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Age Discrimination in Hiring: Evidence from Online Job Ads*

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Abstract

We analyze explicit age discrimination in hiring decisions and job seekers' responses in the Chinese labor market, using a large-scale dataset of job postings with ad-level group characteristics of applicants. In nearly 48% of postings, employers explicitly exclude certain age groups, with significant variation across firm types, sizes, industries, and occupations. We show that employers' explicit age requests are shaped by statistical and taste-based discrimination reflected in job skill requirements and ageist language, as well as constraints such as expected processing costs, and competition in labor demand. Our findings align with a labor demand model where employers decide whether to consider (undesired) candidates from an additional age group based on their search factors and preferences. On the supply side, we leverage the distribution of applicant characteristics such as age and education level to show that age requirements are interpreted as signals rather than strict barriers. Nonetheless, explicit age restrictions substantially alter the applicant pool by attracting younger applicants while discouraging skilled workers.

Keywords: Age Discrimination, Search Frictions, Labor Demand, Labor Supply
JEL Codes: J71, J23, J22

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"Forty is the old age of youth; fifty the youth of old age."

– *Victor Hugo*

1 Introduction

Despite decades of legal protections, age discrimination remains a persistent and costly barrier in labor markets worldwide (Lipnic, 2018). Many advanced economies, including the United States and the European Union, have enacted strict anti-discrimination laws, making explicit age requirements in hiring illegal. However, evidence from the literature continues to show that older workers face significantly longer unemployment spells (Johnson and Neumark (1997), Button and Neumark (2014, 2022)),[1] fewer training opportunities (Perron, 2021), and most significantly, hiring disadvantages (Riach and Rich (2002), Lahey (2008), Riach and Rich (2010), Neumark (2012), Carlsson and Eriksson (2019), Neumark et al. (2019a)). While these studies document the existence of age discrimination, less is yet known about the underlying drivers of such hiring practices and how job seekers respond to them.[2] Moreover, the lack of evidence on explicit age discrimination has made it difficult to systematically analyze employer decision-making and applicant behavior at scale.

In this paper, we examine employer age discrimination and applicant responses by leveraging a large-scale dataset of job postings from China, where explicit age restrictions remain legal and widespread, appearing in nearly half of all postings in our sample. Our dataset comprises the full text of 8.8 million job listings, each contains a dedicated field for the employer to list age preference, offering rare visibility into firms' stated age

[1]Longer unemployment spells may not directly indicate age discrimination, as older workers might be more selective in their job search, expecting better opportunities that align with their experience. However, it reflects the greater difficulty they face in securing their desired employment, highlighting their disadvantaged position in the labor market. Stronger age discrimination protections also did not help older workers to weather the economic downturn better (Button and Neumark, 2014).

[2]Notable exceptions include Van Borm et al. (2021) who find older age stigmas such as lower technological skills, flexibility, and trainability reduce the probability of job interview in an online scenario experiment and Burn et al. (2022) who demonstrate ageist languages related to health, personality, and skills can predict differential hiring by age.

preferences at scale.[3] Although we lack data on interview or hiring outcomes, as well as applicant-level data, we observe distributional characteristics of applicants at the job ad level, such as the number of applications and the share of applicants from a certain age group or education level. This unique combination of employer-declared age preferences, detailed job content, and aggregate applicant responses allows a systematic analysis of the barriers and biases driving employers' age discrimination decisions, as well as the responses of the job seekers. Unlike prior studies relying on experimental methods, we directly observe and quantify age discrimination at scale, reducing measurement error and enabling a comprehensive analysis. To the best of our knowledge, besides Helleseter et al. (2020) who study how explicit gender preferences vary by age,[4] this is the first study to explore the determinants and consequences of *explicit age discrimination* in the labor market.

We first show significant discrimination against older workers in job postings, with sharp increases at age thresholds that are multiples of five. Notably, age discrimination begins as early as the 30s, consistent with anecdotal evidence that employers perceive workers over 35 as less adaptable to new technologies and less willing to endure long hours. As a result, firms across various industries explicitly favor younger employees, though the extent varies by occupation. These patterns are largely driven by idiosyncratic firm-level decisions. While our analysis focuses on China, age discrimination is not unique to this context and is also prevalent in countries such as the US, albeit in a less explicit form without stating a specific age range (Johnson and Neumark (1997), Riach and Rich (2010), Neumark et al. (2019a), Carlsson and Eriksson (2019), Helleseter et al. (2020), and Neumark (2024)).

To understand why some employers impose explicit age requirements in job postings whereas others do not, we propose a labor demand model where employers decide whether

[3]The data span all sectors of the Chinese economy, and the distribution of job types mirrors that of the private sector in nationally representative labor force surveys.

[4]They find employers request younger women for customer-facing roles and shift their preference toward older men for managerial roles using Chinese and Mexican job ad data.

to consider candidates from an additional, less preferred age group.[5] We extend the framework of Kuhn and Shen (2013), who study gender discrimination, to the context of age discrimination, where firms are assumed to have initial expectations about the value of workers from each age group. The difference in values could include both perceived productivity differences reflecting statistical discrimination (Aigner and Cain, 1977), and taste-based preferences for different age groups.[6] As we are interested in discrimination heterogeneity by skill requirement, we further incorporate a disutility term[7] that allows employers' discrimination to vary by skill level, which operates through biased beliefs favoring younger or older workers for certain skills.[8] Crucially, different from Kuhn and Shen (2013), our extension allows a firm to either broaden (i.e. drop the age restrictions) or narrow (i.e. impose an age requirement) its search for applicants when the skill requirement of the job rises. We define youth-favoring skills as those in which younger applicants are often *perceived* to be more proficient, such as social and software skills.[9] In our set-up, firms decide whether to rule out an age group based on the trade-off between the potential benefits of a broader talent pool and the extra disutility from recruiting a discriminated worker, as well as the additional screening cost.

Empirically, we identify three key categories of predictors that are strongly associated with firms' use of explicit age requirements and their preference for workers under 40.[10] The first category highlights practical constraints of firms, such as the expected number of applicants and labor market competition. Consistent with our model, firms with higher processing costs due to larger applicant pools and those facing less competition

[5]For simplicity, our model assumes older workers as the discriminated group, as Figure 1 shows that among 48% of all job ads specify age requirements, over 83% (more than 40% of all ads) exclude workers above 40, while far fewer ads exclude those aged 18-29. Although some job ads may favor experienced workers, this preference is largely captured by experience requirements, which we explicitly control for in the empirical analysis. Notably, only 0.7% of job ads require 10 or more years of experience. In our empirical study, we further analyze ageist language that favors experienced workers.

[6]We present evidence of taste-based and statistical discrimination later when we compare age discrimination decisions across different jobs and firms. Similar to Kuhn and Shen (2013), the main implications of our model hold in the empirical analysis regardless of the sources of the discrimination.

[7]We will also explain later that this additional disutility term leads to predictions more consistent with the empirical evidence.

[8]As literature emphasizes the importance of multidimensional skills in explaining wage differences (Deming and Kahn (2018) and Dorn et al. (2024)), we also leverage the detailed texts of the job postings to explore this discrimination heterogeneity by skills.

[9]We also define ageist language using phrases that favor either young or older workers, following Burn et al. (2022).

[10]Our main results are also robust to different maximum age thresholds, which we will show later.

in labor demand are more likely to narrow their search and exclude older workers.[11] The second category involves search concerns of the employers as firms with higher skill requirements tend to search broadly for the most suitable candidates. Third, indicators of taste-based discrimination, such as ageist language and references to youth-favoring skills, are positively correlated with explicit age restrictions and narrower candidate pools favoring younger workers.

To study how applicants respond to these age-based exclusions, we analyze the distributional characteristics of the applicants at the job ad level, a rare feature not available in other job ad data. We propose a labor supply model in which applicants could interpret an explicit age requirement as a *signal* of the firm's preference for younger workers. Older applicants must account for both the disutility of working in a discriminatory environment and the uncertainty regarding whether the age requirement is strictly enforced. This uncertainty affects their expected payoff through the probability of receiving an offer. However, older workers may still apply for jobs with high skill requirements or wages, as these positions often have smaller qualified applicant pools due to the discriminating signal, increasing the likelihood that firms treat the age requirement as soft. In such cases, the potential payoff is higher, making the application more attractive despite the stated age preference.

Our results reveal substantial non-compliance with stated age requirements, with older workers applying for positions that explicitly request younger ones. Non-compliance is more prevalent in job ads with higher skill requirements. However, explicit age discrimination remains effective in discouraging older applicants while attracting younger ones. This highlights an implicit trade-off for firms between targeting younger workers and expanding their applicant pool to include more skilled candidates. Consistent with Bohren et al. (2023)'s suggestion that statistical preference might come from inaccurate beliefs, we provide suggestive evidence that firms may unknowingly sacrifice the quality of workers with explicit age requests.

[11] However, screening cost alone is unlikely to explain all the variations in the use of age discrimination, with its small albeit significant explanatory power.

We contribute to three strands of the literature. First, while labor economists have extensively examined the labor supply and retirement decisions of older people, less is known about the muted demand for older workers (Allen, 2023),[12] despite clear evidence that older workers face greater reemployment challenges (Lumsdaine and Mitchell (1999), Chan and Stevens (2001), Lipnic (2018), and Bui et al. (2020)). Prior work by Helleseter et al. (2020) finds that firms' explicit gender preferences in job ads shift from favoring women to favoring men when hiring older rather than younger workers, using data from Mexico and China. Building on this insight, our paper further examines explicit age discrimination and the responses of the applicants to such discrimination. Unlike most research that focuses on workers in their 50s or nearing retirement age (Vandenberghe (2022) and Allen (2023)), we show that age discrimination can begin even before age 40. Understanding the barriers to hiring older workers and their broader labor market implications is essential for designing effective policy responses to aging populations. Age discrimination has become a confronting reality when pension reforms and policymakers are increasingly focused on keeping older individuals in the workforce.[13] The effectiveness of such policies, we argue, hinges on their alignment with the labor market incentives of the employers as well as the workers.

Secondly, we contribute to the literature on age discrimination in hiring and its broader implications in the labor market. Experimental methods, particularly correspondence studies, have provided rigorous evidence that older applicants receive fewer interview callbacks than younger counterparts, with older women facing even greater discrimination than older men (Neumark (2012, 2024), and Neumark et al. (2016)). Prior research has also examined the effects of legal protections for older workers (Neumark and Stock (1999), Neumark and Song (2013), Button and Neumark (2014), Neumark et al. (2017), Neumark et al. (2019b), Burn et al. (2020), and Button et al. (2022)) and the impact of ageist language on the applicant behavior (Burn et al., 2022). Despite these significant

[12]Neumark and Yen (2020) find that the relative cohort size of the older cohort to the younger cohorts matters for the relative change in supply and demand.

[13]Many countries, such as France, have raised the retirement age (National Assembly, 2023). The UK rolled out a £22 million package to support those over 50 (Davies, 2022). The literature has shown retirement decisions respond strongly to changes in public pension schemes and retirement age (Staubli and Zweimüller (2013), Brinch et al. (2015), (Atalay and Barrett, 2015), Blundell et al. (2016), Manoli and Weber (2016), and Gelber et al. (2020)).

advances, an economy-wide analysis of age discrimination remains absent from this vibrant literature. In settings without explicit age requirements, researchers focus on the consequences of implicit age discrimination. For example, Burn et al. (2022) show that ageist language stereotypes can predict age discrimination in hiring. Moreover, due to practical constraints, the experiment approach tests the responses of the job applicants in selected locations and occupations (Burn et al., 2024). In contrast, our use of explicit age requirements allows us to complement this literature by conducting a precise, economy-wide analysis of age discrimination. Since such practices are banned in many advanced economies, little is yet known about the factors driving explicit age discrimination and how job seekers respond to it.

Lastly, we contribute to the broader literature on labor market discrimination. Similar to Kline et al. (2022), we document substantial firm-level variation in the discrimination decisions against certain demographic groups of workers. Additionally, we provide suggestive evidence that employers might not be optimizing when imposing age restrictions: while these requirements attract younger applicants, they are negatively associated with applicant education levels. This aligns with the findings from Card et al. (2023) and Kuhn and Shen (2023) that when explicit gender discrimination was banned, employers adjusted their hiring strategies after recognizing that previously excluded workers were equally or more qualified. Our findings suggest that some employers fail to internalize the fact that older workers can possess higher qualifications, highlighting a policy-relevant case for legislative intervention in China.

The rest of the paper is organized as follows: Section 2 provides a detailed description of our main dataset and defines key variables. Section 3 documents some important empirical facts. Section 4 presents our models. Section 5 tests the model with our main empirical analysis and Section 6 concludes.

2 Data

2.1 Job postings on 51job.com

Our primary dataset consists of job advertisements from 51job.com, the largest online job board in China[14] that specializes in advertising professional, high-education, and private sector jobs. It features over 10 million job openings and attracts more than 100 million job seekers annually. Unlike most job board data in the literature that primarily contains employer job descriptions, our dataset also includes detailed information on group characteristics of applicants at the job ad level, including gender, age, education level, work experience, and current salary.

Each job posting contains detailed information on the vacancy, firm, and job requirements. Vacancy information includes job title, wage range, benefits, number of openings, and posting date. Firm-level details cover name, location, type, size, and industry. Job requirements, such as education, experience, and age, are explicitly listed in dedicated fields. Additionally, the job description text thoroughly outlines specific job tasks and skill requirements, such as major, language proficiency, and software expertise.

Our baseline analysis focuses on the minor groups of occupation and industry, defined by 51job.com. The job board categorizes occupations into 11 major groups, 65 minor groups, and 952 detailed occupations, and industries are classified into 11 major and 60 minor industries. When posting a job advertisement, each employer selects one detailed occupation and one minor industry.

Job seekers on 51job.com follow a standardized application process. They begin by creating a standardized resume online, which includes demographic details (gender and age), education level, work experience, and current annual salary range. They then search for jobs based on criteria such as the desired location, wage expectations, education, experience, and firm characteristics. After reviewing the full-page description of a job advertisement, applicants can submit their resumes directly to employers.

[14] 51job.com is the first publicly traded company specializing in human resource services in China.

2.2 Data and sample

For our analysis, we scraped approximately 8.8 million job ads posted between November 1, 2018, and April 30, 2019.[15] We imposed several sample restrictions to improve estimation accuracy: (1) restricting the sample to job ads from mainland China; (2) excluding observations missing key information such as posted wage, occupation, industry, or city-level location; (3) removing ads in languages other than Chinese and English, as well as those entirely in English; (4) filtering out extreme values by dropping ads in the top 99.9% and bottom 0.1% of the wage distribution and those with excessively long or short job descriptions (top 99% and bottom 1%); and (5) including only ads that received at least two applicants. After applying these restrictions, our final sample retains 88% of the original dataset, covering approximately 7.7 million ads.

Given the limited time series coverage, we aggregate all job postings across months and analyze age discrimination using a cross-sectional framework while controlling for the time of collection or ad posted date. Following Deming and Kahn (2018), this aggregation method effectively reduces the influence of temporal fluctuations in skill requirements and job characteristics driven by external factors.

Table 1 presents descriptive statistics for job ads (Panel A), firm characteristics (Panel B), and application information (Panel C) based on our sample of 7,722,319 job ads. Among these ads, 47.8% specify age requirements, with a conditional mean age limit of 28.8 years. This highlights the significant prevalence of age-based discrimination in China's labor market.

[Insert Table 1 here]

Explicit age requests are rarely observed in developed countries due to legal prohibi-

[15] A full-year dataset covering November 1, 2018, to October 31, 2019, is available, and we can extend our analysis upon request.

tions.[16] However, until the writing of this paper, such practices remain legal in China, offering several advantages for our analysis. Firstly, the excluded age groups determined by the employers are explicit. There is no need for detection using experimental methods. It also reduces measurement error when inferring age discrimination, which we define as treating a job applicant less favorably because of age. Secondly, the frequent mentions of explicit age requirements in the online job market provide a comprehensive view of age discrimination across a huge Chinese economy. Therefore, we can dissect the extent of age discrimination by sectors of the economy and don't face the practical constraint of limiting our analysis to selected occupations, which is often the case using experimental methods.

