

Age Discrimination in Hiring: Evidence from Online Job Ads*

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Abstract

We analyze explicit age discrimination in an online job market and job seekers' responses to it in China, using nearly 8 million job postings with ad-level group characteristics of applicants. In nearly half of job postings, employers explicitly state age restrictions and often exclude older applicants. To rationalize this, we develop a dynamic game in which older workers incur a disutility from employment at a biased firm, while biased employers trade off a larger applicant pool against higher screening costs. Consistent with the model's predictions, empirical results show that age restrictions encourage younger workers but discourage middle-aged and older workers, although some ineligible candidates still apply to high-wage or high-skill positions. Firms are more likely to impose age limits when jobs demand high work intensity, low skill levels, or when they face greater hiring costs and weaker market competition. Our results highlight that explicit age preferences, by altering both the composition of applicants and the costs of screening, can sustain discriminatory hiring equilibria even in competitive labor markets.

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 that render explicit age restrictions in hiring illegal. However, evidence from the literature continues to show that older workers experience longer unemployment spells (Johnson and Neumark, 1997; Button and Neumark, 2014, 2022),¹ receive fewer training opportunities (Perron, 2021), and most notably, face hiring disadvantages (Riach and Rich, 2002; Lahey, 2008; Riach and Rich, 2010; Neumark, 2012; Baert et al., 2016; Carlsson and Eriksson, 2019; Neumark et al., 2019a; Yu et al., 2025). Although age discrimination is well documented, its underlying causes and job seekers’ responses remain less well understood.² In particular, the lack of evidence on explicit age discrimination has prevented researchers from studying these demand and supply dynamics at scale.

In this paper, we analyze explicit age discrimination in hiring and job seekers’ responses in the context of China’s online labor market. Employers can legally state age ranges in job ads, and they did so in nearly half of all postings in our data, typically excluding older applicants. Using 8.8 million job ads that combines vacancy text, a dedicated field for age preferences, and ad-level distributions of applicant age and education,³ we go beyond detecting discrimination: we study which firms and jobs

¹Longer unemployment spells do not necessarily imply 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 in securing desired employment. Stronger age discrimination protections also did not help older workers to weather the economic downturn (Button and Neumark, 2014).

²Notable exceptions include Van Borm et al. (2021); Feng (2025) who reveal muted demand for older workers through online experiments. Burn et al. (2022) demonstrate ageist language related to health, personality, and skills predicts differential hiring by age. Burn et al. (2024) studies the impact of implicit age discrimination on deterring older workers’ applications.

³While our evidence comes from a major online job board rather than the full universe of hiring, the platform spans a wide range of cities, occupations, and industries, making it informative about a large segment of the labor market where online recruitment is prevalent.

are more likely to post explicit age limits, how these limits reshape the age and skill composition of the applicant pool, and how job characteristics and local market conditions are associated with the presence and tightness of age caps.

We interpret explicit age preferences in job ads as a form of discrimination, consistent with Arrow’s classic definition of discrimination as valuing worker characteristics unrelated to productivity (Arrow, 1971). While age preferences may partially reflect productivity considerations, our evidence suggests this explanation alone is insufficient. First, we document substantial variation in explicit age preferences across employers within the same local labor market (defined by industry and occupation-city cells), indicating a lack of consensus regarding age-related productivity differences. Second, age caps cluster at thresholds that are multiples of five and begin as early as the early thirties,⁴ a pattern inconsistent with smooth, inverted U-shaped wage or productivity profiles over prime working ages. Individuals at the margin of these age cutoffs possess similar expected productivity, yet those just above the threshold are disadvantaged even before applications.⁵ Taken together, these age caps are more consistent with the use of rigid HR screening rules than with productivity-based hiring, and they conflict with the legal conception of age discrimination in advanced economies, where even statistical discrimination based on age is prohibited.⁶ Accordingly, throughout the paper, we use the terms “explicit age preferences” and “explicit age discrimination” interchangeably.

Ageism is a global problem,⁷ and in the Chinese context, two additional features help interpret explicit age caps. First, many job ads exclude applicants above 35. The so-called “curse of 35”, widely discussed on social media, captures the perception that workers in their mid-thirties become less attractive to employers, who view them as less adaptable to new technologies and less willing to endure long working hours. Second, explicit age caps

⁴See Figure 1 and Section 3.1.

⁵Yu et al. (2025) similarly shows that the same individuals who have just crossed an age threshold face worse hiring outcomes.

⁶The U.S. Equal Employment Opportunity Commission prohibits age-based language in job ads unless age constitutes a bona fide occupational qualification. Similarly, Germany’s Federal Anti-Discrimination Agency deems ads specifying an age range (e.g., “25–45”) discriminatory if they exclude older applicants without justification.

⁷WHO published a global report on ageism (WHO, 2021), and the literature has detected its presence against older workers in different regions.

are disproportionately used in jobs that emphasize competition and high intensity. In a labor market where overtime is common and labor law enforcement is weak, phrases such as “ability to work under pressure” in job ads often signal demanding work schedules that de facto favor younger workers without family responsibilities. These patterns suggest that older workers may experience a higher disutility from employment at age-biased firms and that biased firms may view screening older applicants as particularly costly, both of which play a central role in the equilibrium framework we develop below.

We propose a simple equilibrium model of a two-sided matching market with younger and older workers, as well as biased and unbiased firms, capturing firms’ incentives, applicants’ responses, and strategic interactions. On the demand side, we extend the framework of Kuhn and Shen (2013) from gender to age discrimination: biased firms discount older workers’ productivity⁸ in the form of Lang et al. (2005), possibly due to either statistical discrimination, or taste-based preferences for different age groups, or both.⁹ Firms choose whether to post an explicit age restriction that discourages older applicants, trading off a larger applicant pool against higher screening costs. On the supply side, older workers incur a disutility from working at biased firms, which is amplified when bias is openly signaled. We solve for subgame perfect equilibria and derive comparative statics that guide our empirical analysis.

The model delivers three main predictions. First, an age-discriminating signal encourages applications from younger candidates but deters middle-aged and older workers, especially those closest to or over the stated maximum age. Second, some older workers will still apply despite being ineligible, but the non-compliance rate against explicit age restrictions in the application pool rises with the wage offered. Third, on the demand side, biased firms are more likely to use explicit age caps when job requirements make screening older workers especially costly, whereas higher skill requirements and lower search costs can induce them to search more broadly without imposing such caps.

Empirically, we study these patterns using fixed effects regressions within job cells

⁸For simplicity, our model assumes older workers as the discriminated group.

⁹Similar to Kuhn and Shen (2013), the main implications of our model hold in the empirical analysis regardless of the source of the discrimination.

defined by industry, occupation, and city, combined with posting month fixed effects to absorb seasonality. On the demand side, we relate the presence and tightness of age limits to measures of work intensity, job skill requirements, anticipated applicant pool size, and local labor market competition. On the supply side, we relate the age and education composition of applicants to the same age restrictions. Our estimates should be interpreted as conditional correlations, not causal claims, but the patterns we document, coupled with various robustness tests, align closely with the comparative statics of the model.

On the supply side, we find that explicit age limits significantly reshape the age and education composition of applicants. Relative to otherwise similar ads without age caps, postings that exclude workers above 40 receive 15.0% more applications from workers in their early twenties and 24.7% and 41.8% fewer from workers in their thirties and forties, respectively. Interestingly, workers who are not excluded by age caps are also less likely to apply. This is consistent with our model that applicants interpret an explicit age restriction as a *signal* of the firm's preference for younger workers, and workers account for the disutility of working in a discriminatory environment. We also show that job ads with age caps attract a less educated applicant pool.¹⁰ Finally, non-compliance is not negligible: a nontrivial share of applicants exceeds the posted maximum age, especially in high-wage and high-skilled positions. For instance, within ads that cap age at 40, a 10 percent higher posted wage is associated with a 0.37 percentage point lower compliance.

On the demand side, we identify three categories of predictors that are strongly associated with firms' use of explicit age restrictions and their preference for workers under 40.¹¹ First, job ads that emphasize demanding work environments are up to 23.3% and 30.1% more likely to include age caps and to exclude older workers, consistent with the model implication that biased firms might filter out older workers who are harder to screen for such roles. Second, firms with higher processing costs due to larger applicant

¹⁰This 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, although this is not explicitly modeled.

¹¹Our results are also robust to different maximum age thresholds

pools are more likely to narrow their search and exclude older workers. Finally, firms with higher skill requirements and those facing higher competition in the local labor market tend to search broadly for the most suitable candidates.

We contribute to three strands of the literature. First, we add to a small but growing literature that explains lower demand for older workers (Neumark and Yen, 2020; Van Borm et al., 2021; Burn et al., 2022; Allen, 2023). Whereas existing studies have primarily focused on workers in their fifties or near retirement (Vandenberghe, 2022; Allen, 2023), we show that explicit age discrimination can arise much earlier, already affecting workers in their thirties and early forties. Closely related, Helleseter et al. (2020) document explicit gender preferences that vary with worker age, and Yu et al. (2025) show hiring disadvantages for slightly older workers in these age ranges in China, focusing on jobs without explicit age restrictions. In contrast, we study the determinants of *explicit* age discrimination targeting workers in their 30s and 40s and, more importantly, applicants' responses to such discrimination. By observing applicants' group characteristics at the ad level, we study labor supply responses prior to any screening by employers.

Second, we contribute to the literature on age discrimination in hiring and its broader implications in the labor market. Experimental methods provide compelling evidence that older applicants receive fewer callbacks (Neumark, 2012; Neumark et al., 2016; Neumark, 2024). Other work examines the effects of legal protections for older workers (Neumark and Stock, 1999; Neumark and Song, 2013; Button and Neumark, 2014; Neumark et al., 2017, 2019b; Burn et al., 2020; Button et al., 2022), as well as the role of ageist language in shaping applicant behavior (Burn et al., 2022, 2024). What remains missing is an economy-wide view of explicit age discrimination, combined with large-scale information on the applicant pool to study its overall impact. In most regulated settings, researchers can observe only implicit age-related language in job advertisements. In contrast, in China, explicit age requests are legal and widely used, and they directly shape the composition of the applicant pool. This institutional environment allows us to treat explicit age caps as direct signals of exclusion and to interpret other language in job ads

as reflecting employers’ actual requirements rather than implicit signaling.

Lastly, we speak to the broader literature on labor market discrimination by embedding explicit age caps into an equilibrium framework. We develop a framework in the spirit of Kuhn and Shen (2013) and Lang et al. (2005), tailored to a setting in which firms knowingly post explicit age requirements, despite their impact on the applicant pool. When biased firms face higher costs of verifying the productivity of older applicants, workers’ application decisions can sustain the use of explicit age restrictions in a subgame perfect equilibrium.¹² This mechanism complements the canonical channel through which discrimination operates via workers’ human capital investment decisions, by highlighting how discriminatory signals in job ads can themselves arise and persist in equilibrium.

The rest of the paper is organized as follows: Section 2 describes the data and key variables. Section 3 documents some important empirical facts that motivate our model. Section 4 presents the equilibrium framework. Section 5 reports our 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, one of the largest online job boards in China¹³ 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,

¹²Our model is consistent with evidence from Card et al. (2023) and Kuhn and Shen (2023), who show that when explicit gender discrimination was banned, firms adjusted their hiring practices after learning that previously excluded applicants were equally or more qualified. Such learning requires firms to incur screening costs, and bans may also affect other dimensions of the matching process as well as prevailing norms.

¹³51job.com is the first publicly traded company specializing in human resource services in China.

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, occupation, 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 clearly specifies job tasks and skill requirements, such as major, language proficiency, and software expertise.

51job 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. Our baseline analysis focuses on the minor groups of occupation and 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 a full-page job advertisement on the platform, applicants can submit their resumes to employers via the platform.

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. 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,¹⁴ occupation, industry, or city-level location; (3) removing ads in languages other than Chinese and English, as well as those entirely in English; (4) dropping ads in the top 99.9% and bottom 0.1% of

¹⁴One data advantage we have for the analysis of the supply side responses is the abundance of posted wage information, with almost all job ads specifying the posted wage. Only 1,121 of 8,792,670 (0.01%) raw ads do not specify a posted wage. This information is crucial, as it significantly influences job-seeking behavior.

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.

Table 1 presents descriptive statistics for job ads (Panel A), firm characteristics (Panel B), and application information (Panel C) based on our sample of 7,720,870 job ads.¹⁵ Among these ads, 47.8% specify age requirements. Conditional on an age being specified, the mean requested age is 28.8 years. This highlights the significant prevalence of age-based restrictions in China’s labor market. Explicit age requirements are more prevalent in our data than explicit gender preferences documented in Kuhn and Shen (2013)¹⁶, which are now rare in our sample, appearing in less than 1% of ads a decade later.¹⁷ Consequently, the limited presence of gender-based restrictions constrains our ability to analyze the interaction between gender and age discrimination.

[Insert Table 1 here]

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 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.

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,

¹⁵We report changes in descriptive statistics in Table A.1 as a result of the sample restrictions. The sample means reported in Table 1 remain broadly the same, with slightly higher education requirements, slightly lower experience requirements when specified, and slightly smaller firm size. The sample also becomes more representative of a domestic working population with less extreme wage values, fewer foreign firms, and fewer job postings that did not attract any applicants.

¹⁶One-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.

¹⁷This decline is driven by newly enacted laws prohibiting gender-based hiring preferences. See Kuhn and Shen (2023).

emerging, and high-turnover industries and occupations are more prevalent than their representation in the population of occupied jobs. Lastly, online job postings often require higher levels of education and professional skills compared to the median position. To assess the representativeness of job vacancies posted on 51job.com 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 A.1.¹⁸ We show job ads on 51job.com 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”, which takes a value of one if the maximum age limit is less than 40.¹⁹ This variable identifies job ads that favor younger workers while excluding older ones.

In Appendix A.2, we define potential predictors of age discrimination, such as work intensity, job skills, job tasks, and youth-favoring stereotypes, using job description data and following the approach of Deming and Kahn (2018), Gelblum (2020), and Burn et al. (2022), respectively. Additionally, we utilize our unique data on applicants to measure the anticipated size of the applicant pool, which allows us to explore why some firms impose age restrictions while others do not, taking into account search costs and competition concerns.

At the same time, using the distributional characteristics of the applicant’s information

¹⁸The 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.

¹⁹We perform robustness checks using other age cutoffs for our main results in Section 5, yielding similar results.

at the ad level, we define the number of applicants in each age group to assess the correlation between age restrictions and the age composition of the applicants. We also define the compliance rate as the number of applicants whose age does not exceed the posted maximum divided by the total number of applicants for a given ad. To capture different thresholds, we construct two versions of this measure using maximum ages of 30 and 40, which correspond to the age groupings on 51job.com: 23 and below, 24–26, 27–30, 31–40, and 41 and above, as described in Appendix A.2. Finally, the number of applicants for each educational qualification allows us to measure the quality of the applicant pool.

3 Some facts

3.1 Explicit age discrimination for different age groups

Our dataset shows a remarkable degree of *explicit* discrimination against older workers. As discussed in Section 2.2, 47.8% of ads state an age range. Age discrimination increases sharply at age cut-offs that are multiples of 5, as shown by the CDF of the upper age limit in Figure 1. Limiting the sample to ads with explicit age restrictions, we plot the percentage of ads with a maximum age limit that excludes older workers (y-axis) aged above each age threshold (x-axis).²⁰ 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.²¹

[Insert Figure 1]

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

²⁰For completeness, we also show the CDF of the lower age limit in Figure 1. Some ads impose restrictions on very young workers, but most workers aged 25 or above no longer face this restriction.

²¹We also report different extents of age discrimination across different firm characteristics, industries, and occupations in Appendix B.

increasingly sideline them. Older employees are often perceived as less adaptable to new technologies and less willing to endure long working hours.

Institutional factors also explain the patterns in Figure 1. 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 40.²² While these policies may intend to promote young talent in government and research, private-sector employers often adopt similar age thresholds for less legitimate reasons. Many firms view workers over 35 as more costly to hire and less flexible due to increased family responsibilities, leading HR departments to use age 35 as a convenient hiring cutoff.

3.2 Variance decomposition of age discrimination

We document variations of explicit age discrimination according to different firm characteristics, industry, and occupation in Appendix B. In summary, domestic private firms, the largest firms, and those in the finance and service industries or occupations are more likely to impose explicit age restrictions and exclude older workers, while state-owned, foreign-owned, non-profit, and healthcare firms are less likely to do so.

To further understand the variation systematically, we decompose its variance into different components by estimating the following regression:

$$AgeDiscr_{a,j,i,oc} = \mathbf{Charac}_a \mathbf{b} + z_j + \delta_t + \eta_i + \theta_{oc} + \epsilon_{a,j,i,oc} \quad (1)$$

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 \mathbf{Charac}_a captures key job characteristics such as work intensity, skills, tasks, and youth-favoring stereotypes variables that potentially predict the use of age discrimination.²³ The terms z_j , δ_t , η_i , and θ_{oc} denote firm, month,

²²See National Civil Service Administration (2020) and National Natural Science Foundation of China (2025) for the age requirements listed on the relevant official websites.

²³We define these variables in Appendix A.2 and analyze them in Section 5.2.

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 2. 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 Figure A.5, slightly over 40% of firms either consistently include or never include age requirements in their job postings.

[Insert Figure 2 here]

3.3 Compliance with explicit age requirements by age groups

Despite having explicit age requirement in a dedicated field, compliance with the age restrictions is not perfect. We define the compliance rate as the ratio of applicants whose age is below or equal to the stated maximum age requirement to the total number of applicants at the ad level. Table A.4 presents compliance rates at maximum age thresholds of 40 and below, as well as 30 and below.²⁴ Applicants' age compliance is far from 100%. Among the job ads with an age cap of 40, the compliance rate is 91.9%, which decreases to 84.5% when the maximum age requirement is more restrictive at 30. These results suggest that some older workers still apply despite explicit age restrictions.

