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Too Old for This Job? Age Requirements in Job Postings and Their Impact on Applications and Hires

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Abstract

How strongly do employer age preferences restrict the hiring of older workers? I study Austrian job postings, in which employers could openly state age limits until the practice was banned in 2004. Age limits were both widespread and strict: more than 30 percent of vacancies stated an upper age limit, and most caps were set between age 40 and 55. To assess the impact of the ban, I link the vacancies to administrative data on applicants and hired workers, predict each job's age requirement from pre-ban postings of the same firm and occupation and compare jobs with stronger and weaker predicted restrictions over time. After the ban, previously restrictive jobs attracted older applicants and hired older workers, with larger effects at the application stage than at the hiring stage. Wages, job duration, sickness absence and vacancy filling duration remained unaffected. In the ad texts, employers replaced direct references to young workers with attributes commonly associated with youth. Taken together, these results suggest that employers hold overly pessimistic beliefs about older workers and partially revise them once a broader pool of applicants emerges.

JEL classification

J63, J14, J23, J24, J68, J71

Keywords

vacancies, age discrimination, screening and hiring

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1 Introduction

How much do age considerations influence the hiring choices of employers? Some recruiters may have strong biases against older workers, assuming they are less adaptable, overqualified or more expensive to hire. Another concern might be that older workers are less productive because they cannot keep up with changing skill requirements. As a result, older jobseekers may face greater difficulty finding employment. In OECD countries, the share of workers aged 55 and over among the long-term unemployed (≥ 1 year) is approximately 12 percentage points higher than that of younger workers (Aitken et al., 2024).

This paper studies the scope of employers' age preferences using a large sample of job vacancies from Austria. Prior to 2004, recruiters commonly specified age limits in job advertisements, creating a unique setting to examine the degree of age restrictions. The analysis proceeds in two parts. First, I examine which age groups were most affected by age restrictions and document heterogeneity in age caps across employers and occupations. Second, I study the effects of the 2004 ban on job ad phrasing, applications and hiring outcomes. The analysis is based on vacancies reported between 2000 and 2010 to the Austrian public employment service AMS, which hosts the largest job board in the country and also tracks a subset of applications made by registered jobseekers. For vacancies mediated by AMS, the data can be linked to administrative records on hired workers, allowing me to study changes in hiring outcomes around the implementation of the ban.

Before being outlawed, explicit age restrictions were widespread in Austrian job postings and often highly restrictive. About one third of vacancies specified an upper age limit, with most caps set between ages 40 and 55 and an average maximum age of 44. Vacancies targeting female workers were less likely to impose age limits, but if stated, those limits were stricter. Moreover, I find that age restrictions were particularly common in business and ICT occupations, whereas manual and service-related jobs imposed fewer and weaker caps. Linking occupation-level age limits to measures of skill change reveals a strong negative relationship: occupations experiencing more rapid changes in skill requirements exhibited much lower age caps. This is consistent with the view that employers avoid hiring older workers because they expect their skill sets to be outdated. Finally, age limits were closely correlated with application and hiring outcomes. Vacancies with stricter age requirements attracted younger applicants and resulted in younger hires, even after accounting for firm and occupation differences.

Overall, the observed patterns suggest that revealed age limits meaningfully shape both applicant pools and hiring decisions.

In the second part, I analyze changes in hiring outcomes due to the ban on discriminatory job ads. As of July 2004, the Austrian law prohibits discriminatory language in job advertisements unless the worker's age constitutes an essential and decisive professional requirement. Although adoption of the new rules was initially slow, age limits almost completely disappeared from vacancy listings within two years. To examine the ban's effect on application and hiring behavior, I follow the approach by Card et al. (2024) and predict employer preferences for every occupation-firm group using observed age requirements in job ads prior to 2004. This allows me to compare jobs with stronger and weaker predicted age requirements before and after the ban in a difference-in-differences setting. Because the predictions entail measurement error, I additionally estimate the relation between observed and predicted limits and use it to correct the estimates for attenuation bias.

Event study results show that the law has a significant and persistent effect on both the age of applicants and the age of hired workers. Comparing vacancies that would have restricted the maximum age to 45 years or below with other job postings, the share of applicants above this age threshold rises by six percentage points, while the share of hires older than 45 years increases by close to three percentage points. The hiring effect is thus about half the size of the application effect. Since the ban changed who applies rather than how employers select among candidates, this ratio measures the pass-through from the applicant pool to hires: about half of the additional older applicants are reflected in older hires. Age preferences therefore still matter at the selection stage, but they are not strong enough to undo the change in the applicant pool. Because job postings also stated gender requirements before the ban, I can similarly classify vacancies by their predicted gender preference. Jobs seeking female workers show a notably lower pass-through, as the ban raises the age of their applicants almost as much as elsewhere but the age of their hires only half as much.

Moreover, I find that, despite removing explicit age limits, employers adjust the wording of job postings. Vacancies with a higher predicted age preference are more likely to rely on paraphrases and attributes commonly associated with younger workers. This shift in wording suggests that employers signal their age preferences in more subtle ways, since the regulation no longer permits explicit age restrictions.

While the ban affected the age distribution of applicants and hires, it did not lead to measurable changes in hiring efficiency or worker performance. To proxy worker productivity, I examine effects on earnings, job duration and sickness absence among hired workers. None of these outcomes changes significantly when comparing jobs with strong and weak age requirements before and after the ban. To assess potential increases in screening costs following the removal of age restrictions, I examine effects on vacancy-filling duration, defined as the number of days between posting and filling a vacancy. As with worker productivity, I find no evidence of meaningful changes, suggesting that hiring efficiency was not adversely affected by the ban on explicit age limits in job postings.

My analysis adds to a number of previous studies that examine the prevalence and causes of age discrimination in the labor market. Most existing evidence is based on experimental audit studies, which use fictitious résumés with randomly assigned ages but otherwise comparable jobseeker characteristics to measure differences in callback rates (Bendick Jr et al., 1997, 1999; Lahey, 2008b; Riach and Rich, 2010; Baert et al., 2016; Farber et al., 2017; Carlsson and Eriksson, 2019; Neumark et al., 2019a). Linking job-ad texts to callback outcomes, Burn et al. (2022) show that ageist language in job postings predicts discrimination against older applicants. Building on this literature, my study provides new evidence on how employers' explicit age restrictions shape application behavior and hiring outcomes, and how employers adjust the phrasing of their ads once such restrictions are banned. Consistent with prior findings, I show that age requirements substantially affect workers from around age 40 and that these restrictions tend to be more stringent for female jobseekers.

Several previous studies have analyzed the impact of other laws against age discrimination (Neumark and Stock, 1999; Adams, 2004; Lahey, 2008a; Neumark et al., 2019b), showing increased retention rates but also negative or zero effects on the hiring of older workers. My study focuses on an anti-discrimination law that specifically outlaws the use of discriminatory job postings. Because this practice was common in earlier years, I can contrast discriminating and non-discriminating employers to show that the explicit signaling of age preferences strongly affects the hiring of older workers.

This paper also adds to a growing literature that exploits vacancy data to study employer preferences. Multiple studies document strong gender preferences in job postings across several countries (Kuhn and Shen, 2012; Delgado Helleseter et al., 2020; Kuhn et al., 2020; Card et al., 2024). Delgado Helleseter et al. (2020) show that in Mexico and China, recruiters searching for female workers impose substantially stricter age restrictions. Because many jobs targeted at women in these countries require workers to be in their early twenties, the authors argue that these requirements may reflect employers' concerns about future parenthood. While I also find a relationship between age and gender preferences, this link is considerably weaker, suggesting that concerns about future parenthood are not the main driver of explicit age restrictions in the Austrian labor market. A recent study by Luo et al. (2025) shows that almost half of Chinese online job ads exclude certain age groups and that these restrictions shift the applicant pool toward younger and less educated jobseekers. In line with their results, I find that explicit age limits discourage older jobseekers from applying, and that this lower applicant age carries over to the workers who are eventually hired.

Closest to my analysis are two recent papers which examine bans on gender preferences in job postings. Kuhn and Shen (2023) study the sudden removal of explicit gender requirements from a Chinese job board and find that it led to a large increase in applications from the previously excluded gender, ultimately resulting in more callbacks. Card et al. (2024) exploit the same reform that I study in this paper to analyze how the removal of gender preferences from job postings affected the hiring of male and female workers. They show that gender diversity increased while firm survival, employment and wages remained unchanged. Jobs for which the authors predict a preference for female workers are more likely to hire male workers, and vice versa. Consistent with these findings, I show similar changes in the age composition of hired workers following the removal of age limits. Moreover, I extend the analysis by examining the initial impact on applications and how employers change the wording of job ads in response to the ban.

Overall, my findings show that recruiters frequently set strict age limits, which are concentrated in, but not exclusive to, specific occupations. Outlawing explicit age requirements leads to an increase in applications from older workers to previously discriminating jobs and improves their hiring prospects, without affecting worker productivity or screening costs. This indicates that banning discriminatory job ads is a low-cost policy intervention which does not lower hiring efficiency.

2 Institutional background and data

2.1 Legal setting

As in many other countries, the Austrian Constitution guarantees the general principle of equality before the law. However, prior to 2004, no specific law prohibited age-based discrimination against jobseekers (Pöschl, 2012). Indeed, it was not unusual to refer to both gender and age in job advertisements. When reporting vacancies to the Austrian public employment service to be put on its job board, employers could even specify a preferred gender and set minimum or maximum age requirements for applicants. Additionally, it was possible to list preferences for such worker characteristics in the ad text.