Although explicit age requirements are more prevalent in our data than explicit gender preferences in Kuhn and Shen (2013),[17] less than 1% of the ads in our sample specify explicit gender requirements after one decade.[18] This limits our ability to investigate the interaction between gender and age discrimination.

Another data advantage is the abundance of posted wage information, with almost all job ads specifying the posted wage.[19] It is crucial for analyzing applicant responses to age discrimination, as wages significantly influence job-seeking behavior.

We acknowledge that job postings on online platforms may not fully represent the broader labor market due to several factors. Firstly, vacancies advertised on these portals disproportionately feature entry-level positions and may under-represent managerial roles and positions requiring extensive work experience. Secondly, job ads in expanding, emerging, and high-turnover industries and occupations are more prevalent than their representation in a population of occupied jobs. Lastly, online job postings often require higher levels of education and professional skills compared to the median position. To

[16]For instance, in the United States, the Age Discrimination in Employment Act (ADEA) of 1967 prohibits such practices, though they were once common (US Department of Labor (1965) and Neumark et al. (2019a)). Similarly, in the European Union, the EU directive 2000/78/EC outlaws age-based discrimination in hiring.

[17]One-third of the firms in their sample had at least one ad with explicit gender discrimination, and about 10% of job ads contained gender preference between 2008 and 2010.

[18]This decline is driven by newly enacted laws prohibiting gender-based hiring preferences. See Kuhn and Shen (2023).

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

assess the representativeness of job vacancies posted on 51job relative to the overall Chinese labor market, we use the 2019 China Labour Statistical Yearbook to compare the distribution of job vacancies across various job characteristics with a representative sample of employees in urban China in Appendix Section A.1.[20] We show job ads on 51job broadly reflect the Chinese economy and represent a substantial segment of the labor market.

2.3 Age discrimination measures

We measure explicit age discrimination in job ads using two main variables. The first one is an "Age Discrimination" indicator, which equals one if a job ad contains an explicit age requirement. In Section 3, we will show that most age discrimination targets older workers. To capture this, we create a second indicator variable, the "Age Max <40" dummy, which takes a value of one if the maximum age requirement is less than 40.[21] This variable identifies job ads that favor younger workers while excluding older ones.

In Appendix Section A.2, we define potential predictors of age discrimination such as job skills, job tasks, and ageist language, using job description data, following the approach of Deming and Kahn (2018), Gelblum (2020), and Burn et al. (2022), respectively. Additionally, utilizing our unique dataset of applicants, we measure the size of the applicant pool to explore why some firms impose age restrictions while others do not. Using the distributional characteristics of applicants' information at the ad level, we also define the share of applicants from each age group. Moreover, the share of applicants for each educational qualification allows us to measure the quality of the applicant pool. We examine these characteristics to study the impact of age discrimination on applicant composition.

[20]The 2019 China Labour Statistical Yearbook, published by the National Bureau of Statistics, provides a comprehensive overview of the Chinese labor market in 2018, including various relevant summary statistics.

[21]We perform robustness checks using other age cutoffs for our main results in Section 5, yielding similar results.

3 Some facts

3.1 Explicit age discrimination for different age groups

We document two stylized facts about explicit age discrimination and provide anecdotal evidence to explain its prevalence in China. First, we identify the age groups most affected by employer-imposed age restrictions. Our dataset shows a remarkable degree of *explicit* discrimination against older workers, as illustrated in Figure 1. More than 40% of job ads with a maximum age requirement exclude workers over 40.[22] In contrast, most job ads do not exclude the age group of 18-29.[23] The middle group, aged 30-40, also faces some discrimination, though at a lower rate,[24] reinforcing the pattern that explicit age restrictions disproportionately affect older job seekers.

[Insert Figure 1 here]

These 40% discriminatory ads against older workers are a conservative lower bound because 52.2% of ads do not explicitly state an age range.[25] Some of these ads may still discriminate implicitly. Our findings paint a bleak picture for older workers, who face very limited employment opportunities when age restrictions are explicitly stated.[26] To account for concerns that certain jobs may be unsuitable for specific age groups due to job characteristics (McLaughlin and Neumark, 2018), we conduct a robustness check by excluding positions that never hire a particular age group. Defining job cells by education requirements, industry, occupation, and city, we compare employers with and without explicit age discrimination within these narrowly defined cells. Our results remain unchanged, as shown in Appendix Figure A.1.

[22]To quantify age discrimination, we count the number of job ads that exclude workers from each age group, which we then divide by the total number of job ads to derive a measure of "percentage of age-discriminating job ads". An ad is considered exclusionary if its minimum age requirement exceeds the upper bound of an age group or if its maximum age requirement falls below the lower bound.

[23]Specifically, this means a minimum age below 29 and a maximum age above 18.

[24]The share of discriminatory ads remains below 10%, primarily because explicit age requirements rarely exclude workers in their early 30s.

[25]The percentages in 1 do not sum to 47.8% (the share of ads with explicit age discrimination) because some ads may exclude multiple age groups.

[26]Out of 47.8% ads with explicit age request, slightly more than 40% only want the young.

Secondly, age discrimination increases sharply at age cut-offs that are multiples of 5, as shown in Figure 2. Limiting the sample to ads with explicit age requirements, we plot the percentage of ads excluding older workers (y-axis) against various age thresholds (x-axis). The prevalence of age cutoffs at 35, 40, and 45 suggests that these restrictions are driven by hiring conventions rather than life-cycle productivity differences, which typically follow a smooth, inverted U-shaped pattern.

[Insert Figure 2]

These findings align with our anecdotal evidence. The "curse of 35," widely discussed on social media, reflects the difficulties workers face once they reach this age, as employers increasingly sideline them. Older employees are often perceived as less adaptable to new technologies and less willing to endure long working hours. In China, where overtime is common and labor laws are weakly enforced, phrases such as "ability to work under pressure" in job ads often signal demanding work schedules that favor younger workers without family responsibilities.

Institutional factors also help explain the patterns in Figure 2. The national civil service exam imposes an upper limit of age 35. Similarly, eligibility for China's Young Scientists Fund requires male applicants to be under 35 and female applicants to be under 40.[27] While these policies may intend to promote young talents in government and research, private-sector employers often adopt similar age thresholds for less benign reasons. Many firms view workers over 35 as more costly and less flexible due to increased family responsibilities, leading HR departments to use age 35 as a convenient hiring cutoff.

3.2 Age discrimination decisions by different firm characteristics

Next, we examine the prevalence of age discrimination across different types of firms. Figures A.2 illustrate the extent to which firms explicitly impose age requirements and

[27] See National Civil Service Administration (2020) and National Natural Science Foundation of China (2025) for the age requirements listed on the relevant official websites.

discriminate against older workers. Compared to private domestic firms, other firms, such as foreign-owned firms, state-owned enterprises, and non-profit organizations, are less likely to have explicit age requirements or exclude older workers.

We then analyze the relationship between firm size and age discrimination decisions in Figure A.3. We find that firms with the largest employment size are much more likely to impose age restrictions than smaller firms. This pattern is consistent with Garen (1985), which suggests that evaluation costs rise with firm size. Firms with over 10,000 employees are often nationally recognized, attracting a large applicant pool and typically following a standardized, multi-stage hiring process. To manage recruitment costs, these firms may resort to narrow searches with explicit age restrictions.

3.3 Age discrimination decisions by industry and occupation

We now present how age discrimination varies across industries and occupations. Figure A.4 shows the industry breakdown according to 51job.com's major industry classifications. The Finance industry exhibits the highest share of job postings with explicit age requirements, followed by the Service industry. Notably, Finance also ranks highest in explicit discrimination against older workers, with Service following closely behind. Long work hours in the Finance industry might partially explain the use of age discrimination. The findings for the Service industry align with Kuhn et al. (2020), which documents a preference for young female workers in client-facing roles. By contrast, the Healthcare industry shows the lowest levels of age discrimination in both measures, likely reflecting the value placed on experience in healthcare professions.

Figure A.5 presents the prevalence of age discrimination by major occupation categories of 51job.com. The Service sector has the highest share of job postings with explicit age requirements, followed closely by Retail/Customer Service, which also ranks highest in discrimination against older workers. In contrast, Healthcare occupations have the lowest levels of explicit age restrictions and are least likely to exclude older applicants, consistent with industry-level patterns.

3.4 Variance decomposition of age discrimination

To further understand the variation in the use of age discrimination, we decompose its variance into different components by estimating the following regression:

$$AgeDiscr_{a,j,i,oc} = \boldsymbol{Charac_a b} + z_j + \delta_t + \eta_i + \theta_{oc} + \epsilon_{a,j,i,oc} \tag{1}$$

where $AgeDiscr_{a,j,i,oc}$ is an indicator variable for whether job ad a, posted by firm j in industry i and occupation-city pair oc has an explicit age requirement or specifies a maximum age below 40. The vector $\boldsymbol{Charac_a}$ captures key job characteristics such as skills, tasks, and ageist language variables that potentially predict the use of age discrimination.[28] The terms z_j, δ_t, η_i, and θ_{oc} denote firm, quarter, industry, and the occupation-city pair fixed effects, respectively.

We then use the predicted value of each component to calculate the variance and covariance of each component. The sum of such variances and covariances (i.e. those on the right-hand side of the Equation 1) equals the variance of the age discrimination decision. We report the share of the variance explained by each component in Figure 3. Overall, it is clear that most of the variation in the use of age discrimination comes from the idiosyncratic behavior of the firms. As shown in Appendix Figure A.6, slightly over 40% of firms either consistently include or never include age requirements in their job postings.

[Insert Figure 3 here]

3.5 Compliance with explicit age requirements by age groups

Turning our analysis to the labor supply side, we analyze the extent to which applicants comply with explicit age restrictions. Appendix Figure A.7 presents compliance rates at the job ad level, calculated as the ratio of applicants whose age is below or equal to the stated maximum age requirement to the total number of applicants. We examine

[28] We define these variables in Appendix Section A.2 and analyze them in Section 5.1.

compliance at maximum age thresholds of 23 and below, 26 and below, 30 and below, and 40 and below.[29]

Our findings in Appendix Figure A.7 indicate a monotonic decline in compliance rates as the maximum age requirement becomes more restrictive. This result is expected, as stricter age limits reduce the share of eligible applicants. Notably, compliance rates often fall well below 100%, suggesting that many older workers still apply despite explicit age restrictions.

4 Model

One possible explanation for fewer than 100% compliance rate is that while firms may use age requirements as a hard screening tool, many applicants either perceive them as a signal of the firm's preference for younger workers,[30] or view *some* firms as having a more lenient stance regarding older applicants.[31]

Reflecting such real-world dynamics of the recruitment process, we propose the following three-stage labor market model with the timeline outlined in Figure 4. In Stage 0, each firm myopically makes a discrimination decision by treating it as a "hardline" constraint: as long as the applicant pool is "good", it will proceed with the exclusive policy against older workers. This corresponds to our simplified demand-side model, focusing on essential dynamics. Applicants then decide where to apply in Stage 1 based on the postings from Stage 0. In Stage 2, however, when the applicant pool is "poor" and lacks sufficient qualifying/satisfying applicants anticipated, the HR department faces

[29]As discussed in Appendix Section A.2, 51job.com categorizes applicants into five age groups: 23 and below, 24–26, 27–30, 31–40, and 41 and above. Our compliance measures rely on these predefined categories.

[30]Such preference may be reflected in differential wage treatment for younger and older employees, tasks or workloads more oriented for younger workers, or a workplace environment more accommodating to younger individuals, all of which influence an applicant's perceived utility beyond the advertised wage.

[31]Our model considers only two groups: a discriminated group and an undiscriminated group. Our focus is on the preference for younger workers, as the data indicate that most age requirements favor younger workers while excluding older ones—48% of all job ads specify age requirements, and among them, over 83% (more than 40% of all ads) exclude workers above 40, whereas less than 5% explicitly exclude those aged 18-29.

the dilemma of whether to expand their pool in seeking a better candidate.[32] We assume that such firms would adopt a more flexible approach by re-admitting older applicants while discounting their skills or qualifications during the evaluation process. Anticipating this potential policy shift, older applicants are encouraged in Stage 1 to apply to jobs that ostensibly do not admit them.

[Insert Figure 4 here]

4.1 Firm decisions

On the demand side, we follow Kuhn and Shen (2013) to inspect the trade-off between discrimination and screening cost in firms' recruitment decisions while we extend the model to study discrimination against age groups and allow for heterogeneity in the discrimination by skill types. Formally, we consider a firm recruiting for a single vacancy. The net value of an individual j from age group g, with skill requirement θ is

$$U_j = \theta(\mu_g + \varepsilon_j).$$

Here, the term μ_g represents the baseline productivity of workers from group g, which could already incorporate both statistical and taste-based discrimination. Given the asymmetry of information for the two sides of the market, μ_g can be viewed as the statistically estimated value from the firm's side, after adjusting for taste-based discrimination. The term $\varepsilon_j \in [\underline{\varepsilon}, \bar{\varepsilon}]$ represents fluctuations in individual productivity as a draw from a probability distribution F, which we do not assume to take a certain specific form. The value to the firm is then amplified by θ, the skill level. This linear setup is for simplification purposes, as it can be replaced by a more general firm value function linking the skill level θ and individual productivity, without affecting our model predictions as long as the marginal effect of θ is positive.[33]

[32] Unfortunately, we don't observe the interview or hiring decisions in Stage 2. However, we can observe the entire job posting in Stage 0 and some distributional characteristics of the applicants in Stage 1.

[33] We abuse the notation θ here: although multiple skills may influence a firm's valuation, and ideally θ should be a vector encompassing each specific skill, we frequently focus on and estimate the impact of one particular skill. Thus, θ is also used without subscripts to denote the level of the skill being considered.

We now introduce a new disutility term $-\kappa_g(\theta)$ as we are interested in discrimination heterogeneity by different skill requirements. As a job posting encompasses a myriad of skill requirements, we allow variations in the extent of disutility incurred to the firm when age considerations directly interact with the skill type. This departure from Kuhn and Shen (2013) helps to accommodate a newly observed search pattern that firms may broaden or narrow the search for the best candidate when skill requirement rises. A priori, we need not restrict the sign of this additional term. It could be either positive (utility) or negative (disutility) depending on which skill is under examination. As it turns out, in our empirical analysis later, this term has to be negative for firms to search in narrower age groups for some skills, which we term as *youth-favoring*.[34] For these skills, larger skill requirements would bring larger subjective disutility, so κ increases in the corresponding skills θ. For the other skills, we set κ being constant across different levels of θ and normalized to 0.[35] Consequently, we can split κ as $\kappa_g(\theta) = \mathbf{1}_{\theta\in\{youth-favoring\}}\bar{\kappa}_g(\theta)$, where $\bar{\kappa}'_g(\theta) > 0$.

We analyze the firm's *marginal* decision on whether to include an additional discriminated age group 2 (with $\kappa_2 > 0$), to the existing (undiscriminated) age group 1 ($\kappa_1 = 0$). Let N^g be the expected number of applicants for the vacancy, and $c > 0$ be the unit search cost for an applicant. Assuming the firm is trying to maximize the expected gain from hiring net of the search cost, its decision problem is to choose the allowed age group(s) G with

$$\Pi^G = \mathbb{E}^G[\max U_j] - cN_G - \mathbf{1}_{G=\{1,2\}}\kappa_2(\theta)P_2, \tag{2}$$

where $G = \{1\}$ or $\{1, 2\}$ represents the firm's choice of age group. P_2 is the probability that the best candidate in terms of net value is from group 2. As in Kuhn and Shen (2013), we compare the difference in "profitability" between narrow and broad searching:[36]

$$\Pi^{12} - \Pi^1 = \left[\theta \int F^{N_1}(\varepsilon)(1 - F^{N_2}(\varepsilon + \Delta\mu))d\varepsilon - \kappa_2(\theta)P_2\right] - cN_2, \tag{3}$$

[34] The term $-\kappa$ incorporates concerns such as elevated cost, diminished physical stamina, increased health risks, or adaptability to new technologies. The older workers might be judged subjectively by the decision-makers in the hiring process to be less favored.

