearly one third of job ads plainly state day offs per week or day offs per month, with 26% of job positions can guarantee a whole weekend. Finally, less than 10% of ads in total indicate working hours per day and around 6% of jobs implement regular 8 to 9 hours work schedule.

Table 3 further details summary statistics of full sample and sample means across different wage quarters for these ad characteristic measures. The share of ads requiring cognitive skills and social skills increases in the line with wage increase, suggesting that well-paid jobs are more likely to specify cognitive and social skill requirements. Some skills such as project management and people management are demanded more as wage rises while the share of other skills such as character or general computer skills falls when wage increases. Considering gender-typical tasks, while jobs with competitive remuneration tend to require male-typical tasks such as solving problems and making decisions, the shares of ads listing female-typical tasks such as documenting and recording information and taking leader's instruction fall as wage increases. Therefore, it implies potential power of those gender-related tasks in accounting for the gender wage gap at early stage. The pattern of the sample means of job attributes across wage levels is quite similar. The share of ads indicating "aspiration", "pressure" and "competition" increases as wage changes from Q1 to Q3 and decreases a little when reaching Q4. Moreover, the rise between Q1 and Q2 is substantial, suggesting implies that those job attributes may help with wage improvement and promotion, especially at early stage of career. The proportion of positions stating alternative work arrangement, business travel and high wage uncertainty grows when switching to high-paying jobs, meaning that those job attributes are exceedingly rewarded in the labor market.

4 Results

4.1 Ad characteristics and share of female applicants

To exam how ad characteristics are associated with gender difference in application behavior, we estimate regressions of the following specification:

$$\begin{aligned} FemaleShare_{jiocf} = \alpha^{FS} + \overline{Characteristics}_{jiocf}\beta^{FS'} \\ + Experience_{jiocf} + Education_{jiocf} + \gamma_i + \zeta_f + \eta_{o\times c} + \epsilon_{jiocf}. \quad (1) \end{aligned}$$

where $FemaleShare_{jiocf}$ is the share of female applicants of job ad j advertising for a job of industry i, occupation o, in city c and posted by firm f. $\overline{Characteristics}_{jiocf}$ is a vector of ad characteristics including job skills, job tasks, job attributes and working time measures. Particularly, for job skills and tasks, and job attributes except wage uncertainty and age discrimination, variables are defined as dummies, meaning we compare ads specifying typical ad characteristics and ads not specifying. For "day off" groups and "working hour" groups, we omit the most regular work schedule, namely "at least 8 day offs per month" and "8-9 hours per day", and treat them as the reference groups. The coefficients $\beta^{FS'}$ on ad characteristics are of our main interest, indicating the variation in the share of female applicants across ads exhibiting different dimensions of ad characteristics. We always add education and experience requirements as controls[23]. In our preferred specification, we further include γ_i, ζ_f and $\eta_{o\times c}$, representing fixed effects of industry, firm, and occupation and city, respectively. The inclusion of fixed effects suggests that the relationship between share of female applicants and ad characteristics is studied within occupation and firm. Standard errors are cluster by occupation and city.

Figure 2 shows estimation results of $\beta^{FS'}$, which exam how gender sorting in application is related with job ad characteristics. The red bar indicates the raw estimates, only controlling for education and experience requirements while the blue bar represents the estimates in equation (1), furthering controlling for industry, firm, and occupation and city fixed effects. Both bars plot at 5% significance level. Compared with the raw estimates, estimation within industry, firm, and occupation and city is more precise, indicated by the much smaller standard error. In terms of economic magnitude, as industry, firm, and occupation and city fixed effects absorb part of variation in the share of female applicants, blue bars move towards to zero reference line, denoting a generally smaller magnitude. Table 4 demonstrates the detailed estimation results of $\beta^{FS'}$, with raw estimates in column 1 and estimates with industry, firm, and occupation and city fixed effects in column 2.

As shown in Figure 2a, female applicants respond deferentially to ads demanding different job skills. Particularly, women tend to apply for jobs require character, writing, financial and computer skills, across and within firms and occupations. Column 1 of Table 4 demonstrate that the coefficients of 0.022 on character skills, of 0.047 on writing skills, of 0.063 on financial skills and of 0.082 on computer skills would on average translate into 2.2%, 4.7%, 6.3% and 8.2% increase in the share of female applicants, respectively. Recall that character is described by keywords and phrases such as "detail oriented" and "meeting deadlines", following the literature discussing the labor market returns to personality traits such as

[23]We follow Deming and Kahn (2018) to control for years of experience required by the employer. Specifically, experience controls include an indicator for whether the ad has any experience requirements and the number of years required if there is a requirement (otherwise 0). For education requirements, we add fixed effects as there are several different types of secondary schools with the same years of schooling in China.

conscientiousness and agreeableness Deming and Kahn (2018). Simultaneously, rather than specific software or programming skills, computer skills stand for general computer skills such as using Microsoft Excel and PowerPoint. Jobs explicitly ask for general computer skills are usually less technical, less professional, and more administrative. As for writing and financial skills, which are highly specific to tasks dealing with documents or accounting, also attracts female applicants. The results also coincide with the phenomenon that women sort into occupations like writer and accountant.

In contrast, listing cognitive or project management skills in ads consistently discourage women to apply for. In terms of economic magnitude, coefficients in column 1 of Table 4 imply that once an ad specify cognitive and project management skill requirements, on average, there would be corresponding 1.3% and 2.0% decrease in the share of female applicants, respectively. While cognitive skills are explicitly measured by keywords such as "math" and "statistics", project management skills are also highly demanded in STEM fields. Hence, our results are in line with the large literature showing and explaining the underconfidence and underrepresentation of women in STEM jobs.[24]

Although the literature shows that women outperform in tasks requiring social and interpersonal skills and prefer positions interacting and communicating with people[25], we find that the positive correlations between social skills and the share of female applicants fade away when eliminating variation across occupations and firms. Furthermore, the correlation between people management skills and the proportion of females becomes negative once add industry, firm, and occupation and city fixed effects. Column 2 of Table 4 indicates that within the comparison of occupation and firm, women prefer ads not listing people management skills 1.6% more than those asking for people management skills. However, for customer service skills, the positive estimates considering industry, firm, and occupation and city fixed effects suggest that customer service skill requirements attract more female

[24]See Carrell, Page, and West (2010), Zafar (2013), Stinebrickner and Stinebrickner (2014) and Mouganie and Wang (2020).

[25]Evidence from the psychology and neuroscience literature indicates that women have a comparative advantage in tasks requiring social and interpersonal skills (see, for instance, Baron-Cohen, Knickmeyer, and Belmonte (2005), Woolley et al. (2010) and Kirkland et al. (2013)). Several studies also show that women tend to prefer jobs that require empathy and interacting with people (see, for example, Fortin (2008), Grove, Hussey, and Jetter (2011), Folbre (2012) and Lordan and Pischke (2016).)

applicants. Those patterns suggest that women indeed tend to sort into occupations or firms emphasize social and interpersonal skills but within occupation and firm, they are inclined to apply for positions require service skills (customer service) rather than management skills (people management). Finally, we do not find significant and consistent connection between the share of female applicants and specific software skills.