Taking effect in July 2004, the Austrian *Equal Treatment Act* requires that workers in the workplace are treated equally regardless of ethnic origin, religion or belief, age, or sexual orientation. While this applies to all areas of the labor market, including working conditions, pay, promotion and dismissal, Section 23 of the law explicitly prohibits discriminatory job advertisements. Employers must not publish job postings that disadvantage applicants based on the characteristics outlined above. Job ads must be formulated in a neutral and inclusive manner and may only refer to qualifications that are objectively required for the position. Posting discriminatory advertisements can lead to fines of up to 360 euros per violation. In addition, the Act provides other legal remedies against discrimination and establishes equality bodies to support victims and promote equal treatment.[1]

Despite the clear outlawing of discriminatory job postings, compliance with the law was low in the first months, as I will show in Section 4. Card et al. (2024) point out that many employers were initially unaware of the new law. To increase awareness, the Ombud for Equal Treatment, a public agency which helped to enforce the anti-discrimination law, ran an information campaign in early 2005, warning employers and employment agencies about unlawful wording and informing them how to advertise jobs in a non-discriminatory manner. In late 2005, the campaign was extended to editorial offices of newspapers, which at the time were the main publishers of job postings.

Beyond the rules for job advertisements, the Act also gives rejected jobseekers a legal claim against discriminatory hiring decisions. Applicants who can credibly establish discrimination are entitled to damages of at least one month's pay.[2] However, if the employer shows that the applicant would not have been hired anyway, compensation is capped at 500 euros (Section 26 Equal Treatment Act). Because applicants rarely observe why they were turned down, and because the amounts at stake are small, these instruments matter little in practice. For 2022 and 2023, the Equal Treatment Commission received six complaints about age discrimination in hiring, similar to earlier reporting periods (Bundesministerium für Frauen, Wissenschaft und Forschung, 2024).

[1] For the complete text of the law (in German), see https://www.ris.bka.gv.at/eli/bgbl/I/2004/66.
[2] The minimum was raised to two months' pay in August 2008.

Schindlauer (2023) concludes that the available sanctions deter victims from seeking legal redress rather than employers from discriminating. In Section 4.2, I return to this point when interpreting the effects of the ban on applications and hiring.

2.2 Data

The analysis is based on vacancy data from the Austrian Public Employment Service (AMS), which operates the largest job board in Austria. In recent years, this platform has covered approximately 50-60 percent of all vacancies nationwide.[3] The vacancy database contains various job characteristics, such as occupation, educational requirements and, where stated, age and gender preferences. Beginning in 2002, the database additionally covers the text of job advertisements, providing further information on each vacancy. Moreover, the entry and removal dates of job postings are recorded. For this analysis, I use vacancy filling duration, i.e., the number of days between posting and removal, as a proxy for screening costs.

The public employment service also maintains records of a subset of applications made to vacancies in its database. To receive income support and job search assistance, unemployed workers must register at their local AMS office and actively search for employment. If caseworkers refer jobseekers to vacancies, or if jobseekers report their applications to caseworkers, the applications are recorded in the database. I use these records to analyze the link between age requirements and the age composition of applicants.

Importantly, the data also report whether an application was successful, which allows linking vacancies with hired workers. For the analysis of hiring outcomes, I use these linkages to merge the vacancies with employment spells in the Austrian Social Security Database (ASSD).[4] The data encompass all employment relations subject to social security contributions, excluding civil servants and self-employed workers.

Using the recorded birth year of workers, I compute their age at the start of each employment spell, which will be the main outcome in the subsequent analysis. Moreover, I measure earnings and job duration as proxies for worker productivity. The ASSD reports daily earnings for each worker-firm-spell on the annual level. In addition, I use data on sick pay spells to proxy worker health, which are only available in the ASSD for sickness spells longer than six to eight weeks.[5]

[3] Coverage is estimated from the annual firm-level vacancy survey conducted by Statistics Austria.

[4] Zweimüller et al. (2009) provide a comprehensive description of the database.

[5] Spells are only recorded when sick leave benefits are paid by the health insurance. During the first

For the descriptive analysis of age requirements, I use data on all vacancies posted in the years 2000 to 2004, when age limits were still commonly stated. The analysis of the ban extends the observation period to the years 2000 to 2010 and is based on the subsample of job postings which can be linked to employment spells. This includes all vacancies for which an application recorded by AMS resulted in a hire, representing 23 percent of the initial sample.

Table A.1 in the appendix compares the full sample of vacancies and the linked vacancy-worker sample with the universe of new employment spells in the years 2000 to 2010. It shows that several large sectors, such as retail and manufacturing, are represented in similar proportions across samples, but the composition differs elsewhere. Compared to all job starters, accommodation and food services as well as administrative and support services are overrepresented in the vacancy sample, and they also remain more prevalent in the linked vacancy-worker sample. By contrast, public administration, transport and storage, and professional services are underrepresented. Despite these sector differences, the age and gender of workers are remarkably similar between the universe of hires and the linked vacancy-worker sample. Slightly less than 50 percent of the workers are female, and their average age is 33 years, with a standard deviation of 11.

3 Descriptive analysis

This section examines the use of age requirements in job postings before the ban took effect. I first document how many vacancies stated age limits and which age groups they targeted. Drawing on the detailed job characteristics in the vacancy database, I then show what distinguished jobs with strict age limits and how these limits related to the age of applicants and hires.

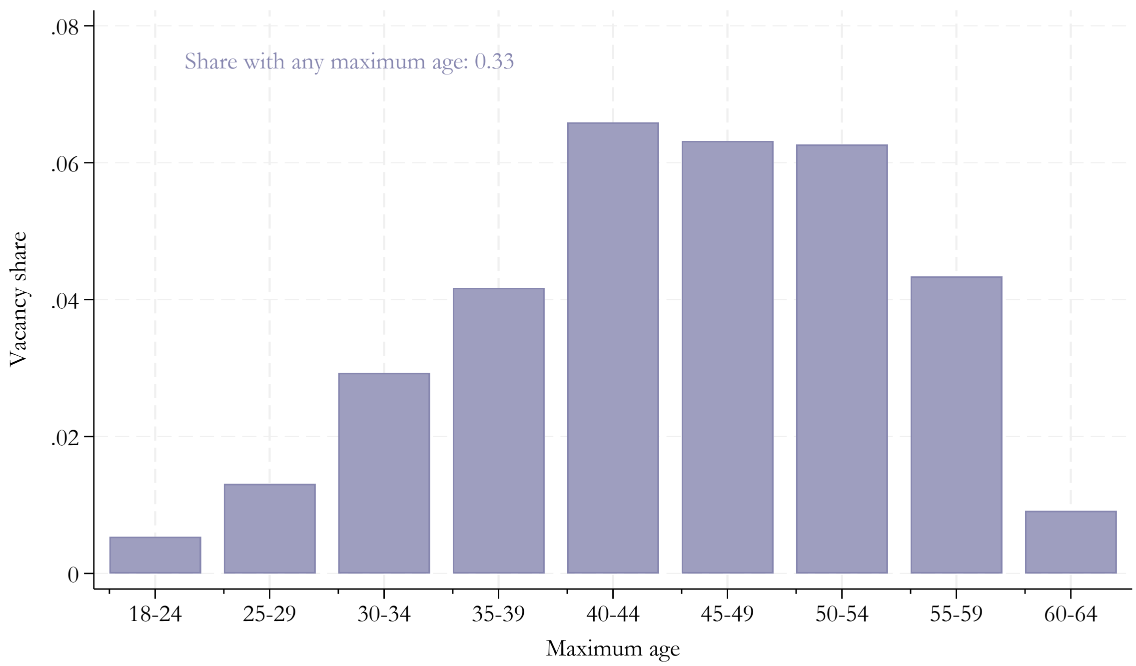
3.1 Distribution of age requirements

Before being outlawed, one third of all postings on the AMS job board stated an upper bound for worker age. As shown by the frequency distribution in Figure 1, almost 60 percent of vacancies set the maximum between age 40 and 55, while only a fourth required applicants to be younger than 40 years. On average, the maximum age requirement was 44 years. Minimum age limits were even more common, but they

weeks of a sickness spell, these benefits are covered by employers.

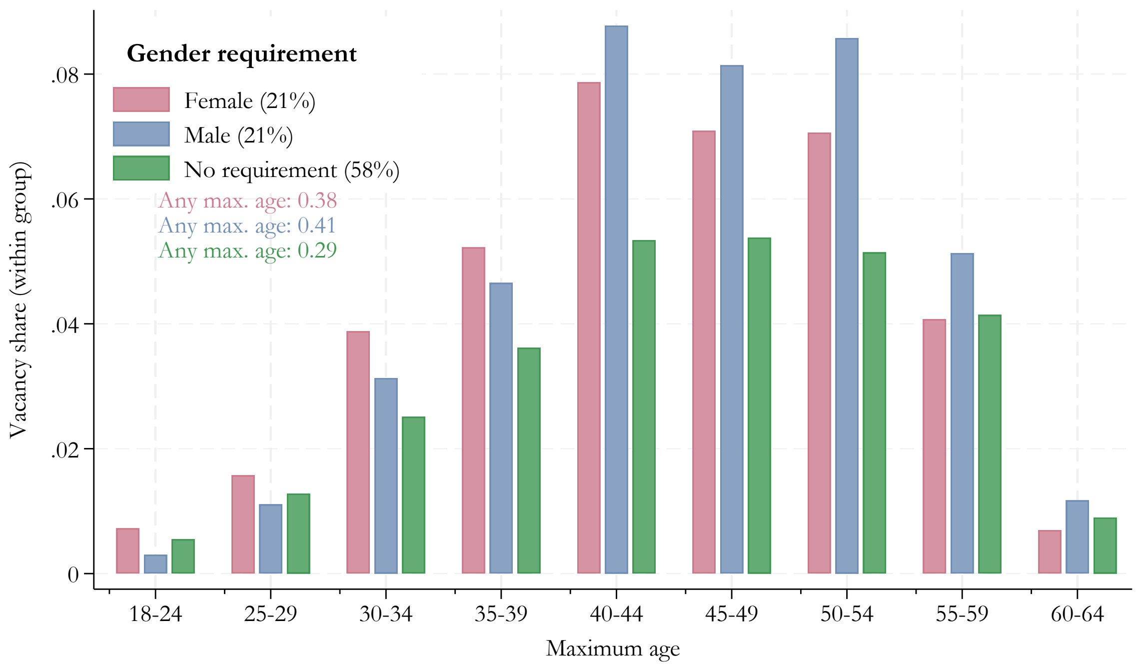
were not binding for most job applicants. Appendix Figure A.1 shows that half of vacancies imposed a lower bound, typically at 19 or 20 years of age. Only seven percent of postings required workers to be older than 25. Given the low variability and limited relevance for most applicants, I focus the remainder of the analysis on maximum age requirements.