4 Model

To examine the interaction between workers (“she”) and firms (“it”), we consider a dynamic game model of a two-sided matching market with 2 workers and 2 firms on each side. Each firm wants to hire one worker, while each worker applies to one firm

²⁴As discussed in Appendix 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.

and competes for the job there.²⁵ The two workers $j \in \mathcal{J} = \{1, 2\}$ represent different age groups: worker 1 corresponds to the undiscriminated, younger workers, while worker 2 represents the discriminated, older ones. For the firms $i \in \mathcal{I} = \{1, 2\}$, we assume that firm 1 (“the biased”) holds a bias against the productivity of older workers, but the other (“the unbiased”) does not. We describe the details of the model below, with superscripts for workers and subscripts for firms in the notations.

On the demand side, we follow Kuhn and Shen (2013) and model a firm’s signaling choice as a tradeoff between the possibility of recruiting a better applicant and the sure search cost incurred when adopting a discriminatory job posting policy. The baseline productivity of each worker, v^j , is independently drawn from a common (uniform) distribution, and this value is *privately* known to the applicant before the firm meets her. The output of a worker is then amplified by the technology, $\theta_i > 0$, of the firm she works for. We model it through the skill requirement level of the job. As the biased firm has a subjective bias against the real productivity of a worker due to age considerations, we follow Lang et al. (2005) to have a disutility term δ for worker 2 in the model, which is worker- and age-specific. This also echoes Kuhn and Shen (2013) where a biased firm views older workers as “systematically” less productive than younger workers.²⁶ In addition, as noted before, biased firms may draw on stereotypes that older workers are less suited to certain job environments, such as those demanding high work intensity. Even when older workers themselves could meet these conditions and apply for the job, employers perceive them as riskier hires, making the verification of their productivity and commitment appear more costly; this is reflected in the extra screening cost γ when a biased firm meets an older worker. Finally, we adopt the simplified, discrete approach to leave room for interaction on the other side, where workers have to balance the higher wage against the potentially high competition for a job.

²⁵The simple case of two workers/firms would suffice to provide interesting economic tradeoffs in the strategic considerations. We allow only one application for each worker to reflect applicant constraints, the limited number of applications that could be made due to monetary, time, or attention limits.

²⁶In Kuhn and Shen (2013), this is reflected by letting the distribution of older worker productivity be a negative shift from that of younger workers. However, as we consider the coexistence of biased and unbiased firms, it is reasonable to translate this perceived productivity difference into the δ term while keeping the real productivity of younger and older workers the same, as is done in Lang et al. (2005), which effectively “shifts” older workers’ productivity distribution negatively in the eyes of the biased firm.

Mathematically, the payoff to the biased firm 1 employing worker j is $u_1^j = \theta_1 v_1^j - w_1 - c_1 N_1^1 - \gamma c_1 N_1^2$, while the payoff to unbiased firm 2 is $u_2^j = \theta_2 v^j - w_2 - c_2 N_2$, where v_1^j is the perceived productivity of worker j in the eyes of the biased firm 1, $\theta_i > 0$ is the skill requirement of firm i , $w_i > 0$ is the wage exogenously given, N_i^j is the number of worker j applying to firm i , $c_i > 0$ is the per applicant search cost, and $\gamma > 1$ captures the biased firm's additional cost of recruiting older workers whom it perceives as "unsuitable" for the job due to discrimination. For the random variables v^1 and v^2 denoting the productivity of workers, we assume they are drawn independently and uniformly from the interval $[1, 2]$. All workers and firms know the probability distribution of v^j . Given the simplifying linear nature of our model, we also assume that the biased firm discounts older workers' productivity linearly by setting $v_1^2 = v^2 - \delta$ for $\delta > 0$, with δ increasing with workers' age.

On the supply side, let $d_1 \in \{0, 1\}$ be the biased firm's choice whether to send a signal discriminating workers by their ages. When working for the biased firm 1, worker 1's payoff is w_1 , while the payoff to worker 2 is $y_1^2 = w_1 - \alpha\delta \cdot (1 + d_1)$ for some $\alpha > 0$, so that the disutility from the bias is $\alpha\delta$ if $d_i = 0$ (i.e., no discriminating signal but still suffers from the bias), and $2\alpha\delta$ if $d_i = 1$ (i.e., heavier disutility upon an openly declared discrimination).²⁷ The payoff from the unbiased firm is the same for everyone, w_2 , and $y_0^j = 0$ for the outside option of not getting a job from any firm, which we assume is small enough to ensure that workers participate. The game proceeds as follows:

1. The biased firm chooses d_1 , indicating whether to send a discriminating signal.
2. Each worker sees her own realization of v^j and chooses which firm to apply to in order to maximize her payoff.
3. Each firm sees those who have applied to it and their realized v^j , chooses one worker

²⁷Here, we assume for simplicity a "symmetric information" setting where the workers know each firm's type (biased/unbiased), and calculate their payoff based on the type. An alternative setting involves "asymmetric information", where workers cannot distinguish between biased and unbiased firms if no signal is posted, and only when a biased firm does post a discriminating signal will the workers figure out its type. In that case, when a worker sees a firm not posting a discriminating signal, she has to treat it equivalently as a "mixed" firm that would reduce her payoff due to her age if the firm is biased. Qualitatively, this choice between a known biased firm and an unknown mixed firm is equivalent to the current setting. Hence, we adopt the former, simpler setting here as it has sufficiently reflected the key tradeoff faced by each side.

from them for the purpose of maximizing its payoff.

4. Each worker and each firm gets the corresponding payoff after the firms' choices in the previous step.

We examine the subgame perfect Bayesian equilibria of this game with backward induction. We present a visualization of the timeline in Figure 3, which also indicates the data availability for each stage.

[Insert Figure 3 here]

4.1 Workers' subgame and thresholds strategies

We first solve the workers' subgame for a fixed discrimination policy d_1 . Let $V_i^j := \{v \in [1, 2] : \text{worker } j \text{ applies to firm } i \text{ when } v^j = v\}$, and $\pi_i^j := \Pr(V_i^j)$ be the probability worker j applies to firm i . We use $y_1^2(d_1) := w_1 - \alpha\delta(1 + d_1)$ to denote the *discounted* wage for worker 2 at the biased firm 1 when it adopts signaling decision d_1 . Below, we drop the argument d_1 for notational simplicity when we consider a fixed discrimination policy d_1 . We can write each worker j 's expected payoff when applying to each firm as²⁸

$$\begin{aligned} W_1^1(v) &= w_1 \left[\underbrace{1 - \pi_1^2}_{\text{no contest}} + \underbrace{\pi_1^2 \Pr(v \geq v^2 | v^2 \in V_1^2)}_{\text{worker 1 wins when worker 2 contests}} \right], \\ W_1^2(v) &= y_1^2 \left[1 - \pi_1^1 + \pi_1^1 \Pr(v \geq v^1 | v^1 \in V_1^1) \right], \\ W_2^j(v) &= w_2 \left[1 - \pi_2^{-j} + \pi_2^{-j} \Pr(v \geq v^{-j} | v^{-j} \in V_i^{-j}) \right]. \end{aligned}$$

Balancing the payoffs from both options, worker j would apply to firm i at productivity v if the payoff there is higher than from the other, i.e. $W_i^j(v) - W_{-i}^j(v) \geq 0$. In other words, the workers use threshold strategies: when her productivity v increases gradually from 1 to 2, she would switch the firm she applies to only at thresholds where $W_1^j(v) - W_2^j(v)$ changes its sign.

Below we make the simplifying assumption that the workers switch sides only when

²⁸Since we assume a continuous distribution of v^j , the event that it is equal to a fixed value has zero probability and hence the difference between strict and weak inequality in the brackets below would not affect the analysis.

the sign changes to strictly positive or negative.²⁹ Then, the number of thresholds is at most countable. To analytically solve for an equilibrium, we further restrict ourselves to *monotone equilibria* where the strategy has at most 1 threshold: intuitively, for a representative worker, when her v^j increases from 1 to 2, her application strategy would never move back to an earlier firm after earlier moving away from it.³⁰ Then the strategy of each worker has one of the two forms:

$$\bar{s}^j(v) = \begin{cases} 1, & v \leq v^{j*}, \\ 2, & v > v^{j*}; \end{cases} \text{ or } \underline{s}^j(v) = \begin{cases} 2, & v \leq v^{j*}, \\ 1, & v > v^{j*}. \end{cases}$$

When $v^{j*} = 2$, \bar{s} represents the degenerate “no switch” strategies always applying to firm 1 in the entire domain, and similarly \underline{s} for always applying to firm 2. For articulation ease, we let $v^{j*} = 1^-$ represent the opposite strategies: for \bar{s} it corresponds to applying to firm 2 from the beginning, and similarly for \underline{s} always applying to firm 1.

4.2 Workers’ equilibrium strategies

We now solve for the equilibrium. There are three generic cases based on how the (discounted) wages rank. We ignore the marginal cases where some of them are equal to each other to focus on the main economic tradeoffs.

	worker 1 (younger) applies to...		worker 2 (older) applies to...	
	firm 1 (biased)	firm 2	firm 1 (biased)	firm 2
$w_2 < y_1^2 < w_1$	always	never	$v^2 > 1 + \delta + \frac{w_2}{y_1^2}$	$v^2 \leq 1 + \delta + \frac{w_2}{y_1^2}$
$y_1^2 < w_2 < w_1$			never	always
$y_1^2 < w_1 < w_2$	$v^1 \leq 1 + \frac{w_1}{w_2}$	$v^1 > 1 + \frac{w_1}{w_2}$		

Summary of equilibrium strategies in different cases of wage order

²⁹Intuitively, when the payoffs from two firms become identical, the worker sticks to the earlier choice of application instead of employing a mixed strategy by randomizing between the firms. As we are examining the equilibrium, this could also be interpreted from a strategic-response perspective: worker j “expects” her opponent $-j$ to adopt such a strategy, perhaps either out of strategic complexity concern, or because she believes her opponent could conform to a certain degree of inertia, avoiding sharp changes in her choice.

³⁰As in the above, this is an assumption on the level of strategic sophistication. Meanwhile, monotonicity is a commonly used simplifying assumption when analyzing equilibrium strategies (Myerson, 1991; Milgrom, 2004; Krishna, 2010).

Case 1: $w_2 < y_1^2 < w_1$. When worker 1 adopts a simple threshold strategy, she must first apply to firm 2 then 1, as $W_1^1(2) = w_1 > w_2 = W_2^1(2)$ (implying $s^1(2) = 1$), i.e. she must adopt $s^1 = \underline{s}$. Now, the payoff functions of worker 2 can be written as

$$W_1^2(v) = y_1^2 \left[\underbrace{v^{1*} - 1}_{\text{no contest}} + \underbrace{(v - \delta - v^{1*}) \mathbf{1}_{v - \delta \geq v^{1*}}}_{\text{worker 2 wins when worker 1 contests}} \right],$$

$$W_2^2(v) = w_2 \left[2 - v^{1*} + (v - 1) \mathbf{1}_{v < v^{1*}} + (v^{1*} - 1) \mathbf{1}_{v \geq v^{1*}} \right].$$

Both are piecewise linear, with turning points $v^{1*} + \delta$, and v^{1*} respectively. In a monotonic equilibrium, they intersect at most once: either they intersect at $v = v^{2*}$, or they never intersect.

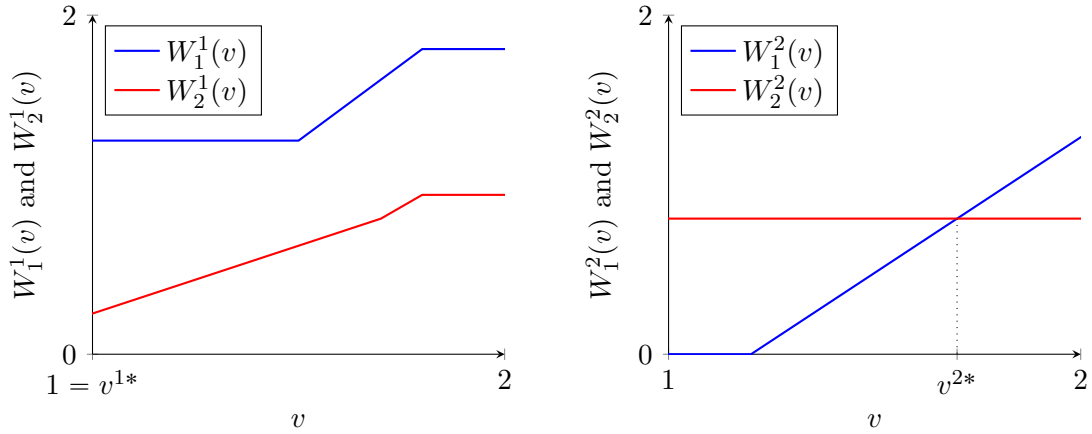
We first assume worker 2 also adopts $s^2 = \underline{s}$, i.e. first applying to firm 2, then 1. Then, worker 1's payoffs are similarly calculated as

$$W_1^1(v) = w_1 \left[\underbrace{v^{2*} - 1}_{\text{no contest}} + \underbrace{(v + \delta - v^{2*}) \mathbf{1}_{v^{2*} \leq v + \delta \leq 2} + (2 - v^{2*}) \mathbf{1}_{v + \delta \geq 2}}_{\text{worker 1 wins when worker 2 contests}} \right],$$

$$W_2^1(v) = w_2 \left[2 - v^{2*} + (v - 1) \mathbf{1}_{v \leq v^{2*}} + (v^{2*} - 1) \mathbf{1}_{v \geq v^{2*}} \right].$$

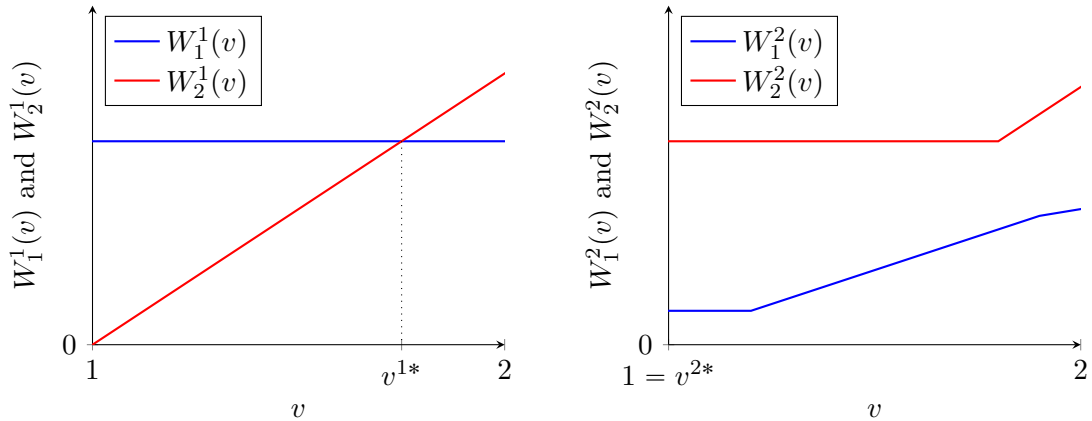
We show in Appendix C.1 that the unique equilibrium consists of $(v^{1*}, v^{2*}) = (1^-, \min\{1 + \delta + \frac{w_2}{y_1^2}, 2\})$, so that worker 2 applies to firm 2 when $v^2 \leq 1 + \delta + \frac{w_2}{y_1^2}$ and firm 1 otherwise, while worker 1 always applies to firm 1 (see figure below for an illustration). We also show in the Appendix C.1 that there is no other monotone equilibrium when worker 2 adopts the other strategy $s^2 = \bar{s}$, and hence the above is the unique monotone equilibrium in this case. Intuitively, worker 1 never applies to firm 2 as it offers a lower wage while potentially being competitive. Worker 2 also applies to the more attractive firm 1 when her productivity is relatively high ($v^1 \geq 1 + \delta + \frac{w_2}{y_1^2}$), but when her productivity is low, she opts to avoid the disadvantaged contest at firm 1 by switching to the less attractive firm 2, as she faces no competition there.

Case 2: $y_1^2 < w_2 < w_1$. This is the simplest case as worker 1 strictly prefers firm 1 while worker 2 strictly prefers firm 2. Hence, $(s^1 = 1, s^2 = 2)$ constitutes a unique separating equilibrium.



Graph of $W_j^i(v)$, $i, j \in \{1, 2\}$ in the interval $v \in [1, 2]$ with $w_1 = 1.8$, $y_1^2 = 1.6$, $w_2 = 0.8$, $\delta = 0.2$ and $v^{1*} = 1^-$, $v^{2*} = 1.7$.

Case 3: $y_1^2 < w_1 < w_2$. Similar to case 1, we can show that the unique equilibrium consists of both worker adopting \bar{s} , with $(v^{1*}, v^{2*}) = (1 + \frac{w_1}{w_2}, 1^-)$: worker 1 applies to firm 1 when $v^1 \leq 1 + \frac{w_1}{w_2}$ and firm 2 otherwise, while worker 2 always applies to firm 2 (see figure below for an illustration). Intuitively, worker 2 never applies to firm 1, as it offers a lower wage while being discriminatory to her. Worker 1 also applies to the more attractive firm 2 when her ability is relatively high ($v^1 \geq 1 + \frac{w_1}{w_2}$), but she has the option to avoid the contest at firm 2 by switching to the less competitive firm 1, as she is relatively more welcomed here.



Graph of $W_j^i(v)$, $i, j \in \{1, 2\}$ in the interval $v \in [1, 2]$ with $w_1 = 0.9$, $y_1^2 = 0.6$, $w_2 = 1.2$, $\delta = 0.2$ and $v^{1*} = 1.75$, $v^{2*} = 1^-$.

