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DISCUSSION PAPER SERIES

IZA DP No. 16672

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Axana Dalle
Ghent University and Research Foundation Flanders

Louis Lippens
Ghent University and Vrije Universiteit Brussel

Stijn Baert
Ghent University, University of Antwerp, Université catholique de Louvain and IZA

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IZA – Institute of Labor Economics

Schaumburg-Lippe-Straße 5–9
53113 Bonn, Germany

Phone: +49-228-3894-0
Email: publications@iza.org

www.iza.org

ABSTRACT

Nothing Really Matters: Evaluating Demand-Side Moderators of Age Discrimination in Hiring*

As age discrimination hampers the OECD's ambition to extend the working population, an efficient anti-discrimination policy targeted at the right employers is critical. Therefore, the context in which age discrimination is most prevalent must be identified. In this study, we thoroughly review the current theoretical arguments and empirical findings regarding moderators of age discrimination in different demand-side domains (i.e. decision-maker, vacancy, occupation, organisation, and sector). Our review demonstrates that the current literature is highly fragmented and often lacks field-experimental evidence, raising concerns about its internal and external validity. To address this gap, we conducted a correspondence experiment and systematically linked the resulting data to external data sources. In so doing, we were able to study the priorly determined demand-side moderators within a single multi-level analysis and simultaneously control multiple correlations between potential moderators and discrimination estimates. Having done so, we found no empirical support for any of these moderators.

JEL Classification: J71, J23, J14

Keywords: ageism, hiring discrimination, heterogeneity, literature review, field experiment, administrative data

Corresponding author:
Axana Dalle
Ghent University
Sint-Pietersplein 6
9000 Ghent
Belgium

E-mail: Axana.Dalle@UGent.be

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1 Introduction

Given the global ageing of the population, the pay-as-you-go retirement systems of many OECD countries stand on shaky ground. This is because, in such a financing system, the pensions of the retired population are financed with the income taxes of the working population (Attanasio et al., 2007; Barr, 2006; Gunderson, 2003; McGrattan & Prescott, 2017; Staubli & Zweimüller, 2013). As the percentage of seniors in the population rises, it becomes increasingly difficult to pay out a tremendous amount of pensions with a limited amount of income taxes (Rouzet et al., 2019; Willmore, 2004). Therefore, an often-suggested solution is to enlarge the working population by raising the retirement age (Breyer & Kifmann, 2002; Harkin, 2012; Kitao, 2014; Munnell & Sass, 2009; Rouzet et al., 2019; Staubli & Zweimüller, 2013).

However, this may be insufficient as this senior workforce must also remain employed – and, thus, be able to find a new job when they become unemployed – to effectively contribute to such financing systems. This seems to be problematic as many field experiments across multiple OECD countries have demonstrated that employers discriminate against senior job candidates in the earliest stages of the recruitment process (Baert et al., 2016; Carlsson & Eriksson, 2019; Challe et al., 2015; Drydakis et al., 2017; Farber et al., 2019; Riach, 2015). Lippens and colleagues' (2023b) summarising meta-analysis of all recent field experiments worldwide indicated that senior job candidates are, on average, 34% less likely to receive a positive response to a job application. This discrimination seems to be especially severe in Europe as these candidates were found to receive even half as many positive responses as their younger counterparts. Moreover, this meta-analysis revealed that age discrimination is globally at least as severe as ethnic discrimination, although it is far less mediatised and researched.

Therefore, it is necessary to tackle age discrimination through an effective and efficient anti-discrimination policy based on theoretical arguments supported by empirical evidence. Specifically, evidence about the context in which age discrimination increases (decreases) is needed to determine the contexts requiring more (less) policy attention. This entails understanding the heterogeneity of age discrimination by characteristics in different domains related to the demand side of the labour market (i.e. decision-maker, vacancy, occupation, organisation, and sector characteristics).

Although some of these characteristics have been addressed by prior research, a clear understanding of this heterogeneity is lacking as the current literature is highly fragmented. This drawback necessitates a profound review of these theoretical arguments and empirical results regarding age discrimination's moderating characteristics. Moreover, there is a need for additional research as the empirical literature suffers from three major limitations.

First, previous studies have been conducted on an ad hoc basis as the primary aim of most has been to detect or explain age discrimination, where a small number of moderating characteristics – often concentrated at one domain – have only been investigated in the margin (Carlsson & Eriksson, 2019; Gordon & Baxter, 1988; Posthuma & Campion, 2009; Richardson et al., 2013; Taylor & Walker, 1998). This fragmentation implies shortcomings in terms of content and methodology. Regarding the former, not all theoretically-relevant moderators have yet been empirically examined and insights into the relative importance of the investigated moderators are lacking. In terms of the latter, the discovered moderation effects might be biased as the included moderators may also have detected variation in unincluded moderators.

Second, the empirical literature offers little understanding of the characteristics that effectively drive the moderation of age discrimination. Many studies have only included specific vacancies, occupations, organisations, or sectors as potential moderators (Carlsson & Eriksson, 2019; Finkelstein & Burke, 1998; Gordon & Baxter, 1988; Richardson et al., 2013; Taylor & Walker, 1998). Consequently, the actual underlying moderating characteristics – which might also affect other unexamined vacancies, occupations, organisations or sectors – remain concealed. For example, it is unclear whether the significant effects that Carlsson and Eriksson (2019) found for all included occupations can be explained by underlying occupational characteristics, such as the required level of education or physical skills.

Third, the empirical research is dominated by surveys (Oude Mulders, 2020; Taylor & Walker, 1998) and vignette experiments (Finkelstein & Burke, 1998; Gordon & Baxter, 1988; Perry et al., 1996; Richardson et al., 2013). These research methods raise questions about participants' socially-desirable answers as well as the internal and ecological validity of the results. Moreover, the population validity of some studies is questionable due to rather low sample sizes and the type of participants. More concretely, certain researchers have selected overly broad populations by including students (Gordon & Baxter, 1988; Perry et al., 1996; Richardson et al., 2013), whereas others have only retained evaluations of top-level decision-makers, such as owners and managers (Finkelstein & Burke, 1998; Posthuma & Campion, 2009). However, in practice, other non-managing employees, such as HR assistants, are often responsible for resume screening (Oude Mulders, 2020; Taylor & Walker, 1998).

Our study aims to close these gaps by providing a more conclusive image of the moderating demand-side characteristics of age discrimination in the hiring process. Therefore, we began with an extensive in-depth literature review to identify all theoretically- and empirically-relevant moderating characteristics on the different demand-side domains (i.e. decision-maker, vacancy, occupation, organisation, and sector). We then conducted a large-scale correspondence experiment covering a diverse set of vacancies, occupations, organisations and sectors which vary in the relevant characteristics identified in our literature review. Next, we collected accurate administrative data regarding these characteristics by consulting multiple databases, both governmental (e.g. Eurostat) and private (e.g. Bel-first). Subsequently, all administrative datasets were structurally linked with the data of our correspondence experiment. Finally, the aggregated dataset is integrated into a mixed-effects multilevel model representing the relationships between the different data domains.

By doing this, our study offers five crucial contributions to the literature. First, based on our profound literature review, we provide a comprehensive overview of the existing theoretical arguments and empirical findings on the moderating characteristics of age discrimination at different domains. Second, compared to prior research, we integrate a broader set of these characteristics into one single model, which enables us to reduce confounding biases and estimate their relative importance. Third, we include numerous vacancies, occupations, organisations and sectors to reveal their underlying moderating characteristics. Fourth, we present an innovative methodological framework enabling the structured data linking of field experiments on (age) discrimination with multiple administrative sources on demand-side characteristics. Fifth and final, by conducting a field experiment, we increase the external and ecological validity as this allows us to reach the real persons responsible for resume screening and eliminates socially-desirable answers.

2 Literature review

Given the highly-fragmented state of the existing literature, we initiated our study with an extensive in-depth literature review to provide an overview of the theoretical arguments and empirical evidence on the moderating demand-side characteristics of age discrimination.

Therefore, we a priori established strategies to ensure that we could efficiently search for relevant studies and consistently assign them to the different demand-side domains (i.e. decision-maker, vacancy, occupation, organization, and sector). On the one hand, we applied a reasonably-broad search strategy as there were no restrictions in terms of publication date or journal. The only requirement was that the studies were published in a scientific journal listed in the Web of Science database. Regarding the keywords, we employed two sequential strategies. First, we searched for a general set of related keywords to determine the different moderating characteristics in this context. More concretely, we combined multiple synonyms for age discrimination (e.g. ageism and unequal treatment of seniors) and moderators (e.g. heterogeneity and contextual factors). Next, we replaced the latter with various synonyms for specific keywords associated with the identified characteristics in order to locate similar studies. For example, we searched for the following specific keywords: labour market tightness and age workforce. On the other hand, the assignment strategy was rather strict as we aimed to provide a clear and concise summary of the literature. More concretely, we allocated each characteristic only to the most specific domain when multiple were applicable. For instance, although the moderating effect of the contract type was investigated in terms of organisation and occupation by Oude Mulders (2020) and Hirsch and colleagues (2000) respectively, we assigned this to the vacancy domain, as per Ahmed and colleagues (2012).

As demonstrated in Table 1, our in-depth literature analysis resulted in a comprehensive set of theoretical arguments and empirical findings regarding moderating demand-side characteristics of age discrimination. Moreover, all of the theoretical arguments related (to some) extent to at least one of the following main economic discrimination theories: statistical-based discrimination (Arrow, 1973), taste-based discrimination (Becker, 1957), and the dual labour market (Bosanquet & Doeringer, 1937). First, the statistical-based discrimination theory argues that employers have insufficient information about the candidate's productivity and, therefore, rely on the available candidate information (e.g. age) as this signals productivity deficits (or qualities). In other words, statistical-based age discrimination is caused by negative productivity perceptions that employers infer from older ages. Second, the theory of taste-based discrimination suggests that employers have an aversion for certain candidates (e.g. senior workers) by which they seek to avoid interactions with them regardless of their productivity. Phrased differently, taste-based age discrimination results from a personal employer's distaste, or even from perceived employee or customer aversion to senior workers. Third, the dual labour market theory proposes that minority job candidates (e.g. seniors) are mainly represented in the secondary labour market segment, which is characterised by relatively worse conditions (e.g. low wages and temporary contracts) compared to the primary segment. This mechanism entails that age discrimination arises from labour market conditions funnelling seniors into the secondary segment.

< Table 1 about here >

In the following subsections, we discuss these theoretical arguments and the (lack of) empirical evidence of the identified characteristics for each domain separately. However, we only elaborate on the characteristics included in our empirical research (Section 3).

2.1 Decision-maker

In line with the theory of taste-based discrimination, female managers may discriminate less against senior candidates than male managers as the former experience more (age) discrimination themselves which makes them more aware of the negative effects of hiring preferences (Oude Mulders, 2020). Although some empirical studies have supported this theoretical argument (Oude Mulders, 2020; Rupp et al., 2005), most studies have found no differences in age discrimination depending on the decision-maker's gender (Baert et al., 2018; Bendick et al., 1997; Van Borm & Baert, 2020; Van Borm et al., 2021).

2.2 Vacancy

In line with the statistical-based discrimination theory, age discrimination should increase when the vacancy includes ageist stereotypes or the mention of on-the-job training. On the one hand, ageist stereotypes reflect the employer's negative perceptions about senior workers' capabilities and, thus, the likeliness to discriminate against them (Burn et al., 2020). This theoretical argument is supported by empirical evidence showing that statements related to negative (positive) ageist stereotypes predict more (less) age discrimination (Burn et al., 2020). On the other hand, prior research has revealed that employers tend to hold negative perceptions about senior employees' trainability, which might lead to more discrimination against these candidates when on-the-job training is required (Van Borm et al., 2020, 2021). Two empirical studies support this view (Hirsch et al., 2000; Turek & Henkens, 2019).

Following the theory of taste-based discrimination, age discrimination is expected to decrease when the vacancy mentions equal rights or higher experience requirements. First, including statements about candidates' equal rights during the hiring process suggests a lack of aversion towards minority candidates (e.g. seniors) and, subsequently, none (or at least less) discrimination (Drydakis et al., 2017). The empirical literature on this characteristic is mixed, as one study found supportive evidence (Drydakis et al., 2017), while another found no significant differences (Bendick et al., 1997). Second, age discrimination may be reduced when vacancies require higher experience levels. These functions often imply more authority, responsibility, and impact on the organisation's bottom line, by which employers cannot rely on their personal distaste (Ruffle & Shtudiner, 2015). Nevertheless, to the best of our knowledge, no empirical research has been conducted on these characteristics.

Applying the dual labour market theory, age discrimination is likely to increase when better contract-types are offered. This is because better labour market conditions, such as full-time and permanent contracts, refer to the primary segment, wherein minority candidates are often barred. However, the empirical results are inconclusive as one study reported less discrimination for part-time contracts (Hirsch et al., 2000), while two others were unable to detect differences depending on the contract-type (Ahmed et al., 2012; Oude Mulders, 2020).

2.3 Occupation

With respect to the statistical-based discrimination theory, age discrimination is supposed to increase (decrease) when employers hold negative (positive) perceptions about candidates' capabilities to meet the job requirements. On the one hand, prior research has revealed that employers hold negative perceptions about senior workers' creativity, flexibility, technological skills, and physical skills, meaning that age discrimination in more likely in occupations requiring such skills (Drydakis et al., 2017; Henkens, 2005; Turek & Henkens, 2019; Van Borm & Baert, 2020; Van Borm et al., 2021). The empirical literature covers supporting evidence regarding the required level of creativity (Turek & Henkens, 2019), technological skills (Hirsch et al., 2000; Turek & Henkens, 2019), and physical skills (Drydakis et al., 2017; Turek & Henkens, 2019; Van Borm & Baert, 2020). However, concerning physical skills, other studies have either revealed no significant effects (Hirsch et al., 2000; Van Borm et al., 2021) or an effect in the opposite direction (Lahey, 2008). Moreover, no empirical research has been conducted on the required flexibility. On the other hand, lower levels of age discrimination might appear in occupations including many administrative tasks as employers evaluate senior employees' administrative abilities more highly than those of younger employees (Turek & Henkens, 2019). Nevertheless, the only empirical research on this characteristic revealed no such differences (Turek & Henkens, 2019). In addition, age discrimination increases in occupations with a higher wage tension as the shorter employment horizon of senior candidates signals them to be less motivated by delayed compensation (Daniel & Heywood, 2007). The empirical literature supports this theoretical argument (Daniel & Heywood, 2007; Hirsch et al., 2000).