Figure 1: Frequencies of maximum age requirements



As discussed in the previous section, Austrian job advertisements also commonly specified the preferred applicant's gender alongside age requirements when this practice was still legal. Previous evidence from Delgado Helleseter et al. (2020) shows that the two requirements are highly correlated in China and Mexico, with employers increasingly seeking male workers as age limits rise. In the Austrian job board data, I also find evidence for such a correlation, but the differences were comparatively modest. Figure 2 shows the distribution of age requirements separately for job postings seeking female or male workers, as well as postings without a gender requirement. Overall, 42 percent of vacancies included a gender requirement, and employers were equally likely to request female or male applicants. Vacancies targeting female workers were somewhat less likely to have an age upper bound but, if set, the age requirements were stricter. Among postings with age limits, 30 percent of female-targeting vacancies sought applicants below age 40, compared with only 22 percent of male-targeting vacancies. On average, the maximum age limit was 44 years in male-targeting postings and 42.5 years in female-targeting postings.

Figure 2: Frequencies of maximum age × gender requirements



3.2 Job characteristics

To further explore the motives behind age caps, I examine how job postings with strong age limits differ from other vacancies. Table 1 summarizes job characteristics for postings without age restrictions and for postings with varying degrees of age limits: up to age 35, ages 36-50 and above age 50. These categories roughly correspond to the bottom quartile, the two middle quartiles and the top quartile of the age-limit distribution, respectively.

About 20 percent of postings seek part-time workers, but this feature shows no clear association with age requirements. Vacancies with strong age limits are somewhat more likely to be full-time positions, whereas those with weaker age restrictions are less likely to be full-time, compared with postings that do not specify any age limit. A clearer pattern emerges for education requirements. Job advertisements with medium to strong age limits often demand higher levels of education. Among vacancies targeting workers up to age 35, more than twice as many require at least higher secondary schooling or a university degree. Differences by firm size are less pronounced. Overall, firms with more than 100 employees more often specify a maximum age requirement, but there is no systematic pattern when comparing the strength of age restrictions.

Table 1: Job characteristics by age restriction

	Age≤35	35<Age≤50	Age>50	No restriction
Full-time	0.852	0.794	0.757	0.804
	(0.355)	(0.404)	(0.429)	(0.397)
Education:				
No/comp. school.	0.388	0.499	0.571	0.567
	(0.487)	(0.500)	(0.495)	(0.495)
Vocational training	0.499	0.441	0.384	0.381
	(0.500)	(0.496)	(0.486)	(0.486)
Higher school./university	0.113	0.060	0.045	0.052
	(0.316)	(0.237)	(0.208)	(0.221)
Firm size:				
Small firm (<10)	0.541	0.494	0.524	0.515
	(0.498)	(0.500)	(0.499)	(0.500)
Medium firm (10-100)	0.361	0.386	0.367	0.399
	(0.480)	(0.487)	(0.482)	(0.490)
Large firm (100+)	0.098	0.120	0.109	0.086
	(0.298)	(0.325)	(0.311)	(0.281)
Observations	79,352	172,860	56,772	614,298

Note: The table reports means with standard deviations in parentheses.

If older workers are perceived as less able to perform certain tasks, age limits may also vary across occupations. To illustrate this, I group the vacancies according to the 2-digit ISCO-08 occupational classification and rank the occupation groups by their average age limits. The ranking incorporates both the incidence of any age requirements and the specific age limits. When no upper bound is listed, I assign 65 years, the statutory retirement age for men at that time.

Table 2 shows the top and bottom 10 occupation groups, along with their average age requirements. Clerical, business and ICT-related occupations have the strictest maximum age restrictions, generally around age 40 (if stated), and higher shares of job postings with any age limit. In contrast, manual, service, agricultural and care-related occupations exhibit the lowest share of age limits. If stated, the average age cap is five to eight years higher compared to the occupation groups with the strongest requirements. Overall, the ranking shows that maximum age limits are much more common and more restrictive in white-collar and administrative roles than in manual and service professions.

Table 2: Occupation groups and maximum age limits (ISCO 2-digit level)

	Av. max. age (65 if none)	Share any max. age	Av. max. age (if any)
General and keyboard clerks	51.4	0.53	39.1
Business and administration associate professionals	52.59	0.54	42.15
Business and administration professionals	52.74	0.52	41.41
Information and communications technicians	52.9	0.48	39.71
Numerical and material recording clerks	53.01	0.53	42.22
Information and communications technology professionals	54.22	0.49	42.99
Science and engineering professionals	54.22	0.43	40.16
Sales workers	54.61	0.46	42.44
Administrative and commercial managers	54.72	0.50	44.43
Science and engineering associate professionals	55.86	0.42	43.04
Building and related trades workers, excluding electricians	59.44	0.30	46.57
Drivers and mobile plant operators	59.62	0.31	47.45
Legal, social, cultural and related associate professionals	60.32	0.22	44.02
Market-oriented skilled forestry, fishery and hunting workers	60.7	0.25	48.06
Teaching professionals	60.77	0.20	43.51
Cleaners and helpers	61.39	0.22	48.39
Food preparation assistants	61.55	0.19	47.29
Personal care workers	61.55	0.18	46.04
Agricultural, forestry and fishery labourers	61.61	0.20	48.29
Health professionals	61.96	0.18	48.21

Note: The table shows the top and bottom 10 occupation groups (2-digit ISCO-08), ranked by their average maximum age limit (65 if none).

To examine the link between age requirements and perceived skill obsolescence of older workers, I next compare occupation-level changes in skill demand. If new skill requirements emerge while previously relevant skills lose importance, the skill set of older workers may be outdated. Employers might be reluctant to hire them if they believe that these workers are less willing or less able to keep pace with recent developments.

For this analysis, I merge external data on occupation-level skill changes by Deming and Noray (2020) with the Austrian job postings. Using US online vacancies from 2007 to 2019, the study identifies about 15,000 unique skills in a large sample of almost 23 million job postings. Based on these data, Deming and Noray (2020) compute the share of vacancies in which each skill appears in the first and last year of their sample. To capture occupation-level skill changes, the absolute value of the difference in shares is computed for each skill s and then summed across skills within each occupation o:

$$\text{SkillChange}_o = \sum_{s=1}^{S} Abs[\text{SkillShare}_{os}^{2019} - \text{SkillShare}_{os}^{2007}].$$

For the most detailed distinction of occupations, the authors use 6-digit SOC-2010 codes, which I map to vacancies in the Austrian database at the 4-digit ISCO-08 level.[6] High values of this measure reflect substantial changes in skill requirements, with strong increases in some skills and strong declines in others over time. On average, the vacancy-weighted skill change is approximately three, with a standard deviation of one.

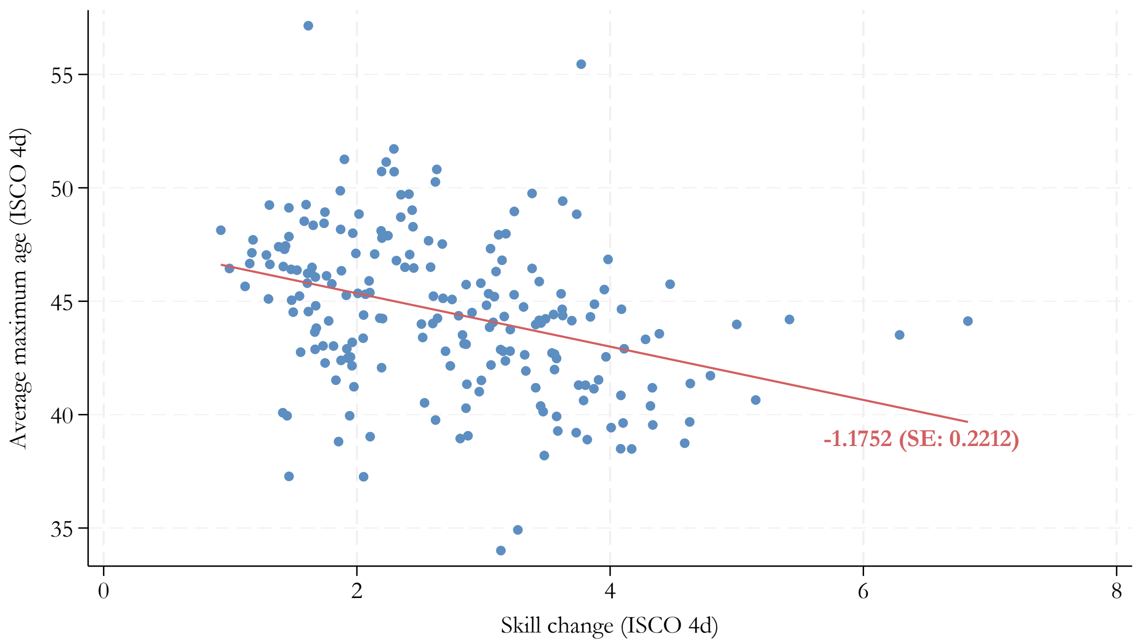
Despite being derived from US vacancy data collected in later years, I assume that the measure reasonably captures occupation-specific changes in the Austrian labor market in the early 2000s. Skill demands are unlikely to differ substantially between two developed economies, and it is plausible that the skill trends observed between 2007 and 2019 had already begun earlier. If employers are concerned about skill obsolescence among older workers, age requirements should be stricter in occupations experiencing more rapid skill change, as older workers may be more likely to lack newly emerging skills or to possess skills that have become less relevant. To test this hypothesis, I compare skill changes to average maximum age requirements on the occupation level, using again the sample of pre-ban vacancies for which age limits are observed. Figure 3 shows that there is indeed a strong negative correlation. Employers hiring for occupations with a one-standard-deviation higher level of skill change set the maximum age cap approximately 1.2 years lower.