4.3 Supply side comparative statics and predictions.

We first examine the effect of a biased firm's search policy on the number of applications it would receive from different age groups. Let m_i^j be the total probability of worker j applying to firm i . Then, it amounts to checking the effect of d_1 on m_1^j . Suppose the biased firm changes its discrimination signal d_1 from 0 to 1, with all other parameters unchanged. Then, the only change in parameters is y_1^2 becoming even lower. Checking the summary table of workers' equilibrium strategy in Section 4.2, one can see that across rows 4 to 5, worker 2 becomes less likely to apply to firm 1, i.e., m_1^2 decreases, if it had not been zero at the beginning. The choice of worker 1 is unchanged as her strategy is not affected by the changes in the parameter, and hence the ratio of m_1^2 over m_1^1 also decreases. Assuming that the bias is against older workers and increasing in age, this means that in the new equilibrium of a narrower search from the biased firm, there is a drop in both the absolute and relative number of applications from older workers.

To dig deep into the heterogeneity in effect on different age groups, we calculate explicitly $|\Delta m_1^2| = m_1^2(d_1 = 0) - m_1^2(d_1 = 1)$. For instance, in the more interesting case 1 where worker 2 has nonzero probability applying to firm 1, we have $m_1^2(d_1 = 0) = 2 - (1 + \delta + \frac{w_2}{y_1^2(d_1=0)}) = 1 - \delta - \frac{w_2}{w_1 - \alpha\delta}$, and $m_1^2(d_1 = 1) = 1 - \delta - \frac{w_2}{w_1 - 2\alpha\delta}$. Hence, $|\Delta m_1^2| = \frac{\alpha\delta w_2}{(w_1 - \alpha\delta)(w_1 - 2\alpha\delta)}$ is increasing in δ , meaning that the magnitude of drop in absolute number of applications is increasing in the level of bias, i.e., age. As there is no change in the undiscriminated group, the magnitude of the relative drop is also increasing with age. The situation is qualitatively the same in other cases. The above analysis is summarized in the following proposition.

Prediction 1.

For a biased firm, a discriminating signal encourages the youngest workers, but discourages workers in all other age groups, with the effect stronger for the older workers.

Similarly, we examine how the wage of a biased firm affects the non-compliance rate in its application pool, defined as $NC = \frac{m_1^2}{m_1^1 + m_1^2}|_{d_1=1}$, the percentage of discriminated workers when the firm has already signaled its bias explicitly. Suppose the biased firm

raises its wage offer w_1 . Again, for case 1, direct calculations gives

$$NC = \frac{1 - \delta - \frac{w_2}{w_1 - 2\alpha\delta}}{2 - \delta - \frac{w_2}{w_1 - 2\alpha\delta}} = 1 - \frac{1}{2 - \delta - \frac{w_2}{w_1 - 2\alpha\delta}},$$

which is increasing in w_1 . Hence, when a biased firm increases its wage, we expect an increase in the non-compliance rate.

Prediction 2.

For a biased firm, the non-compliance rate in its application pool rises with the wage offered.

4.4 Firms' signals and demand side comparative statics

The comparison below explains what changes when the biased firm switches from $d_1 = 0$ to $d_1 = 1$.

<i>consequences</i>	<i>good or bad for firm i?</i>
fewer applications arrive (<u>good</u>)	discriminated workers stay away \Rightarrow saves search costs for every application deterred
potential loss of a good hire (<u>bad</u>)	a deterred applicant could have been the best \Rightarrow lowers average productivity of the hire

Firm 1 will discriminate if and only if the cost saved dominates the drop in productivity.

Explicitly, focusing on case 1, moving from $d_1 = 0$ to $d_1 = 1$ changes payoff by

$$\mathbb{E}[\pi_1(1)] - \mathbb{E}[\pi_1(0)] = -\theta_1 \underbrace{\Delta v_1}_{\text{loss in hired quality}} + \gamma c_1 \underbrace{\Delta N_1^2}_{\text{apps saved}},$$

with $\Delta v_1 \equiv \mathbb{E}[v_1(0)] - \mathbb{E}[v_1(1)]$ is the expected difference in bias-adjusted worker quality and $\Delta N_1 \equiv \mathbb{E}[N_1^2(0)] - \mathbb{E}[N_1^2(1)] > 0$ is the difference in the expected number of applications by worker 2. Setting the difference above to zero and solving for c gives $c_1^* = \frac{\theta_1}{\gamma} \frac{\Delta v_1}{\Delta N_1}$, where $\frac{\Delta v_i}{\Delta N_i}$ depends only on wages and the productivity distribution and bias level (see Appendix C.2 for detailed calculations). The biased firm discriminates iff $c_1 > c_1^*$, i.e., the search cost saved outruns the extra productivity of the marginal applicant it scares away.

With this threshold condition, we derive the following comparative statics on the biased firm side: when a job is more demanding in terms of work intensity, longer working hours, worker ambition, etc., the higher γ would lower the threshold, so that the biased firm is more likely to send an age-discriminating signal. On the contrary, when the skill requirement θ_1 is higher, or the expected number of applicants $N_1^{(0)}$ is lower, there will be a higher discrimination threshold c_1^* , so that the firm is less likely to include explicit age restrictions.

Prediction 3.

A biased firm will be more likely to search narrowly when the job requires a high work intensity from the workers.

Prediction 4.

A biased firm will be more likely to search broadly when the job demands higher skill requirements.

Prediction 5.

A biased firm will be more likely to search narrowly when it expects more applicants or faces less competition in the industry.

5 Testing model implications

In this section, we bring the model to the data. We first study how explicit age limits shape application behavior, focusing on the size and composition of the applicant pool as well as compliance with stated age caps. We then turn to firms' posting decisions, relating the use of explicit age restrictions to job characteristics that proxy for work intensity, skill requirements, and expected screening costs and competition within narrowly defined labor market cells.

5.1 Labor supply: applicant response

The central premise of our labor supply model is that applicants interpret explicit age restrictions as signals and decide whether to apply based on their own age.

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

$$AppResp_{a,i,oc} = \mathbf{1}\{AgeDiscr_a\}b + \delta_t + \eta_i + \theta_{oc} + \epsilon_{a,i,oc} \quad (2)$$

Here, $AppResp_{a,i,oc}$ represents applicants' response, measured by the number of applicants in each age group, or the quality of the application pool. The indicator $\mathbf{1}\{AgeDiscr_a\}$ equals one if the ad a states an explicit age requirement or sets a maximum age below 40. We further include month fixed effects δ_t for seasonality, industry fixed effects η_i , and occupation-city fixed effects θ_{oc} , which absorb time-invariant variation of narrowly defined labor market segments. Standard errors are clustered at the occupation-city level. These supply-side specifications are descriptive and we cannot rule out confounding factors or reverse causality.³¹ We therefore do not claim strict causality and instead document correlations between explicit age restrictions and the size and composition of applicant pools.

5.1.1 Applicant Composition

Our model predicts that job postings discriminating against older workers will attract more young applicants, while older applicants will be deterred. Notably, even medium-aged applicants who fall within the stated age range may refrain from applying if they perceive a strong preference for younger candidates. We test this prediction in Table 2. Using Equation (2), we separately regress the number of applicants from each age group on an indicator for explicit age discrimination or an indicator that the maximum

³¹For example, estimating (2) with the number of applicants as the outcome may suffer from reverse causality. Firms that receive fewer applicants may expand their search and are less likely to post age limits.

allowed age is below 40.³²

[Insert Table 2 here]

Panel A of Table 2 reveals that explicit age discrimination attracts the youngest applicants (23 or younger) and the oldest applicants (41 or older), while deterring those in the middle age ranges (**Prediction 1**). This pattern is consistent with age limits that combine a preference for very young applicants with occasional preferences for older candidates, which reduces applications from the middle of the age distribution. To elucidate the mechanism, we regress the number of applicants in each age group on an Age Max <40 indicator. Panel B of Table 2 confirms that job ads specifying an age limit below 40 tends to have more younger applicants and fewer older and middle-aged applicants. Specifically, the number of applicants aged 26 or younger rises, whereas the number of those aged 27 or older declines. The youngest group’s size increased the most by 15.0% and the oldest group’s size decreased the most by 41.8%. Many applicants aged between 27 and 40 are not excluded by the explicit age restrictions, and yet many give up applying if they perceive a strong preference for younger workers from employers. The number of applicants in the age group 27-30 declined by 8.2% and that of 31-40 declined by 24.7%.³³

As older applicants are deterred by age discrimination, we examine whether the observed quality of the applicant pool declines. We test this using Equation (2), relating either the Age Discrimination indicator or the Age Max <40 indicator to the number of high-skilled applicants, defined as those with a university degree or above. Table A.7 presents our findings. In our preferred specification of Column (2), jobs that state an explicit age group receive 2.3 fewer applications from university-educated applicants on average (8.1% fall in relative magnitude). Postings that cap age at below 40 receive 5.0 fewer applications from high-skilled candidates (17.7% in relative magnitude).

³²We observe age only in 51job.com categories: 23 or younger, 24 to 26, 27 to 30, 31 to 40, and 41 or older. Exact ages are unavailable.

³³In Table A.5, we test robustness of Table 2 using the share of applicants by age group as outcome variables. We also re-estimate the correlations with only month fixed effects and with additional controls for experience requirements and log wage in Table A.6. All results are similar.

5.1.2 Compliance rates

As shown in Table A.4, there is substantial non-compliance with maximum age caps. Motivated by this pattern and to test our model’s prediction that higher posted wages raise noncompliance (**Prediction 2**), we estimate how wages relate to compliance rates using Equation (3). Compliance rates are defined as the number of applicants whose age does not exceed the posted maximum divided by the total number of applicants for an ad. We construct two versions of this measure using maximum age thresholds of 30 and 40.³⁴ Job characteristics $\mathbf{Charac}_a\mathbf{b}$ include posted wage. To account for potential differences in experience requirements, we always include experience controls.

$$AppCompliance_{a,i,oc} = \mathbf{Charac}_a\mathbf{b} + \delta_t + \eta_i + \theta_{oc} + \epsilon_{a,i,oc} \quad (3)$$

Table 3 shows that higher posted wages are associated with lower compliance. Specifically, for ads with an explicit age limit, a 10 percent increase in the posted wage is associated with a decline of about 0.3 to 0.6 percentage points in the compliance rate. This is consistent with the directed search mechanism in the model. Once a firm posts an age cap and thereby signals discriminatory hiring, for older applicants, the wage has to partially compensate for the expected penalty associated with discrimination. In contrast, no such penalty is incurred by the young applicants. Then, raising the posted wage results in a higher percentage rise in the effective wage for older applicants, therefore providing a stronger incentive for application. As a result, the share of these older applicants among all applicants rises with the wage offer, implying a higher noncompliance rate and therefore lower measured compliance. This interpretation also aligns with broader evidence that posted wages shape applicant flows in online vacancy markets, a key ingredient of directed search (Banfi and Villena-Roldan, 2019; Marinescu and Wolthoff, 2020). In our setting, the wage gradient shows up not only in the level of applicant inflows, but also in composition: higher wages disproportionately draw in

³⁴For example, applicants aged 40 or younger are counted as compliant under the Age Max 40 threshold. These thresholds align with 51job.com’s age groupings: 23 and below, 24 to 26, 27 to 30, 31 to 40, and 41 and above, as described in Appendix A.2.

older workers despite posted age caps, lowering measured compliance.

[Insert Table 3 here]

To further study predictors of compliance beyond wages, we examine how job skills and tasks relate to compliance rates. This analysis identifies job types for which workers are more or less likely to disregard explicit age restrictions. It also tests whether higher skill requirements draw relatively more experienced older applicants who view the age cap as a signal rather than a binding constraint. As before, we estimate Equation (3) with the compliance rate as the outcome, and for this exercise, we also control for posted wage. We have four different job characteristics, including education requirements, as well as measures of cognitive skills, and job tasks such as those related to problem-solving and decision-making. 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 defined in Appendix A.2.

Table 4 relates job requirements to applicants' compliance with posted maximum age thresholds. All requirement measures negatively affect compliance, regardless of whether the maximum age is defined as 30 or 40. Postings that mention a university degree requirement, cognitive skills, and tasks such as problem solving or decision making tend to exhibit lower compliance rates, meaning that older applicants are more likely to apply despite the stated age cap. The pattern is broadly similar across specifications, including those with industry and occupation-city fixed effects. We interpret these correlations as suggestive evidence that older applicants update their beliefs about enforcement based on the content of the posting, and are more willing to apply for jobs that emphasize higher-level cognitive demands.

[Insert Table 4 here]

5.2 Labor demand: firm perspective

We then test the predictions of the labor demand side model, which reconciles firms' search motives and discrimination. While searching broadly helps employers to identify the best candidate from multiple age groups, employers might discount older workers' productivity, as well as face a higher search cost, due to the perceived difficulties in verifying productivity. We test **Predictions 3 to 5** of our model from Section 4. In particular, we test the following regression model:

$$AgeDiscr_{a,i,oc} = \mathbf{Charac}_a \mathbf{b} + \delta_t + \eta_i + \theta_{oc} + \epsilon_{a,i,oc} \quad (4)$$

where $AgeDiscr_{a,i,oc}$ is an indicator variable equal to one if job ad a includes an explicit age requirement or specifies a maximum age cap below 40. The vector \mathbf{Charac}_a includes job characteristics such as work intensity, processing costs, labor market competition, job skill requirements, and references to stereotypes favoring the youth.³⁵ The coefficient \mathbf{b} captures the relationship between these job characteristics and the use of explicit age discrimination.

As before, we include month fixed effects (δ_t) to account for seasonality and 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 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.

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, as shown in Figure A.5. 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

³⁵These variables are defined in Appendix A.2.

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.³⁶ Instead, we test the model’s predictions regarding the factors driving firms’ use of age restrictions.

5.2.1 Employers’ age bias with work intensity

We first test the hypothesis that firms’ age discrimination is driven by a bias that older workers are less capable of handling a demanding work environment (**Prediction 3**). Under such biased perceptions, firms would find it difficult to screen older workers, even if older applicants see themselves as meeting the job requirements and apply. As a result, firms are more likely to exclude older applicants when the job involves high work intensity. To test this prediction, we examine the correlation between high work intensity requirements in job ads and the firm’s decision to impose explicit age limits. The explicit age limit could act as a signal to shape the applicant pool, as shown in Section 5.1. We construct three indicator variables —“Ambition”, “Competition”, and “Overtime”— to measure work intensity, based on keywords detailed in Table A.3.

Figure 4 reports the correlation between work intensity and the use of age discrimination, using Equation (4). Each colored interval corresponds to the confidence interval from a distinct regression, with each regression using only one work intensity measure as its predictor³⁷. Different interval colors correspond to different specifications. Figure 4a has the Age Discrimination indicator as the dependent variable, whereas Figure 4b uses the Age Max <40 indicator defined in Section 2.3.

Figure 4a shows a strong and statistically significant positive correlation between the three measures of work intensity and the probability that a firm imposes an explicit age restriction. When job ads mention keywords related to ambition, competition, and overtime, they are more likely to impose an explicit age restriction. This relationship

³⁶For example, it is unlikely that there are no confounders influencing the use of age discrimination and job characteristics in Equation (4), despite detailed time, industry, occupation-city pair fixed effects.

³⁷In Table A.8, we show robustness of these results in a multivariate regression

is consistent both within each job cell defined by industry, occupation-city pairs (blue intervals), and across such job cells (red intervals).

Figure 4b shows that when firms demand high work intensity, they also tend to exclude older workers by setting a maximum age limit below 40. This result is also consistent both within and across job cells. In Figure A.6, we show results are robust to different maximum age limits at 35, 45, and 50.

[Insert Figure 4 here]

We report regression coefficients of Figure 4 in Table 5. Within detailed job cells, the presence of keywords related to Ambition is associated with a 6.6 percentage point increase in the probability of age discrimination (13.8% increase in relative magnitude). This correlation is even stronger for keywords associated with Competition and Overtime, which are linked to increases of 10.2 and 11.1 percentage points, respectively (21.4% and 23.3% increases in relative magnitude). Table A.9 demonstrates the robustness of the results with an experience control.

[Insert Table 5 here]

Column (4) of Table 5 shows consistent positive correlations between work intensity measures and discrimination against workers over 40. Specifically, the presence of keywords related to ambition is correlated with a 6.6 percentage point increase in the use of the age cap (19.8% in relative magnitude), while Competition and Overtime increase it by 9.2 and 10.1 (relative increases of 27.6% and 30.1%, respectively) within detailed job cells. These results support the notion that firms advertising highly demanding jobs are more likely to use age discrimination to explicitly filter out older workers. This corroborates the stereotypical belief related to the “curse of 35” that older workers lack the stamina or willingness to thrive in competitive, high-pressure environments with long work hours.

We provide further evidence of employers’ age biases by analyzing the role of youth-

favoring stereotypes in job descriptions in Table A.10. Following Burn et al. (2022), we test the association between age discrimination and three specific types of youth-favoring stereotypes: “Learning”, “Communication”, and “Software” using keywords detailed in Table A.3. We find consistent results that the use of youth-favoring stereotypes is associated with favoring young workers, as they are perceived as quick learners, more sociable, and able to embrace new technology.

5.2.2 Job skills and tasks

We further test the model prediction that firms search more broadly with a smaller likelihood for age discrimination practices when they require more job skills and tasks (**Prediction 4**). Our model implications and results are consistent with Kuhn and Shen (2013). We estimate this relationship using five different proxies, including education requirement and posted wages, as well as measures of cognitive skills, and job tasks such as those related to problem-solving and decision-making.

Figure 5 reports the association between skill requirements and firms’ use of explicit age restrictions, using Equation (4). Across both panels, we find a consistent and statistically significant negative relationship between skill requirements and age restrictions. Positions with higher skill requirements are less likely to state an explicit age range and less likely to exclude older workers. This negative association holds both within job cells and across cells, suggesting a skill targeting pattern in which firms facing higher skill demands tend to broaden their search rather than tighten it through age restrictions.