According to the taste-based discrimination theory, senior candidates should be penalised more severely when higher levels of employer, employee, and customer contact are required as employers discriminate to avoid interactions with candidates who are often disliked (Becker, 1957). However, the existing empirical literature, which only covers customer contact, was unable to detect differences regarding this characteristic (Bendick et al., 1997; Lahey, 2008; Van Borm & Baert, 2020; Van Borm et al., 2021). In contrast, age discrimination is reduced by labour market tightness and union density (for a specific occupation). The reduction by labour market tightness is explained by the fact that employers in such a context risk the vacancy remaining open for an extended period, which makes it more expensive to satisfy a taste for discrimination (Baert et al., 2015). However, no empirical studies were found in the context of age discrimination. The decline in age discrimination by union density can be explained by the will and power of unions to create equal rights that prevent employers from acting on their personal distaste (Harcourt et al., 2005). Supporting empirical evidence was found at the organisation level (Hirsch et al., 2000).

Following the dual labour market theory, we expect there to be less age discrimination when outdoor work is required or work hazards are common, as these are worse conditions that are representative of the secondary segment. Nevertheless, the empirical literature revealed no such differences concerning working hazards (Hirsch et al., 2020) and appears not to have covered outdoor work.

2.4 Organisation

Applying to statistical-based discrimination theory, age discrimination is likely to decrease in large organisations, when no employment agencies are involved, in less innovative organisations, and among more highly-educated workforces. The first argument can be explained by larger organisations' ability to learn of candidate's true candidate productivity more quickly and to complement the productivity of younger and older workers by which they have to rely less on ageist stereotypes (Baert et al., 2018; Ollier-Malaterre et al., 2013; Oude Mulders, 2020). The empirical evidence is rather mixed as some studies have appeared to support this theoretical expectation, while others have either found evidence in the opposite direction (Loretto & White, 2006) or no differences at all (Baert et al., 2018; Hirsch et al., 2000; Lahey, 2008). The second argument relates to employment agencies' lack of information about their clients' specific requirements by which they want to select candidates that make a good overall impression and do not signal any negative stereotypes (Bendick et al., 1997; Ruffle & Shtudiner, 2015). This is empirically supported by Bendick and colleagues (1997). The third argument relates to employers' negative perceptions about senior workers' adaptability and scepticism towards technological innovations, which lead to higher levels of age discrimination in innovative sectors (Henkens, 2005). Nevertheless, the limited empirical evidence points to a reverse effect, as age discrimination appears less severe in innovative sectors (Kunze et al., 2013). The fourth argument is clarified by the reduced interest in a correct estimation of the candidate's productivity, as highly-educated employees could share their knowledge with senior colleagues and, thus, enabling the latter to become more productive (Winters, 2018). Although a positive effect of a more highly-educated workforce was found on the overall employment rates (Winters, 2018), no empirical research has been conducted on the hiring probabilities of senior candidates specifically.

With respect to the taste-based discrimination theory, age discrimination is expected to decrease in non-profit, stock-listed, and multinational organisations as well as among a senior workforce. First, non-profit organisations are assumed to promote equality and, thus, to have no aversion for certain candidates (Baert et al., 2018). This was empirically supported by Baert and colleagues (2018) who found lower levels of age discrimination in non-profit organisations compared to commercial ones. Second, stock-listed organisations might be afraid to satisfy their taste for discrimination against senior candidates as this could result in corporate lawsuits causing declines in stock value (Ursel & Armstrong-Stassen, 2006). Nevertheless, no empirical research on this issue was found. Third, multinationals might rely less on their taste for discrimination as they can pinpoint and exploit social schisms in the host markets (e.g. the exclusion of senior workers) as a competitive advantage (Siegel et al., 2008). However, there is a lack of empirical research on this characteristic. Fourth, employees have a preference to work with those similar to them, which results in less age discrimination in organisations with an ageing workforce (Festinger, 1954; Lahey, 2008; Posthuma & Campion, 2009; Rupp et al., 2005). However, no empirical studies on this characteristic were found.

2.5 Sector

Finally, following the taste-based discrimination theory, discrimination should decrease in competitive sectors as it is more costly when employers satisfy their taste for discrimination in a competitive market (Becker, 1957). Nevertheless, to the best of our knowledge, no empirical research has been conducted on these characteristics.

3 Data

To address the discovered gaps in the literature (Section 1), we developed an innovative methodological framework to provide more validated empirical evidence for a broader set of theoretically-relevant demand-side characteristics. More concretely, we structurally linked data from a correspondence experiment on age discrimination (Subsection 3.1) to administrative data on characteristics in the different demand-side domains (Subsection 3.2).

3.1 Field experiment

In the first stage, we conducted a correspondence experiment as this is the golden standard for identifying hiring discrimination in practice (Baert, 2018; Bertrand & Mullainathan, 2004; Lippens et al., 2023b; Verhaeghe, 2022). More concretely, in such experiments, real-life hiring decisions of genuine persons responsible for resume screening can be observed, which increases the external validity compared to prior survey and vignette studies. Moreover, this research method allowed us to distinguish employer discrimination from supply-side determinants of labour market outcomes and to eliminate selection based on unobservable characteristics. This is because we controlled all candidate information, of which we only randomly varied a limited number of characteristics (Pager, 2007; Riach & Rich, 2002).

For this study, we sent fictitious candidate pairs to 712 current vacancies of genuine employers in the Flemish (Belgian) labour market between February 2020 and May 2021. The employers' subsequent reactions were monitored and classified as either negative (i.e. rejection or no reaction) or positive (i.e. invitation for a job interview or request for more information). Since both candidates only differed in age, we were able to interpret the relationship between the candidates' ages and the employers' reactions causally. In the following subsections, we elaborate on the vacancies and resumes employed in our experimental design, as visualised in Figure 1.

< Figure 1 about here >

3.1.1 Selection of vacancies

To collect real open vacancies, we consulted the database of the Public Employment Agency of Flanders as this is Flanders' major job search channel. However, we only searched for one vacancy of each organisation because of the following reasons: to avoid biases of overrepresentation, to limit the burden on employers, and to prevent the experiment from detection.

We selected vacancies for multiple occupations at different educational levels (i.e. upper secondary vocational education, upper secondary technical education and lower tertiary education) and in a diverse set of sectors (with a special focus on administrative and support services, wholesale and retail, industry, human health and social work activities, construction, and transport and storage) to capture sufficient variation in the demand-side characteristics. Nevertheless, to avoid gender biases, we only retained gender-neutral occupations, meaning that the number of male and female job seekers varied between 12.5% and 87.5%. This selection resulted in our retention of 75 occupations, of which the following five jumped out as we applied for more vacancies related to these occupations compared to all others: shop assistant (N = 78), construction site manager (N = 52), technical industrial manager (N = 50), administrative assistant (N = 49) and sales representative (N = 41).

3.1.2 Construction of resumes

In order to apply for the selected vacancies, representative and realistic-looking pairs of resumes and cover letters were needed. To avoid order effects and the detection of the experiment by employers, we created two templates (types A and B) for each candidate's resume and cover letter, which we sent in an alternating order to the selected vacancies on consecutive days.[1] These templates differed in layout, wording, and personal information that should be irrelevant for hiring decisions but increase the external validity (e.g. name and address). These differences were relatively small due to the comparable candidates' features (e.g. typical Flemish name and address in middle-class neighbourhoods around the organisation). Moreover, they could not bias the differences in hiring probability since the ages were randomly assigned to the templates.

The random assignment of candidates' ages within pairs was done by keeping the day and month of birth fixed on both templates and allocating one of four years of birth on each template. This approach allowed us to test pairwise combinations of candidates aged 38, 44, 50, and 56 years without combining the ages 38 and 56, such that there always was an age difference of 6 or 12 years between the younger and the older candidate in each pair. The youngest age used was 38 years, which ensured that unequal treatment based on maternity leave was

[1] The resume and cover letter templates are available (in Dutch) upon request.

minimised due to the low probability of a woman becoming pregnant after this age (Baert et al., 2016). Moreover, candidates aged 38 would likely have enough experience to compete with more senior candidates (Lahey, 2008; Neumark et al., 2019). The oldest age used was 56 years, which deviated sufficiently from the retirement age of 65 years in our experimental context (Van Borm et al., 2021). This strategy enabled us to distinguish age discrimination from unequal treatment based on the return on hiring investment. Furthermore, employers did not receive a wage subsidy for hiring candidates aged 56, which allowed us to disentangle age discrimination from unequal treatment based on profit maximisation.

As the senior candidates had more post-educational years on their resumes, we followed Baert and colleagues (2016) to tackle this problem. More concretely, we randomly assigned the senior candidates within each pair to one of the three following activities undertaken during their additional post-educational years: (i) relevant work experience for the vacancy, (ii) irrelevant work experience as a teacher for higher educated candidates or as a maintenance worker for lower educated candidates, and (iii) inactivity due to household and child care activities.

Finally, we added information about the education and work experience to templates that matched the general requirements of the selected occupations. For example, candidates for a vacancy concerning an administrative clerk had a bachelor’s degree in commerce, whereas candidates applying for a position as a production operator had a secondary degree in mechanics. All candidates graduated at the age of 18 or 21, depending on their type of education: secondary or higher. They started their professional career – in a similar occupation as the one applying for – immediately following their graduation. At the time of the experiment, they had also been employed in a similar job since 2011.

3.2 Administrative data

In the second stage, we enriched the data of our correspondence experiment with administrative data to detect possible changes in hiring probabilities due to characteristics in different demand-side domains: the decision-maker, the vacancy, the occupation, the organisation and the sector. In the following subsection, we discuss the consulted administrative databases and how this was structurally connected with the data of the correspondence experiment. In the second subsection, we explain how these administrative data were operationalised and evaluated in terms of their descriptive statistics by response category.

3.2.1 Data collection and connection

We consulted multiple public and private databases to collect administrative data on the characteristics identified in our literature review (Section 2) and presented in Table 1. Despite our study capturing many of these characteristics, it was impossible to collect data on all of them due to practical constraints. Moreover, although we initially assigned each characteristic to the most specific domain, for some characteristics, we were only able to obtain data on higher domains. This was the case for wage tension and union density (initially assigned to the occupation domain), as well as the age of the work force and the degree of innovation (initially assigned to the organisation domain), as only sector data was available. In addition, as we only obtained data on one of the decision-maker characteristics (i.e. their gender), we allocated this to the vacancy domain for ease of reading and analysis. This strategy is reasonable because each vacancy was linked to one specific decision-maker, as we only applied to one vacancy in each organisation involved. Ultimately, all of the collected datasets were structurally connected to the data of the correspondence experiment using an identifier for each domain. An overview of the consulted databases and the structural connection is presented in Figure 2 and discussed below.

< Figure 2 about here >

For the vacancy (and decision-maker) domain, we were able to collect data on seven theoretically-relevant characteristics: the gender of the decision-maker, the offer of a fulltime contract, the offer of a permanent contract, the presence of ageist stereotypes, the presence of equal opportunity statements, the provision of on-the-job training, and the required level of experience. All data on these characteristics were extracted using R-scripts that automatically searched for specific terms in the vacancies to which we applied in the correspondence experiment. An overview of the employed search terms can be found in Table A.1. A first search strategy, similar to that used by Ahmed and colleagues (2012), whereby synonyms, antonyms, and common translations of the characteristics were used as search words, was applied to five characteristics: fulltime contracts, permanent contracts, the presence of equal opportunity statements, on-the-job training, and required experience. A second search strategy, consisting of a list of search words based on the study of Burn and colleagues (2020), was employed to obtain data on the presence of ageist stereotypes. Data on the gender of the decision-maker were retrieved through a third search strategy inspired by Baert and colleagues (2018). We automatically extracted email addresses from the vacancies in order to manually check whether these included a typical male or female first name. In cases where the gender of the first name was not apparent (e.g. when abbreviations were used), we searched for the decision-maker's LinkedIn profile to determine their gender.

Regarding the occupation domain, data on eleven characteristics were found. More concretely, this concerned the labour market tightness, as well as the levels of ten required skills and tasks: creativity, flexibility, technological skills, administrative tasks, physical skills, employer contact, employee contact, customer contact, outdoor work, and work hazards. Most data were retrieved from the Occupational Information Network (National Center for O*NET Development, 2022a, 2022b, 2022c) by linking the Flemish job titles to their American equivalents, as per Van Borm and Baert (2020). In addition, the Public Employment Agency of Flanders (2021) offered a proxy on the labour market tightness for each occupation. These data could be directly linked to the occupations of the correspondence experiment as the same job titles were used.

In the organisation domain, we collected data related to the following six characteristics: organisation size, education of the workforce, stock market listing status, profit motive, multinational status, and employment agencies. Bel-first (2022), a database on Belgian and Luxembourgish organisations, provided all data about these characteristics based on the organisations' national identification numbers. Specifically, we used the number of full-time employees and the number of full-time employees with a higher educational degree as a proxy for the organisation size and the workforce's education, respectively. Moreover, we determined the profit motive based on the organisation's legal form (i.e. non-profit associations, private non-profit associations, and public non-profit associations were extracted as organisations with a non-profit motive) and identified employment agencies based on the NACE identifier (i.e. 78,100 employment arbitration, 78,200 employment agencies, and 78,300 other human resources provision).[2] Finally, as Bel-first does not offer direct data on the multinational status of organisations, we used 11 available variables to construct an indicator for this characteristic.[3]

With respect to the sector domain, we retrieved data on five theoretically-relevant characteristics: age of the workforce, innovation intensity, product market competition, union density and wage tension as a function of seniority. These data were found in five different databases based on the first two numbers of the NACE identifier, retrieved earlier via Bel-first. First, the Centre of Expertise for Labour Market Monitoring (2020) provided data on the age of the workforce, namely the number of employees over the age of 50. Second, the number of innovative organisations published by the statistics office of the Belgian Federal Government (Eurostat, 2018) demonstrated the innovation intensity. Third, the Federal Public Service Economics (Prijzenobservatorium, 2021) provided data on the product market competition via the Herfindahl-Hirschman Index (HHI). This index refers to the sum of squares of all market shares, meaning that a high HHI represents a high market concentration and, thus, a low market competition (Berson, 2012). Fourth, union density data were obtained from the European Social Survey (2018) via the number of current trade union members. Fifth and final, the Belgian wage tension as a function of seniority was found via The Central Council for Business (Centrale Raad voor het Bedrijfsleven, 2020) based on each organisation's joint committee, retrieved earlier via Bel-first.

[2] NACE is the abbreviation of Nomenclature statistique des Activités économiques dans la Communauté Européenne.