Regarding gender-typical tasks, Figure 2a demonstrates a coherent pattern with the definition of male-typical and female-typical tasks—in general, describing a female-typical task is correlated with the increase of female applicants and denoting a male-typical task in job content discourage women to apply. Our results suggest that women are more likely to apply for positions involving helping and caring for others, documenting and recording information, following instructions or receiving tasks from leaders or supervisors, and doing chores like printing and copying documents. In terms of economic magnitudes, the estimate in column 1 of Table 4 indicates that a high level of helping and caring for customers or coworkers is accompanied with a 3% and 6% increase in the share of female applicants, respectively. The estimate for documenting and recording information is largest in absolute value—jobs spending time documenting and recording information attract more than 9% of female applicants. Simultaneously, tasks with low promotability risk the percentage of female applicants by 2% to 3% (the estimate for following leader's instruction is 0.030 and that for doing chores is 0.026). However, while Gelblum (2020) defines "working and communicating with others and displaying a cooperative attitude" as a female-typical tasks, we show that women instead are less likely to choose positions requiring cooperation with others on the job. In fact, Gelblum (2020) also does not find no significant gender differences in willingness to pay regarding the tasks "working and communicating with others and displaying a cooperative attitude" in the hypothetical choice experiment. As we only utilize keyword "cooperate" to define this task and distinguish it from social and customer service skills, one potential explanation for our finding is that there might exist some unobservable characteristics for ads specifying "cooperate" tasks but not social or customer services skills that hinder women's application.

The estimate results are more coincident concerning male-typical tasks. Women do not favor job content containing operating and repairing machines, solving problems, making decisions and tasks related to high-tech at the job search stage. Specifically, according to the estimates in column 1 of Table 4, indicating operating, repairing or maintaining equipment in job description significantly keeps female applicants away—15.9% decrease in the share of female applicants. Even comparing within firms and occupations, column 2 of Table 4 shows that this male-typical task is related to 5.4% fall in the proportion of women. Compared with other positions, there would be 3% and 3.1% fewer women sending their resume to those involving solving problems and making decisions regularly, respectively. Finally, jobs comprising of tasks covering high-tech generally attract 8.7% fewer women across firms and occupations and 2.5% fewer female applicants within firms and occupations.

According to Figure 2b, the coefficients of “aspiration”, “pressure” and “competition” and the 95% confidence intervals of these estimates are negative and persistent within occupation and firm comparison. The share of female applicants consistently falls when job ads list “aspiration”, “pressure” or “competition”. As shown in column 1 of Table 4, the coefficients of -0.038 on “aspiration”, -0.015 on “pressure” and -0.025 on “competition” are all statistically significant at the less than 1% level. The economic magnitude implies that once an ad desires aspirant employees, indicates working pressure or specifies a competitive compensation scheme, on average, there will be 3.5%, 1.5%, and 3.0% decrease in the share of female applicants, respectively. When adding industry, firm, and occupation and city fixed effects, we still see negative and significant association between those job attributes and share of female applicants. The persistent pattern suggests that women disproportionately shy away from jobs asking for aspiration, acknowledging some extent of working pressure or indicating competitive working environment regardless of industries, firms, and occupations.

Considering alternative work arrangements, estimates in Figure 2b show a negative and statistically significant relationship between flexibility and the share of female applicants. In accordance with the findings of Mas and Pallais (2020) [26], we find women are less likely to choose jobs with time or location flexibility in real world setting, even accounting for

[26]According to Mas and Pallais (2020), whether alternative work arrangements can potentially affect the gender wage gap depends on the definition of flexibility in setting. If jobs with flexible working time and location are not typically linked to more family-friendly outcomes, they would probably fail to attract women's sorting into these jobs. Indeed, Mas and Pallais (2020) examine the association between difference measure of work arrangements and gender and find that women are less likely to work in position with a more flexible schedule, working from home often, or with a non-regular employment relationship.

variation across firms and occupations. The reason that we do not find women's higher value on flexibility as choice experiments in the literature is probably that flexible working hours and work from home do not typically lead to more family-friendly outcomes but potentially imply some less family-friendly attributes like overwork and irregular work schedules.

Similarly, we find that female applicants consistently avoid positions requiring business travel at a regular basis or at short notice, both across and within firms and occupations. Compared with other positions, Table 4 shows that stating a travel requirement on average will lead to 6.8% decrease in the share of female applicants. After controlling for industry, firm, and occupation and city fixed effects, column 2 of Table 4 indicates that women still systematically stay away from jobs with travel—4.8% fall in female applicant composition is associated with this job attribute. Due to heavier family responsibilities, women are expected to spend more time in household and tend to dedicate less time to commuting time and business travel.[27] Another possible explanation for women's circumvention of business travel is that they find it harder to adapt to job's inflexibility and arrange travel at particular time.

Almost half of ads in our sample explicitly state some extent of age requirements, mainly listing a preferred age range for job applicants. Figure 2b reveals a persistently positive correlation between age constrain and the share of female applicants. In other word, women are more likely to obey firm's age requirements—according to estimates in column 2 of Table 4, listing age requirements plainly will attract 14.2% more female applicants even when eliminating variation across occupations and firms. Moreover, we find that women prefer positions aiming at young workers. One year old increase in the required age minimum and maximum is related to 0.2% fall in the proportion of female applicants, respectively. One possible reason for women's sorting into jobs demanding young employees is the equilibrium effect. Specifically, the literature documents more robust evidence of age discrimination against women (Kuhn & Shen, 2013; Neumark, Burn, & Button, 2019; Carlsson & Eriksson, 2019) and Helleseter, Kuhn, and Shen (2020) define the phenomenon that female-targeted ads tend to set young age range and male-targeted ads tend to ask for middle-aged applicants as "age twist". As a result, to improve the callback rate and react to the gender-biased age

[27]See White (1986), Bøler, Javorcik, and Ulltveit-Moe (2018), Petrongolo and Ronchi (2020) and Le Barbanchon, Rathelot, and Roulet (2021).

discrimination, women are more likely to select ads listing explicit age requirements and those demanding young workers.

Figure 2b also documents evidence of the gender difference in preference for wage uncertainty. As shown by column 1 of Table 4, 10% growth in the proportion of floating wage is associated with approximately 0.6% decrease in the share of female applicants. After after considering differences across firms and occupations, there would still be 0.2% fewer female applicants with the existence of 10% increase of wage uncertainty.

Finally, we explore the gender difference in response to working schedule specified in job description. As ads with "at least 8 day offs per month" are omitted, we compare them with other "day off" groups. As seen in Figure 2b, except the raw estimate of "6-8 day offs per month" with large standard error, other estimates of "No specify day off", "less than 6 day offs per month" and "6-8 day offs per month" are negative and statistically significant. In terms of the economic magnitude, column 2 of Table 4 records regression results accounting for industry, firm, and occupation and city fixed effects. Estimates suggest that compared with ads ensuring weekends, ads no specifying day off information, ads with less than 6 day offs and ads with 6-8 day offs per month attract on average 1.9%, 1.6% and 0.6% less share of female applicants, respectively. Third, we examine whether working hour per day is correlated application behavior by gender. Focusing on the precise estimates within occupation and firm, we find that compared with regular "8-9 hours per day", women are less likely to apply for ads not specifying hour and ads with "more than 9 hours per day" and are more likely to sort into jobs with "less than 8 hours per day", which coincides with the findings in the literature.