Taken together, these patterns show that age limits were most common in occupations with higher education requirements and rapidly changing skill demands, while manual and service jobs imposed fewer and weaker restrictions. This is consistent with

[6]In cases of non-unique mapping between the SOC and ISCO classifications, categories are weighted by their relative frequency in the vacancy data.

the hypothesis that employers use upper age limits as a screening device where they expect the skills of older applicants to be outdated.

Figure 3: Skill change and average maximum age requirements (ISCO 4-digit level)



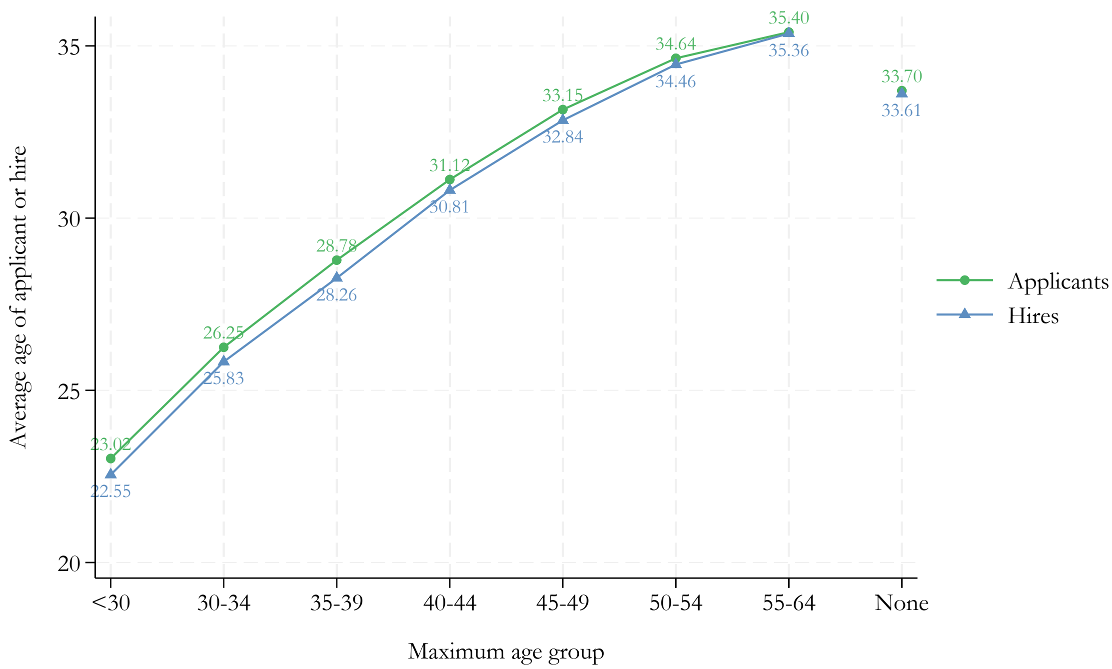
Note: Pre-ban vacancies (2000-2004). Occupations with less than 100 vacancies omitted.

3.3 Applications and hiring

If maximum age requirements in job postings affect job search behavior, tighter age caps should drive down the age of applicants and ultimately lead to lower ages of hired workers. Before analyzing the impact of banning age restrictions in the next section, I descriptively examine the relationship between age caps and these outcomes. The analysis in the remainder of the paper is based on the subsample of vacancies for which the hired worker can be observed.

Figure 4 plots the average age of applicants and hires for vacancies with different strengths of age limits, revealing a strong correlation with both outcomes of similar magnitude. While the average age of applicants and hires is just 23 years for vacancies targeting workers aged 30 or younger, the averages increase to about age 34 in job ads with weak or no stated age requirements. Across all age-cap groups, the mean age of applicants is only slightly higher than that of hired workers.

Figure 4: Age of applicants and hires by maximum age groups



To examine the impact of correlated firm- and occupation-specific age differences, I next regress both outcomes on the vacancies' age requirement and include firm and occupation fixed effects. Again, I set the age cap to 65 if no requirement is listed in the job posting. As shown in Appendix Table A.2, decreasing the age limit by one year is associated with applicants and also hires who are on average 0.15 years younger. Accounting for differences across occupations and firms reduces the coefficient for hires to 0.12, while leaving the effect for applicants unchanged. This indicates that the correlation between age limits and age outcomes is relatively robust: vacancies with age requirements attract younger applicants, which partially translates into younger hires.

4 Impact of the ban

This section examines how the ban on age requirements in job postings influenced the eventual age of applicants and hires, along with other hiring outcomes. I first describe the difference-in-differences strategy, which compares jobs with stronger and weaker predicted age requirements before and after the ban, and how I correct the estimates for measurement error in the predictions. I then present the effects on the age of applicants and hired workers, show how employers adjusted the wording of their job ads and finally examine effects on worker productivity and screening costs.

4.1 Empirical strategy

Because the ban applied to all job postings equally, I follow the strategy of Card et al. (2024) and distinguish jobs by their predicted extent of discrimination. This approach rests on the idea that the ban binds only for jobs that would otherwise have specified age limits, while jobs without such requirements are effectively untreated and serve as a control group. The predictions allow me to classify jobs by the strength of their age requirements even after the law took effect, when these limits could not be expressed any longer. Here, I assume that employers' preferences for worker age are not affected by the anti-discrimination law, but only their ability to state them openly. Otherwise, the prediction accuracy would change with the treatment.

As Card et al. (2024) do for gender requirements, I predict the jobs' age requirements using the leave-out mean within their occupation-firm group. This grouping captures both the variation in age requirements across occupations, as shown in the previous section, and the role of employer-specific preferences. For each job advertised in the years before the ban, I first compute the difference between the respective maximum age requirement and age 65.[7] If no age preference is listed, I set the difference to zero. The resulting index captures the intensity of age discrimination, taking values between zero and 47. The index is zero when no age requirement is stated and reaches its maximum of 47 when the stated age limit is 18 years. I then compute the leave-out mean of this index for each 3-digit occupation group within each firm.[8] Next to the age-limit index, I additionally define binary variables, which indicate whether a job has an age limit below a given age threshold τ. Here, the group-specific leave-out means are the shares of job ads with age restrictions below age τ.

Using the predicted age requirements, I then estimate difference-in-differences regressions to identify the impact of the ban. Specifically, for hiring outcome y_i of vacancy i, I estimate the following equation:

$$y_i = \beta_0 + \beta_1 \, A_i + \beta_2 \, A_i \times D_i + \psi_k + \kappa_o + \lambda_t + \varepsilon_i. \tag{1}$$

[7]During the period of observation, the statutory retirement age in Austria was 65 for men and 60 for women.

[8]The AMS 3-digit grouping distinguishes about 260 occupations in the estimation sample.

A_i denotes the leave-out mean of the age-limit index or of an age-threshold indicator (as defined above), and dummy variable D_i indicates whether the ad was listed in the post-period, which starts in 2005. The law took effect only in July 2004 and, as discussed in Section 2.1, age limits disappeared from postings very slowly at first, leaving 2004 largely untreated. Moreover, the regressions include firm (ψ_k), occupation (κ_o) and year (λ_t) fixed effects. The main coefficient of interest is β_2, which captures the differential change in outcomes after the ban for vacancies with stricter predicted age limits. In this setting, the common trends assumption requires that, in the absence of the ban, outcomes would have evolved similarly for vacancies with high and low predicted age limits.

To illustrate the timing of effects, I further estimate an event-study design:

$$y_i = \beta_0 + \beta_1 A_i + \sum_{\substack{s=2000 \\ s\neq 2004}}^{2010} \beta_{2,s} A_i \times I(year_i = s) + \psi_k + \kappa_o + \lambda_t + \varepsilon_i \tag{2}$$

This specification resembles the difference-in-differences model in Equation (1), apart from replacing the single interaction term with a full set of interactions between A_i and calendar-year indicators, with 2004 omitted as the reference year.