[Insert Figure 5 here]

We report the corresponding estimates from Figure 5 in Table 6 to quantify the magnitude of these relationships. Economically, the correlations are nontrivial. Based on Columns (2) and (4), positions with higher skill requirements are associated with a more than 2 percentage points lower probability of posting an explicit age range, and a 2 to 5 percentage points lower probability of excluding older workers. These estimates are

descriptive and should be interpreted with caution. Nonetheless, Tables A.11 and A.12 show that the results are robust to including all skill proxies in a single specification and to adding experience requirements as controls.

[Insert Table 6 here]

5.2.3 Application processing costs

One key trade-off in our model, consistent with Kuhn and Shen (2013), is that firms can reduce application processing costs at the expense of a smaller application pool (**Prediction 5**). Without a direct measure of c , we approximate it using the expected number of applications, defined as the total number of applications in a detailed job cell in Appendix A.2. Here, we define a detailed job cell by its 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, “Competitive” and “Very Competitive” based on an HHI index which measures the job ads concentration in a job cell.³⁸

[Insert Figure 6 here]

Figure 6, using Equation (4), examines two additional forces highlighted by the model: the expected size of the applicant pool and the competitive pressure firms face within a job cell. The estimates show a positive and statistically significant association between the expected number of applicants and the probability that a posting imposes an age restriction. Simultaneously, competition is negatively and significantly related to firms’

³⁸See details in Appendix A.2. The “Competitive” indicator corresponds to job cells with an HHI index between 1500 and 2500, and “Very Competitive” job cells have an HHI index below 1500. These thresholds were also used in section “Market Concentration” of “Horizontal Merger Guidelines” by the U.S. Department of Justice and the Federal Trade Commission in 2010.

age discrimination choices. Put together, when firms anticipate fewer applicants or face more intense competition, they are less likely to rely on explicit age screening, both in terms of stating an age range and excluding older workers. These patterns are evident both within job cells and in comparisons across cells. 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 7 summarizes the results from Figure 6, 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 1.9%. Firms in “High Competition” and “Very High Competition” job cells are 8.5% and 17.8% less likely to impose age restrictions compared to firms in less competitive job cells, respectively. Similarly, Column (4) shows that a 100% increase in the expected number of applicants increases the likelihood of explicitly requesting younger workers under age 40 by 2.4%. Firms in “Competitive” and “Very Competitive” job cells are 8.7% and 20.2% less likely to specify a preference for younger workers, respectively. Table A.13 confirms the robustness of our results when controlling for experience requirements, mitigating concerns that age restrictions merely reflect experience-related hiring preferences.³⁹

[Insert Table 7 here]

6 Conclusion

This paper documents the prevalence and consequences of explicitly stated age restrictions in online recruitment and examines how these restrictions interact with firms’ incentives and workers’ directed search. Using a large-scale vacancy dataset from China that links postings to ad-level applicant distributions, we show that explicit age restrictions are widespread with age caps frequently excluding applicants in their forties and older, well

³⁹We also examine the role of the expected number of applications using separate regressions in the Table A.14. 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%.

before statutory retirement ages. On the demand side, firms' use of age restrictions reflects biases that favor younger applicants and correlates with job attributes such as high work intensity, low skill level, high recruitment costs, and low local labor market competition. On the supply side, we find that age caps substantially reshape applicant compositions with younger and less educated applicants, while noncompliance is non-trivial and systematically higher in high-wage and high-skilled vacancies.

Our findings have several implications for both labor market efficiency and policy design. Understanding why firms adopt age caps is essential for designing effective interventions. First, reliance on explicit age limits suggests that firms prioritize immediate search cost reductions over potential long-run productivity gains. Policymakers could encourage hiring practices that treat workers of different ages equally, for example, by promoting age-neutral screening tools or discouraging age caps in postings. Second, while eliminating discrimination is difficult, policy should target sources of bias tied to job features that firms perceive as ill-suited to older workers, such as high work intensity. 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, in light of China's rapid population aging, policy design should account for the interaction between age discrimination, labor supply constraints, and retirement rules. Encouraging lifelong learning initiatives could help older workers remain competitive and adaptable in the labor market.

Beyond policy, our results show age discrimination in China can begin as early as the mid-thirties, instigating fewer job opportunities, less job stability, and higher risks of premature labor force exit as workers age. Future research could examine workers' adaptation margins, including career switching, skill upgrading, and strategic job search behaviors. Additionally, investigating how firms adjust hiring when policy interventions alter the costs or visibility of age-based screening could provide valuable insights into the effectiveness of anti-discrimination measures, in the spirit of related evidence from policy changes that restrict discriminatory language in job postings (Card et al., 2023; Kuhn and Shen, 2023).

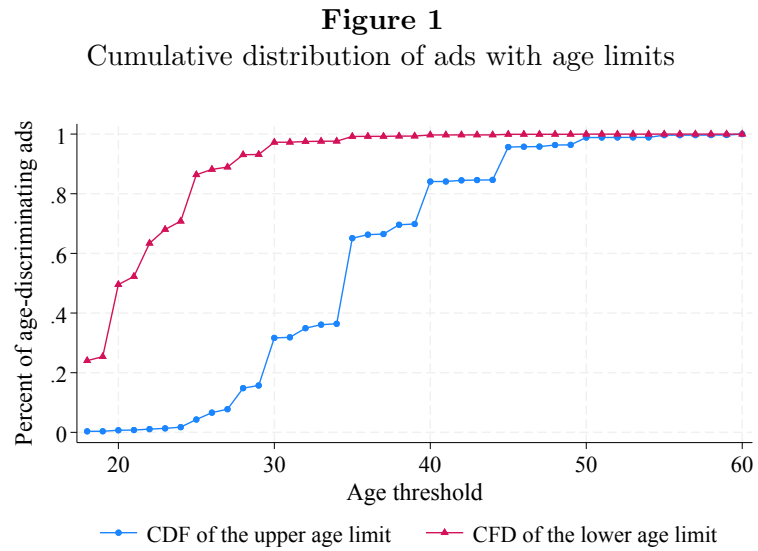
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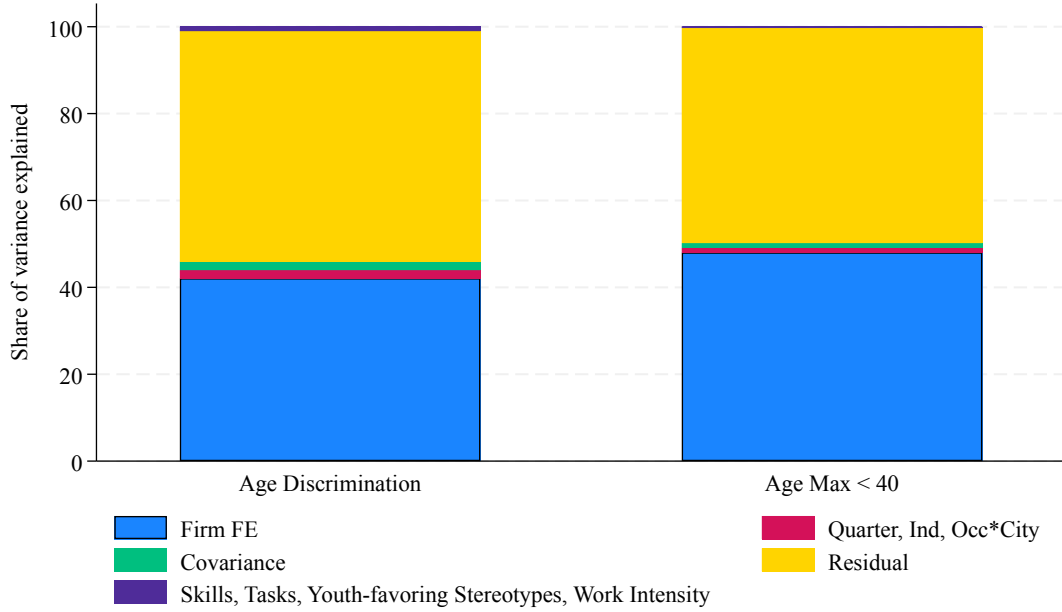
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Figures and tables



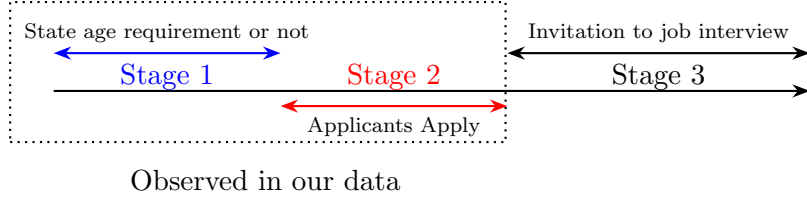
Notes: Figure 1 reports the cumulative distribution of maximum and minimum age thresholds among age-discriminating job ads. The y-axis, “percent of age-discriminating ads”, is defined as the cumulative density of ads with a maximum (minimum) age limit that excludes applicants above (below) each age threshold. See discussion in Sections 1 and 3.1.

Figure 2
 Variance decomposition of age discrimination decisions



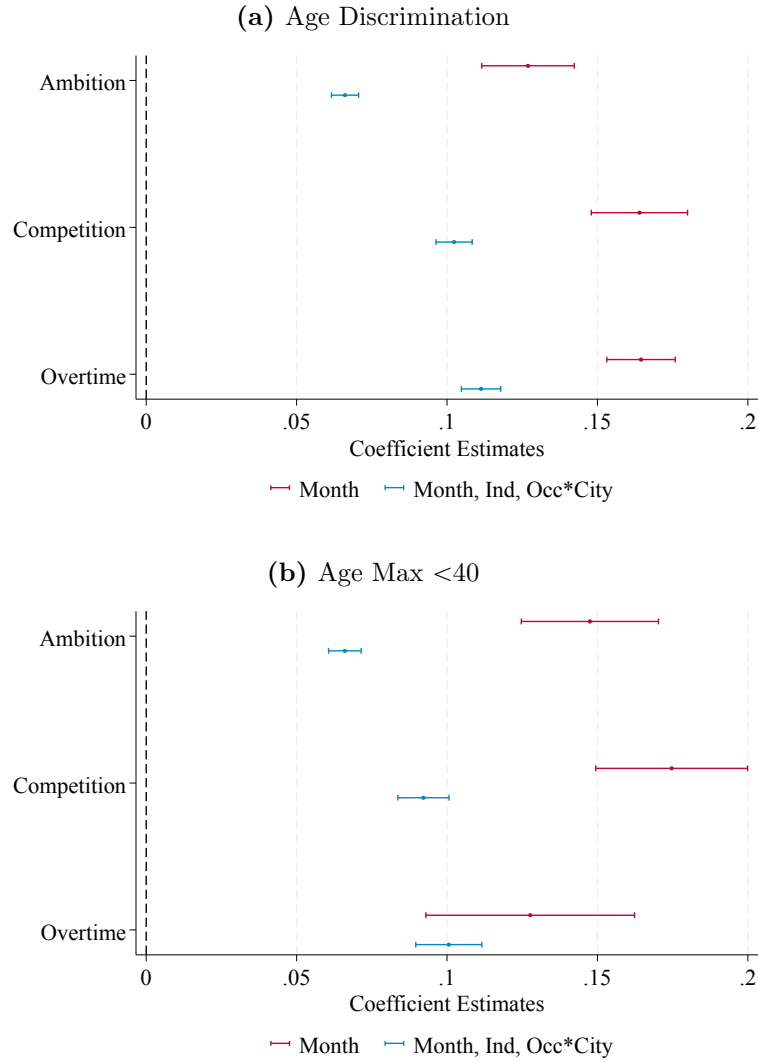
Notes: Figure 2 shows the variance decomposition of age discrimination decisions. The x-axis lists the two dependent variables: an indicator equal to one if the employer explicitly states an age requirement (“Age discrimination”) and an indicator equal to one if the stated age range has a maximum below 40 (“Age Max < 40”). The y-axis shows, for each outcome, the share of its total variance that is explained by different sets of covariates. 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. See discussion in Section 3.2.

Figure 3
 Timeline of discrimination and decision process



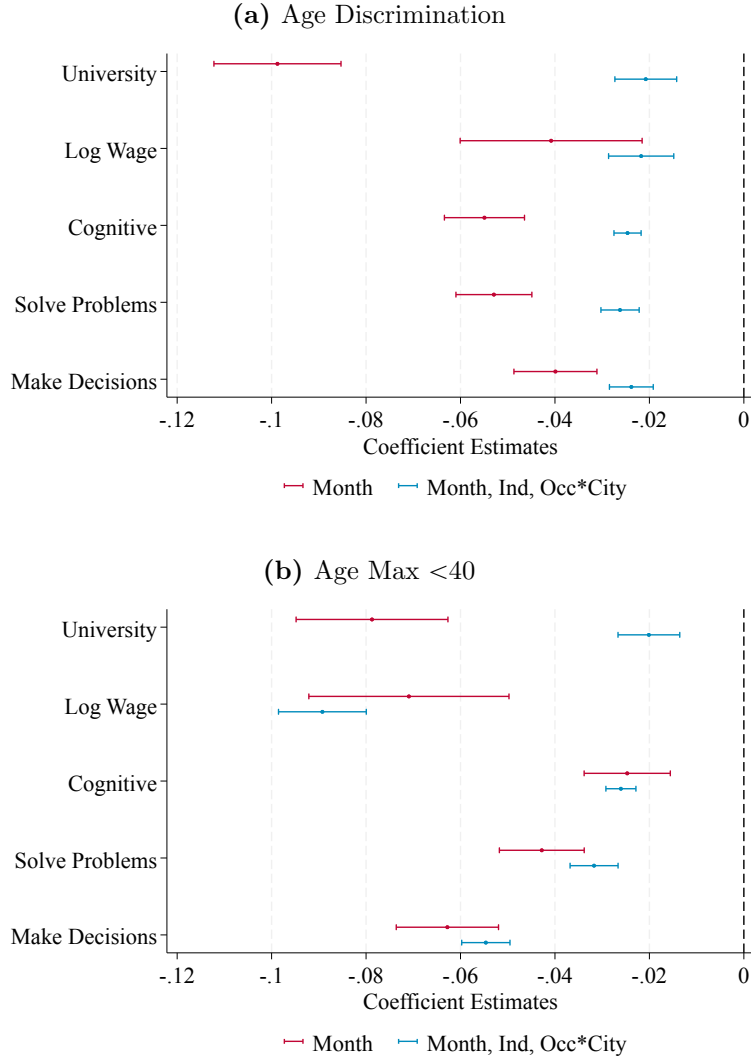
Notes: Figure 3 shows an illustration of a three-stage decision process during recruitment. In Stage 1, firms explicitly state age restrictions, and in Stage 2, applicants decide where to apply based on job postings, age-discrimination decisions and their own characteristics. In Stage 3, the HR departments assess the applicant pool and decide whether or not to stick with the initial age restriction. Only Stage 1 and some group characteristics of applicants in Stage 2 are observable in our data. We do not observe interview and hiring decisions in Stage 3. See discussion in Section 4.

Figure 4
Work intensity and age discrimination decisions



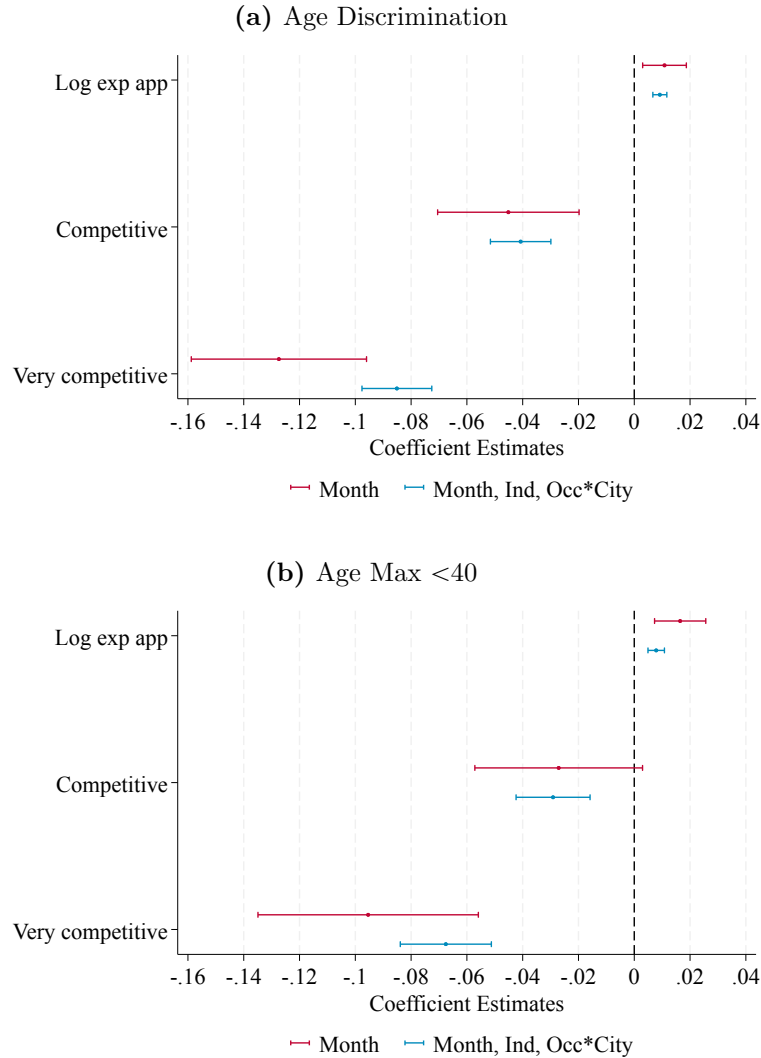
Notes: Figure 4 plots regression coefficients of age discrimination decisions on each work intensity measure. The outcome variable in Panel (a), “Age Discrimination”, is an indicator equal to one if the employer explicitly states an age requirement. The outcome variable in Panel (b), “Age Max < 40”, is an indicator equal to one if the stated age range has a maximum below 40. Work intensity measures are constructed from job ad keywords listed in Panel A of Table A.3. All coefficients are estimated using equation (4) in separate regressions, where each work intensity measure is included individually. Red intervals show estimates that control for period fixed effects, and blue intervals show estimates that additionally control for industry and occupation-city fixed effects. Each interval is a 95% confidence interval based on standard errors clustered at the occupation-city level. The corresponding coefficient estimates are reported in Table 5. Figure A.6 reports regression coefficients using different cut-offs for the maximum age requested. See discussion in Section 5.2.