4.2 Ad characteristics and wage

We also investigate whether wage differentials are associated with ad characteristics specified by the employer by estimating the following regression specification:

$$\begin{aligned} lnWage_{jiocf} = \alpha^W &+ \overline{Characteristics}_{jiocf}\beta^{W'} \\ &+ Experience_{jiocf} + Education_{jiocf} + \gamma_i + \zeta_f + \eta_{o\times c} + \mu_{jiocf}. \end{aligned} \quad (2)$$

where $lnWage_{jiocf}$ is the log of the posted wage in a job ad, independent variables are the same as equation (1). The coefficients on the vector of ad characteristics $\beta^{W'}$ measures how the posted log wage varies as the employer specifies different job skill requirements, task content, workplace attributes and working time. Estimates of $\beta^{W'}$, return to ad characteristics, are displayed in Figure 3. Similar to Figure 2, the red bar represents the raw estimates and the blue bar plots estimates with industry, firm, and occupation and city fixed effects, both at 5% significance level. Details of coefficient magnitudes are contained in the column 3 and 4 of Table 4.

Suggested by Figure 3a, the returns to most skills are positive in the labor market.[28] In particular, the positive association between cognitive and social skills and posted wage in our results are consistent with that in Deming and Kahn (2018).[29] Column 3 of Table 4 shows that when an ad explicitly expresses cognitive or social skill requirements, on average, there would be 5.0% or 6.8% increase in the posted wage, respectively. Even in the highly controlled specification (2), the pattern of results is similar to the raw estimates. Besides cognitive and social skills, the correlations between the majority of skills including customer service, project management, people management, financial, specific software and ad wages are all positive and significant at 1% significance level, holding with and without industry, firm, and occupation and city fixed effects. Regarding writing skills, the negative return pattern appears when adjusting for variation across industry, firm, and occupation and city. Finally, we find negative relationships between character and computer skills and log wage, respectively. As mentioned in 5.2, specifying character and general computer skills might be a signal of lower-paying jobs where emphasize obedience and tasks with low promotability, even though those skills themselves are valuable in the labor market.

Concerning task content and work activity, on the one hand, we find that all the female-typical tasks except cooperating with co-workers are associated with less competitive pay-

[28] Besides return to cognitive skills, a fruitful body of studies analyze the labor market return to noncognitive skills, including social skills (Kuhn & Weinberger, 2005; Heckman, Stixrud, & Urzua, 2006; Lindqvist & Vestman, 2011; Borghans, Ter Weel, & Weinberg, 2014; Deming, 2017; Deming & Kahn, 2018).

[29] Also using online job ads data, Deming and Kahn (2018) categorize a wide range of keywords from job posting textual data into 10 general skills and study variation in skills demands for professionals across firms. Focusing on social and cognitive skills, they find positive associations between both social and cognitive skills and average wage at occupation level.

ment in the labor market. Suggested by column 3 of Table 4, work activities such as helping and caring for others will signal a 2.7% and 3.3% decrease in the average wage, respectively. Furthermore, job applicants need to pay more if they prefer job task including documenting and recording information, following leader's direction and doing chores. In detail, jobs involving those tasks are compensated from 5% less (doing chores) to 11% less (documenting and recording information). Jobs requiring regular cooperation with others instead are rewarded in the labor market— they acquire 4.6% higher salary. On the other hand, Figure 3b shows positive and coherent relationships between male-typical tasks and average wage, both across and within firms and occupations. Particularly, work content encompassing operating and repairing equipment, problem solving, decision making and tasks related to high-tech predict a 4.2%, 2.6%, 7.6% and 8.4% higher payments, respectively.

As for job attributes except age discrimination, Figure 3b indicates a positive correlation between each job attributes and posted wage, regardless of raw estimates or estimates with detailed controls. According to column 3 of Table 4, in terms of economic magnitude, the average increase of posted wages is 8% for "aspiration", 3.9% for "pressure", 10.7% for "competition", 8.1% for "flexibility" and 0.9% for "travel" when an ad lists those job amenities, respectively. Moreover, 10% increase in the wage uncertainty, or the fluctuating wage part, is associated with 5% higher average wage. Ads listing "aspiration", "pressure" and "competition" usually demand high work intensity. Jobs specifying "flexibility" are usually accompanied with long hours and irregular schedule. Moreover, work containing frequent business travel requires greater employee's commitment and adoption to firm's need. Hence, firms compensate employees for higher salaries.

Regarding age discrimination,we find that low-paying jobs tend to specify explicit age requirements. Shown in column 4 of Table 4, relative to ads without preferred age range, jobs with age requirements on average pay one third lower wage. Furthermore, jobs demanding older workers post a higher salary. One year old rise in the required age minimum and maximum is related to 0.4% and 0.6% increase in the average posted wage. Employers' reward to older ages is not surprising as they hire for less entry-level, more professional, more experienced and usually managerial positions.

Compared with ads with "at least 8 day offs per month", ads no specifying day off information have a higher wage. As for "less than 6 day offs per month" and "6-8 day offs per month", although the raw estimates are noisy, the estimates after adding industry, firm, and occupation and city fixed effects are positive and statistically significant. The results demonstrate that compensate employees' sacrifice of weekends for higher wages. Take "No specify day off" as an example, compared with ads with "at least 8 day offs per month", ads no specifying day off information tend to offer 5.6 % higher wages without controls and 3.5% higher wages with industry, firm, and occupation and city fixed effects. Finally, we investigate whether firms pay more for workers' longer working hours. However, probably due to the small sample of ads specifying working hours, estimates of set of working hours are noisy and ambiguous.

4.3 Ad characteristics and gender wage gap

We first display the estimates on the share of female applicants in equation (1) and the estimates on log wage in equation (2) together in Figure 4, with detailed controls including education and experience requirements, industry, firm, and occupation and city fixed effects. Clearly, for most ad characteristics, the directions of two estimates are opposite. Suggested by Figure 4a, ads requiring some job skills, such as character and general computer skills, attract women to apply for but indicate low-paying signals. Positions demanding high-return skills, such as cognitive, project management and people management skills instead discourage female applicants. In terms of female-typical tasks, we find that women prefer job content such as helping people, caring for others, document information, follow leader's instruction and doing chores but need to compensate for those desired tasks by accepting lower wages. However, female applicants are less likely to select ads demanding a cooperative attitude even though it signals high-paying jobs. As for male-typical tasks, results are more consistent. Women tend to shy away from jobs associated with operating and repairing equipment, solving problems, make decisions and tasks covering high-tech , while those tasks exhibiting high returns in the labor market.

According to Figure 4b, with heavier family responsibilities, women tend to avoid job attributes associated with high work intensity such as "aspiration" and "competition", job characteristics related to irregular working schedule and frequent business travel such as "flexibility" and "travel", even though those job attributes are highly rewarded by employers. Due to gender difference in willingness to take risk, women are also less likely to choose positions with high wage uncertainty although on average they display a more competitive remuneration. Compared with male applicants, females tend to obey firm's age discrimination, especially for jobs demanding young workers. Finally, women are inclined to sort into jobs requiring shorter working time at the cost of lower wages. Motivated by the opposite directions, we believe that those ad characteristics may translate into gender wage gap, even at the job application stage.