[3] More concretely, the countries of the: organisations, foreign organisations, subsidiaries, global ultimate owner, global domestic owner, shareholders, controlling shareholders, immediate shareholders, branches, head offices, and direct management. If one of these variables contained a foreign country (i.e. not Belgium), we marked this as an indication of a multinational status.

3.2.2 Data operationalisation

Where possible, we operationalised these collected data as continuous variables to capture a more nuanced perspective. However, due to the scraping strategies, all vacancy characteristics were operationalised as categorical variables, of which most were binary (Table A.1). More concretely, the variables on full-time contracts, permanent contracts, presence of equal opportunity statements, ageist stereotypes, and on-the-job training equalled 1 if the vacancy contained terms related to those variables and 0 otherwise. For the required experience, we created four categories: unimportant or unspecified, none, less than two years, and at least two years. Finally, three categories were assigned to the gender of the decision-maker: male, female, and unknown (i.e. when no first names were mentioned in the email addresses).

Almost all occupation characteristics were operationalized as continuous variables in the analyses. Specifically, variables retrieved from the Occupational Information Network ranged from 0 (not required) to 1 (highly required). This was the case for the required level of: creativity, independency, computer skills, physical skills (which is a proxy for blue-collar jobs), administrative activities (which is a proxy for white-collar jobs), contact with people inside the organisation, contact with people outside the organisation, flexibility, outdoor work, and hazards. Only the labour market tightness was operationalised as a categorical variable, equalling 1 if the occupation was marked as a bottleneck job and 0 otherwise.

In addition, two of the six organisation characteristics were operationalized as continuous variables. On the one hand, as the number of full-time employees was expected to be skewed to the right, we took the natural logarithm into account, ranging from 0.000 to 10.123, as an indication of the organisation size (Baert et al., 2018; Ting, 2021). On the other hand, the fraction of full-time employees with a higher educational degree was computed by dividing the number of full-time employees with such a qualification by the total number of full-time employees. This fraction was used as a proxy for the education of the workforce and varied between 0.000 and 1.000. The remaining four organisation characteristics were operationalised as categorical variables with only two categories. Specifically, the variables on non-profit motive, multinational status, and employment agencies equalled 1 if an indication in that direction was found and 0 otherwise. Only the stock market listing status comprised four categories, namely: unlisted, delisted, listed and unknown.

Furthermore, all sector characteristics were operationalised as continuous variables. First, as an indication of the age of the workforce, we calculated the fraction of employees above the age of 50 in each sector by dividing the number of such employees by the total number of employees. This fraction ranged from 0.153 to 0.428 (i.e. almost half of the employees were found to be older than 50). Second, the fraction of innovative organisations were computed by dividing the number of innovative organisations by the total number of organisations in each sector to obtain a proxy for the innovation intensity. This fraction covered a range from 0.458 to 1.000 (i.e. all organisations in the sector were innovative). Third, an indication of the product market competition was calculated by taking the opposite of the Herfindahl-Hirschman Index (HHI). This opposite index ranged from 0.016 (i.e. low competition) to 1.000 (i.e. high competition). Fourth, in order to obtain a proxy for union density, the fraction of employees affiliated with a trade union was calculated by dividing the total number of current trade union members by the total number of participants in the survey. This fraction ranged from 0.091 to 0.583 (i.e. more than half of the employees had trade union affiliations). Fifth, the wage tension as a function of seniority of each joint committee was implemented by the average wage tension of the joint committees for blue- and white- collar workers. This variable covered a range from 100 (i.e. no wage tension) to 170 (i.e. high wage tension).

Finally, it must be noted that multiple databases and vacancies contained missing values. In the case of continuous variables, we imputed the missing values with the mean value of the corresponding variable. Missing values of categorical variables were either allocated to a separate category (e.g. 'unknown' when the gender of the decision-maker was missing) or to the highest possible category, as this was the most logical outcome when no specific information was given (e.g. 'fulltime contract' when the type of contract was missing).

4 Results

In this section, we present the results from our statistical examination of the merged dataset to reveal which of the theoretically-relevant demand-side characteristics effectively moderate age discrimination in practice. However, first, we set the scene by investigating whether age discrimination occurred in our correspondence experiment. Otherwise, the evaluation of possible moderating characteristics would make no sense.

4.1 Age discrimination

4.1.1 Estimation

To identify age discrimination, we considered the differences in the probability of receiving a positive response between younger and older candidates. As such, we calculated positive response rates for both groups of candidates separately, from which we subsequently derived discrimination ratios and net discrimination rates across different supply-side characteristics (Subsection 3.1) and demand-side characteristics (Subsection 3.2) .

The discrimination ratio (Equation 1) is equal to the positive response rate for the older candidate $(t + b)/ n_{old}$ divided by the positive response rate for the younger candidate $(c + b)/ n_{young}$. Here, t is the number of positive responses for older candidates only, c is the number of positive responses for younger candidates only, b is the number of vacancies for which both candidates received a positive response, n_{old} is the number of older candidates and n_{young} is the number of younger candidates.

In addition, the net discrimination rate (Equation 2) is the difference between the number of positive responses for older candidates only and the number of positive responses for younger candidates only (c – t), divided by the total number of positive responses across both groups (c + t + b).

Finally, the significance of the differential treatment was computed using the standard specification of McNemar's test.

$$DR = \frac{(t+b)/_{n_{old}}}{(c+b)/_{n_{young}}} \tag{1}$$

$$NDR = \frac{c-t}{(c+t+b)} \tag{2}$$

4.1.2 Discrimination ratios

The results presented in Table A.2 confirm that senior candidates experience discrimination during the hiring process.[4] On average, they receive 16.97% fewer positive responses than comparable younger candidates (*DR* = 83.03%, *NDR* = 14.11%, p < 0.001). However, the results by specific age indicate that the oldest candidates are particularly penalised. Specifically, candidates aged 56 receive 27.74% fewer positive responses (*DR* = 72.26%, *NDR* = 22.76%, p = 0.001) than their younger counterparts, while no significant differences were found for other ages. This aligns with prior research by Carlsson and Eriksson (2019), demonstrating that the likelihood of a positive response progressively decreases the closer a candidate gets to retirement age.

Given the post-educational years problem (Subsection 3.1), we also report the treatment effect by the difference in post-educational years and the activity undertaken during these years. Concerning the former, we identified age discrimination for candidates who differed by 12 years (*DR* = 75.70%, *NDR* = 20.63%, p = 0.001) as well as for those who only differ by 6 years, albeit to a lesser extent (*DR* = 87.79%, *NDR* = 10.00%, p = 0.037). Regarding the latter, we uncovered age discrimination for candidates who filled their additional post-educational years with relevant experience (*DR* = 80.86%, *NDR* = 16.36%, p = 0.011), inactivity (*DR* = 83.73%, *NDR* = 13.46%, p = 0.048), and in all probably – given the marginal evidence – irrelevant experience as well (*DR* = 84.61%, *NDR* = 12.50%, p = 0.061). This finding contrasts with those of Baert and colleagues (2016), indicating that age discrimination is mainly driven by irrelevant experience.

[4] The absolute numbers of the positive responses for younger and older candidates across the employer characteristics are available upon request.

Furthermore, we also observed age discrimination for other supply- and demand-side characteristics. Nevertheless, our aim was not to investigate age discrimination across different demand-side characteristics, but rather whether certain of these characteristics correlate with the level age discrimination.

4.2 Moderating demand-side characteristics

4.2.1 Estimation

Therefore, we conducted a moderation analysis for each domain of demand-side characteristics separately as well as one in which all of the domains were integrated together.[5] Given the correlation between the assignment of the fictitious candidates to a pair and their treatment, we clustered the standard errors at the vacancy domain in all further analyses (Abadie et al., 2017; Vuolo et al., 2018).

Regarding the separate analyses for each domain, we employed two random intercept models with the probability of receiving a positive reaction as the dependent variable. The first set of models included only one predictor, namely the candidate's age, which was classified as 'younger' or 'older' given the candidate pairs. The second set of models also contained the interaction terms of the candidate's age with the different demand-side characteristics on that specific domain in addition to their main terms. We only added random slopes to the second set of models on occupation and sector domains as it seemed illogical to model slopes for 712 different vacancies and organisations. Moreover, we already considered the clustering of the candidate pairs within vacancies and organisations by specifying a random intercept, as we only applied to one vacancy in each organisation.

Next, we established a mixed-effects multilevel model as this appears to be highly appropriate given the rather complex nested structure of the demand-side characteristics (Bliese et al., 2018; Giovannetti & Velucchi, 2022; Lester et al., 2021). For example, decision-makers working for organisations within the same sector have more in common – and are thus more related to each other – than decision-makers working for organisations within different sectors. The nested structure of our characteristics is visualised in Figure 3. This figure shows that the candidates were cross-classified in vacancies, occupations, and organisations as their resumes were sent to various vacancies for different jobs across organisations. In contrast, vacancies and organisations were strictly nested in sectors as we allocated one specific sector to each organisation's vacancy. Finally, occupations had multiple memberships regarding sectors because some occupations (e.g. administrative assistant) were present in different sectors.

[5] It must be noted that we excluded two variables from the analyses as over 95% of their observations were allocated to one category. This was the case for the equal opportunity statements in the vacancy domain and the stock market listing status in the organisation domain.

< Figure 3 about here >

Our generalised linear mixed-effects multilevel model consisted of fixed- and random-effects terms to estimate the odds of a positive response (Equation 3). The fixed part (Equation 4) entailed the main variables of interest as well as their interaction terms with the candidate's age alongside their coefficients. The random part (Equation 5) consisted of the random intercepts for each domain (i.e. candidate, vacancy, job, organisation, and sector) and the random slopes for characteristics in the occupation and sector domain. In these equations, the intercept on the candidate domain is represented by α, while β_n represents the vector of the model coefficients where n is the number of variable groups and their vectors of interactions with age. The vectors of the variables (i.e. main effects) are depicted by AGE, VAC, OCC, ORG and SEC for the candidate, vacancy, occupation, organisation, and sector domain respectively. More concretely, we included the candidate's age, six vacancy characteristics, ten occupation characteristics, five organisation characteristics, and five sector characteristics as discussed in Section 3.3. Similarly, $AGE * VAC, AGE * OCC, AGE * ORG,$ and $AGE * SEC$ refer to the vectors of the interaction terms with these variables (i.e. moderations effects). Finally, the error terms $t, u, v,$ and w relate to the candidate, vacancy, occupation, and sector domain, respectively, with v_1 and w_1 as vectors for the error terms in the occupation and sector domains. No specific error terms for the organisation domain were integrated since these occur at the same tier as the vacancy domain's error terms, making both interchangeable.

$$logit(P(Y = 1) = F + R \tag{3}$$

$$F = \alpha + (AGE * \beta_1) + (VAC * \beta_2) + (OCC * \beta_3) + (ORG * \beta_4) + (SEC * \beta_5) + (AGE * VAC * \beta_6) + (AGE * OCC * \beta_7) + (AGE * ORG * \beta_8) + (AGE * SEC * \beta_9) \tag{4}$$

$$R = t + u_0 + v_0 + OCC * v_1 + w_0 + SEC * w_1 \tag{5}$$

We conclude this section with a brief discussion of the statistical power of our different models to evaluate the sufficiency of our sample size of 712 fictitious candidates in the minority or majority group. Regarding our mixed-effects multilevel model, this sample size allowed us to detect minimal effects of 0.10 with a statistical power (1-β) of 0.85 and a statistical significance level (α) of 0.05. For the domain-specific models, we could detect even smaller effects with this sample size. On the one hand, in the vacancy and organisation models, minimal effects of 0.03 could be identified with a power of 0.80 and 0.90 respectively. On the other hand, minimal effects of 0.05 could be observed with a power of 0.70 in the occupation model and 0.75 in the sector model. The detailed results can be found in Table A.3.

4.2.2 Moderation effects

Surprisingly, the results of the nine models in Table 2 indicate that demand-side characteristics do not moderate age discrimination. However, we found weak evidence for the moderating effect of female decision-makers when only vacancy characteristics were taken into account (p = 0.066) as well as for vacancies requiring less than two years' experience both in the separate vacancy model (p = 0.088) and in the full model (p = 0.0919).

Nevertheless, as the decision-maker's gender and the required experience consisted of more than two categories, we employed Holm's correction for multiple hypotheses testing (Holm, 1979). This analysis revealed that the marginal evidence is not robust as the significance of the interaction with female decision-makers (p = 0.132) and less than two years' required experience (p = 0.263 and p = 0.276 for the vacancy and full model, respectively) disappear entirely.

< Table 2 about here >

Furthermore, we checked the robustness of the aforementioned models' null results by comparing them with those of two alternative models to ensure that they were not driven by our model specification. On the one hand, we adapted our models using categorical variables instead of continuous ones to capture a more generalised perspective in which moderators might be easier to detect. To do so, we labelled the variable's scores as 'high' ('low') when the value was in the top (bottom) half of the variable's distribution. As demonstrated in Table A.4, similar marginal evidence was found and was even extended to the required level of creativity according to the occupation, albeit only in the full model. Nevertheless, in line with the results for Holm's correction, we expect that these results were driven by coincidence. On the other hand, we modified our models by only including candidate pairs in which candidates differed by 12 years, thus, eliminating candidate pairs with a difference of only 6 years. This was done as larger age differences may result in more outspoken effects. However, the results presented in Table A.5 further support our evidence for null results, as no significant moderating effects were found.

5 Conclusion

This study has investigated the context in which age discrimination is most severe as such insights are required to establish an efficient anti-discrimination policy targeted at the right employers. More concretely, we examined the heterogeneity in age discrimination in different demand-side domains (i.e. decision maker, vacancy, occupation, organisation, and sector) through an innovative methodological framework. First, we established a correspondence experiment in which resumes of fictitious candidate pairs differing in age were sent to 712 genuine vacancies in the Flemish (Belgian) labour market. Subsequently, we consulted multiple public and private administrative databases to collect accurate data on the theoretically-relevant characteristics determined in our in-depth literature review. Finally, all datasets were structurally connected and integrated into one mixed-effects multilevel model to find empirical evidence regarding these theoretically-relevant characteristics.

In doing so, we addressed two crucial deficiencies of the existing empirical research. First, compared to prior surveys and vignette experiments, our field experiment allowed us to eliminate tendencies towards socially-desirable answering and increased the external validity. This is because we reached the genuine decision-maker who makes the real-life hiring decision for the vacancy we applied to. Second, earlier research has been merely conducted ad hoc and has failed to capture all relevant characteristics. By selecting our characteristics a priori, we captured a remarkably broader set of characteristics in various demand-side domains (i.e. decision-maker, vacancy, occupation, organisation, and sector). This strategy enabled us to eliminate some alternative interpretations of our results and provide a more conclusive image of the theoretically-relevant moderating demand-side characteristics of age discrimination.