[35] Actually κ could decrease with θ. We set a constant κ for simplicity and this will not affect our model prediction.

[36] Calculation gives $\Pi^1 = \theta\mu^1 + \theta \int \varepsilon dF^{N_1}(\varepsilon) - cN_1$, and $\Pi^{12} = \theta\mu^1 + \theta \int \varepsilon dF^{N_1}(\varepsilon)F^{N_2}(\varepsilon + \Delta\mu) - \kappa_2(\theta)P_2 - c(N_1 + N_2)$.

where $\Delta\mu = \mu_1 - \mu_2$ is the cross-group difference in perceived baseline productivity. Two quick observations follow from the comparison. When the search cost c rises, the difference narrows down, so it is more likely for the firm to choose $G = 1$, i.e. to search narrowly and discriminate against age group 2. Similarly, when N_1 decreases, the difference is widened, so that the firm is more likely to choose $G = \{1, 2\}$, i.e. to search broadly by including age group 2. Notably, these predictions are in line with their counterparts in Kuhn and Shen (2013).

Proposition 1.

The effects of search cost and competition on search decisions are unambiguous. When the search cost c or the number of applicants N_1 rises, it is more likely for the firm to search narrowly.

Corollary 1.

When there is fiercer competition among firms in the same industry, those firms are more likely to search broadly.

However, the introduction of the disutility term κ_g leads to different implications on the effect of skill level. We use $[*]$ to represent the difference term in the square brackets in equation 3. For non-youth-favoring skills, $[*]$ is always increasing in θ as $\kappa_2(\theta) \equiv 0$, and so is the difference $\Pi^{12} - \Pi^1$. Meanwhile, for youth-favoring skills, when the effect of κ_2, dominates in $[*]$, i.e. when $\bar{\kappa}'_g P_2$ is larger than the integral, increasing θ leads a smaller difference $\Pi^{12} - \Pi^1$.

Proposition 2.

The effect of skill requirements on search decisions depends on the skill type. For non-youth-favoring skills, when the skill requirement is higher, the firm is less likely to search narrowly. For youth-favoring skills, when the skill requirement is higher, a firm could be more likely to search narrowly.

Therefore, our model predicts a contingent shift in decision patterns when a firm requires higher skill levels, where heterogeneity in discrimination by skill types plays a crucial role. When a firm narrows its search when a specific skill requirement increases, this suggests additional perceived disutility, independent of prior beliefs of productivity differences and average taste-based differences across groups, as they alone cannot account for this behavior. Conversely, if, as noted by Kuhn and Shen (2013), a firm broadens its search with higher skill requirements, then this additional disutility is absent or less dominant.

4.2 Applicant decisions

Turning to the supply side, we adopt an approach similar to the racial discrimination model by Lang et al. (2005), replacing racial groups with age groups. Their model predicts a separate labor market where white and black workers apply and are employed in separate firms. However, this result rests on two important assumptions: (i) each worker is limited to a single application throughout the process, and (ii) discriminating firms hold a hardline decision over racial groups, i.e. strictly prefer any white worker over any black worker. In contrast, our applicants (i) are allowed to apply costly to several job vacancies, and (ii) treat firms' age requirements as potentially soft rather than hard restrictions.

We assume that an applicant balances the benefits and costs of each application to decide whether to apply to a certain firm. Applicant j will apply to firm i if and only if the expected payoff V_j^i is greater than a flat application cost. The probability of applicant j applying to i rises when V_j^i increases, so it is sufficient to focus on the effect of the firm's wage and discrimination decisions on V_j^i.

Consider an applicant j from age group g_j and skill level θ_j, and a target firm i with skill requirement θ^i, wage offer w^i, the applicant pool N^i, Stage 0 discrimination policy $d_0^i \in \{0, 1\}$, and Stage 2 discrimination decision $d_2^i \in \{s(oft), h(ard)\}$. The expected payoff for j from applying to i can be written as

$$\begin{aligned} V_j^i &= V(d_2^i; g_j, \theta_j, \theta^i, w^i, d_0^i, N^i) \\ &= P_j^i \cdot v_j^i \\ &= q(d_2^i; g_j, \theta_j, \theta^i, w^i, d_0^i, N^i) \cdot [w^i - r(g_j) \cdot d_0^i]. \end{aligned}$$

Here P_j^i summarizes the probability of applicant j being offered the job by firm i and is a function q of variables $d_2^i, g_j, \theta_j, \theta^i, w^i, d_0^i, N^i$. Term v_j^i is the discrimination-adjusted wage: when firm i posts a discriminating policy $d_0^i = 1$ in Stage 0, applicant j could suffer a disutility r when working for i. We set $r = 0$ for the youngest age group as a baseline and further $r' > 0$: applicants with a higher age suffer more from an age-discriminating firm.[37]

If $d_0^i = 0$, i.e. the firm does not discriminate at the beginning, the value of d_2^i should be immaterial: the offer probability P_j^i can be written as $\boldsymbol{q} = q(g_j, \theta_j, \theta^i, w^i, d_0^i = 0, N^i)$. If $d_0^i = 1$, i.e. firm i posts a discriminating job ad in Stage 0, only when the firm decides to be flexible in Stage 2 will a discriminated applicant j have a chance to get offered the job. Assume for simplicity that the firm treats all applicants equally after re-include the discriminated group, i.e. $q(d_2^i = s; g_j, \theta_j, \theta^i, w^i, d_0^i = 1, N^i) = \boldsymbol{q}$, we can thus rewrite for those discriminated groups $P_j^i = Prob(d_2^i = s) \cdot \boldsymbol{q}$.

Hence, when a firm turns from $d_0^i = 0$ to 1, P_j^i decreases for older applicants due to the discount term $Prob(d_2^i = s)$, but rises for younger applicants. Moreover, for older applicants, v_j^i also decreases as $r(g_j) > 0$ and $r' > 0$. Hence, the share of an age group decreases with age.

Proposition 3.

When a firm searches narrowly with a discriminating ad, compared with a broadly searching firm, the number of older applicants decreases, while the number of younger applicants increases. The shares of each age group also change accordingly. Moreover, the share of an age group decreases with age.

Moreover, when facing a discriminating job with $d_0^i = 1$, those non-discriminating jobs serving as outside options will become more lucrative to discriminated workers with higher θ_j as P_j^i increases with θ_j.[38] Therefore, we also have the following corollary

[37] As we mentioned earlier, such disutility can either be in the form of differentiated wage/workload arrangement for younger and older employees, or a working environment that is less friendly to older workers.

[38] While it is reasonable to argue that $r(g_j)$ is weakly higher for more educated and skilled applicants, the prediction holds without this assumption.

prediction at the group level.

Corollary 2.

The share of more educated and skilled applicants decreases for a discriminating firm.

We now use backward induction to analyze more equilibrium comparative statics, i.e. the properties of functions V and q in equilibrium. For the firm's decision d_2^i, it is less likely to be soft when the applicant pool, N^i, increases in (relative) quality or quantity. Specifically, when θ^i, the job requirements rise, d_2^i is more likely to be soft due to the decreasing relative quality of the applicant pool. So, here $Prob(d_2^i = s)$ rises with θ. Taken together, from the applicants' point of view, these contribute to a higher P_j^i, thus implying a higher probability for those older applicants as age is positively correlated with the level of job requirements. Hence, higher skill levels, education, and experience requirements lead to a higher non-compliance rate through a tighter applicant pool.

Proposition 4.

Within narrowly searching firms, higher skill, education, and experience requirements lead to higher non-compliance rates.

5 Testing model implications

We begin by testing the predictions of the labor demand side model, which reconciles firms' search-related factors and discrimination. The model suggests a critical implication for employers' hiring practices: their search strategy, whether broad or narrow, is influenced by both search-related factors and preferences for specific skills.

5.1 Labor demand: firm perspective

We validate the model's implications from Section 4 using job ad data from 51job.com. In particular, we test our model's predictions of age discrimination decisions using the following regression model:

$$AgeDiscr_{a,i,oc} = \boldsymbol{Charac_a b} + \delta_t + \eta_i + \theta_{oc} + \epsilon_{a,i,oc} \tag{4}$$

where $AgeDisc_{a,i,oc}$ is an indicator variable equal to one if job ad a in industry i and occupation-city pair oc includes an explicit age requirement or specifies a maximum age below 40.[39] The vector $\boldsymbol{Charac_a}$ includes job characteristics such as processing costs, labor market competition, job skill requirements, and ageist language.[40] The coefficients $\boldsymbol{b}$ capture the relationship between these job characteristics and the use of explicit age discrimination. We include quarter fixed effects (δ_t) to account for seasonality.

In our preferred specification, we further control for industry (η_i) and occupation-city (θ_{oc}) fixed effects, allowing us to identify correlations between age requirements and job characteristics within narrowly defined labor market segments. Alternatively, we also examine correlations in a separate baseline specification across industry and occupation-city pairs (i.e. without η_i and θ_{oc}). We cluster standard errors at the occupation-city level.

Additionally, we conduct a robustness check by including experience requirements as an additional control. Since experience is positively correlated with age, this control mitigates concerns that age restrictions merely reflect experience requirements.

A key distinction between equation 4 and equation 1 is the exclusion of firm fixed effects. This allows us to retain over 40% of firms that consistently either include or exclude explicit age requirements in their job ads. More importantly, it enables a direct comparison across firms within the same industry and occupation-city pair, allowing us to investigate why some firms impose age restrictions while others do not.

Establishing causality requires strong assumptions, including the absence of reverse causality and unobserved confounders. We do not claim strict causality here.[41] Instead, we test the model's predictions regarding the factors driving firms' use of age restrictions.

[39]We will also show later that our results are not sensitive to the maximum age thresholds.

[40]These variables are defined in Appendix Section A.2.

[41]For example, ageist stereotype influences both ageist language and the use of age discrimination in equation 4.

5.1.1 Job skills and tasks

To investigate the relationship between firms' age discrimination practices and job skills and tasks, we regress the likelihood of a firm imposing an explicit age requirement on eight different job characteristics, including traditional indicators such as an education requirement and posted wages, as well as measures of cognitive and social skills, and job tasks such as software use, high-tech tasks, problem-solving, and decision-making. We define these variables in the Appendix Section A.2. While posted wages and education requirements are explicitly listed in job ads, other measures are indicator variables capturing the presence of specific keywords in job descriptions, as detailed in Appendix Table A.3.

We estimate separate regressions for each of these measures using equation 4 and report the results in Figure 5. Each colored bar represents a confidence interval from a separate regression, with different colors corresponding to specifications with varying fixed effects. Figure 5a has the Age Discrimination dummy as the dependent variable whereas Figure 5b uses Age max <40 dummy defined in Section 2.3.

[Insert Figure 5 here]

Figure 5a presents a generally negative correlation between job requirement and the probability of explicit age restrictions, except for imprecise estimations on social skills. After controlling for industry and occupation-city fixed effects, we observe statistically significant negative relationships for most skills, except for software and social skills. This pattern reveals a negative skill-targeting relationship: firms with higher skill requirements tend to broaden their search rather than impose age restrictions. However, for skills or tasks stereotypically associated with younger workers—such as software and social skills—higher requirements do not reduce explicit age restrictions (in the case of software) or may even increase age discrimination (in the case of social skills).

Figure 5b further examines firms' discrimination against older workers. Most skill measures are negatively correlated with exclusionary age restrictions, consistent with Figure

5a. However, when jobs require software proficiency or social skills—both stereotypically associated with younger workers—firms are more likely to exclude older applicants. These findings provide evidence for heterogeneity in age discrimination by skill types. Firms are more likely to incur a utility cost for hiring older workers for software and social skills.

At first glance, the positive coefficients for software and social skills are consistent with taste-based discrimination, reflecting strong stereotypes that younger workers outperform older workers in programming and interpersonal skills. However, statistical discrimination may also play a role, as employers may base their hiring decisions on prior experience with younger hires. Taste-based discrimination alone cannot fully explain firms' age discrimination practices, as firms would then be expected to systematically target their preferred age groups and always explicitly state age preferences, which is not the case — there is substantial variation in age discrimination practices across firms. For job skills or tasks with negative coefficients, such as education requirement, cognitive, problem-solving, decision-making, tasks related to high-tech, and jobs with higher log wage offered, firms are less likely to include age discrimination. In such cases, the desire to search broadly for the best candidate dominates.

We also present the estimates from Figure 5 in Table 2, which quantify the magnitude of these correlations. However, as we cannot rule out reverse causality completely, these estimates should be interpreted with caution. Columns 3 and 6 demonstrate the robustness of our results with experience controls, which one might worry about being highly correlated with the use of age discrimination.[42]

[Insert Table 2 here]

[42] As another robustness check, we incorporate all skill variables into a single regression analysis and report the findings in Appendix Table A.4. Furthermore, Appendix Figure A.8 confirms that our results in Figure 5b are not sensitive to changes in the maximum age threshold.

5.1.2 Ageist language

We provide further evidence of taste-based discrimination by analyzing the role of ageist language in job descriptions in Figure 6. Following Burn et al. (2022), we test the association between age discrimination and three specific types of ageist language: “Learning”, “Communication”, and “Experience”. Additionally, we introduce a novel measure related to the ability to handle “Pressure”. These variables are defined in Appendix Section A.2, and the keywords used to identify them are listed in Appendix Table A.3. While “Experience” favors older workers, other ageist descriptions favor young workers as they are perceived as quick learners, more sociable, and able to cope with “pressure” which is often associated with long overtime hours of work that disadvantages older workers who have more family responsibilities. We estimate separate regressions for each language variable using equation 4 and report our results in Figure 6, where each bar represents a separate regression.

[Insert Figure 6 here]

Figure 6a shows that job ads using ageist language favoring younger workers are more likely to impose explicit age requirements, except for “Communication”. Conversely, when job ads emphasize “Experience”, they are less likely to include an explicit age restriction. These patterns persist across both across (red) and within industry and occupation (blue) specifications, with smaller but still significant coefficient estimates for “Learning”, “Experience”, and marginally significant for “Pressure” for the latter estimation.

Figure 6b further illustrate the relationship between ageist language and discrimination against older workers. Specifically, the coefficients for “Learning”, “Communication” and “Pressure” are positive and statistically significant, indicating that firms using these terms are more likely to exclude older applicants. By contrast, “Experience” reduces the likelihood of age discrimination, consistent with firms valuing older applicants for roles requiring greater experience.

Table 3 summarizes the estimates from Figure 6. The table details the magnitudes of these estimates which one should interpret with caution due to potential reverse causality. Columns 3 and 6 of Table 3 confirm robustness when controlling for experience requirements.[43]

[Insert Table 3 here]

5.1.3 Application processing costs

Another key trade-off in our model, as well as Kuhn and Shen (2013), is that firms can reduce application processing costs at the expense of a smaller application pool. Our model predicts that an increase in N, the expected number of applicants, will raise the expected total processing costs, consequently leading firms to narrow their search by restricting applications to preferred age groups. Conversely, competition in the labor market reduces the pool of qualified applicants, causing firms to search more broadly and reduce the use of age discrimination.

Although we lack a direct measure of c, the processing costs per application in Section 4.1, we approximate it using the expected number of applications, defined as the size of the applicant pool in a job cell in Appendix Section A.2. In short, we calculate the total number of applications in a job cell defined by a job ad's education requirement, industry, occupation, and city. This measure is preferable to the actual number of applicants per job ad, as it mitigates reverse causality concerns — individual firms are unlikely to substantially influence the total number of applications in a job cell. By contrast, applicant numbers at the job ad level are heavily influenced by other ad-specific characteristics. To capture labor market competition, we also define two indicator variables, "High Competition" and "Very High Competition" for firms' competition in a job cell, based on the number of firms posting job ads within a given job cell.[44]

[43] A joint regression including all ageist language variables (Appendix Table A.5) produces similar patterns. Appendix Figure A.9 shows that our results in Figure 6b are not sensitive to changes in the maximum required age cutoff.