Because the leave-out means are computed from a limited number of vacancy observations, the predicted requirement A_i is a noisy measure of the age limit that an employer would have set. This induces attenuation bias, implying that the coefficients of Equations (1) and (2) understate the actual impact of the ban. As pointed out by Card et al. (2024), both equations can be interpreted as the reduced form of a two-stage procedure in which the predicted age limit A_i instruments for the actual age limit $\tilde{A}_i$. Using all vacancies before the ban, the first stage regresses the observed age limit on its prediction:

$$\tilde{A}_i = \pi_0 + \pi_1 A_i + \kappa_o + \mu_j + \lambda_t + \xi_i, \tag{3}$$

where μ_j, κ_o and λ_t denote industry, occupation and year fixed effects, respectively. Assuming that the relation between predicted and actual requirements is stable over time, the effect of the actual age limit is obtained by dividing the reduced-form coefficient β_2 by the first-stage coefficient π_1. Because coefficient and standard error are rescaled by the same factor, this correction leaves t-statistics and significance levels unchanged.

Table 3 presents the first-stage estimates for the age-limit index and different age thresholds. As shown in Panel A, a one-year lower predicted age limit corresponds to a 0.80-year lower observed limit. The correction factor is therefore 1.24, implying that the corrected effects exceed the reduced-form estimates by roughly a quarter. Panel B shows that the first-stage estimates for the age thresholds increase from 0.70 for a maximum age below 35 years to 0.82 for a maximum age below 55 years. Predictions are thus somewhat less precise for the most restrictive age caps, which are used by fewer employers, and the correction factors decrease accordingly from 1.43 to 1.23.

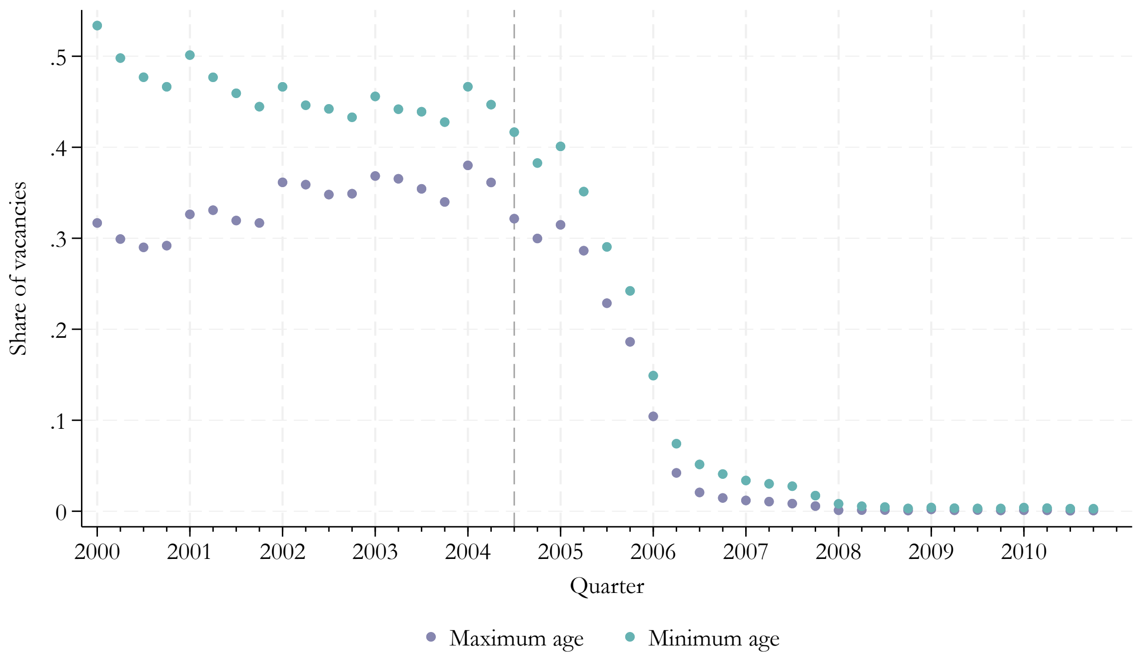
Table 3: Observed and predicted age limits before the ban (first-stage estimates)

	Coefficient	Mean of dep. var.	Correction factor	R^2
Panel A: Continuous measure				
Age limit index (65 − max. age)	0.804*** (0.003)	7.64	1.24	0.50
Panel B: Discrete measures				
Maximum age below 35	0.701*** (0.006)	0.05	1.43	0.34
Maximum age below 40	0.750*** (0.004)	0.09	1.33	0.40
Maximum age below 45	0.782*** (0.003)	0.16	1.28	0.46
Maximum age below 50	0.803*** (0.002)	0.23	1.25	0.49
Maximum age below 55	0.815*** (0.002)	0.30	1.23	0.50

Note: 194,922 observations. All regressions include year, occupation (3-digit) and industry (2-digit) fixed effects. In Panel A, the dependent variable is the age-limit index. In Panel B, the dependent variable indicates whether a vacancy states a maximum age below the respective threshold. The last columns report the mean of the dependent variable, the correction factor applied to the reduced-form estimates and the R^2 of the regression. Standard errors are reported in parentheses. * p<0.10, ** p<0.05, *** p<0.01

As explained in Section 2.1, the Equal Treatment Act came into effect in July 2004, but many employers did not immediately adapt to the new regulations. This is evident in the AMS vacancy database, where many job postings continue to state age limits in later periods. Figure 5 depicts the share of vacancies with maximum and minimum age requirements by quarter of vacancy entry. Postings with maximum age caps exhibited a moderate upward trend in the years preceding the ban. After a gradual decline in the first months, the share started to fall rapidly. By the first quarter of 2006, it had dropped to 10 percent, and by 2007 age limits had vanished almost entirely.

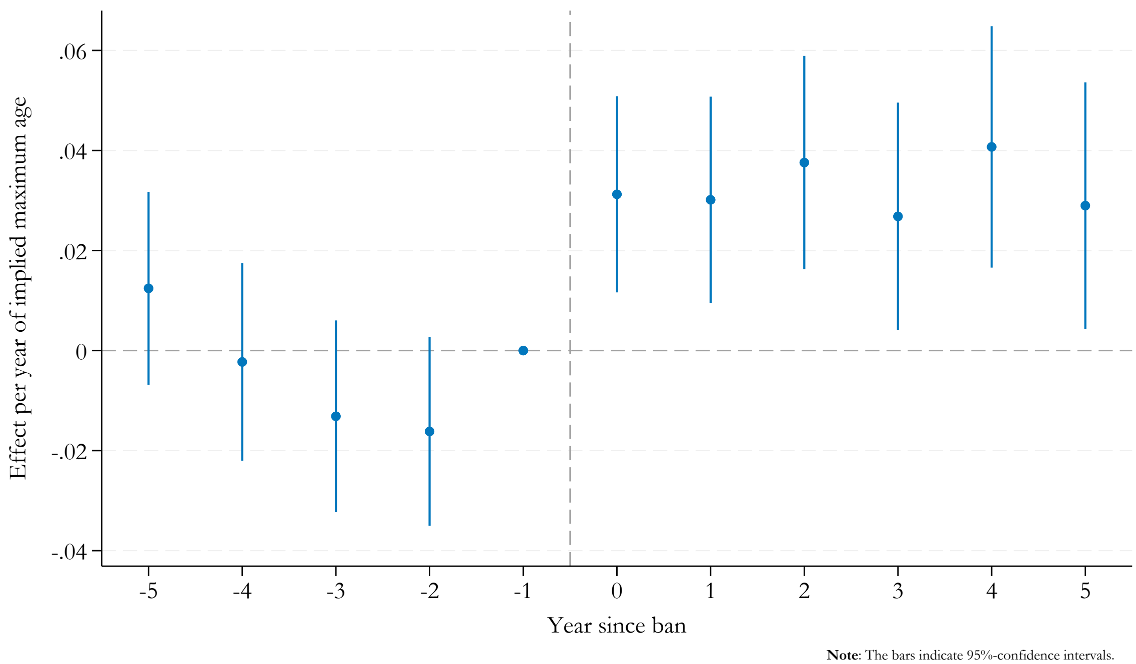
Figure 5: Changes in share of vacancies with age requirements



4.2 Impact on the age of applicants and hires

The descriptive analysis showed that vacancies with stricter age caps attract and hire considerably younger workers. If this pattern reflects a response to the stated restrictions, the ban should lead to an older pool of job applicants and, in turn, older hires among vacancies that would otherwise have listed age limits. Figure 6 plots the results of the event study specification outlined in Equation (2), where the outcome is the age of hired workers and vacancies are compared by the predicted age-limit index. All estimates are rescaled to correct for attenuation bias as described above. Prior to the ban, differences by predicted age requirement are relatively stable across years. Since 2005, hired workers are consistently older in vacancies with stronger predicted age limits. Jobs whose implied maximum age restriction is one year lower hire workers who are, on average, 0.03 to 0.04 years older relative to the pre-ban period. Considering that many jobs require workers to be 40 years or younger, which corresponds to a difference of 25 years from the statutory retirement age, the point estimate implies that firms with such age caps hire workers who are almost one year older.

Figure 6: Impact of the ban on the age of hired workers



If the increase in the age of hires is driven by changes in the applicant pool, the ban should also raise the average age of applicants. To examine this, I estimate the difference-in-differences specification of Equation (1) for the age of both hired workers and applicants. Table 4 shows that, for the age of hired workers, the attenuation-corrected coefficient on the interaction between the post-period indicator and the predicted maximum age requirement is 0.035. This estimate closely mirrors the average of the event-study coefficients in the post-ban years, as depicted in Figure 6. For the age of applicants, I find a corrected coefficient on the interaction term of 0.062, showing that the positive age effect is stronger for applicants than for eventual hires. In other words, removing age requirements from job postings leads to an increase in older applicants for jobs that previously discouraged them from applying, which partially translates into an increase in the age of hired workers at these jobs.