Motivated by the is the stylized fact in the literature that occupations tend to be more female-dominated also tend to pay lower wages[30], we investigate whether differential job choice by gender in terms of ad characteristics could have implications in explaining the gender wage gap. We start by estimating the following specification:

$$lnWage_{jiocf} = \alpha^{Raw} + \varphi^{Raw} FemaleShare_{jiocf} + \tau_{jiocf}. \tag{3}$$

where we use $lnWage_{jiocf}$, the log of the posted wage, to approximate wage in employment and use $FemaleShare_{jiocf}$, the share of female applicants, to proxy the female share of employment. The coefficient of the share of female applicants φ^{Raw} estimates the raw correlation between the average wage and the proportion of female workers. Then, we conduct a sequential decomposition analysis by adding industry, firm, and occupation and city controls, education and experience requirements and the set of nontraditional ad characteristics step by step, resulting in the final equation:

$$\begin{aligned} lnWage_{jiocf} = \alpha^{Full} + \varphi^{Full} FemaleShare_{jiocf} + Experience_{jiocf} + Education_{jiocf} \\ + Characteristics_{jiocf}\beta^{'} + \gamma_i + \zeta_f + \eta_{o\times c} + \sigma_{jiocf}. \end{aligned} \tag{4}$$

γ_i, ζ_f and $\eta_{o\times c}$, represents fixed effects of industry, firm, and occupation and city, suggesting that the analysis is within firm and occupation. We observe how the coefficients φ on the share of female applicants changes when eliminating variation across industries, firms and occupations, variation regarding education and experience requirements and consider-

[30] For example, see Groshen (1991), Macpherson and Hirsch (1995), Altonji and Blank (1999), Blau, Ferber, and Winkler (2013), Blau and Kahn (2017) and Cortés and Pan (2018).

ing the difference in ad characteristics gradually. The magnitude of change in φ implies the extra power of those three aspects in explaining gender wage gap.

To further compare the relative importance of each ad characteristics including the traditional and nontraditional ones within firm and occupation, we perform a full decomposition following Gelbach (2016). Specifically, we compare this specification with equation (4):

$$lnWage_{jiocf} = \alpha^{Base} + \varphi^{Base} FemaleShare_{jiocf} + \gamma_i + \zeta_f + \eta_{o\times c} + \nu_{jiocf}. \tag{5}$$

We access the magnitude variation between φ^{Base} and φ^{Full}, and explore the percent of the change can be attributed to a certain ad characteristic, conditional on other ad characteristics.

Table 5 documents the results decomposing the gender wage gap into ad characteristics, with the results of sequential decomposition in panel A and those of full decomposition in panel B. The first column of panel A denote the estimate result of the raw specification, without fixed effects of industry, firm, occupation and city or any ad characteristics. The coefficient -0.60 suggests that a 10% increase in the share of female applicants for a particular position will on average signal a 6% lower wage. According to column 2, variation across firms and occupations lead to roughly 17.7% change in coefficients on share of female applicants. Traditional explanatory variables in the labor market, education and experience requirements, explain another 27.2%. Finally, adding the the full set of nontraditional ad characteristics can lead to an extra 21.1% fall in the gender wage gap at the application stage.

Regarding the full decomposition, the coefficient on the share of female applicants changes from -0.50 to -0.28 from the base estimation (5) to the full estimation (4), roughly a 43% change. In terms of the total change -0.21173 within firm and occupation, education and experience requirements explain about half, with working experience contribute to the most part. Ten general job skills account for nearly 12% change and ten gender-specific job tasks explain approximately 20%. Variation in "aspiration", "pressure" and "competition" together lead to roughly the same 3% as wage uncertainty. Variation in flexibility, travel and working time plays essentially zero role in explaining the gender wage gap, probably due to a large amount of ads not specifying that information. Lastly, age discrimination explain more than 7% of the gap explained by the full set of covariates, conditional on other ad characteristics simultaneously. We also report the proportion each job skill, male-typical and female-typical task, and job attribute account for in Table A2. Particularly, general computer skills represent a substantial part, contributing to 6.5% of the total change alone. The explaining power of female-typical tasks such as documenting and recording information and male-typical tasks like decision making are also distinct—both lead to about 5% of the total gender wage gap.

5 Conclusion

In this paper, we provide empirical evidence on gender differences in job choices and gender wage gaps based on ad characteristics. We do this by exploiting data from job vacancies posted in a comprehensive online job board in China. Using keywords and phrases from the actual text of job ads, we construct measures of ad characteristics including job skills such as cognitive skills and social skills, male-typical and female-typical tasks, job attributes such as workplace competition, alternative work arrangement and wage uncertainty, and working time schedule. We document the pattern that the correlation between most ad characteristics and the share of female applicants move oppositely with the correlation between ad characteristics and log wages, even after controlling for education and experience requirements and detailed industry, firm, and occupation and city fixed effects. While some job characteristics predict high wages, they discourage women to apply for. Specifying some ad characteristics attracts more female applicants but is a signal of low-paying jobs. This implies that our measures of ad characteristics add explanatory power beyond traditional variables in typical labor market data. Conducting a sequential decomposition analysis, we show that controlling for education and experience requirements reduce the negative correlation between the share of female applicants and log wage by 27% and adding non-traditional job characteristics further decrease the correlation by 21% after residualizing on industry, firm, and occupation and city fixed effects. Following Gelbach (2016), we find that the full set of ad characteristics beyond education and working experience jointly explain nearly half of the observed gender wage gap at the application stage within narrowly defined occupations and labor markets.

Turning to specific job characteristics, we first document consistent evidence that women tend to avoid ads listing cognitive and project management skills, which have positive return in the labor market and are highly demanded in STEM fields. Second, we show that women are inclined to choose occupations or firms emphasizing social and interpersonal skills but within occupation and firm, they are more likely to sort into positions requiring customer service skills and escape from those demanding people management skills. Third, we find that women are consistently more likely to apply for jobs asking for character, writing and general computer skills, which may denote low-paying signals as they are usually accompanied with obedience and tasks with low promotability.

Concerning job tasks, we show evidence that women favor job content such as helping and caring for others, documenting and recording information, following instructions from leaders or supervisor and doing chores. However, jobs involving those female-typical tasks usually offer less competitively pay. In contrast, male-typical tasks including operating and repairing equipment, solving problems, making decisions and working with high-tech are well compensated in the labor market, although female applicants are less likely to choose those positions.

The share of female applicants consistently falls when job ads list "aspiration", "pressure" or "competition", suggesting that women have less career aspiration and disproportionately shy away for competitive pressure. Moreover, women with heavier family responsibilities tend to avoid jobs with flexibility and business travel as they are usually accompanied with irregular schedule and working away from home for a long time, respectively. Probably responding to gender-biased age discrimination, women consciously sort into ads explicitly listing age requirements and demanding young applicants. However, a large proportion of those jobs are entry-level jobs with low wages. Compared with men, women, on average being more risk-averse, prefer jobs with low wage uncertainty but miss opportunity to obtain higher average payment. Finally, we find that women are more reluctant to apply for jobs that can not promise weekends or ask for long working hours.

Our findings confirm that gender differences in the valuation of non-pecuniary job characteristics and those differences at the job application stage can further translate into gender wage gaps in the labor market. Hence, in terms of policies trying to close the gender wage gap, ad characteristics we examined can be potentially channels that policy makers can utilize to influence the gender differences in job choices.