[44] See details in Appendix Section A.2. "High Competition" corresponds to job cells with 6 to 17 firms (between the 75th and 90th percentiles), and "Very High Competition" includes job cells with at least 18 firms (above the 90th percentile).

We analyze these three variables in a single regression using equation 4 and report the coefficient estimates in Figure 7.

[Insert Figure 7 here]

Using our preferred specification (represented by blue bars), which includes industry and occupation-city fixed effects and yields more precise estimates, we find a positive and statistically significant correlation between the expected number of applicants and the likelihood of imposing age restrictions in Figure 7. Figure 7a suggests that as the expected number of applicants increases, firms are more likely to narrow their applicant pool by specifying a preferred age group. Similarly, Figure 7b indicates that firms are also more likely to discriminate against older workers, consistent with our model's predictions.

We also report a statistically significant negative association between firms' age discrimination decisions and the level of competition they face in the labor market, using our preferred (blue) specification. Our hypothesis posits that heightened competition incentivizes firms to broaden their search and reduce age discrimination against older workers. This hypothesis is in line with our findings in Figure 7a and Figure 7b, which show that firms in "High Competition" and "Very High Competition" job cells are less inclined to specify explicit age requirements or discriminate against older workers compared to firms in less competitive environment. The coefficient magnitude is larger for firms in highly competitive markets, supporting a monotonic relationship between competition intensity and the likelihood of using age discrimination.

Table 4 summarizes the results from Figure 7, providing coefficient magnitudes. According to our preferred specification of column 2, a doubling of the expected number of applicants increases the likelihood of explicitly requesting an age group by 1.1%. Firms in "High Competition" and "Very High Competition" job cells are 2.0% and 5.9% less likely to impose age restrictions compared to firms in less competitive job cells, respectively. Similarly, column 5 shows that a 100% increase in the expected number of applicants increases the likelihood of explicitly requesting younger workers under age 40 by 1.3%. Firms in "High Competition" and "Very High Competition" job cells are 1.8% and 5.9% less likely to specify a preference for younger workers, respectively. Columns 3 and 6 confirm the robustness of our results when controlling for experience requirements, mitigating concerns that age restrictions merely reflect experience-related hiring preferences.[45]

[Insert Table 4 here]

5.2 Labor supply: applicant response

We examine how job seekers perceive firms' explicit age requirements and how they respond to such restrictions. The central premise of our labor supply model is that applicants interpret explicit age requirements as a signal and, based on their own age and these perceived signals, decide whether to apply for a particular job.

To test applicants' responses given the age restrictions, we utilize the ad-level applicant characteristics defined in Appendix Section A.2 and estimate the following equation:

$$AppResp_{a,i,oc} = \mathbf{1}\{\boldsymbol{AgeDiscr_a}\}\boldsymbol{b} + \delta_t + \eta_i + \theta_{oc} + \epsilon_{a,i,oc} \tag{5}$$

$AppResp_{a,i,oc}$ represents applicants' response, measured by the number of applicants per job ad, the quality of the application pool, or the age distribution of job applicants. Additionally, $\mathbf{1}\{\boldsymbol{AgeDiscr_a}\}$ is an indicator variable equal to one if the job ad includes an explicit age requirement or specifies a maximum age below 40.

To test what predicts the compliance rate of applicants with the maximum age requirement of the explicit age request, we estimate the following equation:

$$Complicance_{a,i,oc} = \boldsymbol{Charac_a b} + \delta_t + \eta_i + \theta_{oc} + \epsilon_{a,i,oc} \tag{6}$$

$Complicance_{a,i,oc}$ is the compliance rate of older applicants applying job ad a in

[45] We also examine the role of the expected number of applications using separate regressions in the Appendix Table A.2. When estimated separately, a doubling of the expected number of applications increases the likelihood of imposing an explicit age requirement by 0.5% and the likelihood of age discrimination against workers aged 40 and above by 0.7%. However, unless the number of applications increases substantially, it is unlikely to be the primary driver of age discrimination.

industry i and occupation-city pair oc.[46] For applicants' labor supply decisions, it is crucial to control for the log wage offered, as it affects the expected return to applying, as outlined in Section 4.2, and consequently shapes applicants' responses. Hence, besides experience requirements, we add the log wage offered as an additional control.

However, the specifications for the supply side cannot rule out potential confounders or reverse causality.[47] Therefore, we also do not claim strict causality here. Instead, we establish correlations between explicit age discrimination and its impact on the applicant pools.

5.2.1 Number of applications

We test whether explicit age discrimination reduces the number of actual applicants, as shown in Table 5. Specifically, we estimate equation 5 with Age Discrimination dummy or Age Max <40 dummy as the independent variable and the number of applicants per job ad as the dependent variable.

[Insert Table 5 here]

Column 3 of Table 5 presents our preferred specification, which includes industry and occupation-city fixed effects, as well as additional controls for log wage and experience requirements. Our findings indicate that when firms explicitly request a certain age group, they receive 2.3 fewer applications on average (4.5% in relative magnitude). When firms restrict applications to workers under 40, they receive 1.1 fewer applications (2.1% in relative magnitude).

[46] To calculate the compliance rate, we divide the number of workers with age at or below the maximum age thresholds by the total number of applicants.

[47] For example, using equation 5 to test the effect of age discrimination on the number of applicants suffers from reverse causality. Firms that wish to reduce the number of applicants will search more narrowly with a higher likelihood of age discrimination.

5.2.2 Application composition

Our model predicts that job postings discriminating against older workers will attract more young applicants, while older applicants will be deterred due to concerns about age discrimination. Notably, medium-aged applicants, even falling within the specified age range, may avoid applying if they perceive a strong preference for younger candidates.

To test this prediction, we first examine the relationship between applicant age composition and firms' age discrimination practices. Using data on applicant age distribution—less than or equal to 23, 24-26, 27-30, 31-40, and 41 or older—we regress the share of applicants in each age group on indicators of explicit age discrimination.[48] Specifically, we estimate equation 5 separately for each age group's share.

Panel A of Table 6 reveals that explicit age discrimination attracts the youngest applicants (aged 23 and below) and the oldest applicants (aged 41 and above), while deterring those in the middle age ranges. To further understand the mechanism and test if ads excluding older workers attract younger applicants while deterring older ones, we regress the proportion of applicants in each age group on an Age Max <40 indicator. Panel B of Table 6 confirms that job ads specifying an age limit below 40 attract a younger applicant pool. Specifically, the share of applicants aged 26 or younger rises, while the share of those aged 27 or older declines. The pattern is monotonic, with the youngest group's share increasing the most and the 30-plus group's share decreasing the most. Even applicants aged 27–30—though technically eligible—may self-select out if they perceive a strong firm preference for younger workers.[49]

[Insert Table 6 here]

[48]The age group categories of the applicants follow the thresholds defined by 51job.com as explained in Appendix Section A.2. Unfortunately, we do not have access to more detailed age information.

[49]To assess the robustness of our findings, we re-estimate the correlations with only quarter fixed effects and with additional controls such as experience requirements and log wage. The results, presented in Appendix Table A.6, confirm that the use of age discrimination increases the share of the youngest and oldest applicants while discouraging those in the middle age range. Moreover, age restrictions against older workers are positively correlated with the share of younger applicants and negatively correlated with the share of older applicants.

As the share of older applicants drops with the use of age discrimination against older workers, we examine whether this leads to a deterioration in the quality of the applicant pool, given that older applicants can have more experience and higher educational qualifications. We test this prediction using equation 5 to estimate the relationship between the Age Discrimination dummy or the Age Max <40 dummy with the share of applicants with a university degree or above. Table 7 presents our findings. Using our preferred specification of Column 3, explicit age restrictions reduce the share of university-educated applicants by 2.7 percentage points (5.8% fall in relative magnitude). When firms only request younger workers aged 40 and below, the share of applicants with a university degree falls by 1.7 percentage points (3.5% fall in relative magnitude).

[Insert Table 7 here]

5.2.3 Compliance rates

As shown in Appendix Figure A.7, we observe substantial non-compliance with maximum age requirements. To investigate the predictors of compliance, we examine how job skills and tasks, as defined in Appendix Section A.2, predict compliance rates. This analysis helps identify the types of jobs for which workers are more or less likely to disregard explicit age restrictions. It also tests our model's prediction that as skill requirement increases, experienced and older applicants are more likely to apply, in anticipation of a non-binding (soft) policy on the age restriction. We estimate this pattern using equation 6. The outcome variable, compliance rate, is defined as the number of applicants complying with the maximum requested age divided by the total number of applicants per job ad. We construct two versions of this measure using maximum age thresholds of 30 and 40.[50]

Table 8 shows that most job requirements—such as requiring a university degree, cognitive and social skills, problem-solving, and decision-making—are negatively associ-

[50] These two thresholds are chosen because 51job.com categorizes applicants into the following age groups: 23 and below, 24 to 26, 27 to 30, 31 to 40, and 41 and above, as explained in Appendix Section A.2. Applicants up until 40 still comply with the Age Max 40 threshold.

ated with compliance. Applicants are less likely to comply when these job requirements are specified. However, this pattern does not hold for more technical skills. Specifically, non-compliance rates do not increase when firms request specific software skills and when firms list job tasks related to high-tech fields.

[Insert Table 8 here]

We interpret these findings as evidence that older applicants strategically assess their likelihood of receiving an offer. When job ads emphasize cognitive and social skills, compliance decreases, meaning older applicants are more likely to apply despite the age restriction, anticipating that firms may be more flexible for positions requiring these skills. In contrast, when job ads emphasize technical skills, older applicants are more likely to follow the stated age restriction. This pattern suggests that firms enforcing technical skill requirements are perceived as less likely to waive age restrictions, leading to higher adherence to the specified limits.

6 Conclusion

In this paper, we investigate the use of explicit age requirements and applicants' responses to it within the unique context of the Chinese labor market, leveraging a large dataset of job postings. We document that nearly half of job ads impose explicit age restrictions, with a disproportionate impact on older workers. Firms' decisions to set age requirements are shaped by recruitment costs, applicant pool quality, and biases that favor younger applicants, particularly in roles requiring software and social skills. On the supply side, we find that job seekers do not fully comply with age restrictions, particularly for high-skill positions, but explicit age requirements still deter older applicants and reduce the overall education level of the applicant pool.

Our findings have important implications for both labor market efficiency and policy design. Understanding the reasons behind firms' age discrimination is crucial for developing effective policy tools to mitigate it. First, firms' reliance on explicit age restrictions suggests that they prioritize immediate search cost reductions over long-term productivity gains. Policymakers could consider incentivizing firms to adopt age-inclusive hiring practices, such as promoting age-neutral recruitment algorithms to mitigate bias or removing explicit age requirements. Second, although eliminating taste-based discrimination may be challenging, efforts should focus on identifying and addressing sources of discrimination, such as firms, co-workers, and customers. Third, regarding the trade-off between young and high-skilled workers, firms should be informed of this dynamic to make more informed hiring decisions. Finally, given China's rapidly aging workforce, policymakers must address how age discrimination interacts with labor supply constraints and retirement policies. Encouraging phased retirement programs and lifelong learning initiatives could help older workers remain competitive and adaptable in the labor market.

Beyond policy, our results also point to the long-term career consequences of early-age discrimination. Since age discrimination in China can begin as early as the mid-30s, affected workers may face limited career advancement opportunities, lower job stability, and premature labor force exit. Future research could explore how workers adapt to these constraints—whether through career shifts, skill upgrading, or strategic job search behaviors. Additionally, investigating how firms' hiring patterns evolve in response to policy interventions could provide valuable insights into the effectiveness of anti-discrimination measures.

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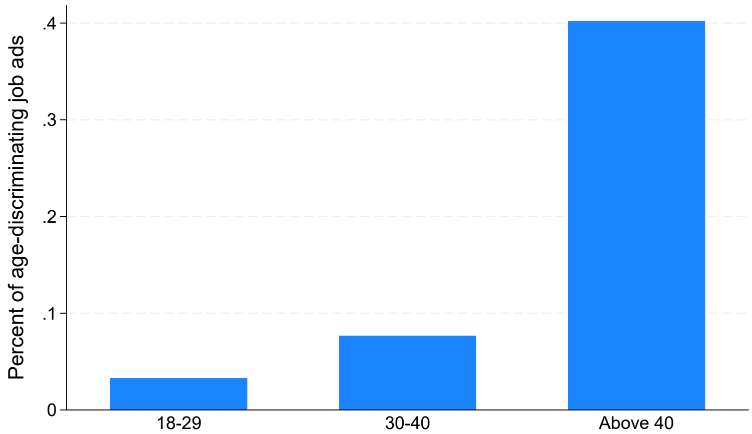
Figures and tables

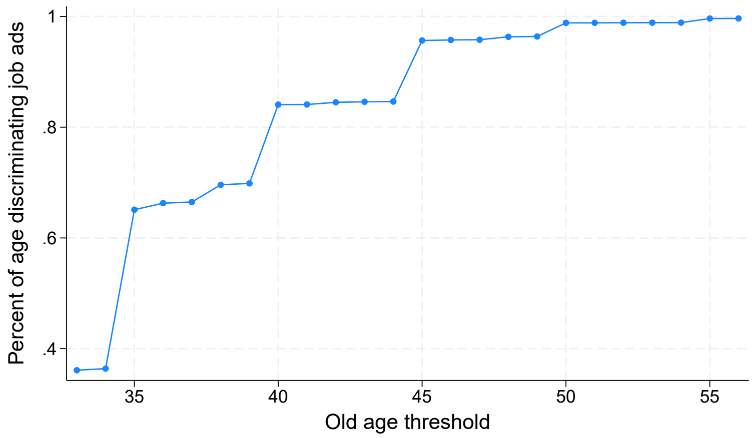
Figure 1
Percentage of Age Discriminating Ads by Age Groups



Notes: Figure 1 reports the percentage of job ads not available to each age group. We calculate the y-axis variable in the following way. We divide the total number of ads not available for each age group by the total number of ads to obtain the "Percentage of age-discriminating job ads. If an ad does not have explicit age discrimination, we regard it as available to all age groups. The job ads are not available if the minimum age required is larger than the upper end of the age group or if the maximum age required is lower than the lower end of the age group. To address concerns that some jobs are not available for a particular age group due to the nature of the job, we construct an alternative measure in Appendix Figure A.1, which removes such job postings. Our result remains unchanged. See discussion in Section 3.1.

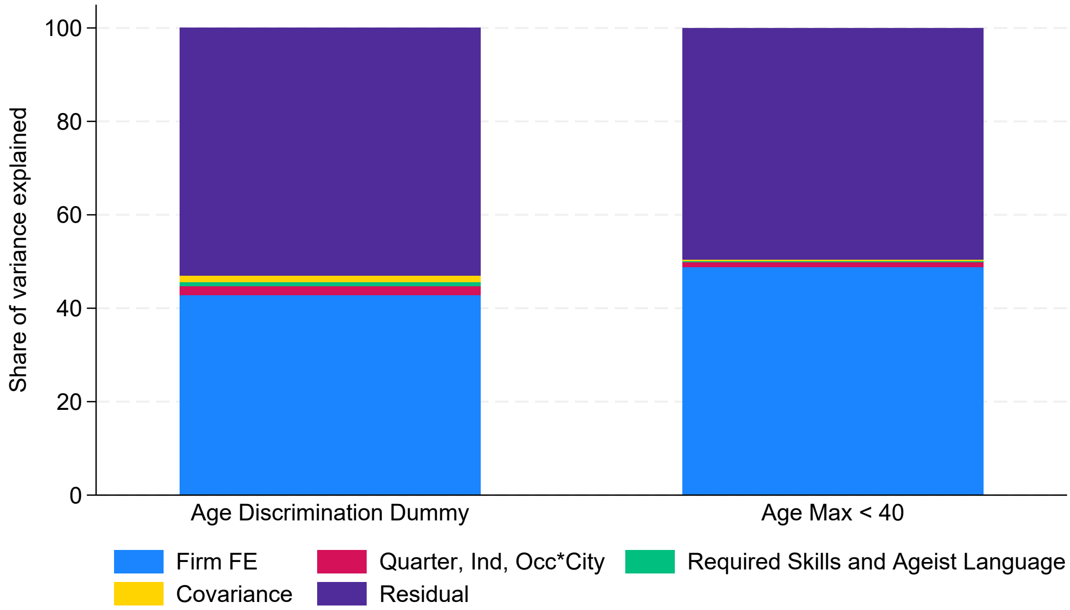
Figure 2

Percentage of Age Discriminating Ads against Older Workers by Old Age Threshold



Notes: Figure 2 reports the percent of age-discriminating job ads as we vary the maximum age threshold used to define the old age threshold. The y-axis variable is defined in the same way as that in Figure 1, i.e. we divide the total number of ads not available for each age group by the total number of ads. We vary the old age threshold from 33 to 56 to examine how the share of age-discriminating job ads varies with this threshold among all ads that have explicit age discrimination. See discussion in Section 3.1.