Figure 5
Job skills and age discrimination decisions



Notes: Figure 5 reports the regression coefficients of each skill variable. The outcome variable in Panel (a), “Age Discrimination”, is an indicator equal to one if the employer explicitly states an age requirement. The outcome variable in Panel (b), “Age Max < 40”, is an indicator equal to one if the stated age range has a maximum below 40. “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. Other skill variables are constructed from job ad keywords listed in Panel C of the Table A.3. All coefficients are estimated using equation (4) in separate regressions, where each skill measure is included individually. Red intervals show estimates that control for period fixed effects, and blue intervals show estimates that additionally control for industry and occupation-city fixed effects. Each interval is a 95% confidence interval based on standard errors are clustered at the occupation-city level. The corresponding coefficient estimates are reported in Table 6. See discussion in Section 5.2.

Figure 6
 Competition in labor demand and age discrimination decisions



Notes: Figure 6 reports regression coefficients of age discrimination decisions on competition levels in labor demand as well as the expected number of applicants. The outcome variable in Panel (a), “Age Discrimination”, is an indicator equal to one if the employer explicitly states an age requirement. The outcome variable in Panel (b), “Age Max < 40”, is an indicator equal to one if the stated age range has a maximum below 40. 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 an indicator if the HHI index is between 1500 and 2500. “Very competitive” is an indicator if the HHI index is smaller than 1500. Low competition, the omitted category, is defined for job cells with high market concentration in labor demand, where $HHI > 2500$. HHI is defined as the total sum of the quadratic employer shares in each job cell defined by university requirement, industry, and occupation-city pairs. These thresholds were also used in “Market Concentration” section of “Horizontal Merger Guidelines” by the U.S. Department of Justice and the Federal Trade Commission in 2010. All coefficients are estimated using (4) in a single regression with all independent variables. Red intervals show estimates that control for period fixed effects, and blue bars show estimates that additionally control for industry and occupation-city fixed effects. Each interval is a 95% confidence interval based on standard errors clustered at the occupation-city level. The corresponding coefficient estimates are reported in Table 7. See discussion in Section 5.2.

Table 1
Sample means, 51job.com job ads

Characteristics	Value
<i>Panel A. Ad characteristics</i>	
Education requirements	
Junior High School and below	0.023
Senior High School	0.073
Secondary Specialized School	0.061
Secondary Technical School	0.012
Junior College	0.402
Bachelor	0.183
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, when specified	2.7
Age requirements	
No age restrictions	0.478
Mean age requested	28.8
Wage	
Mean wage	99223.3
Number of positions advertised	
Unspecified	0.156
Mean number, when specified	5.6
<i>Panel B. Firm characteristics</i>	
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	0.137
State-owned enterprise	0.041
Non-profit organization	0.002
<i>Panel C. Application information</i>	
Ads with more than 1 applicant	1.000
No. of applicants	53.5
No. of applicants with university degree	28.2

Notes: Table 1 reports summary statistics for job ads, firm characteristics, and application information in the 51job.com data. Job postings are scraped 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 are specified, or measured as the posted wage if only the minimum or maximum wage is specified. Firm characteristics are reported by employers on 51job.com. Table A.1 reports changes in the sample means relative to the original sample without any sample restrictions. See discussion in Section 2.2.

Table 2
Age discrimination and applicant numbers of different age groups

	Number of Applicants by Age Group				
	(1)	(2)	(3)	(4)	(5)
	≤23	24-26	27-30	31-40	≥41
Panel A: Age Discrimination					
	0.3607	-0.3584	-0.6402	-0.6989	0.1382
	(0.1531)	(0.1024)	(0.0817)	(0.1165)	(0.0723)
Panel B: Age Max < 40					
	1.7129	0.4007	-0.8313	-3.8019	-2.6713
	(0.2090)	(0.1285)	(0.1137)	(0.3401)	(0.2692)
Observations	7,720,870	7,720,870	7,720,870	7,720,870	7,720,870
Cluster No.	15,669	15,669	15,669	15,669	15,669
R^2	0.132	0.130	0.151	0.171	0.148
Mean of Y	11.411	10.159	10.158	15.380	6.385
Month FE	✓	✓	✓	✓	✓
Industry FE	✓	✓	✓	✓	✓
Occ*City FE	✓	✓	✓	✓	✓

Notes: Table 2 reports regression estimates of the association between employers' age requirement decisions and the number of applicants in each age group. The outcome variable is the number of applicants in a given age group for each job ad. The age group categories 23, 24–26, 27–30, 31–40, and 41 or older follow the thresholds defined by 51job.com, as explained in Appendix A.2. The independent variable in Panel A, “Age Discrimination”, is an indicator equal to one if the employer explicitly states an age requirement. The independent variable in Panel B, “Age Max < 40”, is an indicator equal to one if the stated age range has a maximum below 40. All coefficients are estimated using equation (2) in separate regressions by age group. All specifications include period fixed effects, industry, and occupation-city fixed effects. Standard errors are clustered at the occupation-city level. Table A.5 reports the regression coefficients of the share of applicants by each group on the use of age discrimination decisions. Table A.6 reports the regression coefficients with different fixed effects or with an additional experience control. See discussion in Section 5.1.

Table 3
Job posted wage and compliance rate at different maximum age thresholds

	Compliance Rate (Max 40)		Compliance Rate (Max 30)	
	(1)	(2)	(3)	(4)
Log wage	-0.0465 (0.0041)	-0.0367 (0.0015)	-0.0596 (0.0071)	-0.0307 (0.0025)
Observations	3,653,569	3,653,569	3,653,569	3,653,569
Cluster No.	13,293	13,293	13,293	13,293
R^2	0.044	0.131	0.029	0.121
Mean of Y	0.919	0.919	0.845	0.845
Month FE	✓	✓	✓	✓
Industry FE		✓		✓
Occ*City FE		✓		✓

Notes: Table 3 reports regression estimates of the association between the compliance rates and the posted wage. 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 posted wage is the mid-value of the wage range posted in the job ad. All coefficients are estimated using equation (3). All specifications include period fixed effects, Columns (2) and (4) additionally control for industry and occupation-city fixed effects. Standard errors are clustered at the occupation-city level. See discussion in Section 5.1.

Table 4
Job requirements and compliance rate at different maximum age thresholds

	Compliance Rate (Max 40)		Compliance Rate (Max 30)	
	(1)	(2)	(3)	(4)
Panel A: University				
	-0.0011	-0.0031	-0.0043	-0.0104
	(0.0017)	(0.0009)	(0.0035)	(0.0018)
Panel B: Cognitive				
	-0.0008	-0.0018	-0.0147	-0.0067
	(0.0011)	(0.0007)	(0.0022)	(0.0009)
Panel C: Solve Problems				
	-0.0040	-0.0057	-0.0079	-0.0068
	(0.0014)	(0.0008)	(0.0021)	(0.0014)
Panel D: Make Decisions				
	-0.0048	-0.0060	-0.0103	-0.0056
	(0.0016)	(0.0009)	(0.0026)	(0.0015)
Observations	3,653,569	3,653,569	3,653,569	3,653,569
Cluster No.	13,293	13,293	13,293	13,293
R^2	0.045	0.131	0.030	0.121
Mean of Y	0.919	0.919	0.845	0.845
Month FE	✓	✓	✓	✓
Industry FE		✓		✓
Occ*City FE		✓		✓

Notes: Table 4 reports regression estimates of the association between the compliance rate and different job requirements. 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 constructed from job ad keywords listed in Panel C of Table A.3. All coefficients are estimated using equation (3). All specifications include period fixed effects, Columns (2) and (4) additionally control for industry and occupation-city fixed effects. Standard errors are clustered at the occupation-city level. See discussion in Section 5.1.

Table 5
Work intensity and age discrimination decision

	Age Discrimination		Age Max < 40	
	(1)	(2)	(3)	(4)
Panel A: Ambition				
	0.1269	0.0661	0.1475	0.0660
	(0.0078)	(0.0023)	(0.0116)	(0.0028)
Panel B: Competition				
	0.1640	0.1023	0.1747	0.0922
	(0.0082)	(0.0031)	(0.0129)	(0.0043)
Panel C: Overtime				
	0.1645	0.1113	0.1277	0.1006
	(0.0058)	(0.0033)	(0.0177)	(0.0056)
Observations	7,720,870	7,720,870	7,720,870	7,720,870
Cluster No.	15,669	15,669	15,669	15,669
R^2	0.011	0.074	0.008	0.089
Mean of Y	0.478	0.478	0.334	0.334
Month FE	✓	✓	✓	✓
Industry FE		✓		✓
Occ*City FE		✓		✓

Notes: Table 5 reports the regression estimates of the association between work intensity measures and employers' age requirement decisions. The outcome variable in Columns (1) and (2), "Age Discrimination", is an indicator equal to one if the employer explicitly states an age requirement. The outcome variable in Columns (3) and (4), "Age Max < 40", is an indicator equal to one if the stated age range has a maximum below 40. Work intensity measures are constructed from job ad keywords listed in Panel A of Table A.3. All coefficients are estimated using equation (4) in separate regressions, where each work intensity measure is included individually. All specifications include period fixed effects, Columns (2) and (4) additionally control for industry and occupation-city fixed effects. Figure 4 plots the confidence intervals. Standard errors are clustered at the occupation-city level. Table A.8 tests for robustness with all work intensity measures included in one regression. Table A.9 tests for robustness with an experience requirement control. Figure 4 tests for robustness with different maximum age limit cutoffs. See discussion in Section 5.2.

Table 6
Job skills, tasks, and age discrimination decision

	Age Discrimination		Age Max < 40	
	(1)	(2)	(3)	(4)
Panel A: University				
	-0.0988	-0.0208	-0.0787	-0.0201
	(0.0069)	(0.0033)	(0.0082)	(0.0033)
Panel B: Log Wage				
	-0.0408	-0.0217	-0.0709	-0.0892
	(0.0098)	(0.0035)	(0.0108)	(0.0047)
Panel C: Cognitive				
	-0.0549	-0.0246	-0.0247	-0.0260
	(0.0043)	(0.0015)	(0.0047)	(0.0016)
Panel D: Solve Problems				
	-0.0529	-0.0262	-0.0428	-0.0317
	(0.0041)	(0.0021)	(0.0046)	(0.0026)
Panel E: Make Decisions				
	-0.0399	-0.0238	-0.0628	-0.0546
	(0.0045)	(0.0024)	(0.0055)	(0.0026)
Observations	7,720,870	7,720,870	7,720,870	7,720,870
Cluster No.	15,669	15,669	15,669	15,669
R^2	0.001	0.070	0.003	0.087
Mean of Y	0.478	0.478	0.334	0.334
Month FE	✓	✓	✓	✓
Industry FE		✓		✓
Occ*City FE		✓		✓

Notes: Table 6 reports the regression estimates of the association between job requirements and the use of age discrimination. The outcome variable in Columns (1) and (2), “Age Discrimination”, is an indicator equal to one if the employer explicitly states an age requirement. The outcome variable in Columns (3) and (4), “Age Max < 40”, is an indicator equal to one if the stated age range has a maximum below 40. Skill and task measures are constructed from job ad keywords listed in Panel C of the Table A.3. All coefficients are estimated using equation (4) in separate regressions, where each skill or task measure is included individually. All specifications include period fixed effects, Columns (2) and (4) additionally control for industry and occupation-city fixed effects. Figure 5 plots the confidence intervals. Standard errors are clustered at the occupation-city level. Table A.12 tests for robustness with an experience control. Table A.11 tests for robustness with all work skill and task measures included in one regression. See discussion in Section 5.2.

Table 7
Search cost, competition in labor demand and age discrimination
decision

	Age Discrimination		Age Max < 40	
	(1)	(2)	(3)	(4)
Ln app pool	0.011 (0.004)	0.009 (0.001)	0.016 (0.005)	0.008 (0.002)
Competitive	-0.045 (0.013)	-0.041 (0.006)	-0.027 (0.015)	-0.029 (0.007)
Very Competitive	-0.127 (0.016)	-0.085 (0.006)	-0.095 (0.020)	-0.068 (0.008)
Observations	7,720,870	7,720,870	7,720,870	7,720,870
Cluster No.	15,669	15,669	15,669	15,669
R^2	0.005	0.071	0.006	0.086
Mean of Y	0.478	0.478	0.334	0.334
Month FE	✓	✓	✓	✓
Industry FE		✓		✓
Occ*City FE		✓		✓

Notes: Table 7 reports the regression estimates of the association between correlations between employers' age requirement decisions and log expected application number, as well as competition among firms. The outcome variable in Columns (1) and (2), "Age Discrimination", is an indicator equal to one if the employer explicitly states an age requirement. The outcome variable in Columns (3) and (4), "Age Max < 40", is an indicator equal to one if the stated age range has a maximum below 40. 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" and "Very Competitive" are indicator variables measuring the extent of labor market competition among firms in a detailed job cell, as measured by an HHI index. Please see the definition details of these two indicator variables in Appendix A.2. All coefficients are estimated using equation (4) with all independent variables included in one regression. All specifications include period fixed effects, Columns (2) and (4) additionally control for industry and occupation-city fixed effects. Standard errors are clustered at the occupation-city level. Figure 6 plots the confidence intervals. Table A.13 tests for robustness with an experience control. Table A.14 reports the regression estimates of the association between log expected number of applicants and employers' age requirement decisions. See discussion in Section 5.2.

Appendix

A Data Appendix

A.1 Data Representativeness

In this section, we examine the representativeness of our 51job.com sample by comparing it with the 2019 China Labour Statistical Yearbook, which contains information and summary statistics related to the general Chinese labor market in 2018. As detailed in Table A.2, job postings on the 51job.com exhibit distinct characteristics relative 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 general urban workforce is under 30 years old, 58% of ads seek applicants with an average age below 30. In terms of educational requirements, about 68% of employed workers in 2018 did not have a college degree or higher, whereas 58% of 51job.com ads explicitly require at least a college degree. Furthermore, while over 35% of employees worked in state-owned enterprises or collectives, less than 5% of job ads were published by firms in those sectors. Although 51job covers a wide range of job types and posts a substantial number of ads, these comparisons indicate that it primarily caters to private-sector firms seeking young and highly educated applicants.

To further understand the relationship between 51job.com ads and the overall Chinese labor market, we compared the distribution of general employment with that of ads on 51job.com across broad occupation and industry categories. Although the industry and occupation categories on 51job.com do not precisely align with those in the yearbook, several conclusions can be drawn. First, the computer science, internet, communications, and electronics industries are significantly overrepresented on 51job.com, accounting for 28% of all vacancies, compared with about 2% of the overall workforce. Second, the most underrepresented industries on 51job.com are trade, consumption, manufacturing,

operations, and service industries, relative to their share in the total working population. Third, ads targeting professional and technical workers are overrepresented on 51job.com, while postings for public servants are underrepresented. Overall, the distribution of vacancies across occupations on 51job.com is similar to that of the nationally representative sample, with a correlation of more than 0.7.⁴⁰ 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 defining several outcome variables that capture workers' application responses to firms' age requirements stated in job advertisements.

Firstly, we examine the number of applicants per job ad, which reflects aggregate applicant inflows in response to firms' hiring criteria. This variable captures how employer-side age requirements are associated with the size of the application pool. This can be further disaggregated at different age groups defined by 51job.com: 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.com, and unfortunately, we do not have access to more detailed age information.

Secondly, we measure the compliance rates of workers at two maximum age cut-offs, 40 and 30. Specifically, we divide the number of applicants with age at or below the cut-offs, 40 and 30, by the total number of applicants at the ad level to define "Compliance Rate (Max 40)" and "Compliance Rate (Max 30)", respectively.

Lastly, we measure the quality of the application pool at the job ad level by looking at the number of applicants holding university degrees or higher.

We also use the applicant numbers to define some search concerns of the firms. Without a direct measure of the search cost, we use the number of applicants within a

⁴⁰Marinescu (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.

narrowly defined job cell as a proxy for the expected number of applications a vacancy in that cell receives. This measure is defined by the total number of applicants in a specific job market, characterized by a firm’s educational requirements, industry, and the occupation-city pairs.

Another search concern for firms is related to the intensity of competition among employers. We define two indicator variables “Competitive” and “Very High Competitive” to characterize how competitive labor demand is in the local labor market faced by each firm. We first calculate the total number of applicants for each firm in each detailed job cell. We then calculate the quadratic share of the number of applicants for each firm. Adding up the quadratic shares of all firms, we get an HHI index that measures labor demand concentration in each detailed job cell. A large HHI index indicates high monopsony power of firms in a detailed job cell, while a small HHI index suggests a higher level of competition between firms. We follow concentration thresholds adopted by the U.S. Department of Justice and the Federal Trade Commission in “Market Concentration” section of “Horizontal Merger Guidelines” in 2011. “Competitive” is equal to 1 if the HHI index is between 1500 and 2500. “Very competitive” is equal to 1 if the HHI index is smaller than 1500. Low competition, the omitted category, is defined for detailed job cells with a high market concentration in labor demand, where $HHI > 2500$.

Beyond search-related measures, we also construct job-attribute variables based on information directly reported by firms and on keywords extracted from the free-text job descriptions. We first define work intensity measures. Some jobs require employees to handle high-pressure situations, including long working hours and competitive environments.⁴¹ To capture these demanding job attributes, we introduce three indicator variables, “Ambition,” “Competition,” and “Overtime”. We define these variables through keywords listed in Panel A of Table A.3.