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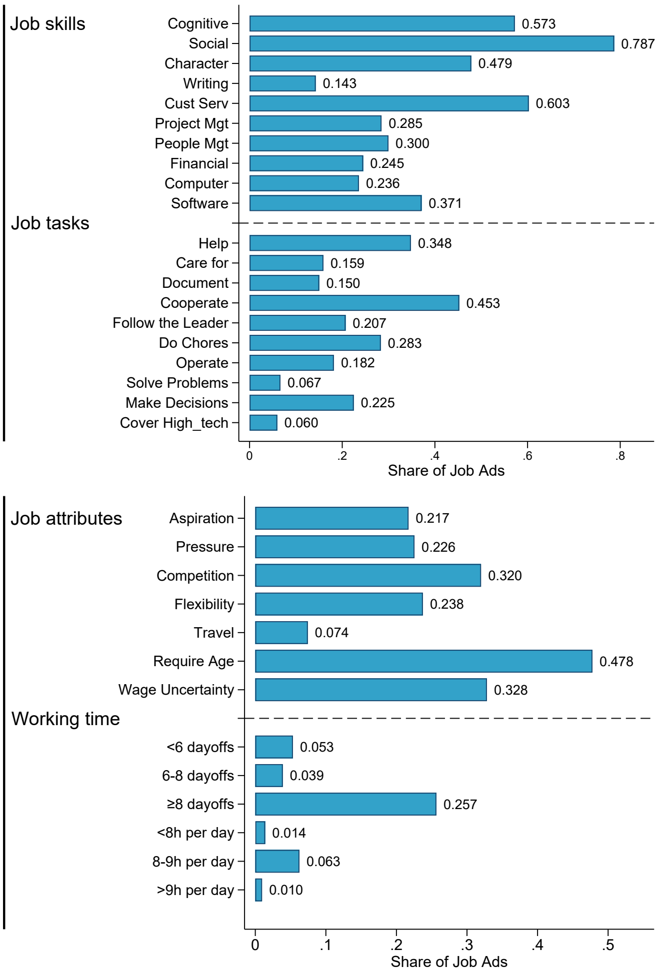
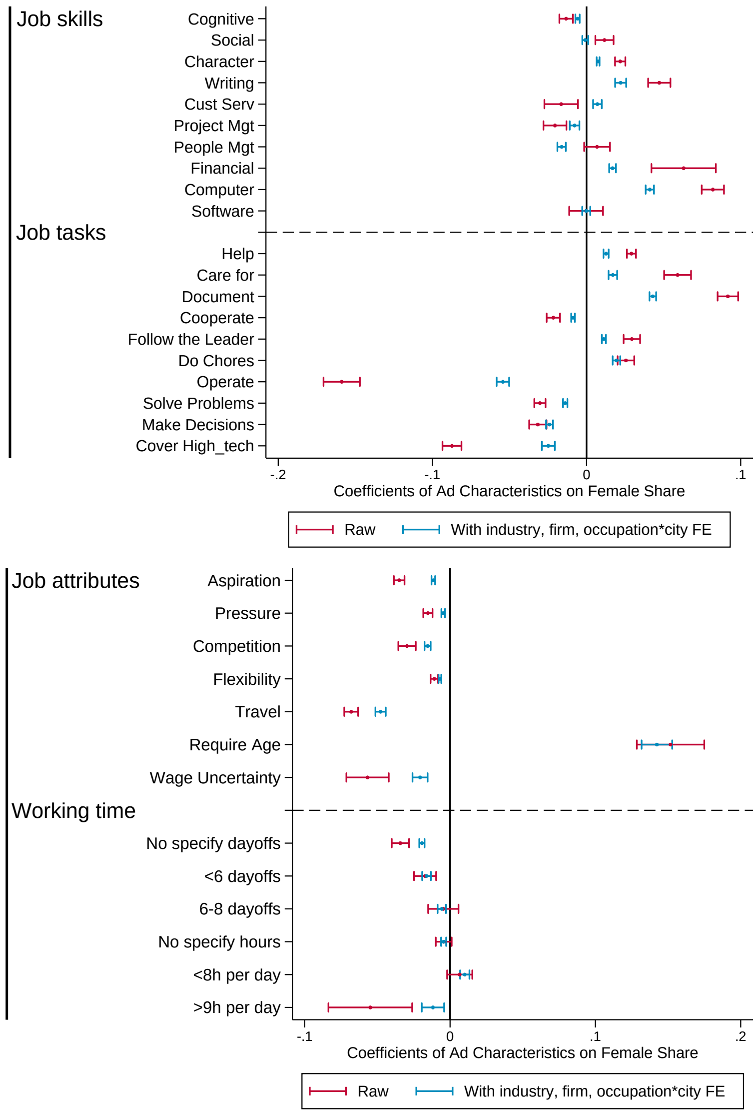
Figures and tables

Figure 1: Share of ads specifying ad characteristics in 51job.com



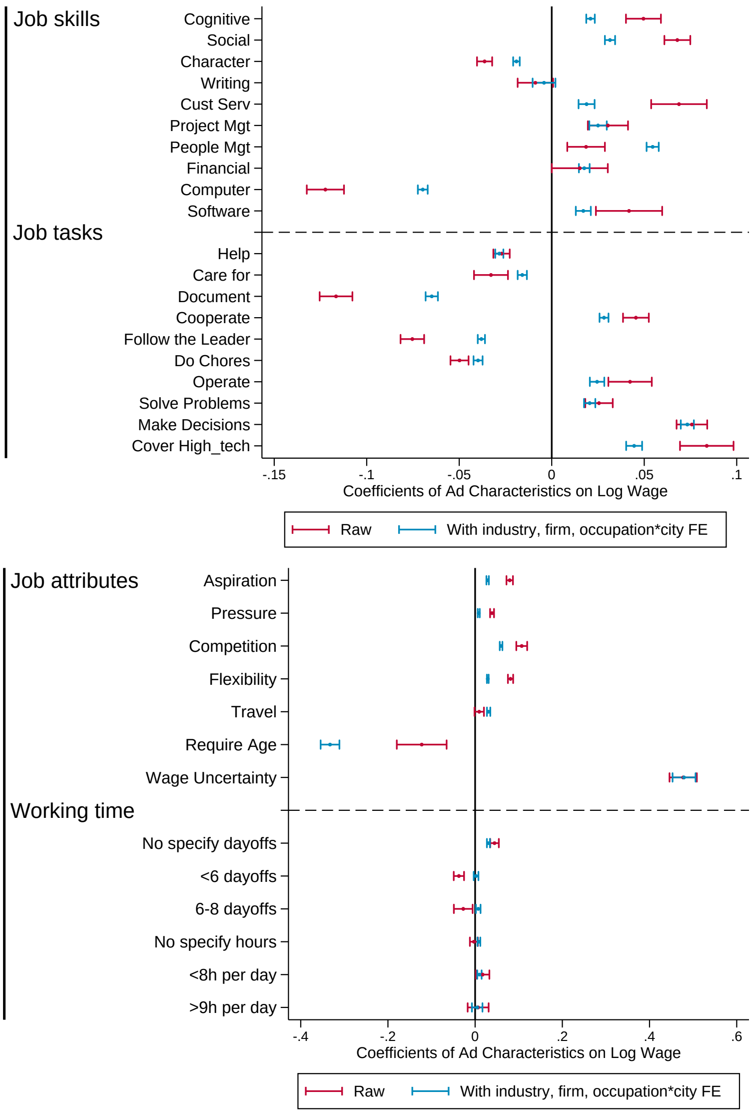
Note: Data refer to job postings scrapped from 51job.com during November 1, 2018, to April 30, 2019. See Table 2 for job characteristics definition.