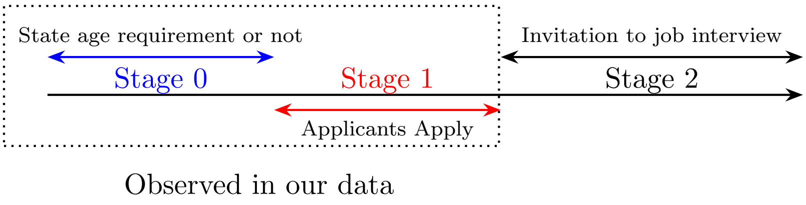
Figure 3
Variance Decomposition of Age Discrimination Decisions



Notes: Figure 3 shows variance decomposition of age discrimination decisions, namely, whether the job post explicitly requests a certain age group and whether older workers aged 40 and above are excluded in the stated age range. We use Equation 1 to calculate the predicted value of each set of variables defined in section A.2 and use the predicted value to obtain the variance of each component and covariances. The sum of such variances and covariances (i.e. those on the right-hand side of Equation 1) accounts for the total variance in the age discrimination decision. Overall, it is clear that most of the variations in the use of age discrimination come from the idiosyncratic behavior of the firms. See discussion in Section 3.4.

Figure 4

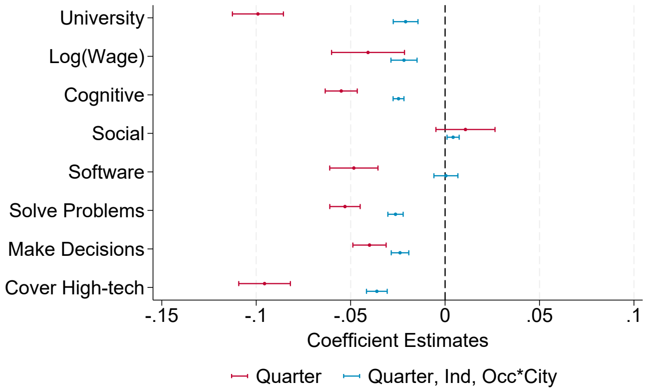
Timeline of Discrimination and Policy Decision Process



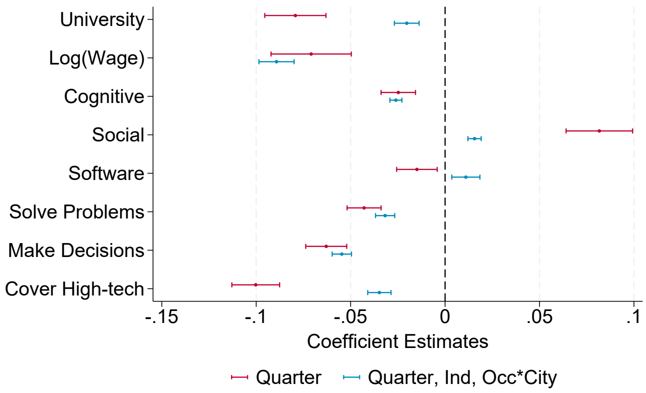
Notes: Figure 4 shows an illustration of a three-stage decision process during the recruitment. In Stage 0, firms explicitly state age restrictions, and in Stage 1, applicants decide where to apply based on the job postings. In State 2, the HR departments assess the applicant pool and decide whether or not to stick with the initial age restriction. Only Stage 0 and some group characteristics of applicants in Stage 1 are observable in our data. We do not observe interview and hiring decisions in Stage 2. See discussion in Section 4.

Figure 5
Job Skills and Age Discrimination Decisions

(a) Age Discrimination



(b) Age Max <40

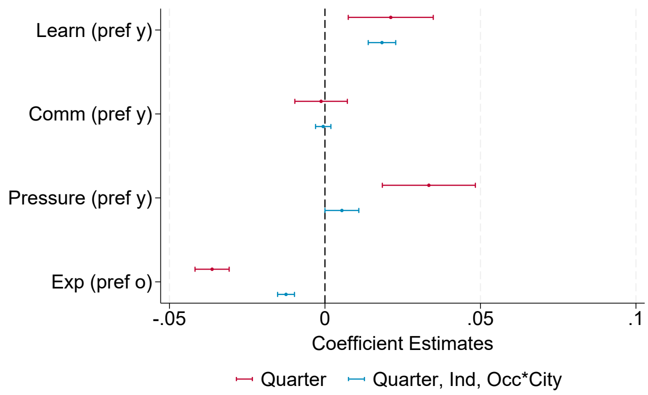


Notes: Figure 5 reports the regression coefficients of each skill variable, defined in Appendix Section A.2. Each bar is a 95% confidence interval from a separate regression. "University" is an indicator variable if the job ad requires at least a university degree. Using the wage range posted in the job ad, we use the mid-value to calculate the log wage. We present a list of relevant keywords used to identify other skill variables in Panel A and Panel B of the Appendix Table A.3. The outcome variable in panel a is an Age Discrimination dummy, which is equal to one if the ad has an explicit age requirement. The outcome variable in panel b is an Age Max <40 dummy, which is equal to one if the maximum age requirement is fewer than 40 (if the ad does not have an explicit age requirement, the maximum age requirement is imputed as 60). All specifications control for period effects and standard errors are clustered at the occupation*city level. The blue specification also has industry and occupation*city fixed effects. We estimate their coefficients using equation 4 and see coefficient estimates and magnitudes reported in Table 2. See discussion in Section 5.1.

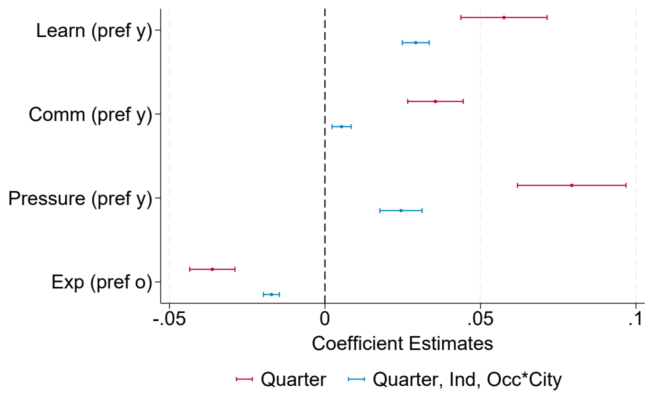
Figure 6

Ageist language and Age Discrimination Decisions

(a) Age Discrimination



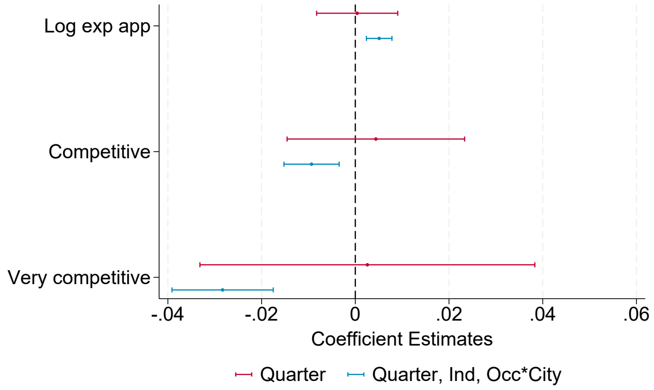
(b) Age Max <40



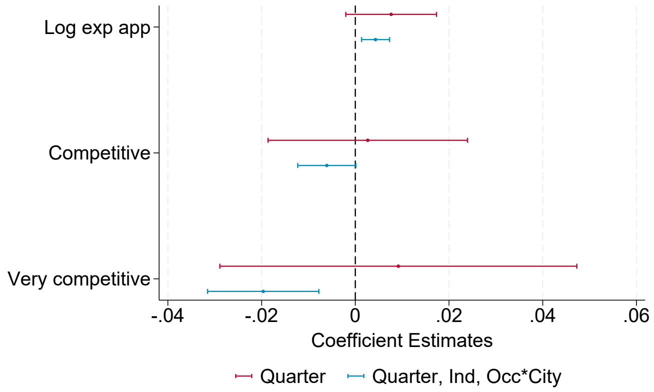
Notes: Figure 6 reports the correlations between each ageist language and age discrimination decisions. Each bar is a 95% confidence interval from a separate regression. We present a list of relevant keywords used to identify ageist language in Panel C of the Appendix Table A.3. We follow Burn et al. (2022) to define specific ageist language associated with three job skills: "Learning", "Communication", and "Experience". We define "Pressure" to account for job requirements that demand long overtime work hours which put older workers at a disadvantage. The outcome variable in panel a is an Age Discrimination dummy, which is equal to one if the ad has an explicit age requirement. The outcome variable in panel b is an Age Max <40 dummy, which is equal to one if the maximum age requirement is fewer than 40 (if the ad does not have an explicit age requirement, the maximum age requirement is imputed as 60). All specifications control for period effects and standard errors are clustered at the occupation*city level. The blue specification also has industry, and occupation*city fixed effects. We estimate their coefficients using equation 4 and see coefficient estimates and magnitudes reported in Table 3. See discussion in Section 5.1.

Figure 7
Competition in Labor Demand and Age Discrimination Decisions

(a) Age Discrimination



(b) Age Max <40



Notes: Figure 7 reports the correlations between age discrimination decisions and the competition levels in labor demand as well as the expected number of applicants. Bars of the same color in the same figure are estimated from a single regression with independent variables all together. Log expected number of applicants is defined as the log total application number within a job cell defined by education, industry, occupation, and city. "Competitive" is a dummy (1 if the total number of firms in the job cell is above the 75th percentile). "Very competitive" is a dummy (1 if the total number of firms is above the 90th percentile in the job cell). The outcome variable in panel a is an Age Discrimination dummy, which is equal to one if the ad has an explicit age requirement. The outcome variable in panel b is an Age Max <40 dummy, which is equal to one if the maximum age requirement is fewer than 40 (if the ad does not have an explicit age requirement, the maximum age requirement is imputed as 60). All specifications control for period effects and standard errors are clustered at the occupation*city level. The blue specification also has industry, and occupation*city fixed effects. We estimate their coefficients using equation 4 and see coefficient estimates and magnitudes reported in Table 4. See discussion in Section 5.1.

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	0.186
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	98,978.4
Number of positions advertised	
Unspecified	0.156
Mean number, when specified	5.6
Panel B. Firm characteristics	
Firm size	
Under 50	0.156
50-150	0.292
150-500	0.233
500-1,000	0.116
1,000-5,000	0.110
5,000-10,000	0.021
10,000+	0.063
Firm ownership type	
Private, domestic	0.819
Foreign	0.136
State-owned enterprise	0.041
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	0.365

Notes: Table 1 reports summary statistics. Job postings are scrapped from 51job.com from 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 is calculated 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 is specified. Firm characteristics are reported by employers on 51job.com. See discussion in Section 2.2.

Table 2

Job Skills, Tasks, and Firm's Decision on Age Discrimination

	Age Discrimination			Age Max < 40		
	(1)	(2)	(3)	(4)	(5)	(6)
Panel A: University						
	-0.0991	-0.0209	-0.0550	-0.0793	-0.0203	-0.0063
	(0.0069)	(0.0033)	(0.0035)	(0.0083)	(0.0033)	(0.0033)
Panel B: Log Wage						
	-0.0408	-0.0218	-0.0553	-0.0709	-0.0893	-0.0651
	(0.0098)	(0.0035)	(0.0052)	(0.0108)	(0.0047)	(0.0054)
Panel C: Cognitive						
	-0.0550	-0.0246	-0.0373	-0.0248	-0.0261	-0.0238
	(0.0043)	(0.0015)	(0.0014)	(0.0046)	(0.0016)	(0.0016)
Panel D: Social						
	0.0108	0.0043	-0.0029	0.0817	0.0156	0.0187
	(0.0080)	(0.0016)	(0.0018)	(0.0090)	(0.0018)	(0.0017)
Panel E: Software						
	-0.0483	0.0004	-0.0049	-0.0149	0.0110	0.0097
	(0.0065)	(0.0032)	(0.0039)	(0.0055)	(0.0038)	(0.0040)
Panel F: Solve Problems						
	-0.0530	-0.0262	-0.0364	-0.0429	-0.0317	-0.0272
	(0.0041)	(0.0021)	(0.0022)	(0.0046)	(0.0026)	(0.0026)
Panel G: Make Decisions						
	-0.0400	-0.0239	-0.0424	-0.0629	-0.0547	-0.0437
	(0.0045)	(0.0024)	(0.0027)	(0.0055)	(0.0026)	(0.0026)
Panel H: Cover High-tech						
	-0.0956	-0.0361	-0.0427	-0.1003	-0.0348	-0.0309
	(0.0070)	(0.0028)	(0.0032)	(0.0065)	(0.0032)	(0.0031)
Observations	7,722,319	7,722,319	7,722,319	7,722,319	7,722,319	7,722,319
Cluster No.	15,670	15,670	15,670	15,670	15,670	15,670
Adjusted R2	0.002	0.069	0.095	0.003	0.085	0.101
Mean of Y	0.478	0.478	0.478	0.334	0.334	0.334
Quarter FE	✓	✓	✓	✓	✓	✓
Industry FE		✓	✓		✓	✓
Occ*City FE		✓	✓		✓	✓
Exp Controls			✓			✓

Notes: Table 2 reports the correlations of each job requirement with the use of age discrimination. Each panel is a separate regression. Standard errors are clustered at the occupation city level. We use equation 4 to estimate. The outcome variables and skill variables are the same as those in Figure 5. Appendix Table A.4 tests for robustness with a long regression. See discussion in Section 5.1.

Table 3

Ageist Language and Age Discrimination Decisions

	Age Discrimination			Age Max < 40		
	(1)	(2)	(3)	(4)	(5)	(6)
Panel A: Learning (Prefer Young)						
	0.0212	0.0183	0.0245	0.0576	0.0292	0.0286
	(0.0070)	(0.0023)	(0.0022)	(0.0071)	(0.0022)	(0.0022)
Panel B: Communication (Prefer Young)						
	-0.0012	-0.0006	-0.0026	0.0355	0.0054	0.0042
	(0.0043)	(0.0013)	(0.0013)	(0.0046)	(0.0016)	(0.0015)
Panel C: Pressure (Prefer Young)						
	0.0334	0.0054	0.0051	0.0794	0.0245	0.0252
	(0.0076)	(0.0028)	(0.0031)	(0.0089)	(0.0035)	(0.0036)
Panel D: Experience (Prefer Old)						
	-0.0363	-0.0125	-0.0236	-0.0362	-0.0172	-0.0192
	(0.0028)	(0.0014)	(0.0016)	(0.0037)	(0.0013)	(0.0013)
Observations	7,722,319	7,722,319	7,722,319	7,722,319	7,722,319	7,722,319
Cluster No.	15,670	15,670	15,670	15,670	15,670	15,670
Adjusted R2	0.001	0.069	0.095	0.001	0.085	0.101
Mean of Y	0.478	0.478	0.478	0.334	0.334	0.334
Quarter FE	✓	✓	✓	✓	✓	✓
Industry FE		✓	✓		✓	✓
Occ*City FE		✓	✓		✓	✓
Exp Control			✓			✓

Notes: Table 3 reports the correlations of each ageist language with the use of age discrimination. Each panel is a separate regression. We use equation 4 to estimate. Standard errors are clustered at the occupation city level. The outcome variables and ageist language variables are the same as those in Figure 6. Appendix Table A.5 tests for robustness with a long regression. See discussion in Section 5.1.