We also present relevant keywords used for stereotypes that favor youth in Panel B of the Table A.3. Informed by the industrial psychology research analyzed in Burn et al.

⁴¹Average weekly work hours per employed person in China are 46.1, compared with 40.2 in Asia and the Pacific, 38.0 in the US, and 34.2 in Germany, according to International Labour Organization (2024).

(2022), we identify specific youth-favoring stereotypes: “Learning”, “Communication”, and “Software”. These phrases may confer an advantage to younger workers who are perceived to learn more quickly, build better relationships with customers or colleagues, and be more adaptive to specific programming or software tools.

We also provide a comprehensive list of the specific phrases and keywords used to classify job skills and job tasks in Panel C. Drawing on the framework in Deming and Kahn (2018),⁴² we test the applicability “Cognitive” skills in predicting firms’ age discrimination tendencies. Following Gelblum (2020) methodology,⁴³ 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.

We also present summary statistics of the defined variables in Table A.4 to demonstrate the extent of variations of these variables in job postings.

⁴²The 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.

⁴³Although Gelblum characterizes tasks as gender-specific, the measurement of these tasks is also applicable to general analysis.

B Age discrimination by firm characteristics, industries, and occupations

B.1 Age discrimination decisions by different firm characteristics

We examine the prevalence of age discrimination across different firm types. Figures A.1 illustrate different firm types' tendency to explicitly impose age restrictions and discriminate against older workers. Compared with 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.

Figure A.2 analyzes the relationship between firm size and age discrimination decisions. 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.

B.2 Age discrimination decisions by industry and occupation

We present how age discrimination varies across industries and occupations. Figure A.3 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, the finance industry also ranks highest in explicit discrimination against older workers, with the service industry following closely behind. Long work hours in the finance industry might partially explain the use of age discrimination, which we further examine in Section 5.2 on labor demand. The findings for the service industry align with Kuhn et al. (2020), who document 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 and the relatively tight labor supply in these occupations.

Figure A.4 presents the prevalence of age discrimination by major occupation categories of 51job.com. The service occupation has the highest share of job postings with explicit age requirements, followed closely by retail or 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.

C Details and Proofs for Section 4

C.1 Proof for workers' equilibrium in Subsection 4.2

We first layout payoffs for worker j when her opponent adopts different strategies $s^{-j} \in \{\bar{s}, \underline{s}\}$:

when worker 2 first applies to 1 then to 2 when her v^2 increases from 1 to 2,

$$W_1^1(v) = w_1 \left[2 - v^{2*} + (v + \delta - 1) \mathbf{1}_{v+\delta < v^{2*}} + (v^{2*} - 1) \mathbf{1}_{v+\delta \geq v^{2*}} \right]$$

$$W_2^1(v) = w_2 \left[v^{2*} - 1 + (v - v^{2*}) \mathbf{1}_{v \geq v^{2*}} \right];$$

when worker 2 first 2 then 1,

$$W_1^1(v) = w_1 \left[v^{2*} - 1 + (v + \delta - v^{2*}) \mathbf{1}_{v^{2*} \leq v+\delta \leq 2} + (2 - v^{2*}) \mathbf{1}_{v+\delta \geq 2} \right]$$

$$W_2^1(v) = w_2 \left[2 - v^{2*} + (v - 1) \mathbf{1}_{v \leq v^{2*}} + (v^{2*} - 1) \mathbf{1}_{v > v^{2*}} \right];$$

when worker 1 first 1 then 2,

$$W_1^2(v) = y_1^2 \left[2 - v^{1*} + (v - \delta - 1) \mathbf{1}_{1 \leq v - \delta < v^{1*}} + (v^{1*} - 1) \mathbf{1}_{v+\delta \geq v^{1*}} \right]$$

$$W_2^2(v) = w_2 \left[v^{1*} - 1 + (v - v^{1*}) \mathbf{1}_{v \geq v^{1*}} \right];$$

when worker 1 first 2 then 1,

$$W_1^2(v) = y_1^2 \left[v^{1*} - 1 + (v + \delta - v^{1*}) \mathbf{1}_{v+\delta \geq v^{1*}} \right]$$

$$W_2^2(v) = w_2 \left[2 - v^{1*} + (v - 1) \mathbf{1}_{v < v^{1*}} + (v^{1*} - 1) \mathbf{1}_{v \geq v^{1*}} \right].$$

We now solve for case 1 with $0 < w_2 < y_1^2 < w_1$. The arguments for the opposite case 3 is similar and omitted here. We already argue in the main text that worker 1 adopts a simple threshold strategy, she must first apply to firm 2 first and then switch 1 as $W_1^1(2) = w_1 > w_2 = W_2^1(2)$ (implying $s^1(2) = 1$ st the highest type $v^2 = 1$), i.e. she must adopt $s^1 = \underline{s}$. First, we assume that worker 2 use the same strategy $s^2 = \underline{s}$, i.e. first applying to firm 2 then to 1.

We solve $W_1^1(v^1) = W_2^1(v^1)$ and $W_1^2(v^2) = W_2^2(v^2)$, where

$$W_1^1(v) = w_1[v^2 - 1 + (v + \delta - v^2) 1_{\{v^2 \leq v + \delta \leq 2\}} + (2 - v^2) 1_{\{v + \delta \geq 2\}}],$$

$$W_2^1(v) = w_2[2 - v^2 + (v - 1) 1_{\{v \leq v^2\}} + (v^2 - 1) 1_{\{v \geq v^2\}}],$$

$$W_1^2(v) = y_1^2[v^1 - 1 + (v - \delta - v^1) 1_{\{v - \delta \geq v^1\}}],$$

$$W_2^2(v) = w_2[2 - v^1 + (v - 1) 1_{\{v < v^1\}} + (v^1 - 1) 1_{\{v \geq v^1\}}],$$

with rules for no root on $[1, 2]$: for the first equation $W_1^1 = W_2^1$, set $v^1 = 1$ if LHS > RHS everywhere and $v^1 = 2$ if RHS > LHS everywhere; for the second equation $W_1^2 = W_2^2$, similarly set $v^2 = 1$ if LHS > RHS everywhere and $v^2 = 2$ if RHS > LHS everywhere.

We proceed in three steps. First, we solve for v^{2*} when $v^1 = 1$. Then, we return to solve v^{1*} given the specific solution of v^2 . Finally, we check that no other solution exists.

Second equation at $v^1 = 1$. Then $W_1^2(v) = 0$ for $v < 1 + \delta$ and $y_1^2(v - \delta - 1)$ for $v \geq 1 + \delta$, while $W_2^2(v) \equiv w_2$. Hence there is a unique interior root

$$v^2 = 1 + \delta + \frac{w_2}{y_1^2} \quad \text{iff} \quad t < 1 - \frac{w_2}{y_1^2},$$

and otherwise no root on $[1, 2]$ (RHS \geq LHS), in which case the boundary rule gives $v^2 = 2$.

First equation given v^2 . Let $A := v^2 - \delta$. On $[1, 2]$,

$$W_1^1(v) = \begin{cases} w_1(v^2 - 1), & v < A, \\ w_1(v - 1 + \delta), & A \leq v \leq 2 - \delta, \\ w_1, & v \geq 2 - \delta, \end{cases} \quad W_2^1(v) = \begin{cases} w_2(1 + v - v^2), & v \leq v^2, \\ w_2, & v \geq v^2. \end{cases}$$

Thus $F_1(v) := W_1^1(v) - W_2^1(v)$ has minimum at $v = A$ with $F_1^{\min} = w_1(v^2 - 1) - w_2(1 - \delta)$, and $F_1(2) = w_1 - w_2 > 0$. For the two v^2 values found above:

$$t \geq 1 - \frac{w_2}{y_1^2}, \quad v^2 = 2 : \quad F_1^{\min} = w_1 - w_2(1 - \delta) > 0;$$

$$t < 1 - \frac{w_2}{y_1^2}, \quad v^2 = 1 + \delta + \frac{w_2}{y_1^2} : \quad F_1^{\min} = w_1 \left(t + \frac{w_2}{y_1^2} \right) - w_2(1 - \delta) = (w_1 + w_2)t + w_2 \left(\frac{w_1}{y_1^2} - 1 \right) > 0.$$

Hence the first equation has no root on $[1, 2]$ in either case, so by the boundary rule it selects $v^1 = 1$, verifying the fixed point.

No other solutions if $v^1 > 1$. Now, suppose $v^1 > 1$. We first solve $W_1^2(v^2) = W_2^2(v^2)$ for $v^2 \in [1, 2]$. Then substitute this v^2 into $W_1^1(v^1) = W_2^1(v^1)$ and show that no fixed point with $v^1 > 1$ can exist. Split v into three regions:

(I) $v < v^1$: here $W_1^2(v) = y_1^2(v^1 - 1)$ and $W_2^2(v) = w_2(v - v^1 + 1)$. Equality implies

$$v = v^1 - 1 + \frac{y_1^2}{w_2}(v^1 - 1) = v^1 + \left(\frac{y_1^2}{w_2} - 1\right)(v^1 - 1) > v^1,$$

which contradicts $v < v^1$. Hence no root in (I).

(II) $v^1 \leq v < v^1 + \delta$: here $W_1^2(v) = y_1^2(v^1 - 1)$ and $W_2^2(v) = w_2$. Equality requires the knife-edge $v^1 = 1 + \frac{w_2}{y_1^2}$; generically, no root in (II).

(III) $v \geq v^1 + \delta$: here $W_1^2(v) = y_1^2(v - \delta - 1)$ and $W_2^2(v) = w_2$. Equality yields

$$v^2 = 1 + \delta + \frac{w_2}{y_1^2}, \text{ which lies in region (III) iff } v^1 \leq 1 + \frac{w_2}{y_1^2}.$$

Therefore, for a fixed $v^1 > 1$:

$$\begin{cases} v^1 > 1 + \frac{w_2}{y_1^2} : & \text{no in-range root; in fact } W_1^2(v) > W_2^2(v) \forall v \in [1, 2], \\ v^1 = 1 + \frac{w_2}{y_1^2} : & \text{roots on } [v^1, v^1 + \delta] \text{ and at } v^2 = 1 + \delta + \frac{w_2}{y_1^2}, \\ 1 < v^1 < 1 + \frac{w_2}{y_1^2} : & \text{unique in-range root } v^2 = 1 + \delta + \frac{w_2}{y_1^2} \in (1, 2). \end{cases}$$

Now, we plug this v^2 into the first equation and solve for v^1 . For fixed v^2 , consider $F_1(v) = W_1^1(v) - W_2^1(v)$. On $[1, 2]$ its minimum occurs at $v = A := v^2 - \delta$ (or at $v = 1$ if $A < 1$), with

$$F_1^{\min} = w_1(v^2 - 1) - w_2(1 - \delta), \quad F_1(2) = w_1 - w_2 > 0.$$

Case A: $v^1 > 1 + \frac{w_2}{y_1^2}$. The second equation has no root and, since $W_1^2 > W_2^2$ everywhere, the boundary selection sets $v^2 = 1$. Then

$$W_1^1(v) = \begin{cases} w_1(v + \delta - 1), & v \leq 2 - \delta, \\ w_1, & v \geq 2 - \delta, \end{cases} \quad W_2^1(v) \equiv w_2,$$

so the only candidate root is $v_{\text{sol}}^1 = 1 + \frac{w_2}{w_1} - \delta$ (if it lies in $[1, 2 - \delta]$; otherwise no root

and the boundary sets $v^1 = 1$). In either sub-case,

$$v_{\text{sol}}^1 \leq 1 + \frac{w_2}{w_1} - \delta < 1 + \frac{w_2}{y_1^2} \leq v^1 \quad (\text{since } w_1 > y_1^2 \text{ and } \delta > 0),$$

hence $v_{\text{sol}}^1 \neq v^1$. No fixed point with $v^1 > 1 + \frac{w_2}{y_1^2}$ exists.

Case B: $v^1 = 1 + \frac{w_2}{y_1^2}$ (*knife-edge*). Any second-equation root satisfies $v^2 \geq v^1$, so

$$F_1^{\min} \geq w_1 \left(\frac{w_2}{y_1^2} \right) - w_2(1 - \delta) = w_2 \left(\frac{w_1}{y_1^2} - (1 - \delta) \right) > 0,$$

because $\frac{w_1}{y_1^2} > 1$ and $\delta > 0$. Thus $F_1(v) > 0$ on $[1, 2]$, so the first equation has no in-range root and (by its boundary rule) sets $v^1 = 1 \neq 1 + \frac{w_2}{y_1^2}$. No fixed point here either.

Case C: $1 < v^1 < 1 + \frac{w_2}{y_1^2}$. Step 1 yields the unique interior solution $v^2 = 1 + \delta + \frac{w_2}{y_1^2}$.

Then

$$F_1^{\min} = w_1 \left(\delta + \frac{w_2}{y_1^2} \right) - w_2(1 - \delta) = (w_1 + w_2)\delta + w_2 \left(\frac{w_1}{y_1^2} - 1 \right) > 0,$$

so again the first equation has no in-range root and must select $v^1 = 1 \neq$ the assumed $v^1 > 1$.

Therefore no fixed point with $v^1 > 1$ exists, and the fixed point solution pair exists as stated.

In a similar way, we can find that if worker 2 use the opposite strategy $s^2 = \bar{s}$, i.e. first applying to firm 1 then to 2, the only possible equilibrium is workers 1 and 2 always applying to firms 1 and 2 respectively, under the condition $\delta > 1 - \frac{w_2}{y_1^2}$, which effectively reduces to the solution above. This completes the solution for equilibrium in case 1.

C.2 Proof for Predictions 3, 4, and 5 in Subsection 4.4

Calculation gives

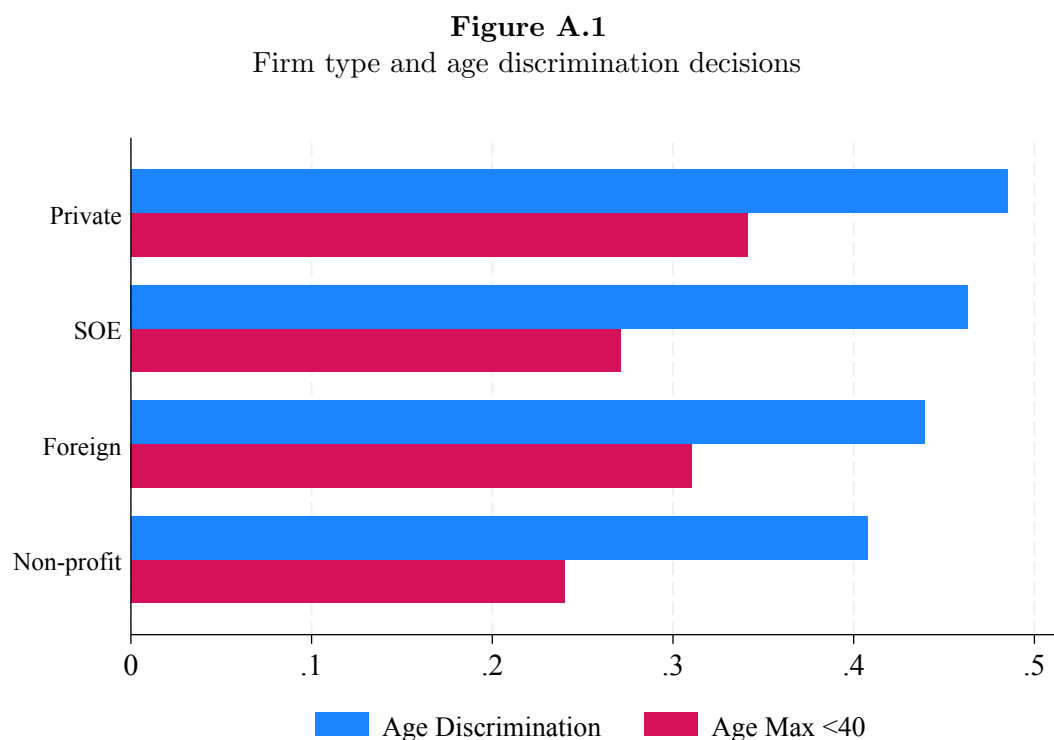
$$\begin{aligned} \mathbb{E}[v_1] &= \mathbb{E}[v^1] \Pr[v^2 \leq v^{2*}] + \mathbb{E}[\max\{v^1, v^2 - \delta\} | v^2 > v^{2*}] \\ &= \frac{3}{2}(v^{2*} - 1) + \int_{v^{2*}}^2 \left[\int_1^{v^2} (v^2 - \delta) dv^1 + \int_{v^2}^2 dv^1 \right] dv^2 \\ &= -\frac{1}{6}\bar{v}(d)^3 - \frac{1}{2}\delta\bar{v}(d)^2 + 2 - \frac{1}{2}\delta, \end{aligned}$$

where $\bar{v}(d) = v^{2*}(d) - 1 = \delta + \frac{w_2}{w_1 - (1+d)\alpha\delta}$, so that $\Delta v_1 = -\frac{1}{6}[\bar{v}(0)^3 - \bar{v}(1)^3] + \frac{1}{2}t[\bar{v}(0)^2 - \bar{v}(1)^2]$. As $\Delta N_1 = \bar{v}(1) - \bar{v}(0)$, we obtain

$$\begin{aligned} c_1^* &= \frac{\theta_1}{\gamma} \frac{\Delta v_1}{\Delta N_1} \\ &\propto \frac{\theta}{\gamma} [\bar{v}(1)^2 + \bar{v}(0)^2 + (\bar{v}(1) + \bar{v}(0))(\bar{v}(1) + \bar{v}(0) - \delta)] \\ &= \frac{\theta}{\gamma} \left[\left(\delta + \frac{w_2}{\delta(w_1 - \alpha\delta)} \right)^2 + \left(\delta + \frac{w_2}{\delta(w_1 - 2\alpha\delta)} \right)^2 \right. \\ &\quad \left. + \left(2\delta + \frac{w_2}{\delta(w_1 - \alpha\delta)} + \frac{w_2}{\delta(w_1 - 2\alpha\delta)} \right) \left(\delta + \frac{w_2}{\delta(w_1 - \alpha\delta)} + \frac{w_2}{\delta(w_1 - 2\alpha\delta)} \right) \right] \end{aligned}$$

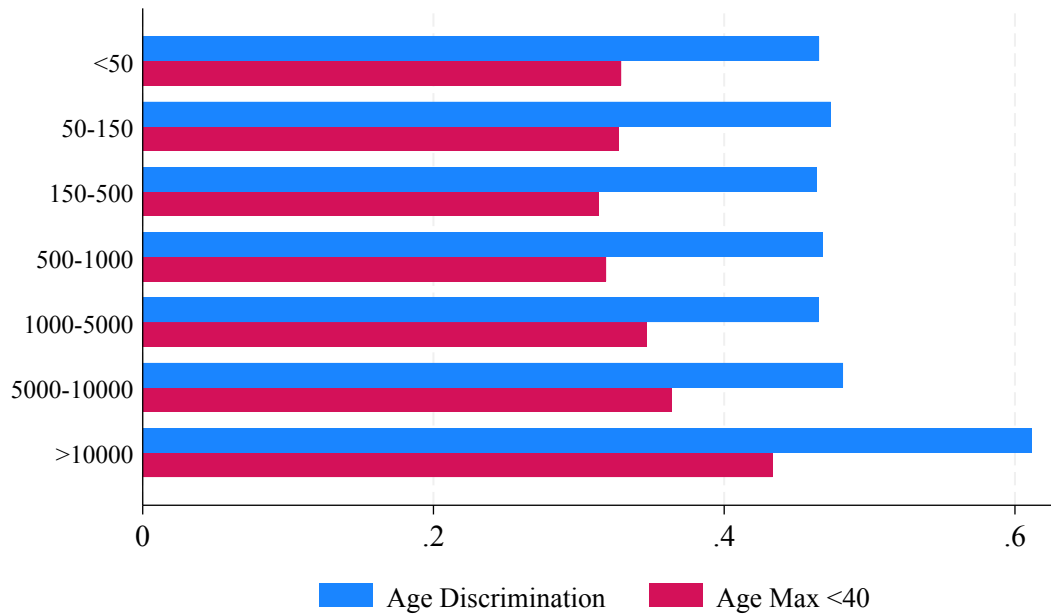
Obviously, c_1^* is decreasing in θ and decreasing in γ .