While the preceding analysis showed that the ban increases the average age of hires, this shift does not necessarily mean that firms now hire workers above their former

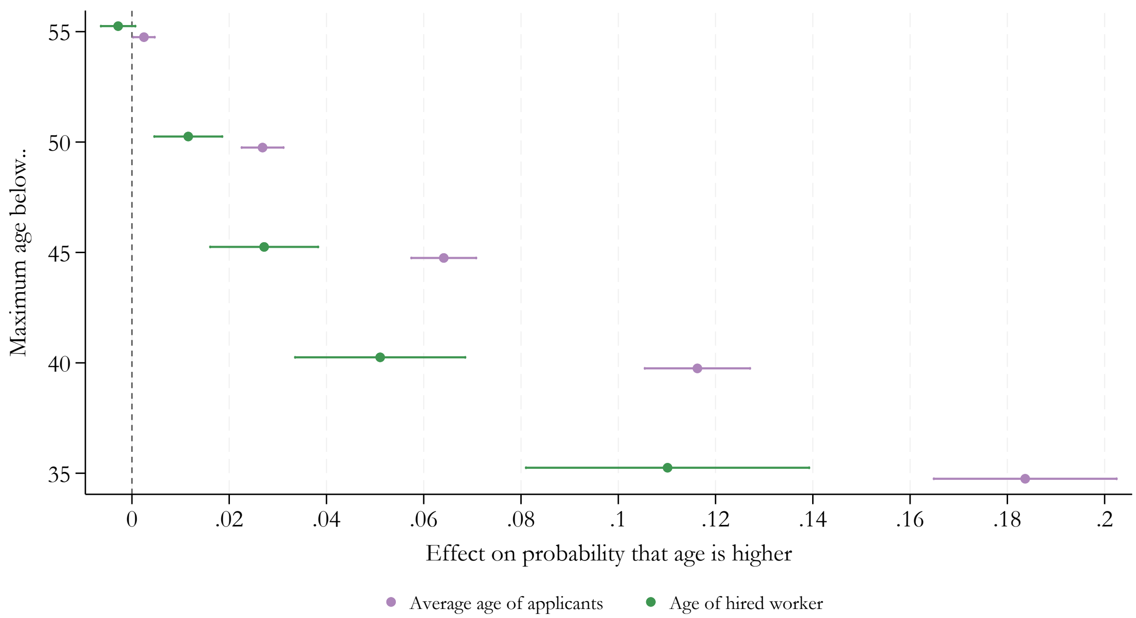
Table 4: Impact of the ban on the average age of applicants and hires

	Average age - Applications	Age - Hired worker
Post × Max. age. pred.	0.050***	0.028***
	(0.003)	(0.004)
Max. age. pred.	-0.073***	-0.063***
	(0.003)	(0.004)
Post	0.886***	0.996***
	(0.034)	(0.052)
Constant	33.427***	33.028***
	(0.025)	(0.039)
Corrected: Post × Max. age. pred.	0.062***	0.035***
	(0.003)	(0.005)
First stage (π_1)	0.804	0.804

Note: 343,145 observations. All regressions include firm and occupation (3-digit) fixed effects. The bottom panel reports the interaction coefficient corrected for attenuation bias, obtained by dividing it by the first-stage coefficient of the observed age-limit index on its predicted value. Standard errors are reported in parentheses. * p<0.10, ** p<0.05, *** p<0.01

age limits. To examine this margin, I next consider the probability of hiring above a given age threshold. Specifically, I use the predicted probability of an age limit below a given threshold to distinguish discriminating from non-discriminating vacancies and estimate the impact of the ban on attracting applicants or hiring workers above this threshold. Figure 7 plots the estimates for five maximum age thresholds, ranging from 35 to 55. Estimates are again corrected for attenuation bias, using the threshold-specific first stages of Table 3. Except for the highest age threshold, the estimated effects are positive and sizable. The stronger the predicted age requirement, the larger the increase in the probability that an applicant or hire is older than the corresponding age cap. In all cases, the applicant effect exceeds the hire effect by a factor of about 2. For vacancies that would have required workers to be younger than 35 years, the estimated increase in the probability of exceeding this age is 18 percentage points for applicants and 11 percentage points for hires. These effects are large relative to the outcomes' baseline shares. In the pre-ban period, 42 percent of applicants and 41 percent of hires were aged 35 or older. The estimates therefore correspond to relative increases of roughly 40 percent at the application stage and about a quarter at the hiring stage.

Figure 7: Impact of the ban on applicants and hires above age threshold



Note: The bars indicate 95%-confidence intervals. Application shares in the pre-ban period: 0.42 (≥ 35), 0.28 (≥ 40), 0.17 (≥ 45), 0.08 (≥ 50) and 0.02 (≥ 55). Hiring shares in the pre-ban period: 0.41 (≥ 35), 0.28 (≥ 40), 0.16 (≥ 45), 0.08 (≥ 50) and 0.02 (≥ 55).

The preceding analysis showed that removing age limits raises applications more than it raises hires. If the ban affects hiring only through the composition of applicants, the application effects can be interpreted as the first stage of the hiring response: employers hire older workers because more of them apply, not because they choose differently among a given set of candidates. A direct effect on hiring decisions would require that employers fear legal consequences when they reject older applicants. While I cannot rule out this channel, it is unlikely to have a relevant impact in this setting. Because rejected applicants do not observe the other candidates, age discrimination in hiring is very difficult to prove, and the expected compensation from a successful claim is low. As pointed out in Section 2.1, the Austrian Equal Treatment Commission receives only very few complaints about age discrimination in hiring each year. The hiring effects should therefore reflect the broader pool of applicants rather than changed hiring decisions.

Under this interpretation, the estimates in Table 4 quantify how strongly hiring responds to the changed applicant pool. Dividing the effect on hires of 0.035 by the effect on applicants of 0.062 yields a pass-through of 0.5 to 0.6: when the average applicant becomes one year older, the average hire becomes about seven months older. The threshold estimates imply a similar rate. For instance, the increase of 11 percentage points in the probability of hiring a worker above age 35 corresponds to roughly 60 percent of the 18 percentage point increase among applicants. This pass-through rate suggests that age preferences at the hiring stage are present but not dominant. If they were very strong, employers would continue to select the youngest candidates from the enlarged pool and the pass-through would be close to zero. Instead, if they were absent, hires would mirror the applicant pool and the pass-through would be one.

As shown in Section 3, vacancies posted before 2004 also routinely stated gender requirements, and age limits tended to be stricter when employers were seeking female applicants. To analyze whether the age effects of the ban differ by gender preferences, I follow Card et al. (2024) and use the leave-out mean of stated gender preferences within the same occupation-firm groups to classify ads as having a predicted preference for female applicants, for male applicants or no gender preference. Table 5 reports the results of the difference-in-differences estimation separately for the three samples, with the average age of applicants as the outcome in Panel A and the age of the hired worker in Panel B. At the application stage, the ban raises the age of applicants in all three groups, and the effect is only slightly smaller for vacancies with a predicted preference for female workers. At the hiring stage, in contrast, the estimate for these vacancies is about half the size of the effects in the other two groups. The pass-through from applicants to hires accordingly falls from 0.64 in jobs seeking male workers to 0.40 in jobs seeking female workers. Older jobseekers increased their applications to these jobs almost as much as elsewhere, but the additional older applicants were less likely to be hired. This suggests that preferences for young workers are more persistent when firms look for female workers.

Since the law banned age and gender requirements at the same time, the estimated effects could partly reflect the removal of gender rather than age preferences. Both requirements are correlated, as employers seeking female workers also tend to request younger applicants (Delgado Helleseter et al., 2020). In the Austrian setting, however, this correlation is considerably weaker, and both requirements could be stated side by side, so employers had no need to express gender preferences through age limits. In addition, the age effects are fully present among vacancies without a predicted gender preference, for which the ban removed hardly any gender requirements.

Table 5: Impact of the ban on the average age of applicants and hires by gender requirement

	Gender requirement		
	Female	*Indifferent*	*Male*
Panel A: Average age of applicants			
Post $\times$ Max. age. pred.	0.043***	0.052***	0.049***
	(0.006)	(0.004)	(0.006)
Corrected: Post $\times$ Max. age. pred.	0.053***	0.066***	0.060***
	(0.007)	(0.005)	(0.007)
Panel B: Age of hired worker			
Post $\times$ Max. age. pred.	0.017*	0.029***	0.031***
	(0.009)	(0.006)	(0.009)
Corrected: Post $\times$ Max. age. pred.	0.021*	0.036***	0.039***
	(0.011)	(0.007)	(0.011)
Pass-through rate	0.40	0.54	0.64
First stage (π_1)	0.799	0.798	0.813
# vacancies	73,281	182,406	77,580

Note: 333,267 observations. All regressions include firm and occupation (3-digit) fixed effects. In each panel, the bottom rows report the interaction coefficient corrected for attenuation bias, obtained by dividing it by the first-stage coefficient of the observed age-limit index on its predicted value, which is estimated separately for each subsample. The pass-through rate is the ratio of the effect on hires to the effect on applicants. Standard errors are reported in parentheses. * p<0.10, ** p<0.05, *** p<0.01

4.3 Impact on ageist language in job postings

Beyond explicit age requirements, employers may also implicitly signal age preferences through the language used in job advertisements. For example, employers could describe the desired worker as *young*, or characterize the company and its workforce as *young* or *young in spirit*, without stating an explicit age limit. Age preferences can also be conveyed more indirectly through attributes commonly associated with younger workers, such as *dynamic* or *energetic*.