Table 4
Search Cost, Competition in Labor Demand and Firms' Decision on Age Discrimination

	Age Discrimination			Age Max < 40		
	(1)	(2)	(3)	(4)	(5)	(6)
Ln app pool	0.000	0.005	0.007	0.008	0.004	0.005
	(0.004)	(0.001)	(0.002)	(0.005)	(0.002)	(0.002)
High Competition	0.004	-0.009	-0.008	0.003	-0.006	-0.008
	(0.010)	(0.003)	(0.003)	(0.011)	(0.003)	(0.003)
Very High Competition	0.003	-0.028	-0.028	0.009	-0.020	-0.026
	(0.018)	(0.006)	(0.006)	(0.019)	(0.006)	(0.006)
Observations	7,722,319	7,722,319	7,722,319	7,722,319	7,722,319	7,722,319
Cluster No.	15,670	15,670	15,670	15,670	15,670	15,670
Adjusted R2	0.000	0.069	0.095	0.002	0.085	0.101
Mean of Y	0.478	0.478	0.478	0.334	0.334	0.334
Quarter FE	✓	✓	✓	✓	✓	✓
Industry FE		✓	✓		✓	✓
Occ*City FE		✓	✓		✓	✓
Exp Controls			✓			✓

Notes: Table 4 reports the correlations between the use of age discrimination and log expected application number, as well as competition among firms. We use equation 4 to estimate. Standard errors are clustered at the occupation city level. The outcome variables are the same as those in Figure 7. Using our preferred specification of column 2, a 100% increase in the expected number of applicants increases the likelihood of explicitly requesting an age group by 1.1%, and firms in a "High Competition" job cell or a "Very High Competition" job cell are 2.0% and 5.9% less likely to have age discrimination against workers relative to firms in a less competitive job cell. From column 5, a 100% increase in the expected number of applicants increases the likelihood of explicitly requesting younger workers aged below 40 by 1.3%, and firms in a "High Competition" job cell or a "Very High Competition" job cell are 1.8% and 5.9% less likely to have age discrimination against workers aged 40 and above. See discussion in Section 5.1.

Table 5
Firm's Decision on Age Discrimination and Number of Applicants

	Number of Applicants		
	(1)	(2)	(3)
Panel A: Age Discrimination			
	-10.0263	-1.1709	-2.3495
	(1.8604)	(0.4073)	(0.3886)
Panel B: Age Max < 40			
	-12.5407	-5.1273	-1.0792
	(1.5795)	(0.7301)	(0.4232)
Observations	7,722,319	7,722,319	7,722,319
Cluster No.	15,670	15,670	15,670
Adjusted R2	0.003	0.160	0.188
Mean of Y	52.534	52.534	52.534
Quarter FE	✓	✓	✓
Industry FE		✓	✓
Occupation*City FE		✓	✓
Additional Controls			✓

Notes: Table 5 reports how age discrimination decisions correlate with the number of applicants. Each panel is a separate regression. We use equation 5 to estimate. Standard errors are clustered at the occupation city level. The outcome variable is the number of applications received by the job ad. Our preferred specification is Column 3 which additionally controls the experience requirements and the log wage offered. When firms explicitly request a certain age group, they receive -2.3 fewer applications on average (4.5% in percentage point) and if firms only request younger workers aged below 40, they receive -1.1 fewer applications (2.1% in percentage point). See discussion in Section 5.2.

Table 6
Firm's Decision on Age Discrimination and Share of Different Age Groups

	Share of Applicants by Age Group				
	(1)	(2)	(3)	(4)	(5)
	⩽23	24-26	27-30	31-40	⩾41
Panel A: Age Discrimination					
	0.0131	-0.0021	-0.0068	-0.0064	0.0022
	(0.0007)	(0.0004)	(0.0004)	(0.0006)	(0.0004)
Panel B: Age Max < 40					
	0.0393	0.0110	-0.0039	-0.0262	-0.0202
	(0.0010)	(0.0007)	(0.0006)	(0.0008)	(0.0013)
Observations	7,722,319	7,722,319	7,722,319	7,722,319	7,722,319
Cluster No.	15,670	15,670	15,670	15,670	15,670
Adjusted R2	0.229	0.114	0.053	0.200	0.204
Mean of Y	0.233	0.179	0.197	0.284	0.107
Quarter FE	✓	✓	✓	✓	✓
Industry FE	✓	✓	✓	✓	✓
Occupation*City FE	✓	✓	✓	✓	✓

Notes: Table 6 reports the correlations between the share of applicants by each age group with the use of age discrimination decisions. We use equation 5 to estimate the coefficients. Standard errors are clustered at the occupation city level. The outcome variable is the share of applicants in each age group. The age group categories, 23, 24-26, 27-30, 31-40, and 41 or older, follow thresholds defined by 51job.com as explained in Appendix Section A.2. The independent variable is the Age Discrimination dummy or the Age Max <40 dummy. In Appendix Table A.6, we test the robustness of our results with only a quarter fixed effect (Panels A and B) or with additional controls including experience requirements and log wage offered (Panels C and D). Our results remain consistent. See discussion in Section 5.2.

Table 7
Firm's Decision on Age Discrimination and High-Skilled Applicants

	Applicant Has A University Degree		
	(1)	(2)	(3)
Panel A: Age Discrimination			
	-0.0643	-0.0290	-0.0271
	(0.0035)	(0.0010)	(0.0009)
Panel B: Age Max < 40			
	-0.0482	-0.0289	-0.0165
	(0.0052)	(0.0014)	(0.0010)
Observations	7,722,319	7,722,319	7,722,319
Cluster No.	15,670	15,670	15,670
Adjusted R2	0.008	0.372	0.425
Mean of Y	0.469	0.469	0.469
Quarter FE	✓	✓	✓
Industry FE		✓	✓
Occupation*City FE		✓	✓
Additional Controls			✓

Notes: Table 7 shows that the share of applicants with a university degree is negatively correlated with the use of age discrimination decisions. Using our preferred specification in column 3, the inclusion of explicit age discrimination and having the age requirement of below 40 will reduce the share of applicants with a university degree by 5.8% and 3.5% respectively. The outcome variable is an indicator variable if the applicant has at least a university degree. Additional controls include experience requirements and log offered wage. Standard errors are clustered at the occupation city level. See discussion in Section 5.2.

Table 8
Firm's Decision on Age Discrimination and Compliance Rate at
Different Maximum Age Thresholds

	Compliance Rate (Max 40)		Compliance Rate (Max 30)	
	(1)	(2)	(3)	(4)
Panel A: University				
	-0.0012	-0.0032	-0.0044	-0.0105
	(0.0017)	(0.0010)	(0.0035)	(0.0018)
Panel B: Cognitive				
	-0.0007	-0.0017	-0.0147	-0.0066
	(0.0011)	(0.0007)	(0.0022)	(0.0009)
Panel C: Social				
	-0.0049	-0.0044	-0.0336	-0.0132
	(0.0019)	(0.0005)	(0.0044)	(0.0010)
Panel D: Software				
	0.0072	0.0013	0.0025	-0.0015
	(0.0016)	(0.0008)	(0.0027)	(0.0017)
Panel E: Solve Problems				
	-0.0039	-0.0057	-0.0080	-0.0068
	(0.0015)	(0.0009)	(0.0021)	(0.0014)
Panel F: Make Decisions				
	-0.0048	-0.0059	-0.0104	-0.0056
	(0.0016)	(0.0009)	(0.0027)	(0.0015)
Panel G: Cover High-tech				
	0.0076	0.0005	0.0204	0.0026
	(0.0019)	(0.0009)	(0.0034)	(0.0014)
Observations	3,609,392	3,609,392	3,609,392	3,609,392
Cluster No.	12,140	12,140	12,140	12,140
Adjusted R2	0.044	0.131	0.029	0.121
Mean of Y	0.919	0.919	0.926	0.926
Quarter FE	✓	✓	✓	✓
Industry FE		✓		✓
Occupation*City FE		✓		✓
Additional Controls	✓	✓	✓	✓

Notes: Table 8 reports correlations between the compliance rate and different job requirements. Each panel is a separate regression. We estimate using equation 6. Standard errors are clustered at the occupation city level. The outcome variable, compliance rate, is defined as the number of applicants complying with the maximum requested age divided by the total number of applicants per job ad. We construct two versions of the compliance rates using maximum age thresholds of 30 and 40. The job requirement variables are the same as those in Table 2, defined in Appendix Section A.2. All regressions additionally control for log wage and experience requirements. See discussion in Section 5.2.

Appendix

A Data Appendix

A.1 Data Representativeness

In this section, we examine the representativeness of our 51job sample. As detailed in Appendix Table A.1, job postings on the 51job platform exhibit distinct characteristics compared to the overall Chinese labor force. Specifically, the postings target a younger demographic with higher educational requirements and are predominantly contributed by private sector firms. While fewer than a quarter of the urban workforce is under 30 years old, 51job ads mostly seek applicants with an average age below 30. In terms of educational requirements, about 67% of employed workers in 2018 had completed their high school education or below, whereas less than 42% of 51job.com ads did not explicitly request a college degree or higher. Furthermore, while over 36% of employees worked in state-owned enterprises or collectives, less than 5% of job ads were published by firms in those sectors. Thus, this comparison indicates that while 51job covers a wide range of job types and posts a substantial number of ads, it primarily caters to private-sector firms seeking young and highly educated applicants.

To further understand the relationship between 51job ads and the overall Chinese labor market, we compared the distribution of general employment with that of ads on 51job across broad occupation and industry categories. Although the industry and occupation categories on 51job do not precisely align with those in the yearbook, several conclusions can be drawn. First, the CS/internet/communication/electronics industries are significantly overrepresented on 51job, accounting for 28% of all vacancies, compared to about 2% of the overall workforce. Second, the most underrepresented industries on 51job are trade/consumption/manufacturing/operation and service, relative to their share in the total working population. Third, ads targeting professional and technical workers are overrepresented on 51job, while postings for public servants are underrepresented.

Overall, the distribution of vacancies across occupations on 51job is similar to that of the nationally representative sample, with a correlation of more than 0.7.[51] Thus, job ads on 51job broadly reflect the Chinese economy and represent a substantial segment of the labor market.

A.2 Variable definitions

We begin by considering the labor market's supply side, where workers assess employers' requirements. We have identified several key features that reflect workers' actions given firms' age discrimination decision.

Firstly, we examine the number of applicants per job ad, an equilibrium outcome, to assess whether firms' age discrimination decisions are associated with the size of the application pool. Intuitively, specifying preferred age groups will turn away workers from other age groups, although it's not clear if the preferred age group will apply more or less than those turned away.

Secondly, we measure the quality of the application pool at the job ad level by looking at the percentage of applicants holding university degrees or higher. Lastly, we examine the age distribution of job applicants, categorized into the following age groups: 23 and below, 24 to 26, 27 to 30, 31 to 40, and 41 and above. It is worth noting that this age distribution follows the arbitrary categorizations adopted by 51job, and we do not have access to more detailed age information. Nevertheless, this information is valuable, especially when prior research has limited evidence on the supply side of labor markets.

Turning to the labor demand side, we first focus on the search concerns of firms. We use the number of applicants to construct the expected number of applications for a job cell which is defined by a firm's educational requirements, industry, and the interaction of occupation and city. We calculate the total number of applications in each job cell

[51] Marinescu (2017), Marinescu and Rathelot (2018), and Marinescu and Wolthoff (2020) found that the vacancies and job applicants on CareerBuilder.com are representative of the U.S. labor market, demonstrating that the distribution of vacancies across occupations is similar to that of the CPS, with a correlation of over 0.7.

by aggregating the actual application numbers of all job ads within the job cell. This measure serves as a proxy for the expected number of applicants.

Another search concern is related to the competition level among the employers. We define two separate indicator variables "High Competition" and "Very High Competition (firm)" at the ad level based on the number of firms in each job cell. The former is equal to one if the number of firms that posted a job ad in a job cell is above the 75th percentile and the threshold for the latter is the 90th percentile.

Drawing on the framework in Deming and Kahn (2018),[52] we tested the applicability of three specific job skills categories - "Cognitive", "Social", and "Software" - in predicting firms' age discrimination tendencies. In Panel A of Appendix Table A.3, we present a list of relevant keywords used to identify skills in each category. We measure cognitive ability requirements by examining both cognitive and educational requirements. The selection of social skills is, in part, informed by Deming (2017) who documents the growing importance of social skills in the labor market. Lastly, Software is relevant to a typical skill-related stereotype that older workers are often viewed as having lower competence, as identified by Burn et al. (2022) in their analysis of ageist language in job advertisements.

As per Gelblum (2020) methodology,[53] we investigate whether job ads feature tasks such as "Cover High-tech" to gauge whether firms prefer younger workers. Additionally, we further refine Gelblum's task categorization by splitting "making decisions and solving problems" into two separate tasks to assess their relative predictive power for age discrimination. These three types of tasks require strong analytical and cognitive skills. Among them, high-tech tasks, in particular, serve as a gauge for whether firms prefer younger workers, who may be perceived as more familiar with emerging high-tech fields such as artificial intelligence. We also present relevant keywords used in Panel B of

[52]The authors define 10 general skills based on keywords commonly found in job postings and their relevance to listed wage and firm performance. The categories include cognitive, social, management, financial, and software skills, among others. These skills were selected for their general applicability across a wide range of professional occupations.

[53]Although Gelblum characterizes tasks as gender-specific, the measurement of these tasks is also applicable to general analysis.

Appendix Table A.3.

Informed by the industrial psychology research analyzed in Burn et al. (2022), we also identify specific ageist language associated with three job skills: "Learning", "Communication", and "Experience". The first two may confer an advantage to younger workers who can learn more quickly and build better rapport with customers or colleagues. In contrast, the "Experience" variable favors older workers who have a wealth of knowledge and practical expertise to draw upon. We list the keywords used in Panel C of Appendix Table A.3.

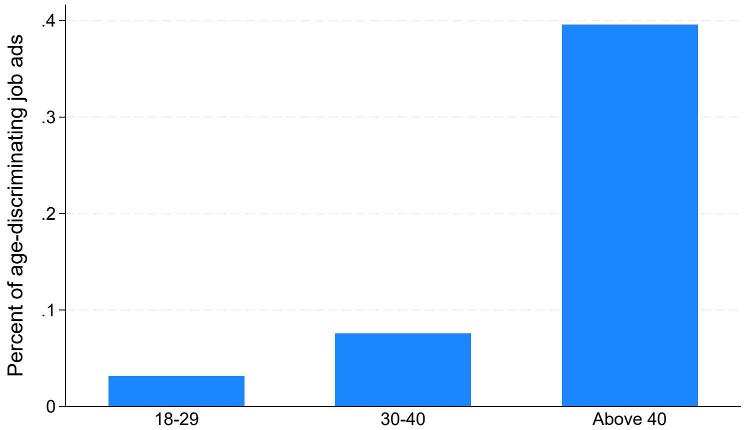
There is ample anecdotal evidence suggesting that many firms require employees to manage high-pressure situations, involving long working hours and a competitive environment.[54] This type of high-stress setting often puts older workers with more family responsibilities at a disadvantage. To capture this crucial aspect, we introduce a new indicator variable, "Pressure" which accounts for the influence of high-pressure work environments on age discrimination decisions. Appendix Table A.3 provides a comprehensive list of the specific phrases and keywords used to classify job skills, job tasks, and ageist language, respectively.

We also present summary statistics of the defined variables in Appendix Table A.7 to demonstrate the extent of variations of these variables across job postings.