Despite the theoretical underpinnings, our mixed-effects multilevel model indicated that none of the investigated demand-side characteristics moderated the age discrimination we observed in our field experiment in the Flemish labour market. This demonstrates the importance of an a priori selection of all theoretically-relevant moderating characteristics in different domains and their integration into one model. For example, the fewer (more) characteristics and domains a study considers, the more (fewer) significant differences it finds. The study by Hirsch and colleagues (2000) is an exception to this, as they examined 12 characteristics in four domains and found significant differences for nine. However, this study relied on a descriptive analysis of administrative data, which was insufficient for identifying them as moderators of age discrimination.

In addition to their academic relevance, our results have important policy implications. Indeed, as we found no empirical evidence for the demand side's context in which age discrimination is less or more prevalent, we can conclude that similar mechanisms across different vacancies, occupations, organisations and sectors drive discrimination. This finding aligns with prior research by Van Borm and colleagues (2021), who argued that age discrimination can be individually explained by the stereotypes employers hold about senior workers and, thus, not as much by the context. Specifically, they found that employers discriminate against senior candidates due to their perception of them as less flexible, trainable, and technologically skilled. Hence, the efficiency of anti-discrimination policies cannot be heightened by targeting specific contexts on the demand side. Instead, they should take context-overarching actions and focus on the specific mechanisms driving age discrimination.

We conclude our article by acknowledging two of our study's limitations and providing suggestions for future research. First, our results are bounded by the investigated discrimination ground and labour market and, thus, only apply to hiring discrimination against senior candidates in the Flemish labour market. Therefore, we recommend that other researchers employ our framework in institutional settings as this would enable the international validation of our results or, perhaps, the detection of location-dependent moderators. Moreover, our methodological framework could also examine hiring discrimination against other minority groups. For example, we have already used a similar framework to observe moderating characteristics of ethnic discrimination (Lippens et al., 2023a). Ultimately, such studies would facilitate cross-country or cross-ground analyses regarding hiring discrimination. Second, our experimental set-up only allowed us to examine one characteristic related to the decision-maker, namely gender. However, our extensive literature review revealed multiple theoretically-relevant decision-maker characteristics, such as age and experience with hiring decisions. Nevertheless, further research can obtain these characteristics by sending a follow-up survey to the decision-makers who participated in the correspondence experiment. Finally, to examine specific relations more closely, we would also stimulate simplified vignette experiments in which a limited selection of theoretically-relevant characteristics vary experimentally.

6 Declarations

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Conflict of interest The authors have no relevant financial or non-financial competing interests to disclose.

Ethical approval Ethical approval for this experiment was obtained from the ethics committees of the Faculty of Social Sciences at Vrije Universiteit Brussel and the Faculty of Economics and Business Administration at Ghent University.

Data availability A minimal set of anonymised data will be made available upon request by the corresponding author with the aim of replicating the study's findings.

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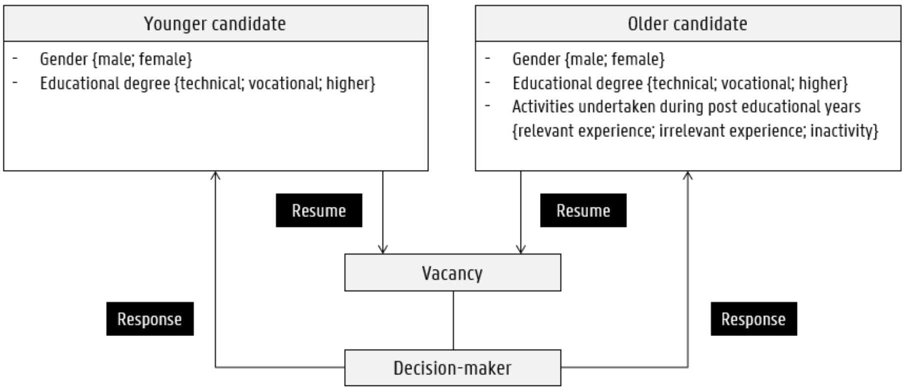
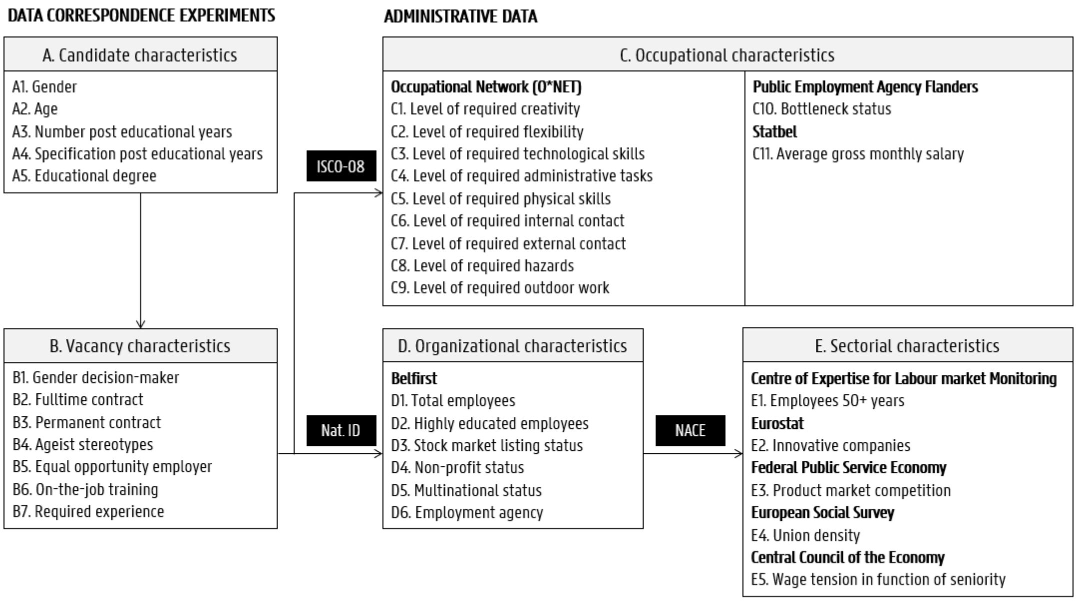
Figures

Figure 1. Correspondence experiment design



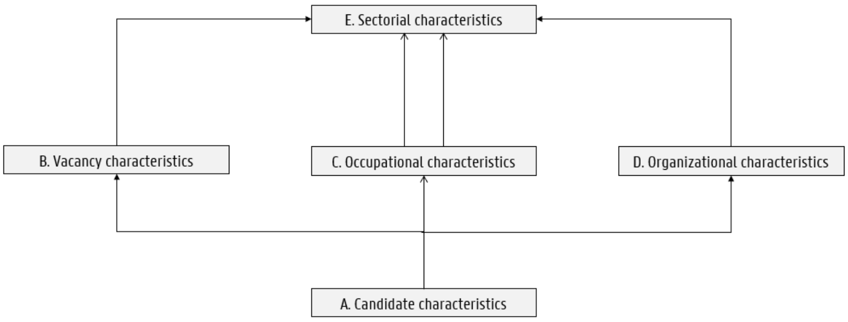
Notes. An identical set of candidate characteristics (i.e. gender, educational level, and work experience) was ascribed within each candidate pair and, thus, only varied between pairs. In contrast, other candidate characteristics (i.e. the name, age, and activities undertaken during the post-educational years) varied within each candidate pair. Both resumes were sent out to the same vacancy.

Figure 2. Data sourcing framework



Notes. Acronyms and abbreviations used: ISCO-08 (International Standard Classification of Occupations 2008); Nat. ID (national identification number); and NACE (*Nomenclature statistique des Activités économiques dans la Communauté Européenne*).

Figure 3. Mixed-effects multilevel model



Notes. Candidates are cross-classified in vacancies, occupations and organisations as their resumes were sent to various job vacancies across organisations. Vacancies and organisations are strictly nested in sectors, as one specific sector is allocated to each organisation. Occupations have multiple memberships by sector as some occur in different sectors.

Tables

Table 1. Theoretical arguments and empirical findings for moderating characteristics of age discrimination

Moderators	Theoretical arguments	Empirical findings
A. Decision-maker		
Gender	Age discrimination is lower among female than male decision-makers as the former experience more ageism, making them more aware of the adverse effects of hiring preferences (Oude Mulders, 2020).	No differences regarding age discrimination were found between female and male decision-makers (Baert et al., 2018; Bendick et al., 1997; Van Borm & Baert, 2020; Van Borm et al., 2021). More age discrimination among male decision-makers than their female counterparts (Oude Mulders, 2020; Rupp et al., 2005).
Age	In line with the social comparison theory, age discrimination is lower among older decision-makers through an in-group bias, while this is higher among younger decision-makers due to an out-group bias (Festinger, 1954; Lahey, 2008; Posthuma & Campion, 2009; Rupp et al., 2005). In addition, age discrimination is higher among younger than older decision-makers as the former experience ambition conflicts and the fear of acting old when surrounded by senior workers (Henkens, 2005).	No differences regarding age discrimination were found between younger and older decision-makers (Oude Mulders, 2020; Van Borm & Baert, 2020; Van Borm et al., 2021). More age discrimination among younger than older decision-makers (Rupp et al., 2005).
Experience	Considering the theory of statistical-based discrimination, age discrimination is higher among more experienced human resource professionals than among less or inexperienced decision-makers, as the former learned from past hires (Lahey, 2008). Based on the taste-based discrimination theory, age discrimination is lower among more experienced human resource professionals than among less or inexperienced decision-makers, as the former are better trained and more knowledgeable of discrimination laws (Lahey, 2008).	No differences regarding age discrimination were found between decision-makers who make hiring decisions less and more than once per semester (Van Borm & Baert, 2020; Van Borm et al., 2021). No differences regarding age discrimination were found between decision-makers with less than, and over 5 years of experience (Van Borm & Baert, 2020; Van Borm et al., 2021). No differences regarding age discrimination were found between students and professional decision-makers (Richardson et al., 2013).
Contact with senior workers	As stated by the contact theory, age discrimination is lower among decision-makers having more contact with senior workers than those with less contact because contact reduces negative stereotypes as more information is available to make qualified perceptions (Henkens, 2005).	Less age discrimination among decision-makers with positive than negative experiences with senior workers (Loretto & White, 2006).
Retirement age norm	In accordance with the statistical-based discrimination theory, age discrimination is higher among decision-makers holding a lower retirement age norm than those of a higher norm, as a lower norm reflects a more negative view of senior workers (Henkens, 2005; Radl, 2012).	No differences regarding age discrimination were found between decision-makers with a high and low retirement age norm (Oude Mulders, 2020).

B. Vacancy		
Full-time contract	Consistent with the dual labour market theory, age discrimination is lower for part-time than full-time contracts, as the former relate to the worse working conditions in the secondary segment where mainly minority candidates are employed (Bosanquet & Doeringer, 1937).	No differences regarding age discrimination were found between full-time and part-time contracts (Ahmed et al., 2012). No differences regarding age discrimination were found between organisations with high and low percentages of part-time contracts (Oude Mulders, 2020). Less age discrimination in part-time than in full-time occupations (Hirsch et al., 2000).
Permanent contract	According to the dual labour market theory, age discrimination is lower for temporary than permanent contracts, as the former relate to the worse working conditions in the secondary segment where minority candidates are predominantly employed (Bosanquet & Doeringer, 1937).	No differences regarding age discrimination were found between permanent and temporary contracts (Ahmed et al., 2012). Less age discrimination in organisations with many flexible contracts than in those with less flexible contracts (Oude Mulders, 2020).
Ageist stereotypes	In line with the statistical-based discrimination theory, age discrimination is higher when negative ageist stereotypes are present in the vacancy than when absent, as they signal the employer's negative perceptions about senior workers' capabilities (Burn et al., 2020).	More age discrimination when negative ageist stereotypes are incorporated than when positive ageist stereotypes are included (Burn et al., 2020).
Equal opportunity statements	Considering the theory of taste-based discrimination, age discrimination is lower when written commitments to equal opportunities are present in the vacancy than when they are absent, as they signal an inclusive environment which reduces biases against senior workers and facilitates opportunities for them (Drydakis et al., 2017).	No differences regarding age discrimination were found between vacancies with and without equal opportunity statements (Bendick et al., 1997). Less discrimination when equal opportunity statements are incorporated than when these are absent (Drydakis et al., 2017).
On-the-job training	Based on the statistical-based discrimination theory, age discrimination is higher when on-the-job training is required than when it is not because decision-makers perceive senior workers as less trainable and, thus, less suitable (Van Borm & Baert, 2020; Van Borm et al., 2021).	More age discrimination when high levels of on-the-job training are required than when lower levels are required (Hirsch et al., 2000; Turek & Henkens, 2019).
Required experience	In accordance with the taste-based discrimination theory, age discrimination is lower in occupations requiring more experience than less as the former jobs have more impact on the organisation's bottom line by which decision-makers cannot afford to discriminate based on irrelevant factors (Ruffle & Shtudiner, 2015). Furthermore, age discrimination is lower in occupations requiring more experience than less, as experience is an age-related factor (Swift, 2006).	N/A
Country	Consistent with the theory of statistical-based discrimination, age discrimination is higher in countries with a strict legalisation of pensions and retirement (e.g. European countries) than in countries with a more lenient legalisation (e.g. the United States), as the former indicates that working at an older age is inappropriate (Lahey, 2010).	No differences regarding age discrimination were found between decision-makers from the US and those from another OECD country (Van Borm et al., 2021).