Figure 2: Correlation between ad characteristics and the share of female applicants



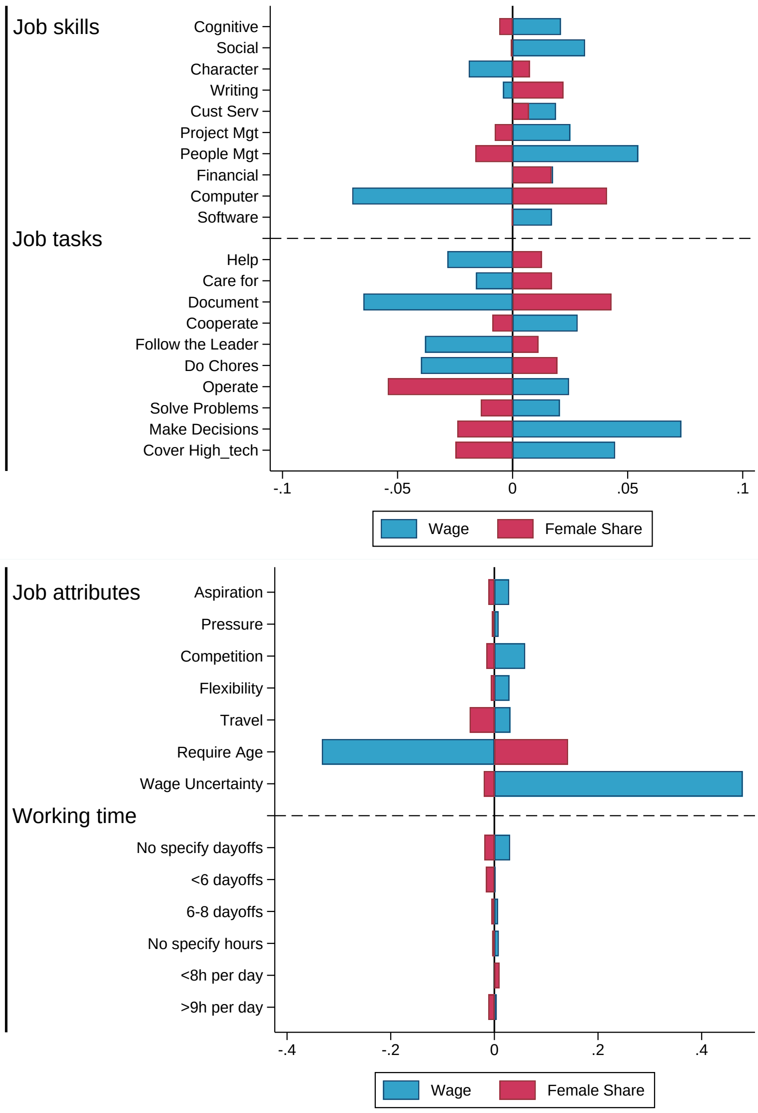
Note: The raw estimates are from regressing the share of female applicants on a full set of ad characteristics, controlling for education and experience requirements. The detailed estimates are from regressing the share of female applicants on a full set of ad characteristics, controlling for education and experience requirements, industry, firm, and occupation and city fixed effects. Each scatter represents the coefficient of corresponding ad characteristics. Each bar represents a 95% confidence interval. Years of experience equal 0 if the ad does not specify requirements. Education is controlled using a set of dummies shown in Table 1. See Table 2 for job characteristics definition. Standard errors are clustered at occupation and city level.

Figure 3: Correlation between ad characteristics and log wage



Note: The raw estimates are from regressing the log wage on a full set of ad characteristics, controlling for education and experience requirements. The detailed estimates are from regressing the log wage on a full set of ad characteristics, controlling for education and experience requirements, industry, firm, and occupation and city fixed effects. Each scatter represents the coefficient of corresponding ad characteristics. Each bar represents a 95% confidence interval. Years of experience equal 0 if the ad does not specify requirements. Education is controlled using a set of dummies shown in Table 1. See Table 2 for job characteristics definition. Standard errors are clustered at occupation and city level.

Figure 4: Correlation between ad characteristics and outcomes



Note: The blue bar represents the coefficients of corresponding ad characteristics on the log wage. The red bar represents the coefficients of corresponding ad characteristics on the share of female applicants. Both regressions contain a full set of ad characteristics and control for education and experience requirements, industry, firm, and occupation and city fixed effects. Years of experience equal 0 if the ad does not specify requirements. Education is controlled using a set of dummies shown in Table 1. See Table 2 for job characteristics definition. Standard errors are clustered at occupation and city level.

Table 1. Sample Means, 51job.com Job Ads

Characteristics	Value
Panel A. Ad characteristics	
Education requirements	
Junior High School and below	0.023
Senior Hign School	0.073
Secondary Specialized School	0.061
Secondary Technical School	0.012
Junior College	0.402
Bachelor	0.182
Master	0.006
Ph.D.	0.000
No requirement	0.240
Experience requirements	
None or less than 1 year	0.474
1 year	0.187
2 years	0.132
3-4 years	0.134
5-7 years	0.059
8-9 years	0.008
10 years and above	0.007
Years of experience, conditional	2.7
Age requirements	
No age restrictions	0.522
Mean age requested	28.8
Wages	
Mean wage	99,116.6
Number of positions advertised	
Unspecified	0.156
Mean number, when specified	5.6
Panel B. Firm characteristics	
Firm size	
Under 50	0.159
50-150	0.295
150-500	0.235
500-1,000	0.117
1,000-5,000	0.110
5,000-10,000	0.021
10,000+	0.063
Firm ownership typec	
Private, domestic	0.820
Foreign	0.136
State-owned enterprise	0.042
Non-profit organization	0.002
Panel C. Application information	
Ads with more than 1 applicant	0.960
Number of total applicants, conditional	52.4
Number of female applicants, conditional	19.3
Share of female applicants, conditional	36.47%

Notes: Data refer to job postings scrapped from 51job.com during November 1, 2018, to April 30, 2019. Wages are measured in RMB per year. 51job.com prompts firms to list a minimum and maximum wage. Mean wage are calculate as the midpoint of the minimum and maximum wage if both specified and measured as the posted wage if only the minimum or maximum wage specified. Firm characteristics are reported by employers on 51job.com.

Table 2. Description of Job Characteristics

	Keywords and Phrases
Panel A: Job Skills	
Cognitive	Problem solving, research, analytical, critical thinking, math, statistics
Social	Communication, teamwork, collaboration, negotiation, presentation
Character	Organized, detail oriented, multitasking, time management, meeting deadlines, energetic
Writing	Writing
Customer service	Customer, sales, client, patient
Project management	Project management
People management	Supervisory, leadership, management (not project), mentoring, staff
Financial	Budgeting, accounting, finance, cost
Computer (general)	Computer, spreadsheets, common software (e.g., Microsoft Excel, PowerPoint)
Software (specific)	Programming language or specialized software (e.g., Java, SQL, Python)
Panel B: Job Tasks	
Help	Help, assist
Care for	Care for, look after, take care of, caring, kind, helpful, considerate, concerned
Document	Document, record
Cooperate	Cooperate
Follow the leader	Leader, manager, supervisor, director
Do chores	Print, copy, fax, upload, type, collect, distribute, purchase, book, chores
Operate	Operate, repair, maintain, machine, vehicles, devices, equipments
Solve problems	Solve problems
Make decisions	Make decisions
Cover high-technology	AI, new energy, new material, aviation, biotechnology, electronic
Panel C: Job Attributes	
Aspiration	Unlimited, challenging, motivated, goal, ambition
Pressure	Stress tolerance, psychological adjustment, tenacity, good mindset, face difficulty
Competition	Performance-based pay, assessment, tournament
Flexibility	Work from home, flexible working time
Travel	Travel, on business, business trip
Age requirements	Whether specify age requirements, required age max, required age min
Wage uncertainty	(wage max-wage min)/wage max; 0-1
Panel D: Working Time	
Less than 6 day offs per month	$<$ 6 day offs per month
6-8 day offs per month	6-8 day offs per month
At least 8 day offs per month	$\geq$ 8 day offs per month
Less than 8 hours per day	$<$ 8h per day
8-9 hours per day	8-9h per day
More than 9 hours per day	$>$ 9h per day

Notes: Shown is the authors definition utilizing open texts of job postings scrapped from 51job.com.