[54] Average work hours per week per employed person in China is 46.1, as compared to an average of 40.2 in Asia and the Pacific, 38.0 in the US, and 34.2 in Germany, according to work statistics from International Labour Organization (2024).

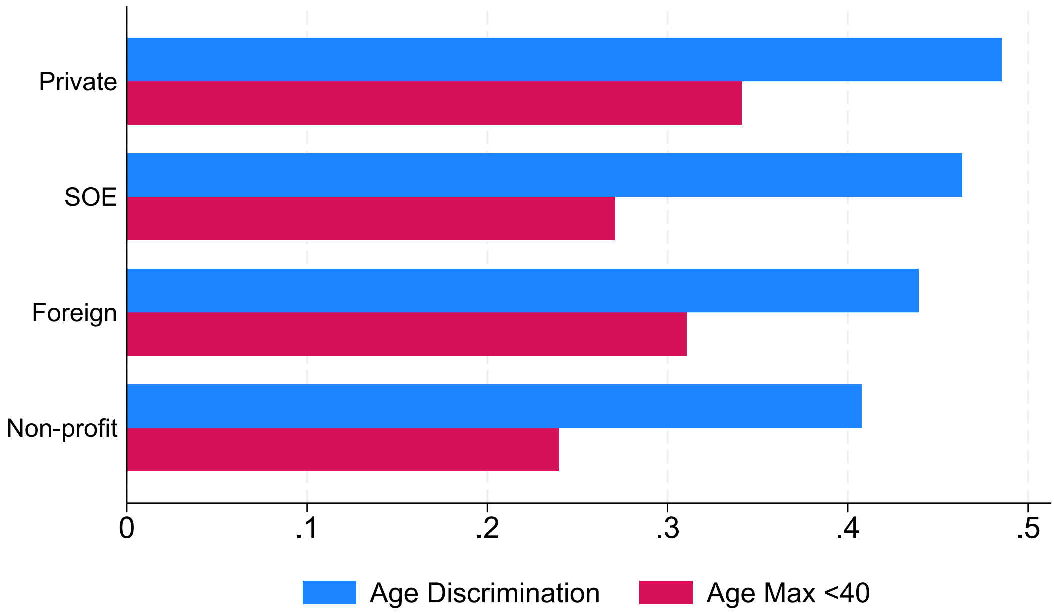
B Appendix figures and tables

Figure A.1
Percentage of Age Discriminating Ads by Age Groups



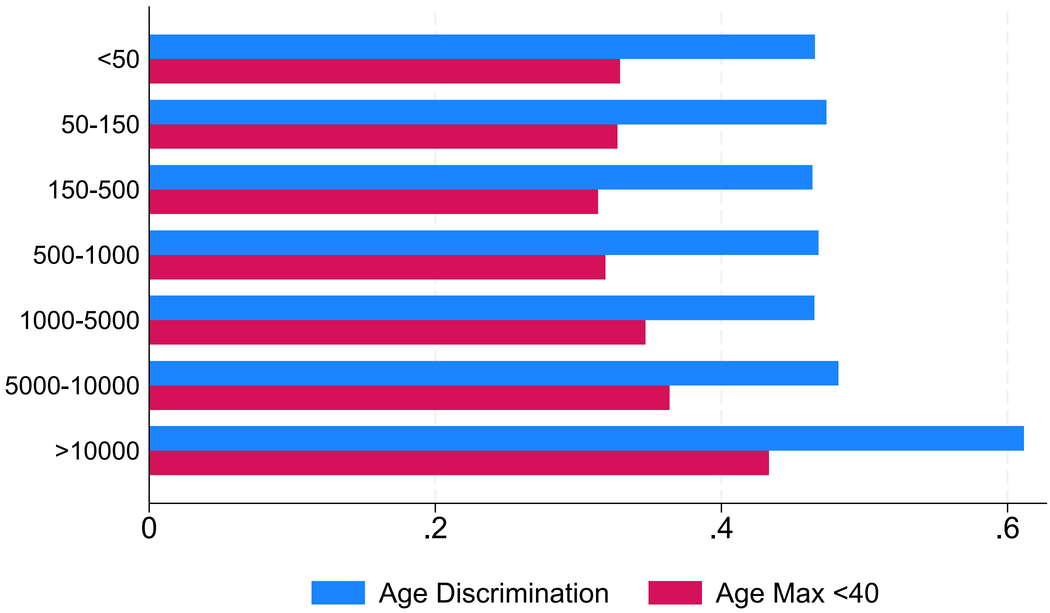
Notes: Appendix Figure A.1 reports the percentage of job ads not available to each age group, after removing job ads in a job cell that never has a job ad available to a particular age group. We construct "Percentage of age-discriminating job ads" in the following way. For each education, industry, occupation*city cell, if there is at least one ad that is available to each age group (18-29, 30-40, or above 40), we assume all ads within that cell are available. Aggregating all cells, we have the total number of ads that should be available to each group in the absence of age discrimination. We divide the total number of ads not available to each age group (18-29, 30-40, or above 40) with explicit age requirements by the total number of ads that should be available to each group in the absence of age discrimination to obtain the percentage of age-discriminating ads. An alternative approach is to divide the total number of available ads by the total number of ads, which is reported in Figure 1. See discussion in Section 3.1.

Figure A.2
Firm Type and Age Discrimination Decisions



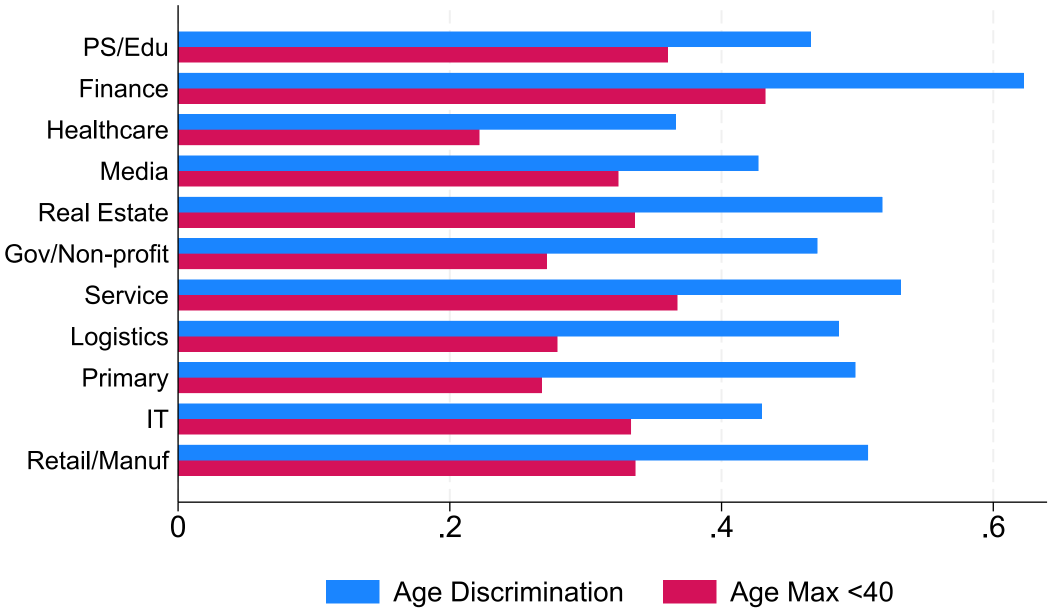
Notes: Appendix Figure A.2 reports the use of age discrimination by each firm type. In particular, domestic privately owned firms are more likely to use age discrimination relative to other firm types. SOEs are state-owned enterprises. The indicator variables on the x-axis are the Age Discrimination dummy which is equal to one if the ad has an explicit age requirement and the Age Max <40 dummy which is equal to one if the maximum age requirement is fewer than 40 (if the ad does not have an explicit age requirement, the maximum age requirement is imputed as 60). See discussion in Section 3.2.

Figure A.3
Firm Size and Age Discrimination Decisions



Notes: Appendix Figure A.3 reports the use of age discrimination by each firm size. In particular, firms with the largest employment size are more likely to use age discrimination relative to other firm sizes. The indicator variables on the x-axis are the Age Discrimination dummy which is equal to one if the ad has an explicit age requirement and the Age Max <40 dummy which is equal to one if the maximum age requirement is fewer than 40 (if the ad does not have an explicit age requirement, the maximum age requirement is imputed as 60). See discussion in Section 3.2.

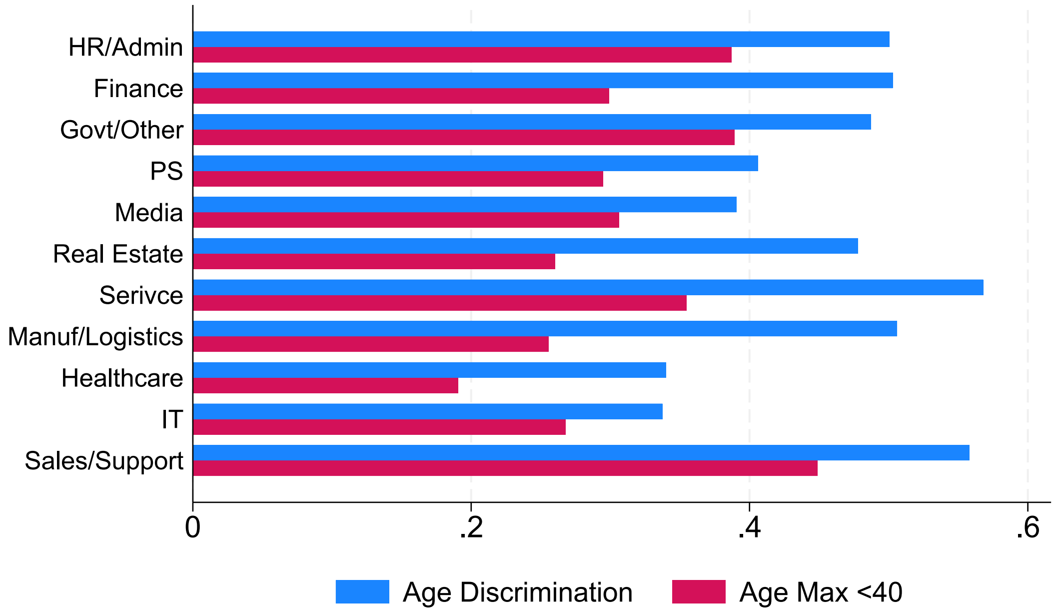
Figure A.4
Industry and Age Discrimination Decisions



Notes: Appendix Figure A.4 reports the share of ads with age discrimination by industry using major groups defined by 51job.com. Major industry groups are Professional Services (PS) or Education, Finance, Healthcare, Media, Real Estate, Government or Nonprofit Organizations, Services, Logistics, Primary Industry (including Energy and Material), IT, and Retail or Manufacturing. The indicator variables on the x-axis are the Age Discrimination dummy which is equal to one if the ad has an explicit age requirement and the Age Max <40 dummy which is equal to one if the maximum age requirement is fewer than 40 (if the ad does not have an explicit age requirement, the maximum age requirement is imputed as 60). See discussion in Section 3.3.

Figure A.5

Occupation and Age Discrimination Decisions



Notes: Appendix Figure A.5 reports the share of ads with age discrimination by occupation using major groups defined by 51job.com. Major occupation groups are Human Resources or Administration or Management, Finance, Government or Others, Professional Services (PS) (including Consulting, Law, Education, and Research), Advertising or Media or Arts, Real Estate, Service, Manufacturing or Logistics (including Operations and Procurement), Healthcare (including Biotechnology or Pharmaceuticals or Nursing), IT (including Telecommunications or Electronics), Sales or Customer Service. The indicator variables on the x-axis are the Age Discrimination dummy which is equal to one if the ad has an explicit age requirement and the Age Max <40 dummy which is equal to one if the maximum age requirement is fewer than 40 (if the ad does not have an explicit age requirement, the maximum age requirement is imputed as 60). See discussion in Section 3.3.

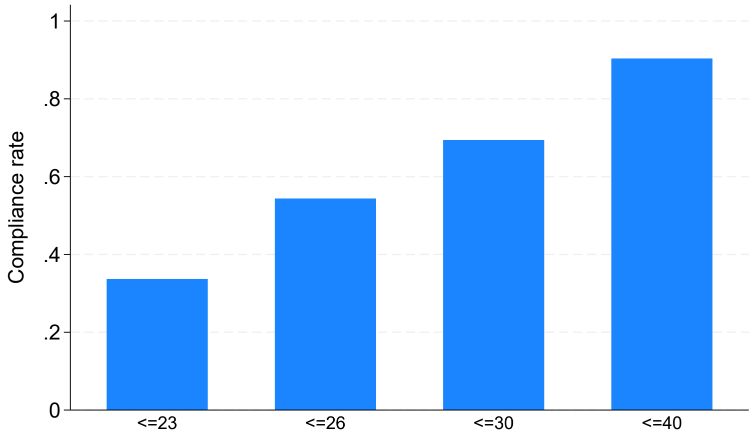
Figure A.6

Histogram of vacancy shares with explicit age discrimination at the firm level

Notes: Appendix Figure A.6 reports the share of ads with age discrimination by firms. It shows over 40% of firms either always or never explicitly request a certain age group. Each firm has a unique firm ID in our data. See discussion in Section 3.4.