		More age discrimination in Europe than in the United States (Lippens et al., 2023).
Metropolitan area	According to the taste-based discrimination theory, age discrimination is higher in urban than rural areas due to the outflow of youth from the latter to the former, resulting in competitiveness and discrimination against seniors (Stypinska & Turek, 2017). In line with the theory of taste-based discrimination, age discrimination might be lower in rural than in urban areas as the agricultural sector is located in rural areas and has a higher share of senior workers (Stypinska & Turek, 2017).	No differences regarding age discrimination were found between vacancies in or outside metropolitan areas (Ahmed et al., 2012). More age discrimination in urban than in rural areas (Johnson & Neumark, 1997; McGuire et al., 2008). More age discrimination in non-metropolitan areas than in urban areas (Shen & Kleiner, 2001).
C. Occupation		
Bottleneck status	Considering the taste-based discrimination theory, age discrimination is lower in occupations which are difficult to fill than those that are easy, as in the former case, rejecting a minority candidate is extra costly as the occupation then risks remaining vacant (Baert et al., 2015).	N/A
Required level of creativity	Based on the statistical-based discrimination theory, age discrimination is higher in occupations requiring higher than lower levels of creativity because decision-makers perceive senior workers as less creative (Turek & Henkens, 2019).	More age discrimination in occupations requiring high levels of creative skills than in those requiring lower levels of creativity (Turek & Henkens, 2019).
Required level of flexibility	In accordance with the statistical-based discrimination theory, age discrimination is higher in occupations requiring higher than lower levels of flexibility because decision-makers perceive senior workers as less flexible (Van Borm & Baert, 2020; Van Borm et al., 2021).	N/A
Required level of technological skills	Consistent with the theory of statistical-based discrimination, age discrimination is higher in occupations requiring higher than lower levels of technological skills because decision-makers perceive senior workers as less technologically skilled (Van Borm & Baert, 2020; Van Borm et al., 2021). According to the statistical-based discrimination theory, age discrimination is higher in occupations requiring higher than lower levels of computer skills because decision-makers perceive senior workers as less computer literate (Turek & Henkens, 2019).	More age discrimination in occupations requiring high levels of computer skills than in those requiring lower levels of computer skills (Hirsch et al., 2000; Turek & Henkens, 2019).
Required level of administrative tasks	In line with the statistical-based discrimination theory, age discrimination is lower in occupations requiring higher than lower levels of office work because decision-makers perceive senior workers' office work more positively (Turek & Henkens, 2019).	No differences regarding age discrimination were found between occupations requiring low or high levels of office work (Turek & Henkens, 2019).
Required level of physical skills	Considering the statistical-based discrimination theory, age discrimination is higher in occupations requiring higher than lower levels of physical skills because decision-makers perceive senior workers as less physically skilled (Drydakis et al., 2017; Henkens, 2005; Turek & Henkens, 2019; Van Borm & Baert, 2020).	No significant differences between occupations requiring low or high levels of physical skills (Hirsch et al., 2000; Van Borm et al., 2021).

		More age discrimination in occupations requiring high levels of physical skills than in those requiring lower levels of physical skills (Drydakis et al., 2017; Turek & Henkens, 2019; Van Borm & Baert, 2020). Less age discrimination in blue-collar (physically demanding) occupations than in white-collar occupations (Lahey, 2008).
Level of employer contact	Based on the theory of employer taste-basted discrimination, age discrimination is higher in occupations requiring higher than lower levels of intensive employer contact (Becker, 1957).	N/A
Level of employee contact	In accordance with the employee taste-basted discrimination theory, age discrimination is higher in occupations requiring higher than lower levels of intensive employee contact (Becker, 1957).	N/A
Level of customer contact	As stated by the customer taste-basted discrimination theory, age discrimination is higher in occupations requiring higher than lower levels of intensive customer contact (Becker, 1957).	No differences regarding age discrimination were found between occupations requiring low or high levels of customer contact (Bendick et al., 1997; Van Borm & Baert, 2020; Van Borm et al., 2021).
Outdoor work	Based on the dual labour market theory, age discrimination is lower in occupations involving more than less outdoor work, as the former relate to the worse working conditions in the secondary segment wherein minority candidates are predominantly employed (Bosanquet & Doeringer, 1937).	N/A
Work hazards	Consistent with the dual labour market theory, age discrimination is lower in occupations involving more than fewer work hazards as the former relate to the worse working conditions in the secondary segment wherein minority candidates are mainly employed (Bosanquet & Doeringer, 1937).	No differences regarding age discrimination were found in the number of occupational hazards (Hirsch et al., 2000).
Wage tension as a function of seniority	Considering the statistical-based discrimination theory, age discrimination is higher in organisations with than without delayed compensations because the shorter employment horizon of senior candidates means they are less well motivated by delayed compensation (Daniel & Heywood, 2007). Moreover, age discrimination increases by the occupational wage tilt when senior workers are paid seniority wages in excess of marginal products (Hirsch et al., 2000).	More age discrimination in occupations and organisations with steep wage profiles than in those with flatter wage profiles (Daniel & Heywood, 2007; Hirsch et al., 2000).
Union density	In line with the taste-based discrimination theory, age discrimination is lower in unionised than in non-unionised organisations because unions have the desire and power to reduce hiring discrimination (Harcourt et al., 2005). Moreover, age discrimination is higher in unionised than non-unionised occupations because unionization is associated with a flatter wage profile and a greater frequency of pension and health insurance coverage (Hirsch et al., 2000).	More age discrimination in highly unionised occupations than in less unionized occupations (Hirsch et al., 2000).
Required level of social skills	According to the theory of statistical-based discrimination, age discrimination is higher in occupations requiring higher than lower levels of social skills because decision-makers perceive senior workers as less	More age discrimination in occupations requiring high levels of social skills than in those requiring lower levels of social skills (Turek & Henkens, 2019).

	socially skilled (Van Borm & Baert, 2020; Van Borm et al., 2021).	
Required level of managerial skills	In line with the statistical-based discrimination theory, age discrimination is lower in occupations requiring higher than lower levels of managerial skills because decision-makers perceive senior workers' managerial skills more positively (Turek & Henkens, 2019).	Less age discrimination in occupations requiring high levels of managerial skills than in those requiring lower levels of managerial skills (Turek & Henkens, 2019).
Environmental non-weather occupation risks	Considering the dual labour market theory, age discrimination is lower in occupations involving more than less non-weather occupation risks, as the former relate to the worse working conditions in the secondary segment wherein minority candidates are more often employed (Bosanquet & Doeringer, 1937).	More age discrimination when extreme environmental non-weather occupation risks are involved than when these risks are absent (Hirsch et al., 2000).
Weekly working hours	Based on the dual labour market theory, age discrimination is lower in occupations with much fewer weekly working hours, as the former relate to the worse working conditions in the secondary segment in which minority candidates are mainly employed (Bosanquet & Doeringer, 1937).	More age discrimination in occupations with a high proportion of employees working over 42 hours a week than in occupations with a lower proportion of employees working long hours (Hirsch et al., 2000).
Flexibility in working hours	In accordance with the dual labour market theory, age discrimination is lower in occupations requiring more than less flexibility in working hours, as the former relate to the worse working conditions in the secondary segment wherein minority candidates are mostly employed (Bosanquet & Doeringer, 1937).	Less age discrimination in occupations with flexitime than in occupations without (Hirsch et al., 2000).
Work shifts	As stated by the theory of the dual labour market, age discrimination is lower in occupations with evening and night shifts than day shifts, as the former relate to the worse working conditions in the secondary segment in which minority candidates are mainly employed (Bosanquet & Doeringer, 1937).	More age discrimination in occupations with evening and night shifts than in those with day shifts (Hirsch et al., 2000).
Average gross monthly wage	Consistent with the dual labour market theory, age discrimination is lower in occupations with low than high wages, as the former relate to the worse working conditions in the secondary segment wherein minority candidates are largely employed (Bosanquet & Doeringer, 1937).	N/A
Female dominance	Age discrimination is higher in female- than male-dominated occupations, as age discrimination begins earlier for women than for men (McGann et al., 2016).	Less age discrimination for females in male-dominated occupations than in female-dominated occupations (Lahey, 2008).
Age type	According to the statistical-based discrimination theory, age discrimination is higher in young- than old-typed occupations because senior workers violate the age norms and are subsequently perceived as deviant (Perry et al., 1996).	More age discrimination in young- than in old-typed occupations (Perry et al., 1996).
D. Organisation		
Organisation size	Age discrimination is lower in larger than in smaller organisations because the former more-suitably comply with explicit regulations that try to prevent ageism and engage in more active benchmarking against competitors (Ollier-Malaterre et al., 2013). In line with the statistical-based discrimination theory, age discrimination is lower in larger than in smaller organisations because of the former's dedicated human resource departments which involve experienced professionals, standardised recruitment procedures, the capacity to invite a higher number of candidates for	No differences regarding age discrimination were found by organisation size (Baert et al., 2018; Hirsch et al., 2000; Lahey, 2008). More age discrimination in larger than in smaller organisations (Loretto & White, 2006). Less age discrimination in larger than in smaller organisations (Oude Mulders, 2020).

	interviews, and the number of hires by which they learn faster about the true distribution of candidates' skills (Baert et al., 2018; Lahey, 2008). Considering the taste-based discrimination theory, age discrimination is lower in larger than in smaller organisations because the former are forced to be more objective due to stronger labour unions, anti-discrimination policies specifically-targeted at large organisations, and the difficulty of monitoring a larger workforce by which the selection of the most productive candidate becomes more important (Baert et al., 2018; Lahey, 2008).	Less discrimination in organisations with an HR department than in those without such a department (Drydakis et al., 2017).
Age workforce	In accordance with the social comparison theory, age discrimination is lower among an older than a younger workforce as decision-makers might take the workforce's preferences into account, which rely on the in- and out-group bias (Festinger, 1954; Lahey, 2008; Posthuma & Campion, 2009; Rupp et al., 2005).	No differences regarding age discrimination were found between organisations with young and old workforces (Lahey, 2008; Oude Mulders, 2020; Van Borm & Baert, 2020). Less age discrimination in organisations with a high percentage of senior workers (Van Borm et al., 2021).
Education workforce	Based on the human capital theory, age discrimination is lower among higher- than lower-educated workforces because the former can share their knowledge with senior co-workers, by which they become more productive and because higher-educated workers increase production efficiency, thus, boosting employment for all types of workers (Winters, 2018).	N/A
Stock market listing status	In accordance with the taste-based discrimination theory, age discrimination is lower in listed than in unlisted organisations because the former want to avoid corporate age discrimination lawsuits as these may cause a drop in share price and a loss in total share value (Ursel & Armstrong-Stassen, 2006).	N/A
Non-profit status	Consistent with the taste-based discrimination theory, age discrimination is lower in public and non-profit organisations than in commercial organisations because the former are expected to promote equality and make efforts to reduce discrimination (Baert et al., 2018).	Less age discrimination in public or non-profit organisations than in commercial organisations (Baert et al., 2018).
Multinational status	According to the outsider's network advantage, age discrimination is lower in foreign multinational organisations operating in host markets than in locally-operating organisations because the former can pinpoint socially-excluded groups in the host markets and exploit them for competitive advantages (Siegel et al., 2018).	N/A
Employment agency	In line with the statistical-based discrimination theory, age discrimination is higher in employment agencies than in organisations recruiting for their own because the former are not fully informed about their clients' preferences and wish to select candidates that make a good overall impression by which they might rely on statistical-based discrimination (Ruffle & Shtudiner, 2015).	More age discrimination when employment agencies were involved than when no such agencies were involved (Bendick et al., 1997).

	Considering the theory of taste-based discrimination, age discrimination is higher in employment agencies than in organisations recruiting for their own because the former assume that senior applicants should automatically be screened out with or without explicit instructions from their client (Bendick et al., 1997).	
Innovation	Consistent with the statistical-based discrimination theory, age discrimination is higher in high- than low-innovative organisations because decision-makers perceive senior workers as less adaptable and more sceptical towards technological innovations (Henkens, 2005).	Less age discrimination in highly innovative organisations than in less innovative organisations (Kunze et al., 2013).
Age customers	Based on the social comparison theory, age discrimination is lower among older than younger customers as decision-makers might take the customers' preferences into account, which rely on the in- and out-group bias (Festinger, 1954; Lahey, 2008; Posthuma & Campion, 2009; Rupp et al., 2005).	Less age discrimination in organisations with higher percentages of customers over the age of 50 than in those with lower percentages of such customers (Lahey, 2008).
E. Sector		
Product market competition	According to the taste-based discrimination theory, age discrimination is lower when there is higher competition in the sector because, in a competitive market, prejudiced organisations are less efficient and will be driven out of the market (Becker, 1957).	N/A

Notes. This table relates to age discrimination against senior job candidates in particular and contains only theoretical arguments and empirical findings regarding their recruitment chances. Due to the research design and available data, it was not possible to include all theoretically- and empirically-relevant characteristics. The characteristics that were included in this study's analyses are indicated in bold.

Table 2. Odds of a positive response: Multilevel analysis (generalised linear mixed-effects model) (N = 1,424)

Moderators	Vacancy		Occupation		Organisation		Sector		Combined model
	Basic	**Extended**	**Basic**	**Extended**	**Basic**	**Extended**	**Basic**	**Extended**	**Extended**
	(1a)	**(1b)**	**(2a)**	**(2b)**	**(3a)**	**(3b)**	**(4a)**	**(4b)**	**(5)**
CHARACTERISTICS									
A. Candidate characteristics									
Age (ref. = younger)									
Older	−0.549*** (0.158)	−0.572*** (0.172)	−0.303** (0.115)	−0.297* (0.118)	−0.549*** (0.158)	−0.562*** (0.159)	−0.305** (0.115)	−0.300* (0.122)	−0.349** (0.134)
B. Vacancy characteristics									
Gender decision-maker (ref. = male)									
Female		0.364 (0.351)							0.062 (0.197)
Unknown		−3.129*** (0.510)							−2.077*** (0.320)
Fulltime contract (ref. = no)									
Yes		0.730 (0.478)							0.168 (0.291)
Permanent contract (ref. = no)									
Yes		0.007 (0.458)							0.340 (0.286)
Ageist stereotypes (ref. = no)									
Yes		0.420 (0.356)							0.147 (0.205)
On-the-job training (ref. = no)									
Yes		0.557 (0.578)							0.373 (0.335)
Experience (ref. = unimportant or unspecified)									
None		0.855 (0.619)							0.185 (0.362)
Less than 2 years		0.363 (0.466)							0.416 (0.274)
At least 2 years		−0.036 (0.450)							0.035 (0.265)