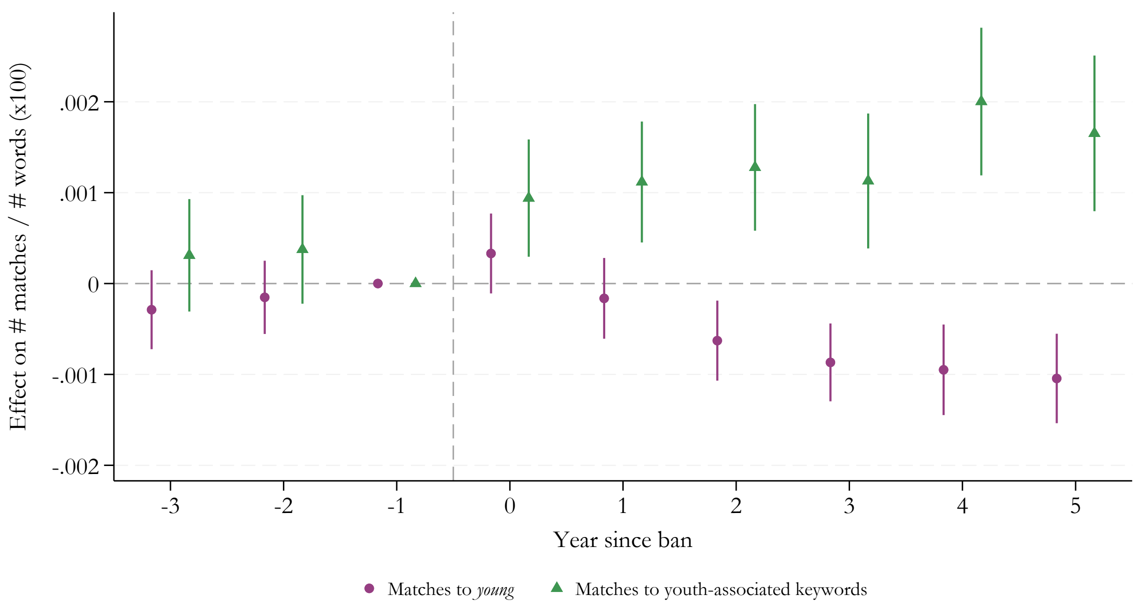
The ban on discriminatory job ads might affect these indirect signals, but it is unclear whether it reduces or increases the use of such *ageist language*. On the one hand, employers with a strong preference to deter applications from older workers might use signals in the ad text as a substitute for stating explicit age ranges. On the other hand, the law requires that jobs are advertised in a neutral and inclusive manner, which may also make the use of suggestive language subject to legal challenge.

To estimate the impact of the ban on the use of ageist language, I analyze ad texts in the AMS vacancy database, which are available for jobs posted since 2002. For each vacancy, I compute the frequency with which keywords appear in the ad text. To adjust for differences in text length, I normalize the keyword counts by the vacancy's total number of words. Figure 8 illustrates event-study estimates separately for the normalized number of matches to the term *young* and to a number of other youth-associated terms.[9] These keywords capture attributes that employers may perceive as declining with worker age. Evidence from recruiters shows that the perceived ability to learn new tasks, flexibility and ambition decline substantially with applicant age, already from age 40 onwards (Carlsson and Eriksson, 2019). Requirements such as *willing to learn*, *agile* or *up-and-coming* demand exactly these attributes, and, because they can be justified as relevant features of the worker profile, such phrasing provides a legal way to discourage older applicants after the ban. Since I compare the same firms and occupations over time, an increase in this vocabulary should reflect a change in wording rather than a change in job content.

Figure 8 plots the results of the event study specification outlined in Equation (2), estimated separately for the term *young* and youth-associated keywords. The outcome is the normalized keyword count, and vacancies are again compared by the predicted age-limit index, with all estimates rescaled to correct for attenuation bias. Since ad texts are only recorded from 2002 onwards, the estimation window covers three years before and five years after the ban. The purple circles show that, in the text of job postings for which I predict stronger age restrictions, the use of the word *young* becomes gradually less common in the years following the ban. Eventually the normalized match count decreases by about 0.001×10^{-2} units for each year by which the implied maximum age is lower, which is a meaningful effect relative to the outcome's sample mean of 0.024×10^{-2}. In contrast, the green triangles in Figure 8 show an increase in the use of keywords that signal a preference for younger workers indirectly. In the years after the ban, the estimated effect rises to up to 0.002×10^{-2}, compared with a sample mean of 0.084×10^{-2} for these keyword matches. The two sets of estimates thus indicate a

[9] The (German) keywords include *resilient* ('belastbar'), *willing to learn* ('lernbereit'), *dynamic* ('dynamisch'), *stress-resistant* ('stressresistent'), *performance-oriented* ('leistungsbereit'), *up-and-coming* ('aufstrebend'), *fresh* ('frisch'), *agile* ('agil'), *energetic* ('energetisch') and *high-energy* ('energiegeladen'), including derived forms such as *resilience* ('Belastbarkeit').

Figure 8: Impact of the ban on the use of age-related terms



Note: The bars indicate 95%-confidence intervals. Keywords include *resilient* ('belastbar'), *willing to learn* ('lernbereit'), *dynamic* ('dynamisch'), *stress-resistant* ('stressresistent'), *performance-oriented* ('leistungsbereit'), *up-and-coming* ('aufstrebend'), *fresh* ('frisch'), *agile* ('agil'), *energetic* ('energetisch') and *high-energy* ('energiegeladen'), including derived forms.

shift in wording: employers stopped referring explicitly to the term *young* and instead increasingly emphasized requirements that are commonly attributed to young workers. This pattern is consistent with employers adapting their wording to comply with the regulation while maintaining their underlying age preferences.

4.4 Impact on worker productivity and screening costs

Many employers may avoid hiring older workers because they perceive them as less productive than younger workers. If these worries are justified and cannot be adequately assessed during the hiring process, average worker productivity could decline due to the ban, as the age of hires increases. To examine this, I estimate the effect of the ban on worker productivity using three proxies: daily earnings, job duration and sick days. For each outcome, I estimate again the event-study specification given by Equation (2). The estimated effects are reported in the first three panels of Figure 9.

If older workers are indeed less productive, or are perceived to be less productive, employers may offer lower wages. In the latter case, wages could fall without a corresponding decline in output, which would raise productivity relative to wage costs.

Using daily earnings of workers in the year of hire as outcome, I do not find evidence in support of such effects. As shown in Panel 9a, differences by the jobs' predicted degree of age restrictions remain stable over time and exhibit no structural break around the enactment of the ban. In addition, workers with lower productivity may be more likely to separate if they do not match job requirements well. Panel 9b shows the effects of the ban on the probability of staying at least one year with the new employer. As for earnings, I estimate that job duration of hires does not change due to the ban.

Another potential concern when hiring older workers is that they may be in poorer health, which can result in longer periods of sickness-related absence. To test this, I use health-insurance data on sickness pay spells, which are available for long absences of at least six weeks.[10] The outcome is defined as the cumulative number of days a worker receives sickness pay during the first five years of employment. Consistent with the results for the other productivity measures, I do not observe ban-related changes in sickness days. The event-study estimates presented in Panel 9c are close to zero and statistically insignificant in all years.

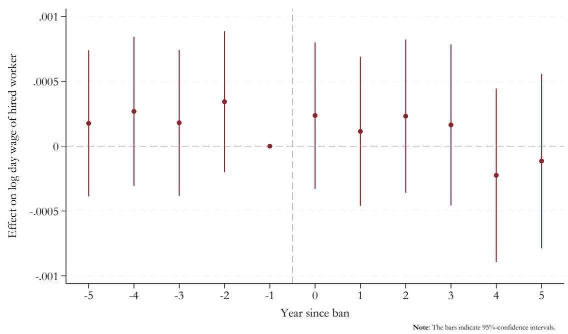
Even if worker productivity remains unchanged, the ban on discriminatory job postings may increase employers' recruitment costs and effort. Because explicit age limits are outlawed, recruiters cannot use this feature anymore to preemptively discourage applications from older jobseekers. To process these additional applications, recruiters may require more time, which could delay hiring. Although direct measures of screening costs are unavailable, I observe the vacancy filling duration, which is defined as the time between a vacancy being posted and recorded as filled in the database.[11] The last panel of Figure 9 presents the corresponding event-study graph, which again shows mostly statistically insignificant differences relative to the base year. The graph exhibits a gradual increase, but this pattern is already present in the pre-ban period. Consequently, the positive differences observed in later years are more likely driven by diverging trends across jobs with different degrees of age restrictions rather than by the ban itself.

Taken together, the results indicate that banning age restrictions increases the hiring chances of older workers in previously discriminating jobs without negative side effects.

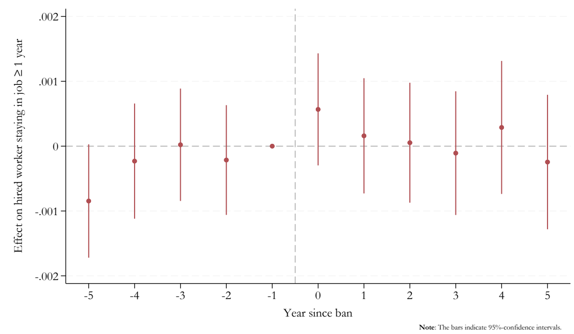
[10] Sickness pay for short-term absences is covered by the employer and is therefore not recorded in the social security database. During the first year of employment, employers are required to cover sickness pay for up to six weeks. From the second year onward, this period increases to eight weeks and remains at that duration through the fifteenth year of employment.