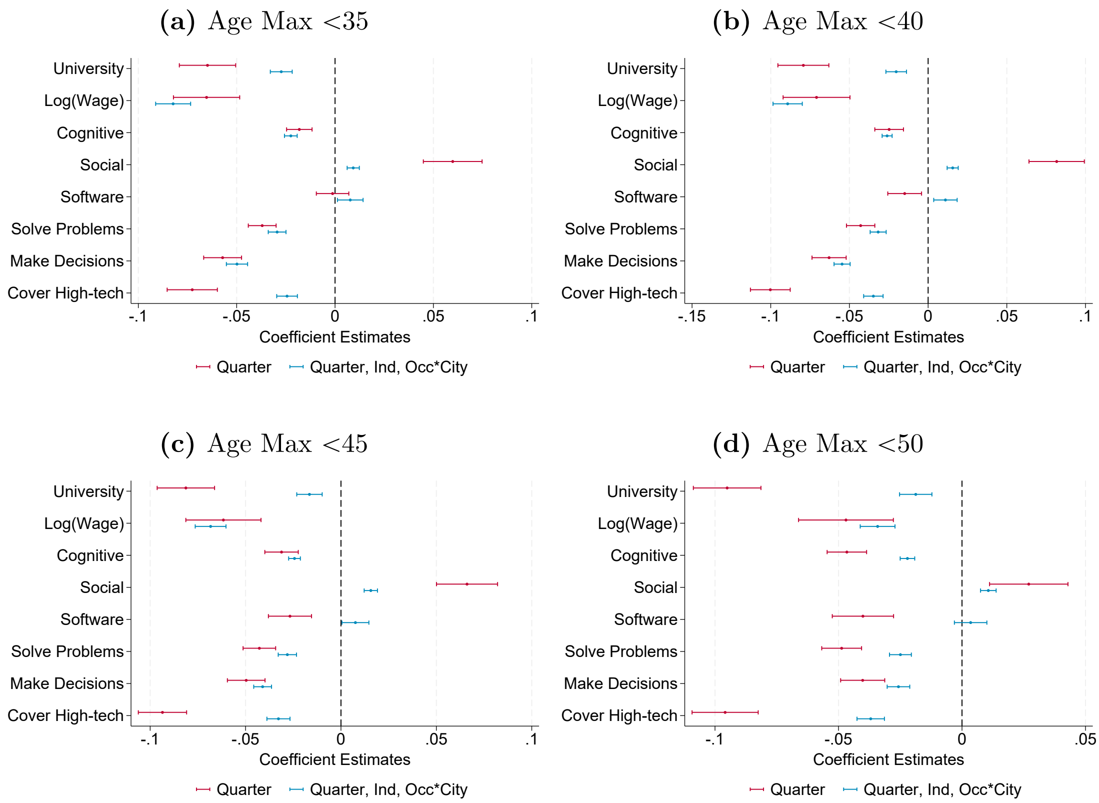
Figure A.7

Compliance rate by age groups



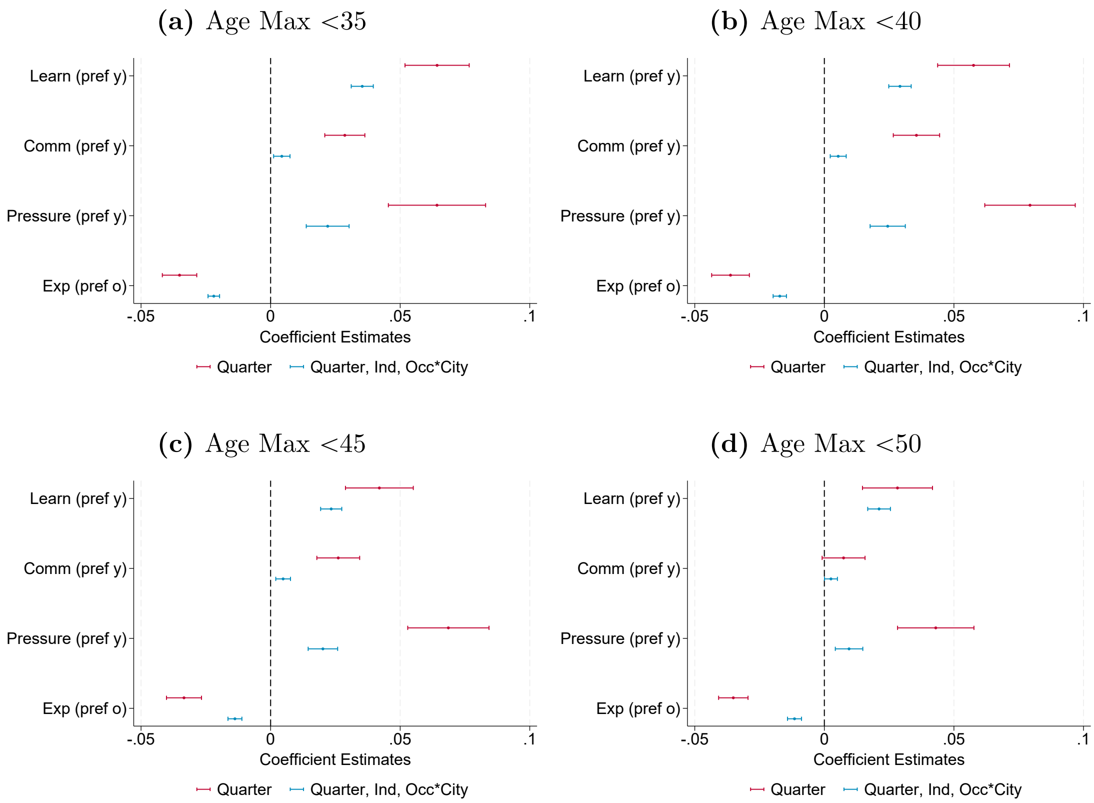
Notes: Appendix figure A.7 reports the raw compliance rates of applicants. We measure the compliance rate at the job ad level, a ratio whose numerator is the number of applicants with an age below or equal to the maximum age requirement specified by the job ads and whose denominator is the total number of applicants. We consider maximum age thresholds of 23 and below, 26 and below, 30 and below, and 40 and below. The age categories of the applicants are defined by 51job.com, which only provides us with the share of workers in each age category: 23 and below, 24 to 26, 27 to 30, 31 to 40, and 41 and above. See discussion in Section 3.5.

Figure A.8
Job Skills and Age Discrimination Decisions



Notes: Appendix Figure A.8 reports the correlations between job skill requirements and different versions of Age Max indicators with different cut-offs for the maximum age requested. The regression specification and independent variables are the same as Figure 5b but outcome variables vary according to the cut-off. See discussion in Section 5.1.

Figure A.9
Ageist language and Age Discrimination Decisions



Notes: Appendix Figure A.9 reports the correlations between ageist language and different versions of Age Max indicators with different cut-offs for the maximum age requested. The regression specification and independent variables are the same as Figure 6 but outcome variables vary according to the cut-off. See discussion in Section 5.1.

Table A.1

Descriptive Statistics, 51job.com Ads Versus 2019 China Labour Statistical Yearbook

	Share in category	
	(1) Yearbook	(2) 51job
Gender		
Male	57.1	63.5
Wage		
Average wage	82,413.0	98,978.4
Age		
29 or below	21.8	58.5
30–39	30.4	39.1
40–49	28.4	2.4
50 or above	19.4	0.1
Education		
High school or below	67.9	40.9
College	15.8	40.2
University or above	16.3	18.9
Industry		
Professional Service/Education/Training	6.3	11.9
Accounting/Finance/Banking/Insurance	2.8	6.8
Pharmacy/Medical	3.3	5.8
Advertising/Media	1.2	3.5
Real Estate/Construction	9.2	12.9
Government/NPO/Others	7.7	3.2
Service	14.2	3.4
Logistics/Transportation	6.0	1.8
Energy/Materials	2.9	2.7
CS/Internet/Communication/Electronics	2.3	28.0
Trade/Consumption/Manufacturing/Operation	44.3	20.0
Occupation		
Senior management	2.6	9.3
Professional and technical	13.2	29.3
Sales and service	41.1	37.7
Production and construction	27.7	21.7
Public servants	15.4	1.9
Firm ownership		
Private sector	64.7	95.8
SOEs and collectives	35.3	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 2019 China Labour Statistical Yearbook contains information and summary statistics related to the Chinese labor market in 2018. The 51job data was collected from November 1, 2018 to April 30, 2019.

Table A.2
Number of Expected Applicants and Firm's Decision on Age Discrimination

	Age Discrimination			Age Max < 40		
	(1)	(2)	(3)	(4)	(5)	(6)
Ln app pool	0.0005	0.0022	0.0043	0.0085	0.0023	0.0021
	(0.0029)	(0.0010)	(0.0011)	(0.0034)	(0.0010)	(0.0010)
Observations	7,722,319	7,722,319	7,722,319	7,722,319	7,722,319	7,722,319
Cluster No.	15,670	15,670	15,670	15,670	15,670	15,670
Adjusted R2	0.000	0.069	0.095	0.002	0.085	0.101
Mean of Y	0.478	0.478	0.478	0.334	0.334	0.334
Quarter FE	✓	✓	✓	✓	✓	✓
Industry FE		✓	✓		✓	✓
Occ*City FE		✓	✓		✓	✓
Exp Controls			✓			✓

Notes: Appendix Table A.2 reports that age discrimination is more likely to be used when the expected number of applicants is high. Using our preferred specification in column 2, a 100% in the log expected number of applications increases the use of age discrimination by 0.5% and column 4 indicates the use of age discrimination against workers aged 40 and above increases by 0.7%. The outcome variables and the predictors are the same as those in Table 4. We use equation 4 to estimate. The Standard errors are clustered at the occupation city level. See discussion in Section 5.1.

Table A.3

Description of Job Skills, Tasks and Ageist Language

	Keywords and Phrases
Panel A. Job Skills	
Cognitive	Problem solving, research, analytical, critical thinking, math, statistics
Social	Communication, teamwork, collaboration, negotiation, presentation
Software (specific)	Programming language or specialized software (e.g., Java, SQL, Python)
Panel B. Job Tasks	
Solve problems	Solve problems
Make decisions	Make decisions
Cover high-technology	AI, new energy, new material, aviation, biotechnology, electronic
Panel C. Ageist Language	
Learning	Participate in training programs, learn new techniques, personal development
Communication	Interpersonal [social] skills, sincere when talking, enjoyable stories
Pressure	Able to withstand pressure
Experience	Solid [more] [useful] experience

Notes: We detail the definitions used for keyword extractions from the open texts of job postings scrapped from 51job.com. See our discussion of the definitions in Appendix Section A.2 and our discussion of the results in Section 5.1.

Table A.4
Job Skills and Firm's Decision on Age Discrimination, Long Regressions

	Age Discrimination			Age Max < 40		
	(1)	(2)	(3)	(4)	(5)	(6)
University	-0.0773	-0.0133	-0.0444	-0.0495	0.0049	0.0053
	(0.0072)	(0.0033)	(0.0032)	(0.0096)	(0.0033)	(0.0031)
Log Wage	-0.0138	-0.0143	-0.0436	-0.0582	-0.0839	-0.0616
	(0.0093)	(0.0037)	(0.0051)	(0.0118)	(0.0052)	(0.0055)
Cognitive	-0.0379	-0.0193	-0.0265	-0.0118	-0.0141	-0.0167
	(0.0031)	(0.0013)	(0.0014)	(0.0034)	(0.0016)	(0.0016)
Social	0.0287	0.0129	0.0109	0.1047	0.0318	0.0309
	(0.0067)	(0.0017)	(0.0019)	(0.0084)	(0.0018)	(0.0017)
Software	-0.0313	0.0038	0.0008	-0.0010	0.0146	0.0123
	(0.0053)	(0.0032)	(0.0038)	(0.0043)	(0.0037)	(0.0039)
Solve Problem	-0.0262	-0.0164	-0.0208	-0.0310	-0.0183	-0.0177
	(0.0037)	(0.0020)	(0.0023)	(0.0045)	(0.0025)	(0.0026)
Make Decision	-0.0194	-0.0158	-0.0299	-0.0534	-0.0386	-0.0353
	(0.0057)	(0.0027)	(0.0029)	(0.0067)	(0.0029)	(0.0028)
Cover High-tech	-0.0641	-0.0316	-0.0321	-0.0696	-0.0248	-0.0254
	(0.0059)	(0.0027)	(0.0032)	(0.0063)	(0.0031)	(0.0033)
Observations	7,722,319	7,722,319	7,722,319	7,722,319	7,722,319	7,722,319
Cluster No.	15,670	15,670	15,670	15,670	15,670	15,670
Adjusted R2	0.011	0.071	0.099	0.019	0.094	0.106
Mean of Y	0.478	0.478	0.478	0.334	0.334	0.334
Quarter FE	✓	✓	✓	✓	✓	✓
Industry FE		✓	✓		✓	✓
Occ*City FE		✓	✓		✓	✓
Exp Controls			✓			✓

Notes: Appendix Table A.4 reports the correlations of job requirements with age discrimination decisions using all independent variables in one regression. The outcome variables and the skill variables are the same as those in Figure 5 and Table 2. We use equation 4 to estimate. The Standard errors are clustered at the occupation city level. See discussion in Section 5.1.

Table A.5
Ageist Language and Age Discrimination Decisions, Long Regression

	Age Discrimination			Age Max < 40		
	(1)	(2)	(3)	(4)	(5)	(6)
Learning (Prefer Young)	0.0194	0.0184	0.0250	0.0475	0.0276	0.0272
	(0.0062)	(0.0022)	(0.0022)	(0.0062)	(0.0023)	(0.0023)
Communication (Prefer Young)	-0.0040	-0.0018	-0.0041	0.0282	0.0029	0.0018
	(0.0036)	(0.0012)	(0.0013)	(0.0037)	(0.0016)	(0.0015)
Pressure (Prefer Young)	0.0319	0.0042	0.0036	0.0711	0.0222	0.0230
	(0.0071)	(0.0028)	(0.0031)	(0.0083)	(0.0035)	(0.0036)
Experience (Prefer Old)	-0.0361	-0.0125	-0.0237	-0.0367	-0.0175	-0.0195
	(0.0028)	(0.0014)	(0.0016)	(0.0035)	(0.0013)	(0.0013)
Observations	7,722,319	7,722,319	7,722,319	7,722,319	7,722,319	7,722,319
Cluster No.	15,670	15,670	15,670	15,670	15,670	15,670
Adjusted R2	0.002	0.069	0.095	0.006	0.086	0.102
Mean of Y	0.478	0.478	0.478	0.334	0.334	0.334
Quarter FE	✓	✓	✓	✓	✓	✓
Industry FE		✓	✓		✓	✓
Occ*City FE		✓	✓		✓	✓
Exp Controls			✓			✓

Notes: Appendix Table A.5 reports the correlations of ageist language with age discrimination decisions using all independent variables in one regression. The outcome variables and the skill variables are the same as those in Figure 6 and Table 3. We use equation 4 to estimate. The Standard errors are clustered at the occupation city level. See discussion in Section 5.1.

Table A.6

Firm's Decision on Age Discrimination and Share of Different Age Groups

	Share of Applicants by Age Group				
	(1)	(2)	(3)	(4)	(5)
	⩽23	24-26	27-30	31-40	⩾41
Panel A: Age Discrimination					
	0.0068	-0.0100	-0.0073	0.0024	0.0082
	(0.0026)	(0.0012)	(0.0009)	(0.0019)	(0.0014)
Panel B: Age Max < 40					
	0.0486	0.0111	-0.0041	-0.0272	-0.0284
	(0.0037)	(0.0018)	(0.0012)	(0.0027)	(0.0027)
Adjusted R2	0.013	0.003	0.001	0.005	0.011
Quarter FE	✓	✓	✓	✓	✓
Panel C: Age Discrimination					
	0.0206	-0.0029	-0.0100	-0.0099	0.0023
	(0.0009)	(0.0005)	(0.0004)	(0.0007)	(0.0005)
Panel D: Age Max < 40					
	0.0291	0.0040	-0.0057	-0.0166	-0.0107
	(0.0010)	(0.0005)	(0.0006)	(0.0008)	(0.0009)
Observations	7,722,319	7,722,319	7,722,319	7,722,319	7,722,319
Cluster No.	15,670	15,670	15,670	15,670	15,670
Adjusted R2	0.354	0.149	0.061	0.277	0.287
Mean of Y	0.233	0.179	0.197	0.284	0.107
Quarter FE	✓	✓	✓	✓	✓
Industry FE	✓	✓	✓	✓	✓
Occupation*City FE	✓	✓	✓	✓	✓
Additional Controls	✓	✓	✓	✓	✓

Notes: Appendix Table A.6 reports the correlations between the share of applicants in each age group and the use of age discrimination decisions. The outcome variables and the regressors are the same as those in Table 6. Standard errors are clustered at the occupation city level. Panel A and Panel B only control for period effects whereas Panel C and Panel D additionally control for industry, occupation*city fixed effects, as well as experience requirements and log wage offered. See discussion in Section 5.2.

Table A.7

Summary Statistics

	N	Mean	SD	Min	Max
Panel A: Labor Demand					
Age Discr Dummy	7,722,319	0.478	0.500	0	1
Age Max <40 Dummy	7,722,319	0.334	0.472	0	1
Expected app pool (10,000)	7,722,319	9.313	24.057	0.0002	338.81
Low competition (firm)	7,722,319	0.077	0.266	0	1
High competition (firm)	7,722,319	0.103	0.304	0	1
Very high competition (firm)	7,722,319	0.820	0.384	0	1
Cognitive	7,722,319	0.573	0.495	0	1
Social	7,722,319	0.787	0.409	0	1
Software (specific)	7,722,319	0.372	0.483	0	1
Solve problems	7,722,319	0.067	0.250	0	1
Make decisions	7,722,319	0.225	0.418	0	1
Cover high-technology	7,722,319	0.060	0.237	0	1
Learning	7,722,319	0.152	0.359	0	1
Communication	7,722,319	0.369	0.483	0	1
Pressure	7,722,319	0.103	0.304	0	1
Experience	7,722,319	0.219	0.414	0	1
Panel B: Labor Supply					
Num of applicants	7,722,319	52.5	122.5	2	8174
% of applicants with uni degree and above	7,722,319	0.469	0.249	0	1
% of applicants $\leqslant 23$	7,722,319	0.233	0.203	0	1
% of applicants 24-26	7,722,319	0.179	0.140	0	1
% of applicants 27-30	7,722,319	0.197	0.132	0	1
% of applicants 31-40	7,722,319	0.284	0.184	0	1
% of applicants $\geqslant$41	7,722,319	0.107	0.136	0	1

Notes: Data refer to job postings scrapped from 51job.com between November 1, 2018 and April 30, 2019. See Appendix Table A.3 for job skills, tasks, and ageist language definition. See discussion in Section 5.