Table 3. Summary Statistics of Job Characteristics

Characteristics	Full Sample: Mean	SD	Min	Max	Sample Means: Wage Q1	Wage Q2	Wage Q3	Wage Q4
Panel A: Job Skills								
Cognitive	0.573	0.495	0	1	0.487	0.561	0.605	0.685
Social	0.787	0.409	0	1	0.701	0.801	0.848	0.854
Character	0.479	0.500	0	1	0.501	0.485	0.474	0.443
Writing	0.143	0.350	0	1	0.131	0.148	0.143	0.154
Customer service	0.603	0.489	0	1	0.527	0.639	0.688	0.615
Project management	0.285	0.451	0	1	0.226	0.277	0.301	0.366
People management	0.300	0.458	0	1	0.250	0.285	0.314	0.378
Financial	0.245	0.430	0	1	0.248	0.224	0.228	0.275
Computer (general)	0.236	0.425	0	1	0.330	0.232	0.181	0.142
Software (specific)	0.371	0.483	0	1	0.346	0.363	0.365	0.420
Panel B: Job Tasks								
Help	0.348	0.476	0	1	0.363	0.347	0.338	0.336
Care for	0.159	0.366	0	1	0.156	0.169	0.178	0.143
Document	0.150	0.357	0	1	0.233	0.141	0.102	0.074
Cooperate	0.453	0.498	0	1	0.350	0.458	0.519	0.549
Follow the leader	0.207	0.405	0	1	0.265	0.209	0.174	0.146
Do chores	0.283	0.451	0	1	0.345	0.284	0.251	0.216
Operate	0.182	0.386	0	1	0.150	0.178	0.182	0.232
Solve problems	0.067	0.249	0	1	0.047	0.063	0.072	0.095
Make decisions	0.225	0.418	0	1	0.135	0.218	0.261	0.338
Cover high-technology	0.060	0.237	0	1	0.037	0.050	0.061	0.101
Panel C: Job Attributes								
Aspiration	0.217	0.412	0	1	0.142	0.239	0.294	0.251
Pressure	0.226	0.418	0	1	0.160	0.243	0.280	0.266
Competition	0.320	0.466	0	1	0.231	0.360	0.414	0.344
Flexibility	0.238	0.426	0	1	0.188	0.243	0.275	0.278
Travel	0.074	0.263	0	1	0.054	0.079	0.089	0.089
Age requirements	0.478	0.500	0	1	0.490	0.497	0.492	0.431
Wage uncertainty	0.328	0.129	0	0.857	0.296	0.325	0.314	0.389
Panel D: Working Time								
Less than 6 day offs per month	0.053	0.225	0	1	0.068	0.059	0.051	0.028
6-8 day offs per month	0.039	0.194	0	1	0.039	0.049	0.045	0.023
At least 8 day offs per month	0.257	0.437	0	1	0.277	0.267	0.247	0.224
Less than 8 hours per day	0.014	0.118	0	1	0.013	0.015	0.017	0.012
8-9 hours per day	0.063	0.242	0	1	0.076	0.071	0.060	0.037
More than 9 hours per day	0.010	0.098	0	1	0.012	0.014	0.008	0.003

Notes: Data refer to job postings scrapped from 51job.com during November 1, 2018, to April 30, 2019. See Table 2 for job characteristics definition. Wage Q1 to Q4 are categorized based quarters of the mean posted wage for each ad.

Table 4. Ad Characteristics and Outcomes

Dependent Variable:	Share of Female Applicants		Log Wage	
	(1)	(2)	(3)	(4)
Cognitive	-0.01324***	-0.00584***	0.04959***	0.02098***
	(0.00224)	(0.00071)	(0.00482)	(0.00118)
Social	0.01163***	-0.00084	0.06791***	0.03151***
	(0.00301)	(0.00098)	(0.00358)	(0.00141)
Character	0.02183***	0.00750***	-0.03629***	-0.01907***
	(0.00171)	(0.00048)	(0.00209)	(0.00091)
Writing	0.04718***	0.02210***	-0.00884*	-0.00415
	(0.00369)	(0.00183)	(0.00489)	(0.00315)
Customer service	-0.01646***	0.00705***	0.06879***	0.01884***
	(0.00555)	(0.00144)	(0.00767)	(0.00221)
Project mgmt	-0.02049***	-0.00776***	0.03039***	0.02504***
	(0.00380)	(0.00160)	(0.00553)	(0.00240)
People mgmt	0.00682	-0.01618***	0.01857***	0.05456***
	(0.00427)	(0.00140)	(0.00519)	(0.00168)
Financial	0.06299***	0.01687***	0.01518**	0.01759***
	(0.01066)	(0.00112)	(0.00772)	(0.00148)
Computer (general)	0.08193***	0.04103***	-0.12234***	-0.06970***
	(0.00368)	(0.00137)	(0.00513)	(0.00136)
Software (specific)	-0.00030	-0.00023	0.04179***	0.01708***
	(0.00559)	(0.00132)	(0.00914)	(0.00207)
Help	0.02911***	0.01267***	-0.02713***	-0.02834***
	(0.00150)	(0.00085)	(0.00226)	(0.00112)
Care for	0.05905***	0.01705***	-0.03284***	-0.01591***
	(0.00445)	(0.00141)	(0.00468)	(0.00127)
Document	0.09167***	0.04297***	-0.11659***	-0.06484***
	(0.00340)	(0.00110)	(0.00452)	(0.00170)
Cooperate	-0.02154***	-0.00878***	0.04551***	0.02827***
	(0.00220)	(0.00061)	(0.00356)	(0.00124)
Follow the leader	0.02938***	0.01123***	-0.07534***	-0.03803***
	(0.00273)	(0.00067)	(0.00325)	(0.00099)
Do chores	0.02555***	0.01939***	-0.04984***	-0.03982***
	(0.00274)	(0.00125)	(0.00249)	(0.00125)
Operate	-0.15883***	-0.05427***	0.04235***	0.02452***
	(0.00602)	(0.00206)	(0.00599)	(0.00199)
Solve problems	-0.03023***	-0.01384***	0.02556***	0.02052***
	(0.00187)	(0.00073)	(0.00379)	(0.00155)
Make decisions	-0.03159***	-0.02403***	0.07577***	0.07331***
	(0.00287)	(0.00114)	(0.00423)	(0.00180)
Cover high-technology	-0.08729***	-0.02478***	0.08381***	0.04456***
	(0.00314)	(0.00215)	(0.00738)	(0.00220)
Aspiration	-0.03501***	-0.01153***	0.07930***	0.02863***
	(0.00187)	(0.00063)	(0.00379)	(0.00143)
Pressure	-0.01525***	-0.00474***	0.03879***	0.00831***
	(0.00163)	(0.00063)	(0.00230)	(0.00116)
Competition	-0.02960***	-0.01545***	0.10689***	0.05952***
	(0.00306)	(0.00108)	(0.00635)	(0.00156)
Flexibility	-0.01081***	-0.00697***	0.08120***	0.02902***
	(0.00131)	(0.00047)	(0.00306)	(0.00102)
Travel	-0.06804***	-0.04782***	0.00937*	0.03094***
	(0.00244)	(0.00182)	(0.00553)	(0.00196)
Age requirements	0.15171***	0.14231***	-0.12253***	-0.33284***
	(0.01184)	(0.00536)	(0.02914)	(0.01099)
Required age min	-0.00115***	-0.00246***	-0.00115**	0.00441***
	(0.00023)	(0.00013)	(0.00058)	(0.00024)
Required age max	-0.00366***	-0.00237***	0.00351***	0.00627***
	(0.00027)	(0.00010)	(0.00052)	(0.00017)
Wage uncertainty	-0.05678***	-0.02064***	0.47714***	0.47922***
	(0.00744)	(0.00266)	(0.01599)	(0.01344)
No specify dayoffs	-0.03418***	-0.01937***	0.04443***	0.03048***
	(0.00303)	(0.00093)	(0.00506)	(0.00176)
Less than 6 dayoffs per month	-0.01720***	-0.01619***	-0.03728***	0.00216
	(0.00388)	(0.00153)	(0.00603)	(0.00276)
6-8 dayoffs per month	-0.00463	-0.00570***	-0.02727**	0.00713***
	(0.00533)	(0.00146)	(0.01098)	(0.00271)
No specify hours	-0.00436	-0.00444***	-0.00289	0.00860***
	(0.00279)	(0.00089)	(0.00465)	(0.00166)
Less than 8 hours per day	0.00663	0.01011***	0.01726**	0.00988***
	(0.00442)	(0.00164)	(0.00786)	(0.00256)
More than 9 hours per day	-0.05489***	-0.01178***	0.00689	0.00469
	(0.01470)	(0.00393)	(0.01227)	(0.00618)
Industry FE, firm FE, occupation×city FE		X		X
Observations	7,722,319	7,722,319	7,722,319	7,722,319