C. Occupation characteristics				
Bottleneck (ref. = no)				
Yes	0.037 (0.235)			0.219 (0.228)
Creativity (c.)	0.207 (1.049)			0.624 (1.036)
Flexibility (c.)	0.779 (1.766)			1.293 (1.752)
Technological skills (c.)	0.330 (1.209)			0.027 (1.201)
Administrative tasks (c.)	−1.674 (1.180)			−1.277 (1.152)
Physical skills (c.)	−0.395 (1.118)			−0.637 (1.094)
Internal contact (c.)	−1.724 (1.992)			−2.381 (1.952)
External contact (c.)	0.852 (1.399)			0.835 (1.335)
Outdoor work (c.)	−0.634 (0.715)			−0.643 (0.667)
Job hazards (c.)	2.241** (0.825)			2.505** (0.830)
D. Organisation characteristics				
Number of employees (c.) [a]		0.075 (0.070)		0.042 (0.044)
Fr. Highly-educated employees (c.)		0.204 (0.790)		0.132 (0.490)
Non-profit status (ref. = no)				
Yes		0.834 (0.512)		0.107 (0.364)
Multinational status (ref. = no)				
Yes		0.218 (0.410)		0.138 (0.249)
Employment agency (ref. = no)				
Yes		1.839*** (0.441)		1.201* (0.601)
E. Sector characteristics				
Fr. employees older than 50 (c.)			0.023 (2.195)	0.831 (2.508)
Fr. innovative organisations (c.)			−0.835 (1.713)	−1.698 (1.750)
Product market competition (c.)			−0.216 (0.730)	−0.757 (0.863)
Union density (c.)			1.105 (1.259)	−0.104 (1.386)
WTS (c.)			0.004 (0.006)	0.003 (0.007)
INTERACTIONS WITH OLDER AGES				

A. Vacancy characteristics				
Age: Older x Gender decision-maker: Female	0.672† (0.365)			0.463 (0.282)
Age: Older x Gender decision-maker: Unknown	0.799 (0.561)			0.458 (0.463)
Age: Older x Fulltime contract: Yes	0.160 (0.508)			0.002 (0.418)
Age: Older x Permanent contract: Yes	−0.645 (0.475)			−0.416 (0.402)
Age: Older x Ageist stereotypes: Yes	−0.230 (0.374)			−0.125 (0.291)
Age: Older x On-the-job training: Yes	−0.103 (0.606)			−0.072 (0.476)
Age: Older x Experience: None	−0.908 (0.661)			−0.674 (0.517)
Age: Older x Experience: Less than 2 years	−0.851† (0.498)			−0.657† (0.389)
Age: Older x Experience: At least 2 years	0.280 (0.472)			0.026 (0.372)
B. Occupation characteristics				
Age: Older x Bottleneck: Yes		−0.087 (0.275)		−0.109 (0.299)
Age: Older x Creativity		−1.338 (1.242)		−1.625 (1.378)
Age: Older x Flexibility		−1.477 (2.118)		−1.672 (2.347)
Age: Older x Technological skills		1.237 (1.483)		0.972 (1.631)
Age: Older x Administrative tasks		−0.064 (1.380)		−0.187 (1.517)
Age: Older x Physical skills		0.403 (1.319)		0.359 (1.443)
Age: Older x Internal contact		−0.370 (2.395)		−0.343 (2.607)
Age: Older x External contact		1.240 (1.633)		1.203 (1.760)
Age: Older x Outdoor work		0.729 (0.776)		0.972 (0.833)
Age: Older x Job hazards		0.165 (0.954)		−0.329 (1.055)
C. Organisation characteristics				
Age: Older x Number of employees			−0.015 (0.073)	−0.011 (0.062)
Age: Older x Fr. Highly-educated employees			0.421 (0.818)	0.278 (0.688)
Age: Older x Non-profit status: Yes			−0.078 (0.524)	0.006 (0.477)
Age: Older x Multinational status: Yes			−0.592 (0.424)	−0.376 (0.348)

Age: Older x Employment agency: Yes						0.273 (0.422)			−0.193 (0.476)
D. Sector characteristics									
Age: Older x Fr. employees older than 50								−2.345 (2.178)	−2.619 (2.984)
Age: Older x Fr. innovative organisations								1.364 (1.970)	1.529 (2.147)
Age: Older x Product market competition								−0.212 (1.002)	−0.445 (1.166)
Age: Older x Union density								−0.090 (1.308)	0.128 (1.638)
Age: Older x WTS								0.004 (0.008)	0.008 (0.010)
STATISTICS									
Intercept	−1.076*** (0.180)	−1.163*** (0.180)	−0.509*** (0.125)	−0.521*** (0.110)	−1.076*** (0.180)	−1.071*** (0.180)	−0.597*** (0.121)	−0.588*** (0.126)	−0.651*** (0.145)
Number of observations	1,424	1,424	1,424	1,424	1,424	1,424	1,424	1,424	1,424
Marginal R^2	0.008	0.174	0.006	0.057	0.008	0.066	0.006	0.014	0.251
Conditional R^2	0.666	0.720	0.103	0.090	0.666	0.678	0.084	0.083	0.307
AIC	1686.6	1606.5	1803.6	1817.4	1686.6	1668.4	1788.5	1807.3	1698.2
BIC	1702.3	1717.0	1819.4	1948.9	1702.3	1736.8	1804.3	1886.2	2024.4

Notes. Abbreviations used: ref. (reference category), c. (continuous), Fr. (fraction), and WTS (Wage tension as a function of seniority). Basic models cover random intercept models with only one predictor (i.e. candidate's age), while extended models comprise random intercept models with multiple predictors (i.e. candidate's age, moderating characteristics and interaction effects) and random slopes. The presented statistics are coefficient estimates with standard errors between parentheses. Standard errors were clustered at the vacancy domain, given the correlation between the assignment of the fictitious candidates to a pair (or cluster) and the treatment of those candidates (Abadie et al., 2017; Vuolo et al., 2018). *** $p < .001$; ** $p < .01$; * $p < .05$; and † $p < .10$.

[a] The natural logarithm of the number of employees was taken into account as we expected this variable to be right-skewed (Baert, De Meyer, Moerman & Omey, 2018; Ting, 2021).

[b] The original marginal significant interaction between older candidates' ages and female decision-makers (Model 1b original $p = 0.066$) disappeared after applying Holm's correction for multiple hypothesis testing (Model 1b adjusted $p = 0.132$).

[c] The original marginal significant interaction between older candidates' ages and less than two years required experience (Model 1b original $p = 0.088$; Model 5 original $p = 0.0919$) disappeared after applying Holm's correction for multiple hypothesis testing (Model 1b adjusted $p = 0.263$; Model 5 adjusted $p = 0.276$).

Appendix

Table A.1. Specific search terms for vacancy characteristics

Operationalisation	Search terms (English)	Search terms (Dutch)
Fulltime contract		
No	Parttime	Deeltijds
Yes	Fulltime, absence of search terms	Voltijds, afwezigheid van zoektermen
Permanent contract		
No	Temporary job, temporary contract, fixed-term contract, interim	Tijdelijke job, tijdelijk contract, contract van bepaalde duur, interim
Yes	Permanent job, permanent contract, open-ended contract, afwezigheid van zoektermen	Vaste job, vast contract, contract van onbepaalde duur, afwezigheid van zoektermen
Equal opportunity employer		
No	Absence of search terms	Afwezigheid van zoektermen
Yes	Equal opportunities, equality, equal, diversity (policies), inclusiveness, inclusive (recruitment) policy	Gelijke kansen, gelijkheid, gelijkwaardig(heid), diversiteit(sbeleid), inclusiviteit, inclusief (aanwervings)beleid
Experience		
Unimportant/unspecified	Not important, absence of other search terms	Niet van belang, afwezigheid van andere zoektermen
None	No (work) experience, experience is an asset, experience is an advantage	Geen (werk)ervaring, ervaring is een troef, ervaring is een voordeel
Less than 2 years	First (work) experience, limited (work) experience, one year of experience	Eerste (werk)ervaring, beperkte (werk) ervaring, een jaar ervaring
At least 2 years	Two years (work) experience, three years (work) experience, four years (work) experience, five years (work) experience, six years (work) experience, seven years (work) experience, eight years (work) experience, and ten years (work) experience	Twee jaar (werk)ervaring, drie jaar (werk)ervaring, vier jaar (werk)ervaring, vijf jaar (werk)ervaring, zes jaar (werk)ervaring, zeven jaar (werk)ervaring, acht jaar (werk)ervaring, en tien jaar (werk)ervaring
On-the-job training		
No	Absence of search terms	Afwezigheid van zoektermen
Yes	Internal training, external training, personal training, training provided, training period, training programme	Interne opleiding/training, externe opleiding/training, persoonlijke opleiding/training, opleiding/training voorzien, opleidings-/trainingsperiode, opleidings/trainingsprogramma

Ageist stereotypes		
No	Absence of search terms	Afwezigheid van zoektermen
Yes	Internal training, external training, personal training, training provided, training period, training programme	Interne opleiding/training, externe opleiding/training, persoonlijke opleiding/ training, opleiding/training voorzien, opleidings-/trainingsperiode, opleidings-/trainingsprogramma
	Frustrated when not hearing, find people speak too softly, hearing worse, hearing impaired, often ask others to repeat, find other people speak too fast	Gefrustreerd wanneer ze niet horen, mensen te zacht vinden praten, slechter horen, slechthorend, vaak anderen vragen het te herhalen, vinden dat andere mensen te snel spreken
	Looking worse in old age, wrinkled, less attractive, not neat, unattractive	Er slechter uitzien op oudere leeftijd, gerimpeld, minder aantrekkelijk, niet netjes, onaantrekkelijk
	Afraid of becoming ill or incapacitated, moves slowly, frail, slow-moving, physically disabled, less activity, less energy, less suitable for a physically demanding job, less physically active, less speed, unhealthy, sedentary, poor posture, worse physical ability, worse health, worse psychomotor speed, trembling hands, sick, worse memory	Bang om ziek of onbekwaam te worden, beweegt langzaam, fragiel, langzaam bewegend, lichamelijk gehandicapten, minder activiteit, minder energie, minder geschikt voor een lichamelijk veeleisende baan, minder lichamelijk actief, minder snelheid, ongezond, sedentair, slechte houding, slechter fysiek vermogen, slechtere gezondheid, slechtere psychomotorische snelheid, trillende handen, ziek, slechter geheugen
	Better common sense, think before they act, better practical judgement, think before they do something, older workers are more cautious than younger workers, caution, self-discipline	Beter gezond verstand, denken na voordat ze handelen, een beter praktisch oordeel, nadenken voor ze iets doen, oudere werknemers zijn voorzichtiger dan jongere werknemers, voorzichtigheid, zelfdiscipline
	Commitment, reliable, more trustworthy, reliability, job retention, loyal, more loyal to the organisation, loyalty, stable, more stable, committed to the organisation, are loyal to the organization	Betrokkenheid, betrouwbaar, betrouwbaarder, betrouwbaarheid, functiebinding, loyaal, loyaler aan de organisatie, loyaliteit, stabiel, stabieler, toegewijd aan de organisatie, zijn loyaal aan de organisatie
	Professionally flexible, more flexible, more old-fashioned, less inclined to try new approaches, less likely to pick up new ideas, older workers are less flexible than younger workers, old-fashioned, less able to adapt to change, talk about the past, resistant to change, focuses from future to past, find it difficult to change, less able to adapt to change, less able to grasp new ideas, are resistant to change	Beroepsmatig flexibel, meer flexibiliteit, meer ouderwets, minder geneigd om nieuwe benaderingen uit te proberen, minder snel nieuwe ideeën oppikken, oudere werknemers zijn minder flexibel dan jongere werknemers, ouderwets, passen zich minder goed aan veranderingen aan, praten over het verleden, resistent tegen verandering, richt zich van toekomst naar verleden, vinden het moeilijk om te veranderen, zich minder snel aanpassen aan veranderingen, zijn minder goed in staat om nieuwe ideeën te begrijpen, zijn resistent tegen verandering
	Prejudiced, lonely, selfish, hopeless, moody, humourless, complains a lot, complaining, critical, less agreeable, less friendly, less cheerful, dejected, unhappy, insecure, easily upset, snobbish, demanding, bitter, annoying,	Bevooroordeeld, eenzaam, egoïstisch, hopeloos, humeurig, humorloos, klaagt veel, klagend, kritisch, minder aangenaam, minder vriendelijkheid, minder vrolijkheid, neerslachtig, ongelukkig, onzeker, snel van streek, snobistisch, veeleisend, verbitterd,

distrustful of strangers	vervelend, wantrouwend tegenover vreemden
Amicable, more conscientious, good-natured, warm personality, benevolent	Amicaal, gewetensvoller, goedmoedig, warme persoonlijkheid, welwillend
Better interpersonal skills, better social skills, more interpersonally adept, sincere when talking, tells nicer stories	Betere interpersoonlijke vaardigheden, betere sociale vaardigheden, meer intermenselijk vaardig, oprecht bij het praten, vertelt leukere verhalen
High performance rating is positively related to young people, younger workers perceived to have higher performance, lower performance, less competence, less economically beneficial, attributed low performance more to the stable factor of lack of competence when the subordinate was old	Een hoge prestatiebeoordeling is positief gerelateerd aan jongeren, jongere werknemers worden geacht een hoger prestatievermogen te hebben, lager prestatievermogen, minder competentie, minder economisch voordelig, schreef lage prestaties meer toe aan de stabiele factor van gebrek aan bekwaamheid toen de ondergeschikte oud was
Lack of willingness to be trained, learn less quickly, less interest in learning, less willingness to be trained, less development potential, less potential for development, less ability and willingness to learn, does not participate in training programmes, learn new techniques, training more suitable for younger workers, personal development, are less interested in attending training	Gebrek aan bereidheid om opgeleid te worden, leren minder snel, minder belangstelling voor leren, minder bereidheid om opgeleid te worden, minder ontwikkelingspotentieel, minder potentieel voor ontwikkeling, minder vermogen en bereidheid om te leren, neemt niet deel aan opleidingsprogramma's, nieuwe technieken leren, opleiding meer geschikt voor jongere werknemers, persoonlijke ontwikkeling, zijn minder geïnteresseerd in het volgen van een opleiding
Sound experience, more experience, have more experience useful in the job, have useful experience	Gedegen ervaring, meer ervaring, meer ervaring hebben die nuttig is in de baan, nuttige ervaring hebben
Work harder, strong work ethic	Harder werken, sterke werkethiek

Notes. The list of ageist stereotypes from Burn and colleagues (2020) was adopted.