[11] To ensure that the vacancy database remains up to date, AMS caseworkers regularly follow up with employers and jobseekers to check whether a vacancy has been filled.

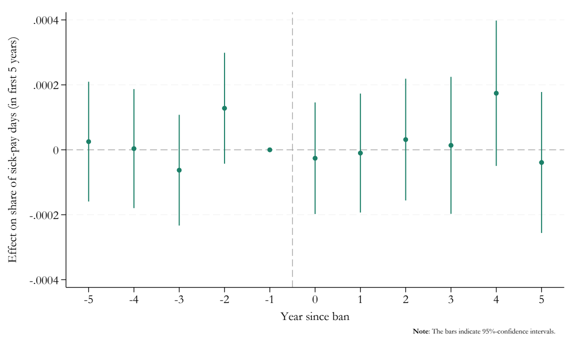
Figure 9: Impact of the ban on screening costs and worker productivity



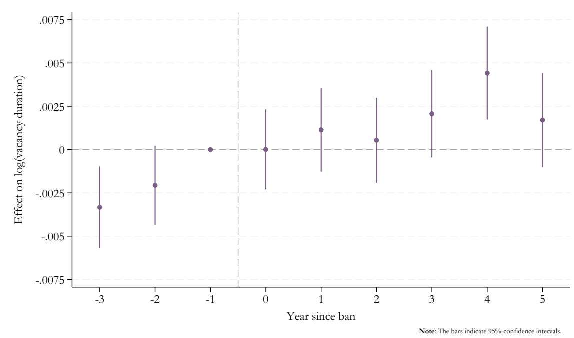
(a) Outcome: Daily earnings of hired worker



(b) Outcome: Long job duration (>1 year)



(c) Outcome: Long-term sickness days



(d) Outcome: Vacancy filling duration

Because the law no longer allows employers to exclude older applicants from the start, the average age of applicants rises in affected vacancies, and part of this increase carries over to hires. Many employers thus appear to be initially pessimistic about the hiring prospects of older workers. This pessimism seems unwarranted, since I do not find evidence that worker productivity deteriorates or screening costs increase in spite of the higher average age.

5 Conclusion

Aging workforces and rising retirement ages have increased attention to the labor market integration of older workers, who often stay unemployed much longer than younger jobseekers. One potential explanation is that employers refrain from hiring older workers because they expect lower performance due to reduced effort or outdated skills. Austrian job postings make such preferences directly observable, since employers could state age requirements openly until the Equal Treatment Act banned the practice in 2004.

I find that, prior to 2004, one third of job advertisements specified a maximum age, typically requiring applicants to be no older than 40 to 55 years. These requirements were particularly common in white-collar occupations and in those with more rapid changes in skill demand, suggesting that employers frequently associate age with skill obsolescence.

In addition, my analysis shows that the ban on discriminatory job postings was effective in reducing age discrimination. To identify the impact of the ban, I first group vacancies by their anticipated extent of age restrictions, as predicted by observed age limits before the ban within the same firm and occupation. I then compare applications and hiring outcomes between jobs with high and low predicted age limits, before and after the ban. Because the predictions measure the intended age limits with error, all estimates are rescaled by the first-stage relation between observed and predicted limits. I find that previously restrictive jobs received relatively more applications from older workers and, to a lesser extent, also hired workers of older age. About half of the increase in applicant age carries over to hires, which shows that age preferences still matter at the selection stage but are not strong enough to fully undo the change in the applicant pool. This pass-through rate is lower in jobs seeking female applicants, where preferences for young workers appear to be more persistent. Despite this age effect, there is no evidence of adverse productivity effects, as earnings, job tenure and sickness absence remained unchanged. Likewise, vacancy filling times do not increase, suggesting that the removal of age restrictions did not substantially raise recruiters' screening costs.

The textual analysis of job ads reveals that employers also adjusted the wording of their postings. Vacancies with stronger predicted age restrictions became less likely to refer to the term *young* explicitly but more likely to demand attributes commonly associated with youth. Employers thus continue to signal their age preferences, but the increase in applications and hires from older workers suggests that such cues deter them less effectively than explicit age limits.

From a policy perspective, the findings indicate that bans on age-discriminatory job advertising are an important tool to meaningfully improve labor market access for older workers without imposing efficiency costs on firms. This is consistent with previous evidence on the ban on gender preferences in job postings (Kuhn and Shen, 2023; Card et al., 2024). Clear guidelines on non-discriminatory job ads can be implemented and enforced at low cost. In contrast, age discrimination beyond job postings is difficult to identify, as jobseekers would need to demonstrate that recruitment decisions were based on age considerations. In Austria, complaints about age discrimination in hiring remain rare, and the available sanctions appear more likely to deter victims from seeking redress than employers from discriminating. At the same time, the limits stated before the ban show how widespread and strong employer preferences for younger workers are. Employers who rule out older jobseekers from the outset are unlikely to judge them neutrally later on. This suggests that the overall extent of age discrimination in hiring is substantially larger than what job postings reveal.

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Appendix

Table A.1: Comparison of estimation samples

	Job starts	Vacancy sample	Vacancy-worker sample
Female	0.46	–	0.48
	(0.50)		(0.50)
Age	32.71	–	33.61
	(10.75)		(10.77)
Sector:			
Retail/Wholesale	0.16	0.16	0.19
	(0.37)	(0.36)	(0.39)
Admin./support service	0.11	0.16	0.14
	(0.31)	(0.37)	(0.35)
Accom./Food	0.13	0.30	0.22
	(0.34)	(0.46)	(0.42)
Manufacturing	0.12	0.10	0.12
	(0.32)	(0.30)	(0.32)
Construction	0.09	0.07	0.08
	(0.29)	(0.25)	(0.28)
Health/Social	0.06	0.04	0.05
	(0.23)	(0.18)	(0.21)
Public admin.	0.06	0.01	0.02
	(0.24)	(0.12)	(0.14)
Transport/Storage	0.06	0.03	0.04
	(0.23)	(0.18)	(0.20)
Prof./Scient./Techn.	0.06	0.03	0.04
	(0.23)	(0.16)	(0.18)
Other	0.16	0.11	0.11
	(0.36)	(0.31)	(0.31)
Observations	8,691,827	2,337,333	535,746

Note: The table reports means with standard deviations in parentheses. The first sample includes all new employment spells. The second sample includes all vacancies on the AMS database, and the third sample includes jobs mediated by AMS. All samples cover the years 2000 to 2010.

Figure A.1: Frequencies of minimum age requirements

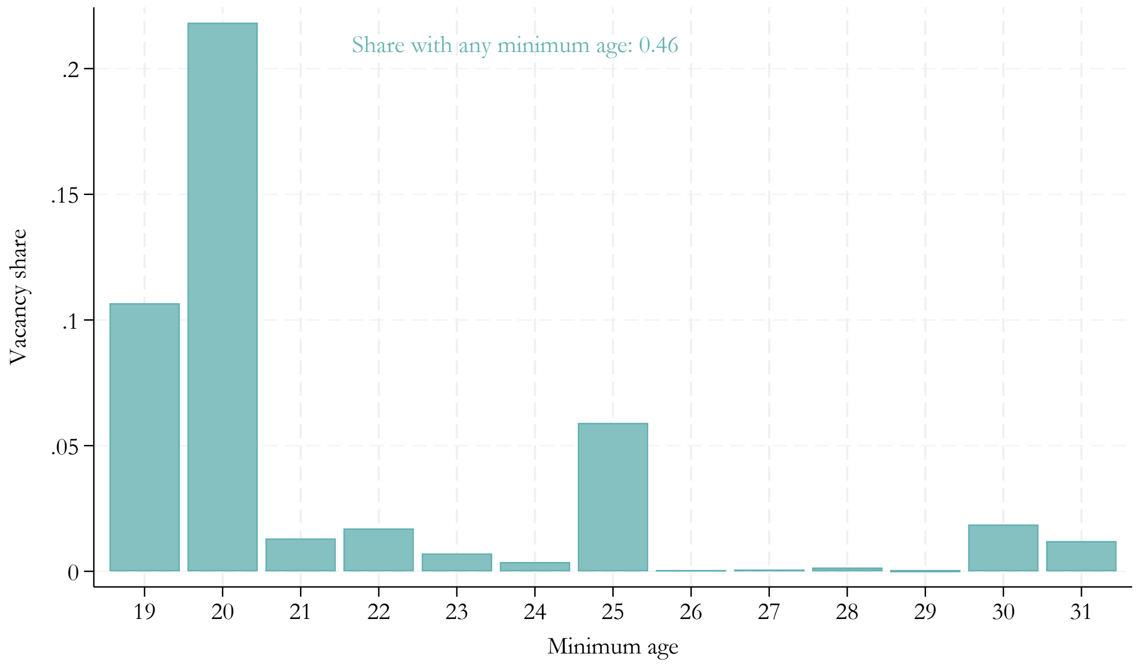

Table A.2: Age of applicants, age of hires and maximum age limits

Outcome: Average age of applicant			
	(1)	(2)	(3)
Maximum age limit	0.153***	0.146***	0.153***
	(0.001)	(0.001)	(0.001)
Constant	24.175***	24.537***	24.137***
	(0.039)	(0.038)	(0.048)
Outcome: Age of hire			
	(1)	(2)	(3)
Maximum age limit	0.159***	0.138***	0.124***
	(0.002)	(0.002)	(0.003)
Constant	23.626***	24.873***	25.646***
	(0.118)	(0.118)	(0.160)
Occupation fixed effects		✓	✓
Firm fixed effects			✓

Note: 198,791 observations. Standard errors are reported in parentheses. * p<0.10, ** p<0.05, *** p<0.01