Notes: All regressions control for education and experience requirements. Years of experience equal 0 if the ad does not specify requirements. Education is controlled using a set of dummies shown in Table 1. The dependent variable for column 1 and 2 is the share of female applicants and that for column 3 and 4 is the log mean wage for each ad. See Table 2 for job characteristics definition. Standard errors are clustered at occupation and city level.

*** = p<0.01, ** = p<0.05, and * = p<0.1.

Table 5. Decomposing the Gender Wage Gap in Jobs Applied into Ad Characteristics

	Panel A: Sequential decomposition				*Panel B: Full decomposition*			
	Dependent Variable: Log Wage				Specification		Explained	
	(1)	(2)	(3)	(4)	Base	Full	Value	%
Share of Female Applicants	-0.60339***	-0.49671***	-0.36130***	-0.28498***	-0.49671***	-0.28498***	-0.21173	42.63%
	(0.02592)	(0.01515)	(0.00927)	(0.00774)	(0.01515)	(0.00774)		
Industry FE, firm FE, occupation×city FE		YES	YES	YES	YES	YES		
Education requirements			YES	YES		YES	-0.0079	3.75%
Experience requirements			YES	YES		YES	-0.1069	50.51%
10 skills				YES		YES	-0.0253	11.96%
10 tasks				YES		YES	-0.0421	19.89%
Pressure+Ambition+Competition				YES		YES	-0.0061	2.87%
Flexibility+Travel				YES		YES	-0.0019	0.88%
Wage uncertainty				YES		YES	-0.0055	2.60%
Working time				YES		YES	-0.0010	0.49%
Age requirements				YES		YES	-0.0149	7.05%
Observations	7,722,319	7,722,319	7,722,319	7,722,319				

Notes: Years of experience equal 0 if the ad does not specify requirements. Education is controlled using a set of dummies shown in Table 1. The dependent variable for all regressions is the log mean wage for each ad. See Table 2 for job characteristics definition. Standard errors are clustered at occupation and city level. All models use the same 7,722,319 observations.

*** = p<0.01, ** = p<0.05, and * = p<0.1.

Table A1. Descriptive Statistics, 51job.com Ads Versus 2018 China Labour Statistical Yearbook

	Share in category	
	(1)	(2)
	Yearbook	51job
Gender		
Male	57.3	36.5
Age		
29 or below	22.7	58.5
30–39	30.0	39.1
40–49	28.7	2.4
50 or above	18.6	0.1
Education		
High school or below	66.9	40.9
College	17.6	40.2
University or above	15.5	18.9
Industry		
Professional Service/Education/Training	6.2	11.9
Accounting/Finance/Banking/Insurance	2.9	6.8
Pharmacy/Medical	3.1	5.8
Advertising/Media	1.2	3.5
Real Estate/Construction	9.0	12.9
Government/NPO/Others	7.5	3.2
Service	14.1	3.4
Logistics/Transportation	5.9	1.8
Energy/Materials	3.0	2.7
CS/Internet/Communication/Electronics	2.1	28.0
Trade/Consumption/Manufacturing/Operation	45.2	20.0
Occupation		
Senior management	2.8	9.3
Professional and technical	13.7	29.3
Sales and service	39.8	37.7
Production and construction	28.0	21.7
Public servants	15.7	1.9
Firm ownership		
Private sector	63.3	95.8
SOEs and collectives	36.7	4.2

Notes. The gender distribution of 51job data is the average share of female applicants across all vacancies. Age and education distributions of 51job refer to ads that stated a requirement for the attribute only. Issued by the National Bureau of Statistics, the 2018 China Labour Statistical Yearbook contains information and summary statistics related to the Chinese labor market in 2017. The 51job data was collected from November 1, 2018 to October 31, 2019.

Table A2. Detailed Full Decomposition

	Explained	
	Value	%
Share of Female Applicants	-0.21173	42.63%
Education requirements	-0.0079	3.75%
Experience requirements	-0.1069	50.51%
Working time	-0.0010	0.49%
10 skills		
Cognitive	-0.0014	0.66%
Social	-0.0011	0.52%
Character	-0.0015	0.71%
Writing	0.0002	-0.07%
Customer service	0.0008	-0.36%
Project management	-0.0020	0.93%
People management	-0.0080	3.79%
Financial	0.0009	-0.40%
Computer (general)	-0.0137	6.47%
Software (specific)	0.0006	-0.30%
10 tasks		
Help	-0.0026	1.21%
Care for	-0.0007	0.32%
Document	-0.0100	4.74%
Cooperate	-0.0027	1.29%
Follow the leader	-0.0036	1.71%
Do chores	-0.0067	3.18%
Operate	-0.0014	0.66%
Solve problems	-0.0007	0.34%
Make decisions	-0.0119	5.62%
Cover high-technology	-0.0017	0.82%
Job attributes		
Aspiration	-0.0014	0.66%
Pressure	-0.0003	0.14%
Competition	-0.0044	2.08%
Flexibility	-0.0006	0.27%
Travel	-0.0013	0.60%
Age requirements	-0.0149	7.05%
Wage uncertainty	-0.0055	2.60%

Notes: All regressions control for industry, firm, and occupation and city fixed effects. Years of experience equal 0 if the ad does not specify requirements. Education is controlled using a set of dummies shown in Table 1. The dependent variable for all regressions is the log mean wage for each ad. See Table 2 for job characteristics definition. Standard errors are clustered at occupation and city level. All models use the same 7,722,319 observations.
*** = $p<0.01$, ** = $p<0.05$, and * = $p<0.1$.