D Appendix figures and tables



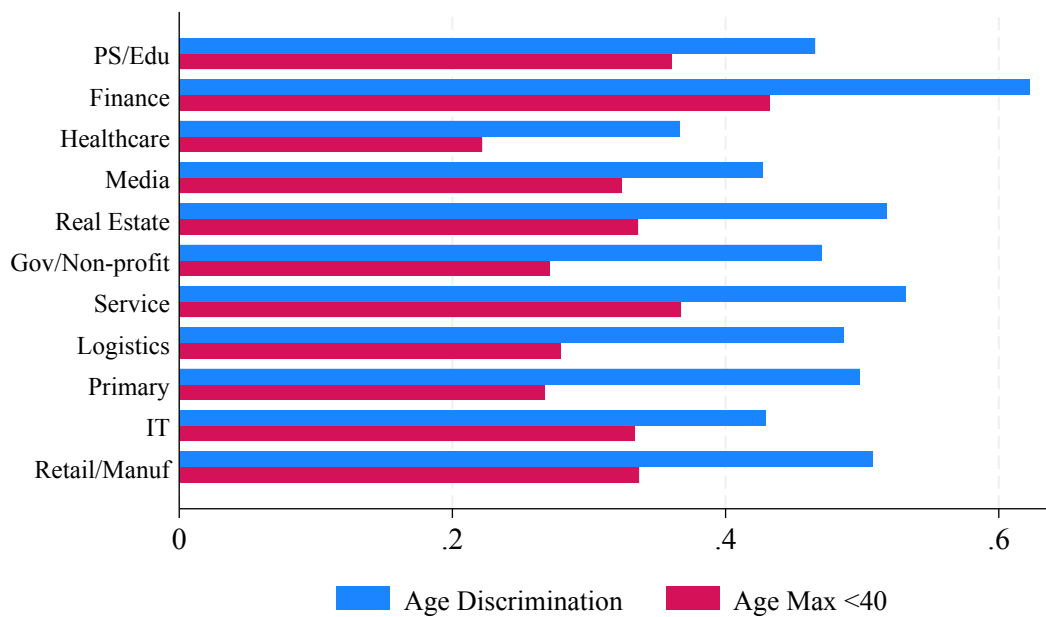
Notes: Figure A.1 reports the prevalence of age discrimination by each firm type. Firm types include domestic private firms, state-owned enterprises, foreign firms, and non-profit organizations. The blue bars show average values of “Age Discrimination”, an indicator variable equal to one if the employer explicitly states an age requirement. The red bars show average values of “Age Max <40”, an indicator equal to one if the stated age range has a maximum below 40. See discussion in Section B.1.

Figure A.2
Firm size and age discrimination decisions



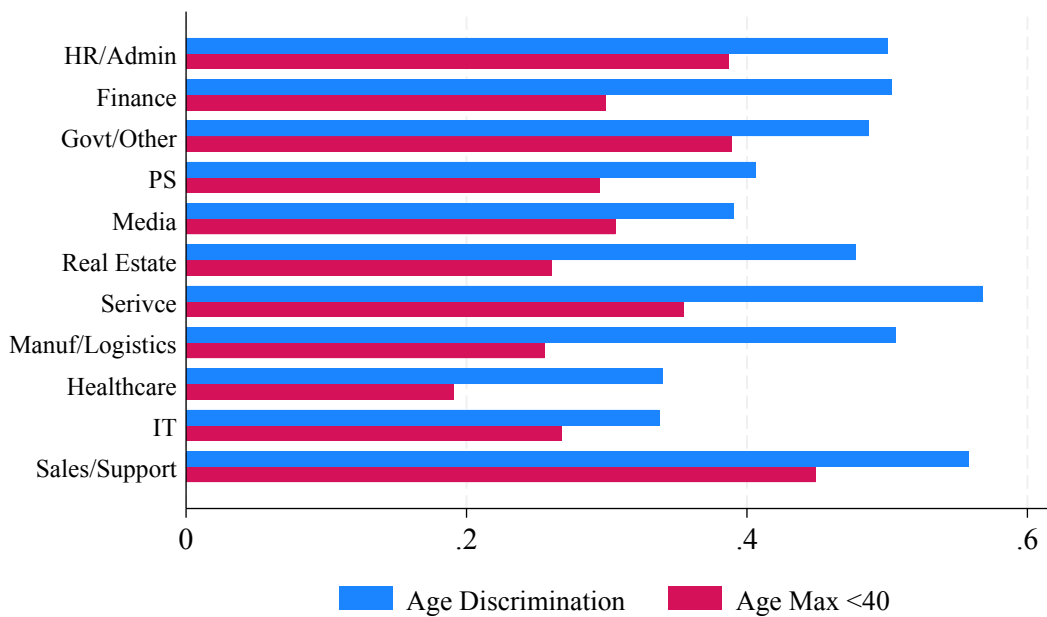
Notes: Figure A.2 reports the prevalence of age discrimination by each firm size. Firm size categories are determined by categories on 51job.com. The blue bars show average values of “Age Discrimination”, an indicator variable equal to one if the employer explicitly states an age requirement. The red bars show average values of “Age Max <40”, an indicator equal to one if the stated age range has a maximum below 40. See discussion in Section B.1.

Figure A.3
Industry and age discrimination decisions



Notes: Figure A.3 reports the share of ads with age discrimination by industry groups. Major industry groups include 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. These categories are defined by 51job.com. The blue bars show average values of “Age Discrimination”, an indicator variable equal to one if the employer explicitly states an age requirement. The red bars show average values of “Age Max <40”, an indicator equal to one if the stated age range has a maximum below 40. See discussion in Section B.2.

Figure A.4
Occupation and age discrimination decisions



Notes: Figure A.4 reports the share of ads with age discrimination by occupation groups. 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. These categories are defined by 51job.com. The blue bars show average values of “Age Discrimination”, an indicator variable equal to one if the employer explicitly states an age requirement. The red bars show average values of “Age Max <40”, an indicator equal to one if the stated age range has a maximum below 40. See discussion in Section B.2.

Figure A.5

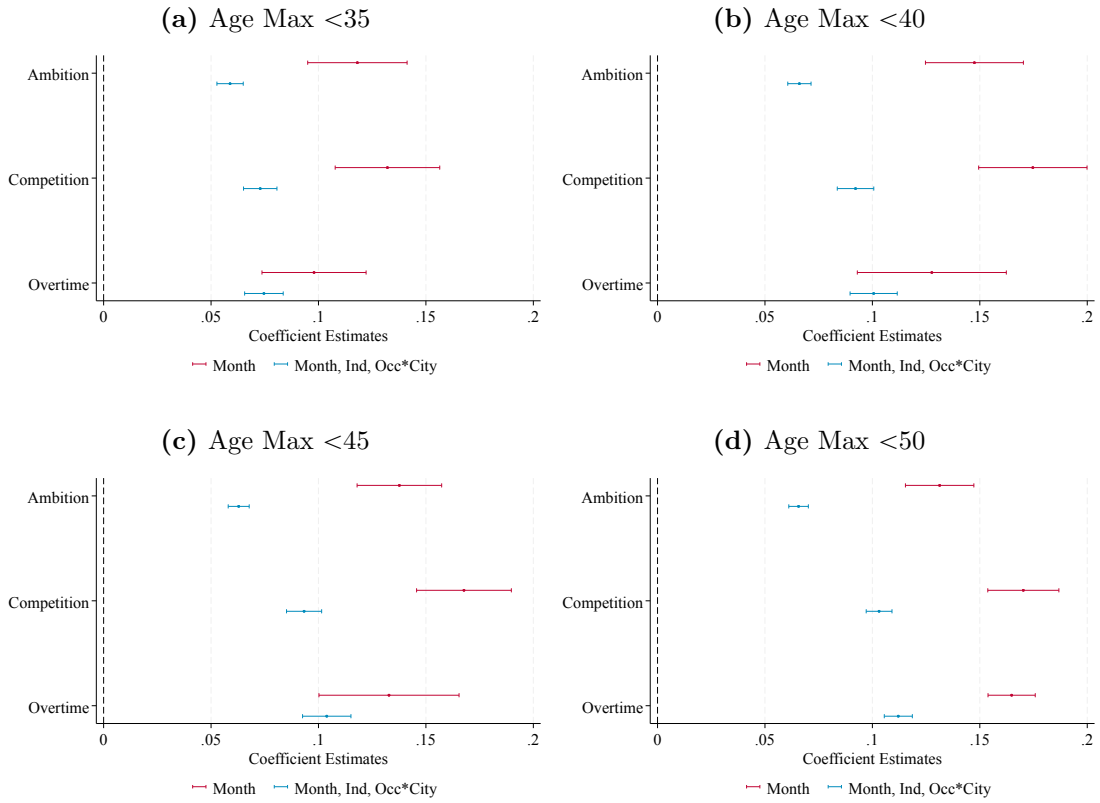
Histogram of vacancy shares with explicit age discrimination at the firm level



Notes: Figure A.5 reports the share of ads with age discrimination at the firm level. Over 40% of firms either always or never explicitly request a certain age group. See discussion in Section 3.2.

Figure A.6

Work intensity and age discrimination decisions with different age thresholds



Notes: Figure A.6 plots regression coefficients of age discrimination decision on each work intensity measure, using different cut-offs for the maximum age requested. The outcome variable in Panel (b), “Age Max < 40”, is an indicator equal to one if the stated age range has a maximum below 40, with the same regression specification as Panel (b) of Figure 4, but other panels have outcome variables that vary according to different maximum age cut-offs. All coefficients are estimated using equation (4) in separate regressions, where each work intensity measure is included individually. Red intervals show estimates that control for period fixed effects, and blue intervals show estimates that additionally control for industry and occupation-city fixed effects. Each interval is a 95% confidence interval based on standard errors clustered at the occupation-city level. See discussion in Section 5.2.

Table A.1
Sample means with or without sample restrictions

Characteristics	Our sample (1)	Original sample (2)
<i>Panel A. Ad characteristics</i>		
Education requirements		
Junior High School and below	0.023	0.025
Senior High School	0.073	0.075
Secondary Specialized School	0.061	0.062
Secondary Technical School	0.012	0.012
Junior College	0.402	0.393
Bachelor	0.183	0.181
Master	0.006	0.006
Ph.D.	0.000	0.000
No requirement	0.240	0.246
Experience requirements		
None or less than 1 year	0.474	0.480
1 year	0.186	0.184
2 years	0.132	0.130
3-4 years	0.134	0.133
5-7 years	0.059	0.059
8-9 years	0.008	0.008
10 years and above	0.007	0.007
Years of experience, when specified	2.7	2.7
Age requirements		
No age restrictions	0.478	0.475
Mean age requested	28.8	28.8
Wage		
Mean wage	99223.3	102119.3
Number of positions advertised		
Unspecified	0.156	0.158
Mean number, when specified	5.6	5.7
<i>Panel B. Firm characteristics</i>		
Firm size		
Under 50	0.156	0.156
50-150	0.292	0.290
150-500	0.233	0.232
500-1,000	0.116	0.116
1,000-5,000	0.110	0.111
5,000-10,000	0.021	0.021
10,000+	0.063	0.064
Firm ownership type		
Private, domestic	0.819	0.814
Foreign	0.137	0.141
State-owned enterprise	0.041	0.043
Non-profit organization	0.002	0.002
<i>Panel C. Application information</i>		
Ads with more than 1 applicant	1.000	0.959
No. of applicants	53.5	50.3
No. of applicants with university degree	28.2	26.6

Notes: Table A.1 reports changes in the summary statistics for job ads, firm characteristics, and application information, after imposing sample restrictions relative to the original sample without any restrictions. Table 1 reports only the means of the sample used for regression analysis. See discussion in Section 2.2.

Table A.2
Descriptive statistics, 51job.com ads versus 2019 China Labour
Statistical Yearbook

	Share in category	
	Yearbook (1)	51job.com (2)
Age		
29 or below	21.8	58.0
30–39	30.4	39.4
40–49	28.4	2.5
50 or above	19.4	0.1
Gender		
Male	57.1	64.1
Wage		
Average wage	82,413.0	102,119.3
Education		
High school or below	67.9	41.9
College	15.8	39.3
University or above	16.3	18.7
Industry		
Professional Service/Education/Training	6.3	12.0
Accounting/Finance/Banking/Insurance	2.8	6.7
Pharmacy/Medical	3.3	5.9
Advertising/Media	1.2	3.5
Real Estate/Construction	9.2	13.3
Government/NPO/Others	7.7	3.2
Service	14.2	3.5
Logistics/Transportation	6.0	1.8
Energy/Materials	2.9	2.8
CS/Internet/Communication/Electronics	2.3	27.1
Trade/Consumption/Manufacturing/Operation	44.3	20.2
Occupation		
Senior management	2.6	9.0
Professional and technical	13.2	28.7
Sales and service	41.1	38.0
Production and construction	27.7	22.3
Public servants	15.4	1.9
Firm ownership type		
Private sector	64.7	95.7
SOEs and collectives	35.3	4.3

Notes: Table A.2 compares the descriptive statistics of 51job.com ads with the summary statistics of the Chinese labor market, based on the 2019 China Labour Statistical Yearbook. Age and education distributions of 51job refer to ads that stated a requirement for the attribute only. The gender distribution of 51job data is approximated by the average share of female applicants across all vacancies. 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 1st November 2018 to 30th April 2019. See discussion in Sections 2.2 and A.1.

Table A.3
Description of work intensity, job skills, tasks, and youth-favoring stereotypes

Keywords and Phrases	
<i>Panel A. Work intensity</i>	
Ambition	Unlimited, challenging, motivated, goal, ambition
Competition	Performance-based pay, assessment, tournament
Overtime	Working more than 9 hours per day, work overtime, Fewer than 8 days off per month
<i>Panel B. Youth-favoring stereotypes</i>	
Learning	Participate in training programs, learn new techniques, personal development
Communication	Interpersonal [social] skills, sincere when talking, enjoyable stories
Software (specific)	Programming language or specialized software (e.g., Java, SQL, Python)
<i>Panel C. Job skills and tasks</i>	
Cognitive	Problem solving, research, analytical, critical thinking, math, statistics
Solve problems	Solve problems
Make decisions	Make decisions electronic

Notes: Table A.3 details the definitions of variables constructed using keyword extractions from the open texts of job postings scraped from 51job.com. See our discussion of the definitions in Section A.2.