Table A.2. Differences in the probability of a positive response: Heterogeneity of differential treatment hiring by candidate, vacancy, occupation, organisation, and sector characteristics (N = 712)

Moderators	Number of vacancies	Positive response rate younger candidate	Positive response rate older candidate	Discrimination ratio	1 – Discrimination ratio	Net discrimination rate	McNemar's Chi² (*p*)
	(1)	(2)	(3)	(4)	(5)	(6)	(7)
A. All characteristics							
Full sample	712	38.06%	31.60%	83.03%	16.97%	14.11%	13.56***
B. Candidate characteristics							
Age							
44 years	141	39.01%	34.04%	87.26%	12.74%	10.45%	1.58
50 years	286	40.21%	36.36%	90.43%	9.57%	8.09%	2.28
56 years	285	35.44%	25.61%	72.26%	27.74%	22.76%	10.89**
Post educational years (difference)							
6 years	425	38.59%	33.88%	87.79%	12.21%	10.00%	4.35*
12 years	287	37.28%	28.22%	75.70%	24.30%	20.63%	10.56**
Post educational years (activity)							
Relevant experience	236	39.66%	32.07%	80.86%	19.14%	16.36%	6.48*
Irrelevant experience	239	38.08%	32.22%	84.61%	15.39%	12.50%	3.50†
Inactivity	237	36.44%	30.51%	83.73%	16.27%	13.46%	3.92*
Gender							
Male	357	40.06%	35.01%	87.39%	12.61%	10.65%	4.63*
Female	355	36.06%	28.17%	78.12%	21.88%	17.83%	9.12**
Educational level							
High school	226	36.28%	29.65%	81.73%	18.27%	15.31%	4.79*
Bachelor	486	38.89%	32.51%	83.59%	16.41%	13.60%	8.82**
C. Vacancy characteristics							
Gender decision-maker							
Male	211	42.65%	29.38%	68.89%	31.11%	27.18%	14.52***
Female	355	46.20%	41.69%	90.24%	9.76%	8.00%	2.91†
Unknown	146	11.64%	10.27%	88.23%	11.77%	8.70%	0.29

Fulltime contract							
No	90	33.33%	25.56%	76.69%	23.31%	19.44%	2.58
Yes	622	38.75%	32.48%	83.82%	16.18%	13.45%	11.10***
Permanent contract							
No	94	39.36%	38.30%	97.31%	2.69%	2.04%	0.04
Yes	618	37.86%	30.58%	80.77%	19.23%	16.25%	15.46***
Equal opportunity employer							
No	699	38.05%	31.47%	82.71%	17.29%	14.38%	13.74***
Yes	13	38.46%	38.46%	100.00%	0.00%	0.00%	0.00
Ageist stereotypes							
No	535	36.82%	31.03%	84.27%	15.73%	13.08%	8.66**
Yes	177	41.81%	33.33%	79.72%	20.28%	16.85%	5.00*
On-the-job training							
No	659	37.78%	31.26%	82.74%	17.26%	14.38%	12.93***
Yes	53	41.51%	35.85%	86.36%	13.64%	11.11%	0.69
Experience							
Unimportant/unspecified	123	34.15%	31.71%	92.86%	7.14%	6.12%	0.53
None	68	45.59%	30.88%	67.73%	32.27%	27.78%	5.00*
Less than 2 years	226	40.27%	26.99%	67.02%	32.98%	28.57%	15.52***
At least 2 years	295	36.27%	35.25%	97.19%	2.81%	2.21%	0.15
D. Occupation characteristics							
Bottleneck occupation							
No	232	31.90%	27.16%	85.14%	14.86%	12.09%	2.69
Yes	480	41.04%	33.75%	82.24%	17.76%	14.89%	11.04***
Creativity							
Lower than or equal to average	415	36.39%	31.33%	86.10%	13.90%	11.17%	4.64*
Higher than average	297	40.40%	31.99%	79.18%	20.82%	18.12%	10.25**
Flexibility							
Lower than or equal to average	398	38.69%	33.42%	86.38%	13.62%	11.11%	4.85*
Higher than average	314	37.26%	29.30%	78.64%	21.36%	18.25%	9.62**
Technological skills							

Lower than or equal to average	254	40.94%	32.68%	79.82%	20.18%	17.21%	7.74**
Higher than average	458	36.46%	31.00%	85.02%	14.98%	12.25%	6.31*
Administrative tasks							
Lower than or equal to average	340	42.65%	33.53%	78.62%	21.38%	18.34%	12.16***
Higher than average	372	33.87%	29.84%	88.10%	11.90%	9.55%	2.92†
Physical skills							
Lower than or equal to average	346	34.97%	27.46%	78.52%	21.48%	17.93%	9.14**
Higher than average	366	40.98%	35.52%	86.68%	13.32%	11.05%	4.88*
Internal contact							
Lower than or equal to average	337	38.58%	31.45%	81.52%	18.48%	15.19%	7.20**
Higher than average	375	37.60%	31.73%	84.39%	15.61%	13.10%	6.37*
External contact							
Lower than or equal to average	339	41.00%	33.33%	81.29%	18.71%	15.57%	8.24**
Higher than average	373	35.39%	30.03%	84.85%	15.15%	12.58%	5.41*
Outdoor work							
Lower than or equal to average	416	37.50%	29.33%	78.21%	21.79%	18.28%	12.30***
Higher than average	296	38.85%	34.80%	89.58%	10.42%	8.57%	2.32
Job hazards							
Lower than or equal to average	441	32.43%	24.72%	76.23%	23.77%	19.88%	12.84***
Higher than average	271	47.23%	42.80%	90.62%	9.38%	7.74%	2.18
E. Organisation characteristics							
Number of employees [a]							
Lower than or equal to average	349	35.24%	29.80%	84.56%	15.44%	12.93%	5.39*
Higher than average	363	40.77%	33.33%	81.75%	18.25%	15.08%	8.19**
Fr. highly educated employees							
Lower than or equal to average	522	36.40%	31.99%	87.88%	12.12%	9.91%	4.94*
Higher than average	190	42.63%	30.53%	71.62%	28.38%	24.47%	10.80**
Stock market listing status							
Unlisted	699	38.34%	31.90%	83.20%	16.80%	13.98%	13.24***
Delisted	1	0.00%	0.00%	.	.	.	.
Listed	4	50.00%	25.00%	50.00%	50.00%	50.00%	1.00

Unknown	8	12.50%	12.50%	100.00%	0.00%	0.00%	0.00
Non-profit status							
No	641	37.44%	31.20%	83.33%	16.67%	13.79%	11.43***
Yes	71	43.66%	35.21%	80.65%	19.35%	16.67%	2.25
Multinational status							
No	122	34.43%	33.61%	97.62%	2.38%	1.96%	0.05
Yes	590	38.81%	31.19%	80.37%	19.63%	16.36%	14.78***
Employment agency							
No	600	34.83%	28.00%	80.39%	19.61%	16.47%	13.89***
Yes	112	55.36%	50.89%	91.93%	8.07%	6.49%	0.71
F. Sector characteristics							
Fr. employees older than 50							
Lower than or equal to average	323	40.87%	37.46%	91.66%	8.34%	6.67%	1.57
Higher than average	389	35.73%	26.74%	74.84%	25.16%	21.74%	15.51***
Fr. innovative organisations							
Lower than or equal to average	603	38.14%	31.34%	82.17%	17.83%	14.91%	12.83***
Higher than average	109	37.61%	33.03%	87.82%	12.18%	9.80%	1.00
Product market competition							
Lower than or equal to average	190	43.16%	37.37%	86.58%	13.42%	11.22%	2.81†
Higher than average	522	36.21%	29.50%	81.47%	18.53%	15.35%	10.84**
Union density							
Lower than or equal to average	357	31.65%	25.49%	80.54%	19.46%	16.42%	7.56**
Higher than average	355	44.51%	37.75%	84.81%	15.19%	12.50%	6.26*
Wage tension in function of seniority							
Lower than or equal to average	494	36.03%	29.96%	83.15%	16.85%	13.95%	8.65**
Higher than average	218	42.66%	35.32%	82.79%	17.21%	14.41%	4.92*

Notes. Abbreviation used: Fr. (fraction). Positive response rates were calculated as the number of positive responses received by a (fictitious) candidate of a given age divided by the number of applications sent by this candidate. The discrimination ratio (i.e. positive response ratio) is calculated as the positive response rate in the minority group (i.e. older ages) divided by the positive response rate in the majority group (i.e. younger ages) (Bertrand & Mullainathan, 2004). The net discrimination rate is calculated as the difference between the number of positive responses for the younger candidates only and the number of positive responses for the older candidates only divided by the total number of positive responses across both groups (Riach & Rich, 2002). The absolute numbers of the positive responses are available upon request. Continuous characteristics were transformed into categorical variables to allow for between-group comparisons. More concretely, the scores were labelled as 'high' ('low') if the value was in the top half (bottom half) of the variable's distribution. *** $p < .001$; ** $p < .01$; * $p < .05$; and † $p < .10$.

[a] The natural logarithm of the number employees was taken into account as we expected this variable to be right-skewed (Baert et al., 2018; Ting, 2021).

Table A.3. Power calculations

Effect size	Power	Minimal required sample size				
		Vacancy model	Occupation model	Organisation model	Sector model	Combined model
0.01	0.60	1424	2727	1124	2582	3973
0.01	0.65	1553	2945	1232	2791	4275
0.01	0.70	1693	3181	1350	3016	4599
0.01	0.75	1849	3440	1481	3264	4953
0.01	0.80	2028	3734	1633	3546	5354
0.01	0.85	2245	4086	1818	3883	5829
0.01	0.90	2530	4541	2062	4319	6441
0.02	0.60	719	1389	567	1314	2041
0.02	0.65	784	1499	621	1419	2192
0.02	0.70	854	1616	679	1531	2354
0.02	0.75	932	1746	745	1655	2531
0.02	0.80	1021	1893	821	1796	2731
0.02	0.85	1130	2069	914	1965	2969
0.02	0.90	1272	2296	1036	2183	3274
0.03	0.60	484	944	381	892	1398
0.03	0.65	527	1017	417	962	1498
0.03	0.70	574	1095	456	1037	1606
0.03	0.75	626	1181	500	1119	1724
0.03	0.80	686	1279	551	1213	1857
0.03	0.85	758	1397	612	1325	2016
0.03	0.90	853	1548	694	1471	2219
0.04	0.60	367	721	288	681	1077
0.04	0.65	399	776	315	733	1152

0.04	0.70	434	835	344	789	1233
0.04	0.75	473	899	377	851	1321
0.04	0.80	518	973	415	922	1421
0.04	0.85	572	1061	461	1006	1540
0.04	0.90	644	1174	523	1115	1692
0.05	0.60	297	588	232	555	884
0.05	0.65	322	631	254	596	945
0.05	0.70	350	678	277	641	1009
0.05	0.75	381	730	304	691	1079
0.05	0.80	417	789	334	747	1159
0.05	0.85	461	859	371	814	1254
0.05	0.90	518	950	420	901	1376
0.06	0.60	250	499	195	470	757
0.06	0.65	271	535	213	505	807
0.06	0.70	294	574	233	542	860
0.06	0.75	320	617	255	584	919
0.06	0.80	350	666	280	631	985
0.06	0.85	386	725	311	687	1064
0.06	0.90	434	801	351	759	1166
0.07	0.60	216	436	169	410	666
0.07	0.65	234	467	184	440	708
0.07	0.70	254	500	201	472	754
0.07	0.75	277	537	220	507	804
0.07	0.80	302	579	241	547	861
0.07	0.85	333	629	268	595	929
0.07	0.90	374	694	303	658	1016
0.08	0.60	191	388	149	365	598
0.08	0.65	207	415	162	391	635

0.08	0.70	225	445	177	419	675
0.08	0.75	244	477	193	450	719
0.08	0.80	266	513	212	485	768
0.08	0.85	294	557	235	527	827
0.08	0.90	329	614	266	582	903
0.09	0.60	171	351	133	330	545
0.09	0.65	186	375	145	353	578
0.09	0.70	201	401	158	378	613
0.09	0.75	219	430	173	406	652
0.09	0.80	239	463	190	437	696
0.09	0.85	263	501	210	474	749
0.09	0.90	294	552	237	522	816
0.10	0.60	156	322	121	302	503
0.10	0.65	169	344	132	323	533
0.10	0.70	183	367	143	345	564
0.10	0.75	198	393	157	370	599
0.10	0.80	216	422	172	398	639
0.10	0.85	238	457	190	432	686
0.10	0.90	266	502	215	475	746

Notes. Power analyses were conducted for each domain-specific model as well as for the combined model as outlined in Subsection 4.2.1. Subsequently, the number of integrated predictors differs among these models: 18 in the vacancy model, 80 in the occupation model, 10 in the organisation model, 71 in the sector model and 179 in the combined model. In all analyses, the statistical significance level (α) is set at 0.05 while the statistical power (1-β) varies between 0.60 and 0.90. We only present minimal effect sizes ranging from 0.01 (representing a micro effect) to 0.10 (indicating a small effect) as our sample size is sufficient to detected effects above 0.10 in all models. The calculated minimal required sample sizes should be compared with our sample size of 712 fictitious candidates in the minority or majority group.

Table A.4. Odds of a positive response: Multilevel analysis with categorical variables (generalised linear mixed model) (N = 1,424)

Moderators	Vacancy		Occupation		Organisation		Sector		Combined model
	Basic	**Extended**	**Basic**	**Extended**	**Basic**	**Extended**	**Basic**	**Extended**	**Extended**
	(1a)	**(1b)**	**(2a)**	**(2b)**	**(3a)**	**(3b)**	**(4a)**	**(4b)**	**(5)**
CHARACTERISTICS									
A. Candidate characteristics									
Age (ref. = younger)									
Older	−0.549*** (0.158)	−0.572*** (0.172)	−0.303** (0.115)	−0.298* (0.119)	−0.549*** (0.158)	−0.557*** (0.160)	−0.305** (0.115)	−0.291* (0.123)	−0.342* (0.134)
B. Vacancy characteristics									
Gender decision-maker (ref. = male)									
Female		0.364 (0.351)							0.038 (0.198)
Unknown		−3.129*** (0.510)							−2.101*** (0.322)
Fulltime contract (ref. = no)									
Yes		0.730 (0.478)							0.130 (0.291)
Permanent contract (ref. = no)									
Yes		0.007 (0.458)							0.428 (0.286)
Ageist stereotypes (ref. = no)									
Yes		0.420 (0.356)							0.129 (0.204)
On-the-job training (ref. = no)									
Yes		0.557 (0.578)							0.395 (0.330)
Experience (ref. = unimportant or unspecified)									
None		0.855 (0.619)							0.237 (0.363)
Less than 2 years		0.363 (0.466)							0.399 (0.273)
At least 2 years		−0.036 (0.450)							0.046 (0.262)
C. Occupation characteristics									

Bottleneck (ref. = no)		
Yes	0.258 (0.236)	0.436† (0.243)
Creativity (ref. = lower than or equal to average)		
Higher than average	0.172 (0.253)	0.301 (0.265)
Flexibility (ref. = lower than or equal to average)		
Higher than average	0.376 (0.258)	0.238 (0.268)
Technological skills (ref. = lower than or equal to average)		
Higher than average	0.390 (0.400)	0.167 (0.421)
Administrative tasks (ref. = lower than or equal to average)		
Higher than average	−0.562* (0.277)	−0.410 (0.282)
Physical skills (ref. = lower than or equal to average)		
Higher than average	0.126 (0.328)	0.075 (0.338)
Internal contact (ref. = lower than or equal to average)		
Higher than average	−0.314 (0.289)	−0.409 (0.301)
External contact (ref. = lower than or equal to average)		
Higher than average	−0.071 (0.290)	−0.039 (0.293)
Outdoor work (ref. = lower than or equal to average)		
Higher than average	−0.161 (0.266)	−0.182 (0.280)
Job hazards (ref. = lower than or equal to average)		
Higher than average	0.775** (0.289)	0.642* (0.304)

D. Organisation characteristics				
Number of employees (ref. = lower than or equal to average) [a]				
Higher than average	0.340 (0.308)			0.170 (0.188)
Fr. highly educated employees (ref. = lower than or equal to average)				
Higher than average	$0.600^{\dagger}$ (0.359)			$0.406^{\dagger}$ (0.221)
Non-profit status (ref. = no)				
Yes	0.719 (0.521)			0.070 (0.363)
Multinational status (ref. = no)				
Yes	0.107 (0.424)			−0.064 (0.253)
Employment agency (ref. = no)				
Yes	1.982^{***} (0.451)			$1.153^{\dagger}$ (0.598)
E. Sector characteristics				
Fr. employees older than 50 (ref. = lower than or equal to average)				
Higher than average			0.036 (0.276)	0.165 (0.310)
Fr. innovative organisations (ref. = lower than or equal to average)				
Higher than average			0.091 (0.295)	−0.004 (0.306)
Product market competition (ref. = lower than or equal to average)				
Higher than average			−0.139 (0.202)	−0.222 (0.238)
Union density (ref. = lower than or equal to average)				
Higher than average			0.358 (0.265)	0.063 (0.300)
WTS (ref. = lower than or equal to average)				
Higher than average			0.200 (0.179)	0.126 (0.204)

INTERACTIONS WITH OLDER AGES				
A. Vacancy characteristics				
Age: Older x Gender decision-maker: Female	0.672† (0.365)			0.492† (0.283)
Age: Older x Gender decision-maker: Unknown	0.799 (0.561)			0.557 (0.464)
Age: Older x Fulltime contract: Yes	0.160 (0.508)			−0.003 (0.419)
Age: Older x Permanent contract: Yes	−0.645 (0.475)			−0.440 (0.403)
Age: Older x Ageist stereotypes: Yes	−0.230 (0.374)			−0.090 (0.290)
Age: Older x On-the-job training: Yes	−0.103 (0.606)			−0.136 (0.472)
Age: Older x Experience: None	−0.908 (0.661)			−0.688 (0.517)
Age: Older x Experience: Less than 2 years	−0.851† (0.498)			−0.655† (0.386)
Age: Older x Experience: At least 2 years	0.280 (0.472)			0.022 (0.368)
B. Occupation characteristics				
Age: Older x Bottleneck: Yes		−0.186 (0.288)		−0.225 (0.310)
Age: Older x Creativity: HTA		−0.463 (0.315)		−0.592† (0.344)
Age: Older x Flexibility: HTA		−0.241 (0.314)		−0.173 (0.344)
Age: Older x Technological skills: HTA		0.418 (0.506)		0.524 (0.559)
Age: Older x Administrative tasks: HTA		0.109 (0.338)		0.066 (0.370)
Age: Older x Physical skills: HTA		0.060 (0.399)		0.135 (0.439)
Age: Older x Internal contact: HTA		0.006 (0.360)		0.017 (0.391)
Age: Older x External contact: HTA		0.234 (0.343)		0.183 (0.374)
Age: Older x Outdoor work: HTA		0.229 (0.316)		0.318 (0.340)
Age: Older x Job hazards: HTA		0.245 (0.335)		0.214 (0.376)
C. Organisation characteristics				
Age: Older x Number of employees:			−0.151 (0.317)	−0.226 (0.267)

HTA									
Age: Older x Fr. highly educated employees: HTA						−0.546 (0.371)			−0.440 (0.315)
Age: Older x Non-profit status: Yes						0.071 (0.530)			0.225 (0.478)
Age: Older x Multinational status: Yes						−0.444 (0.435)			−0.270 (0.355)
Age: Older x Employment agency: Yes						0.163 (0.423)			−0.246 (0.531)
D. Sector characteristics									
Age: Older x Fr. employees older than 50: HTA								−0.368 (0.258)	−0.345 (0.350)
Age: Older x Fr. innovative organisations: HTA								0.128 (0.323)	0.269 (0.369)
Age: Older x Product market competition: HTA								−0.006 (0.266)	−0.105 (0.331)
Age: Older x Union density: HTA								0.106 (0.250)	0.072 (0.348)
Age: Older x WTS: HTA								−0.053 (0.249)	0.048 (0.288)
STATISTICS									
No positive response|Positive response	−1.076*** (0.180)	−1.163*** (0.180)	−0.509*** (0.125)	−0.520*** (0.105)	−1.076*** (0.180)	−1.107*** (0.185)	−0.597*** (0.121)	−0.589*** (0.123)	−0.660*** (0.141)
Number of observations	1424	1424	1424	1424	1424	1424	1424	1424	1424
Marginal R^2	0.008	0.174	0.006	0.060	0.008	0.069	0.006	0.026	0.248
Conditional R^2	0.666	0.720	0.103	0.083	0.666	0.688	0.084	0.081	0.299
AIC	1686.6	1606.5	1803.6	1817.6	1686.6	1665.5	1788.5	1804.0	1704.5
BIC	1702.3	1717.0	1819.4	1949.2	1702.3	1733.9	1804.3	1882.9	2030.7

Notes. Abbreviations used: ref. (reference category), Fr. (fraction), WTS (Wage Tension in function of the Seniority) and HTA (Higher Than Average). Continuous characteristics were transformed into categorical variables consisting of two categories. More concretely, the scores were labelled as 'high' ('low') if the value was in the top half (bottom half) of the variable's distribution. Basic models cover random intercept models with only one predictor, while extended models comprise random intercept models with multiple predictors (i.e. candidate's age, moderating characteristics and interaction effects) and random slopes. The presented statistics are coefficient estimates with standard errors between parentheses. Standard errors were clustered at the vacancy domain given the correlation between the assignment of the fictitious candidates to a pair (or cluster) and the treatment of those candidates (Abadie et al., 2017; Vuolo et al., 2018). *** $p < .001$; ** $p < .01$; * $p < .05$; and † $p < .10$.

[a] The natural logarithm of the number employees was taken into account as we expected this variable to be right-skewed (Baert, De Meyer, Moerman & Omey, 2018; Ting, 2021).

Table A.5. Odds of a positive response: Multilevel analysis only for pairs with 12 years difference (generalised linear mixed model) (N = 574)

Moderators	Vacancy		Occupation		Organisation		Sector		Combined model
	Basic	**Extended**	**Basic**	**Extended**	**Basic**	**Extended**	**Basic**	**Extended**	**Extended**
	(1a)	**(1b)**	**(2a)**	**(2b)**	**(3a)**	**(3b)**	**(4a)**	**(4b)**	**(5)**
CHARACTERISTICS									
A. Candidate characteristics									
Age (ref. = younger)									
Older	−0.784** (0.256)	−0.908** (0.303)	−0.421* (0.181)	−0.418* (0.184)	−0.784** (0.256)	−0.802** (0.260)	−0.455* (0.188)	−0.467* (0.197)	−0.610* (0.241)
B. Vacancy characteristics									
Gender decision-maker (ref. = male)									
Female		0.567 (0.538)							0.115 (0.318)
Unknown		−3.055*** (0.791)							−2.290*** (0.564)
Fulltime contract (ref. = no)									
Yes		0.311 (0.731)							0.250 (0.469)
Permanent contract (ref. = no)									
Yes		−0.539 (0.733)							−0.116 (0.471)
Ageist stereotypes (ref. = no)									
Yes		−0.015 (0.556)							−0.255 (0.355)
On-the-job training (ref. = no)									
Yes		−0.148 (0.950)							−0.168 (0.596)
Experience (ref. = unimportant or unspecified)									
None		0.117 (0.945)							−0.339 (0.576)
Less than 2 years		0.034 (0.727)							0.288 (0.458)
At least 2 years		−0.366 (0.704)							−0.055 (0.447)
C. Occupation characteristics									

Bottleneck (ref. = no)				
Yes	0.228 (0.295)			0.265 (0.341)
Creativity (c.)	−0.576 (1.414)			0.038 (1.661)
Flexibility (c.)	1.471 (2.346)			1.666 (2.819)
Technological skills (c.)	−0.440 (1.726)			0.245 (1.933)
Administrative tasks (c.)	−2.331 (1.524)			−1.776 (1.802)
Physical skills (c.)	−0.434 (1.514)			−0.818 (1.719)
Internal contact (c.)	2.324 (2.926)			−1.179 (3.328)
External contact (c.)	0.610 (1.787)			0.269 (2.114)
Outdoor work (c.)	−1.399 (0.890)			−0.917 (1.011)
Job hazards (c.)	0.903 (1.117)			0.672 (1.243)
D. Organisation characteristics				
Number of employees (c.) [a]		$0.194^{\dagger}$ (0.107)		0.096 (0.069)
Fr. highly educated employees (c.)		0.572 (1.199)		0.322 (0.801)
Non-profit status (ref. = no)				
Yes		1.009 (0.812)		−0.015 (0.528)
Multinational status (ref. = no)				
Yes		−0.360 (0.629)		−0.450 (0.413)
Employment agency (ref. = no)				
Yes		2.236^{**} (0.702)		0.596 (0.629)
E. Sector characteristics				
Fr. employees older than 50 (c.)			−3.881 (2.904)	$-6.049^{\dagger}$ (3.494)
Fr. innovative organisations (c.)			−3.635 (2.772)	−2.953 (2.872)
Product market competition (c.)			−1.114 (1.430)	−1.538 (1.653)
Union density (c.)			4.144^{*} (1.785)	$3.868^{\dagger}$ (1.988)
WTS (c.)			0.011 (0.010)	0.016 (0.011)
INTERACTIONS WITH OLDER AGES				
A. Vacancy characteristics				

Age: Older x Gender decision-maker: Female	0.669 (0.578)			0.592 (0.477)
Age: Older x Gender decision-maker: Unknown	0.232 (1.035)			0.030 (0.901)
Age: Older x Fulltime contract: Yes	−0.404 (0.799)			−0.534 (0.674)
Age: Older x Permanent contract: Yes	0.521 (0.787)			0.475 (0.690)
Age: Older x Ageist stereotypes: Yes	0.264 (0.604)			0.251 (0.517)
Age: Older x On-the-job training: Yes	−1.428 (1.136)			−0.915 (0.960)
Age: Older x Experience: None	0.039 (1.028)			0.333 (0.838)
Age: Older x Experience: Less than 2 years	−0.964 (0.825)			−0.604 (0.686)
Age: Older x Experience: At least 2 years	0.565 (0.772)			0.331 (0.662)
B. Occupation characteristics				
Age: Older x Bottleneck: Yes		−0.107 (0.429)		−0.221 (0.503)
Age: Older x Creativity		−0.463 (2.034)		−0.745 (2.439)
Age: Older x Flexibility		−1.910 (3.493)		−2.174 (4.146)
Age: Older x Technological skills		1.242 (2.485)		0.229 (2.823)
Age: Older x Administrative tasks		0.471 (2.218)		0.891 (2.647)
Age: Older x Physical skills		−0.306 (2.187)		−0.351 (2.511)
Age: Older x Internal contact		−2.092 (4.136)		−0.273 (4.829)
Age: Older x External contact		0.367 (2.620)		−0.280 (3.071)
Age: Older x Outdoor work		1.776 (1.239)		2.198 (1.463)
Age: Older x Job hazards		0.306 (1.451)		−0.239 (1.775)
C. Organisation characteristics				
Age: Older x Number of employees			0.055 (0.115)	0.029 (0.101)
Age: Older x Fr. highly educated employees			0.875 (1.294)	0.412 (1.139)
Age: Older x Non-profit status: Yes			−0.145 (0.860)	0.304 (0.759)

Age: Older x Multinational status: Yes						−0.833 (0.676)			−0.594 (0.601)
Age: Older x Employment agency: Yes						−0.067 (0.678)			0.691 (0.790)
D. Sector characteristics									
Age: Older x Fr. employees older than 50								0.977 (3.350)	3.812 (4.980)
Age: Older x Fr. innovative organisations								1.489 (3.549)	1.054 (3.875)
Age: Older x Product market competition								−0.560 (1.960)	−1.549 (2.374)
Age: Older x Union density								−3.037 (2.172)	−4.257 (2.823)
Age: Older x WTS								0.001 (0.014)	0.006 (0.016)
STATISTICS									
No positive response|Positive response	-1.156^{***} (0.296)	-1.208^{***} (0.279)	-0.528^{***} (0.136)	-0.523^{***} (0.127)	-1.156^{***} (0.296)	-1.045^{***} (0.273)	-0.610^{***} (0.175)	-0.547^{***} (0.166)	-0.642^{***} (0.169)
Number of observations	574	574	574	574	574	574	574	574	574
Marginal R^2	0.016	0.221	0.013	0.048	0.016	0.127	0.014	0.052	0.349
Conditional R^2	0.669	0.718	0.038	0.050	0.669	0.672	0.124	0.134	0.366
AIC	668.2	650.2	725.1	755.4	668.2	659.0	700.7	714.6	714.5
BIC	681.2	741.6	738.2	864.2	681.2	715.6	713.8	779.8	984.4

Notes. Abbreviations used: ref. (reference category), c. (continuous), Fr. (fraction) and WTS (Wage Tension in function of the Seniority). Basic models cover random intercept models with only one predictor, while extended models comprise random intercept models with multiple predictors (i.e. candidate's age, moderating characteristics and interaction effects) and random slopes. The presented statistics are coefficient estimates with standard errors between parentheses. Standard errors were clustered at the vacancy domain given the correlation between the assignment of the fictitious candidates to a pair (or cluster) and the treatment of those candidates (Abadie et al., 2017; Vuolo et al., 2018). *** p < .001; ** p < .01; * p < .05; and † p < .10.

[a] The natural logarithm of the number employees wat taken into account as we expected this variable to be right-skewed (Baert, De Meyer, Moerman & Omey, 2018; Ting, 2021).