Table A.4
Summary Statistics

	N	Mean	SD	Min	Max
<i>Panel A: Labor Demand</i>					
Age Discrimination	7,720,870	0.478	0.500	0	1
Age Max < 40	7,720,870	0.334	0.472	0	1
Ambition	7,720,870	0.217	0.413	0	1
Competition	7,720,870	0.321	0.467	0	1
Overtime	7,720,870	0.117	0.321	0	1
Cognitive	7,720,870	0.573	0.495	0	1
Solve problems	7,720,870	0.067	0.250	0	1
Make decisions	7,720,870	0.225	0.418	0	1
Expected applicant pool	7,720,870	9.491	24.332	0.0002	341
Low competition (firm)	7,720,870	0.077	0.266	0	1
Competitive (firm)	7,720,870	0.103	0.304	0	1
Very competitive (firm)	7,720,870	0.820	0.384	0	1
Learning	7,720,870	0.152	0.359	0	1
Communication	7,720,870	0.369	0.483	0	1
Software	7,720,870	0.372	0.483	0	1
<i>Panel B: Labor Supply</i>					
No. of applicants	7,720,870	53.493	122.907	2	8174
No. of applicants with university degree	7,720,870	28.243	79.540	0	6228
No. of applicants ≤ 23	7,720,870	11.411	48.662	0	4834
No. of applicants 24-26	7,720,870	10.159	35.654	0	2874
No. of applicants 27-30	7,720,870	10.158	21.906	0	1373
No. of applicants 31-40	7,720,870	15.380	38.292	0	2562
No. of applicants ≥ 41	7,720,870	6.385	23.353	0	1774
Compliance rate (Max 30)	3,653,569	0.919	0.120	0	1
Compliance rate (Max 40)	3,653,569	0.845	0.191	0	1

Notes: Table A.4 reports summary statistics of labor demand variables and labor supply variables constructed from the texts of job postings scraped from 51job.com. See Table A.3 and Section A.2 for variable definitions. See discussion of compliance rates in Section 3.3

Table A.5
Age discrimination decisions 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	-0.0022	-0.0068	-0.0063	0.0023
	(0.0007)	(0.0004)	(0.0004)	(0.0006)	(0.0004)
Panel B: Age Max < 40					
	0.0392	0.0110	-0.0039	-0.0261	-0.0202
	(0.0010)	(0.0007)	(0.0006)	(0.0008)	(0.0013)
Observations	7,720,870	7,720,870	7,720,870	7,720,870	7,720,870
Cluster No.	15,669	15,669	15,669	15,669	15,669
R^2	0.230	0.115	0.053	0.201	0.206
Mean of Y	0.233	0.179	0.197	0.284	0.107
Month FE	✓	✓	✓	✓	✓
Industry FE	✓	✓	✓	✓	✓
Occ*City FE	✓	✓	✓	✓	✓

Notes: Table A.5 reports the regression estimates of the association between the share of applicants by each age group and employers' age discrimination decisions. 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 A.2. The independent variable in Panel A, "Age Discrimination", is an indicator equal to one if the employer explicitly states an age requirement. The independent variable in Panel B, "Age Max < 40", is an indicator equal to one if the stated age range has a maximum below 40. All coefficients are estimated using equation (2) in separate regressions by age group. All specifications include period fixed effects, industry, and occupation-city fixed effects. Standard errors are clustered at the occupation-city level. Table 2 reports the regression coefficients of the number of applicants by each group on the use of age discrimination decisions. See discussion in Section 5.1.

Table A.6
Firm's Decision on Age Discrimination and Applicant Numbers of
Different Age Groups

	Number of Applicants by Age Group				
	(1) ≤23	(2) 24-26	(3) 27-30	(4) 31-40	(5) ≥41
Panel A: Age Discrimination					
	-3.4160 (0.9064)	-3.2040 (0.6157)	-1.9917 (0.2598)	-1.5450 (0.3205)	0.0379 (0.1570)
Panel B: Age Max < 40					
	-0.4249 (0.6366)	-1.2984 (0.4586)	-1.9844 (0.2661)	-5.3208 (0.4497)	-3.6553 (0.3332)
R^2	0.000	0.001	0.002	0.005	0.006
Month FE	✓	✓	✓	✓	✓
Panel C: Age Discrimination					
	0.2832 (0.1322)	-0.7444 (0.1102)	-1.0070 (0.0822)	-1.0418 (0.1404)	0.1207 (0.1033)
Panel D: Age Max < 40					
	1.1042 (0.1372)	0.1058 (0.0965)	-0.3061 (0.0898)	-1.1742 (0.1537)	-0.8483 (0.0901)
Observations	7,720,870	7,720,870	7,720,870	7,720,870	7,720,870
Cluster No.	15,669	15,669	15,669	15,669	15,669
R^2	0.135	0.132	0.178	0.265	0.249
Mean of Y	11.411	10.159	10.158	15.380	6.385
Month FE	✓	✓	✓	✓	✓
Industry FE	✓	✓	✓	✓	✓
Occ*City FE	✓	✓	✓	✓	✓
Experience Control	✓	✓	✓	✓	✓

Notes: Table A.6 reports regression estimates of the association between the number of applicants by each age group and employers' age discrimination decisions, with different fixed effects or controls. 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 A.2. The independent variable in Panel A, "Age Discrimination", is an indicator equal to one if the employer explicitly states an age requirement. The independent variable in Panel B, "Age Max < 40", is an indicator equal to one if the stated age range has a maximum below 40. All coefficients are estimated using equation (2) in separate regressions by age group. In Panels A and B, all specifications include only period fixed effects. In Panels C and D, all specifications additionally include industry and occupation-city fixed effects, as well as experience and wage controls. Standard errors are clustered at the occupation-city level. Table 2 reports the regression coefficients with period, industry, and occupation-city fixed effects. See discussion in Section 5.1.

Table A.7
Age discrimination decisions and the number of high-skilled applicants

	Applicant Has A University Degree	
	(1)	(2)
Panel A: Age Discrimination		
	-8.7842 (1.2674)	-2.2688 (0.2628)
Panel B: Age Max < 40		
	-9.7977 (1.0994)	-4.9895 (0.5659)
Observations	7,720,870	7,720,870
Cluster No.	15,669	15,669
R^2	0.004	0.166
Mean of Y	28.243	28.243
Month FE	✓	✓
Industry FE		✓
Occ*City FE		✓

Notes: Table A.7 reports regression estimates of the association between the number of applicants with a university degree and the use of age discrimination decisions. The outcome variable is the number of applicants with at least a university degree. The independent variable in Panel A, “Age Discrimination”, is an indicator equal to one if the employer explicitly states an age requirement. The independent variable in Panel B, “Age Max < 40”, is an indicator equal to one if the stated age range has a maximum below 40. All coefficients are estimated using equation (2) in separate regressions. Column (1) includes period fixed effects, and Column (2) additionally includes industry and occupation-city fixed effects. Standard errors are clustered at the occupation-city level. See discussion in Section 5.1.

Table A.8

Work intensity and age discrimination, a multivariate analysis

	Age Discrimination		Age Max < 40	
	(1)	(2)	(3)	(4)
Ambition	0.0705 (0.0044)	0.0456 (0.0020)	0.0898 (0.0072)	0.0478 (0.0024)
Competition	0.1272 (0.0066)	0.0844 (0.0029)	0.1375 (0.0097)	0.0749 (0.0038)
Overtime	0.1230 (0.0057)	0.0912 (0.0031)	0.0814 (0.0160)	0.0822 (0.0053)
Observations	7,720,870	7,720,870	7,720,870	7,720,870
Cluster No.	15,669	15,669	15,669	15,669
R^2	0.033	0.080	0.039	0.095
Mean of Y	0.478	0.478	0.334	0.334
Month FE	✓	✓	✓	✓
Industry FE		✓		✓
Occ*City FE		✓		✓

Notes: Table A.8 reports regression estimates of the association between the use of age discrimination decisions and work intensity measures. The outcome variable in Columns (1) and (2), “Age Discrimination”, is an indicator equal to one if the employer explicitly states an age requirement. The outcome variable in Columns (3) and (4), “Age Max < 40”, is an indicator equal to one if the stated age range has a maximum below 40. The independent variables are the same as those in Figure 4, constructed from job ad keywords listed in Panel A of Table A.3. All coefficients are estimated using equation (4) with all independent variables included in one regression. All specifications include period fixed effects, Columns (2) and (4) additionally control for industry and occupation-city fixed effects. Standard errors are clustered at the occupation-city level. Table 5 reports regression coefficients in separate regressions. See discussion in Section 5.2.

Table A.9

Work intensity and age discrimination, with an experience control

	Age Discrimination		Age Max < 40	
	(1)	(2)	(3)	(4)
Panel A: Ambition				
	0.0661	0.0792	0.0660	0.0688
	(0.0023)	(0.0026)	(0.0028)	(0.0028)
Panel B: Competition				
	0.1023	0.1180	0.0922	0.0988
	(0.0031)	(0.0032)	(0.0043)	(0.0041)
Panel C: Overtime				
	0.1113	0.1273	0.1006	0.1006
	(0.0033)	(0.0035)	(0.0056)	(0.0051)
Observations	7,720,870	7,720,870	7,720,870	7,720,870
Cluster No.	15,669	15,669	15,669	15,669
R^2	0.074	0.101	0.089	0.105
Mean of Y	0.478	0.478	0.334	0.334
Month FE	✓	✓	✓	✓
Industry FE	✓	✓	✓	✓
Occ*City FE	✓	✓	✓	✓
Exp Control		✓		✓

Notes: Table A.9 reports regression estimates of the association between the use of age discrimination decisions and work intensity measures. The outcome variable in Columns (1) and (2), “Age Discrimination”, is an indicator equal to one if the employer explicitly states an age requirement. The outcome variable in Columns (3) and (4), “Age Max < 40”, is an indicator equal to one if the stated age range has a maximum below 40. The independent variables are the same as those in Figure 4, constructed from job ad keywords listed in Panel A of Table A.3. All coefficients are estimated using equation (4) in separate regressions. All specifications include period fixed effects, industry and occupation-city fixed effects, Columns (2) and (4) additionally control for the experience requirement. Standard errors are clustered at the occupation-city level. Table 5 also reports regression coefficients in separate regressions with a specification that only includes period fixed effects. See discussion in Section 5.2.

Table A.10
Youth-favoring stereotypes and age discrimination decisions

	Age Discrimination		Age Max < 40	
	(1)	(2)	(3)	(4)
Panel A: Learning				
	0.0210	0.0183	0.0574	0.0291
	(0.0070)	(0.0023)	(0.0070)	(0.0022)
Panel B: Communication				
	-0.0013	-0.0006	0.0354	0.0053
	(0.0043)	(0.0013)	(0.0045)	(0.0016)
Panel C: Software				
	-0.0483	0.0004	-0.0148	0.0110
	(0.0065)	(0.0032)	(0.0055)	(0.0038)
Observations	7,720,870	7,720,870	7,720,870	7,720,870
Cluster No.	15,669	15,669	15,669	15,669
R^2	0.002	0.069	0.001	0.085
Mean of Y	0.478	0.478	0.334	0.334
Month FE	✓	✓	✓	✓
Industry FE		✓		✓
Occ*City FE		✓		✓

Notes: Table A.10 reports regression estimates of the association between the use of age discrimination decisions and youth-favoring stereotypes. The outcome variable in Columns (1) and (2), “Age Discrimination”, is an indicator equal to one if the employer explicitly states an age requirement. The outcome variable in Columns (3) and (4), “Age Max < 40”, is an indicator equal to one if the stated age range has a maximum below 40. The independent variables are constructed from job ad keywords listed in Panel C of Table A.3. All coefficients are estimated using equation (4) in separate regressions. All specifications include period fixed effects, Columns (2) and (4) additionally control for industry and occupation-city fixed effects. Standard errors are clustered at the occupation-city level. See discussion in Section 5.2.

Table A.11

Job skills and age discrimination decisions, a multivariate analysis

	Age Discrimination		Age Max < 40	
	(1)	(2)	(3)	(4)
University	-0.0857 (0.0077)	-0.0139 (0.0033)	-0.0562 (0.0106)	0.0051 (0.0033)
Log wage	-0.0140 (0.0101)	-0.0144 (0.0038)	-0.0515 (0.0127)	-0.0826 (0.0052)
Cognitive	-0.0378 (0.0034)	-0.0180 (0.0013)	0.0017 (0.0042)	-0.0100 (0.0016)
Solve problems	-0.0260 (0.0036)	-0.0156 (0.0020)	-0.0254 (0.0045)	-0.0160 (0.0026)
Make decisions	-0.0161 (0.0057)	-0.0150 (0.0027)	-0.0448 (0.0067)	-0.0366 (0.0030)
Observations	7,720,870	7,720,870	7,720,870	7,720,870
Cluster No.	15,669	15,669	15,669	15,669
R^2	0.009	0.070	0.010	0.093
Mean of Y	0.478	0.478	0.334	0.334
Month FE	✓	✓	✓	✓
Industry FE		✓		✓
Occ*City FE		✓		✓

Notes: Table A.11 reports regression estimates of the association between the use of age discrimination decisions and job skills. The outcome variable in Columns (1) and (2), “Age Discrimination”, is an indicator equal to one if the employer explicitly states an age requirement. The outcome variable in Columns (3) and (4), “Age Max < 40”, is an indicator equal to one if the stated age range has a maximum below 40. The independent variables are the same as those in Figure 5 and Table 6, constructed from job ad keywords listed in Panel C of Table A.3. All coefficients are estimated using equation (4) with all independent variables included in one regression. All specifications include period fixed effects, Columns (2) and (4) additionally control for industry and occupation-city fixed effects. Standard errors are clustered at the occupation-city level. Table 6 also reports regression coefficients in separate regressions. See discussion in Section 5.2.

Table A.12

Job skills and age discrimination decisions, with experience control

	Age Discrimination		Age Max < 40	
	(1)	(2)	(3)	(4)
Panel A: University				
	-0.0208	-0.0548	-0.0201	-0.0062
	(0.0033)	(0.0035)	(0.0033)	(0.0033)
Panel B: Log Wage				
	-0.0217	-0.0553	-0.0892	-0.0651
	(0.0035)	(0.0052)	(0.0047)	(0.0054)
Panel C: Cognitive				
	-0.0246	-0.0373	-0.0260	-0.0238
	(0.0015)	(0.0014)	(0.0016)	(0.0016)
Panel D: Solve Problems				
	-0.0262	-0.0364	-0.0317	-0.0272
	(0.0021)	(0.0022)	(0.0026)	(0.0026)
Panel E: Make Decisions				
	-0.0238	-0.0423	-0.0546	-0.0437
	(0.0024)	(0.0027)	(0.0026)	(0.0026)
Observations	7,720,870	7,720,870	7,720,870	7,720,870
Cluster No.	15,669	15,669	15,669	15,669
R^2	0.070	0.096	0.087	0.102
Mean of Y	0.478	0.478	0.334	0.334
Month FE	✓	✓	✓	✓
Industry FE	✓	✓	✓	✓
Occ*City FE	✓	✓	✓	✓
Exp Control		✓		✓

Notes: Table A.12 reports regression estimates of the association between the use of age discrimination decisions and job skills. The outcome variable in Columns (1) and (2), “Age Discrimination”, is an indicator equal to one if the employer explicitly states an age requirement. The outcome variable in Columns (3) and (4), “Age Max < 40”, is an indicator equal to one if the stated age range has a maximum below 40. The independent variables are the same as those in Figure 5 and Table 6, constructed from job ad keywords listed in Panel C of Table A.3. All coefficients are estimated using equation (4) in separate regressions. All specifications include period fixed effects, industry and occupation-city fixed effects, Columns (2) and (4) additionally control for the experience requirement. Standard errors are clustered at the occupation-city level. See discussion in Section 5.2.

Table A.13
Search cost, competition in labor demand and age discrimination
decision with experience control

	Age Discrimination		Age Max < 40	
	(1)	(2)	(3)	(4)
Ln app pool	0.009 (0.001)	0.013 (0.001)	0.008 (0.002)	0.008 (0.001)
Competitive	-0.041 (0.006)	-0.046 (0.006)	-0.029 (0.007)	-0.032 (0.007)
Very Competitive	-0.085 (0.006)	-0.101 (0.007)	-0.068 (0.008)	-0.075 (0.008)
Observations	7,720,870	7,720,870	7,720,870	7,720,870
Cluster No.	15,669	15,669	15,669	15,669
R^2	0.071	0.097	0.086	0.102
Mean of Y	0.478	0.478	0.334	0.334
Month FE	✓	✓	✓	✓
Industry FE	✓	✓	✓	✓
Occ*City FE	✓	✓	✓	✓
Exp Control		✓		✓

Notes: Table A.13 reports regression estimates of the association between the use of age discrimination decisions and log expected application number, as well as competition among firms. The outcome variable in Columns (1) and (2), “Age Discrimination”, is an indicator equal to one if the employer explicitly states an age requirement. The outcome variable in Columns (3) and (4), “Age Max < 40”, is an indicator equal to one if the stated age range has a maximum below 40. The independent variables are the same as those in Table 7. All coefficients are estimated using equation (4) with all independent variables included in one regression. All specifications include period fixed effects, industry and occupation-city fixed effects, Columns (2) and (4) additionally control for the experience requirement. Standard errors are clustered at the occupation-city level. Table 7 also reports regression coefficients with a specification that only includes period fixed effects. Standard errors are clustered at the occupation-city level. See discussion in Section 5.2.

Table A.14

Number of expected applicants and age discrimination decisions

	Age Discrimination		Age Max < 40	
	(1)	(2)	(3)	(4)
Ln app pool	0.0006 (0.0029)	0.0023 (0.0010)	0.0086 (0.0034)	0.0023 (0.0010)
Observations	7,720,870	7,720,870	7,720,870	7,720,870
Cluster No.	15,669	15,669	15,669	15,669
R^2	0.000	0.069	0.002	0.085
Mean of Y	0.478	0.478	0.334	0.334
Month FE	✓	✓	✓	✓
Industry FE		✓		✓
Occ*City FE		✓		✓

Notes: Table A.14 reports regression estimates of the association between the use of age discrimination decisions and log expected application number. The outcome variable in Columns (1) and (2), “Age Discrimination”, is an indicator equal to one if the employer explicitly states an age requirement. The outcome variable in Columns (3) and (4), “Age Max < 40”, is an indicator equal to one if the stated age range has a maximum below 40. The independent variable is the same as that in Table 7. All coefficients are estimated using equation (4). All specifications include period fixed effects, Columns (2) and (4) additionally control for industry and occupation-city fixed effects. Standard errors are clustered at the occupation-city level. Table 7 also reports regression coefficients with a specification that includes competitions among firms. Standard errors are clustered at the occupation-city level. See discussion in Section 5.2.