I Z A Institute
of Labor Economics
Initiated by Deutsche Post Foundation

DISCUSSION PAPER SERIES

IZA DP No. 17497

Not a Lucky Break? Why and When a Career Hiatus Hijacks Hiring Chances

Liam D'hert
Louis Lippens
Stijn Baert

DECEMBER 2024

I Z A Institute
of Labor Economics

Initiated by Deutsche Post Foundation

DISCUSSION PAPER SERIES

IZA DP No. 17497

Not a Lucky Break? Why and When a Career Hiatus Hijacks Hiring Chances

Liam D'hert
Ghent University

Louis Lippens
Ghent University

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

DECEMBER 2024

Any opinions expressed in this paper are those of the author(s) and not those of IZA. Research published in this series may include views on policy, but IZA takes no institutional policy positions. The IZA research network is committed to the IZA Guiding Principles of Research Integrity.

The IZA Institute of Labor Economics is an independent economic research institute that conducts research in labor economics and offers evidence-based policy advice on labor market issues. Supported by the Deutsche Post Foundation, IZA runs the world's largest network of economists, whose research aims to provide answers to the global labor market challenges of our time. Our key objective is to build bridges between academic research, policymakers and society.

IZA Discussion Papers often represent preliminary work and are circulated to encourage discussion. Citation of such a paper should account for its provisional character. A revised version may be available directly from the author.

ISSN: 2365-9793

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

Not a Lucky Break? Why and When a Career Hiatus Hijacks Hiring Chances*

Sustaining social security systems amidst an ageing population requires (re)integrating the unemployed and inactive into work. However, stigma surrounding non-employment history can create barriers to finding a job. Whilst unemployment stigma is well-documented, inactivity stigma remains under the radar. To address whether, why, and when inactivity hinders hiring, we employed a vignette experiment where real-life recruiters rated fictitious applicants with varying non-employment breaks on hireability and productivity. Results reveal employers rank candidates by their reason for being out of work: those with training breaks rank highest, followed by former caregivers, the previously ill and the unemployed, and last, the discouraged. Productivity perceptions match this pattern. Trainees score highest for skills, motivation, cognition, discipline, reliability, flexibility, and trainability. Caregivers excel in perceived social skills but fall short on flexibility. The previously ill are seen as more motivated than the unemployed but likely raise health concerns. The discouraged trigger the harshest stigma, particularly for motivation and self-discipline. Longer lapses hurt hiring chances, but not for training breaks.

JEL Classification: C91, E24, J21, J64

Keywords: career break, unemployment, inactivity, hiring chances, factorial survey experiment

Corresponding author:
Liam D'hert
Ghent University
Sint-Pietersplein 6
9000 Ghent
Belgium
E-mail: Liam.Dhert@UGent.be

* Funding: This research received financial support from FWO (Research Foundation – Flanders) under grant number G073924N. Louis Lippens acknowledges funding from FWO under grant number 12AM824N. Declaration of interest: The authors have no conflicts of interest to declare. Data availability. Data and code are available at https://osf.io/sgp9c. Acknowledgements: We thank Morien El Haj for her valuable suggestions and Sarah Slabbaert for her research work in the initial stages of this study as part of her master's thesis.

1. Introduction

Following the decline in employment rates due to the COVID-19 crisis (ILO, 2024a), the number of individuals in work has now returned to pre-pandemic levels, with growth in labour force participation exceeding expectations (ILO, 2024b). However, this upward trend seems to have reached its peak. The Organisation for Economic Co-operation and Development (OECD, 2024) projects a slowing labour force expansion in the coming years, whilst the International Labour Organization anticipates a moderate decline in overall labour force numbers (ILO, 2024b).

This scenario challenges the European Union's ambitious objective of employing at least 78% of people aged 20 to 64 by 2030 (Goodger & Makay, 2024). Nevertheless, securing this target is key to sustaining social security systems, which are strained by an ageing population (Feist, 2024; Harasty & Ostermeier, 2020; ILO, 2024b; OECD, 2024), and countering the drop in economic growth caused by unstaffed jobs in today's tight labour market (Gammarano, 2019; ILO, 2024b; OECD, 2024). In response to these challenges, it is crucial to engage those who can work but currently remain outside the labour force – those often referred to as 'the inactive' (Baert, 2021; Harasty & Ostermeier, 2020).

This group of inactive individuals, who are neither employed nor seeking work, stands apart from the unemployed, who are jobless yet actively looking for employment and thus receiving unemployment benefits (Aysun et al., 2014; Baert, 2021). The unemployed, along with the employed, comprise the labour force, whereas the inactive parallel the potential labour force (Baert, 2021). The inactive can be further categorised into five groups based on their reasons for not working: full-time education or training; caregiving for children, adults with disabilities, or other family members; long-term illness; discouragement due to perceived job scarcity; and early retirement (Baert, 2021; ILO, 2016).

Although encouraging the non-employed (i.e. the unemployed and inactive) into work is the bottom line in boosting employment rates, empirical evidence strongly suggests that a gap in employment history hinders workers' future job prospects. From a supply-side perspective, those with prolonged periods of not working struggle to secure employment due to weakened professional connections (Calvó-Armengol & Jackson, 2004), skill decay (Becker, 1962; Keane & Wolpin, 1997), and mental barriers (Ayllón, 2013; Clark et al., 2001).

On the demand side, where the focus shifts to employers' assessments, existing research has revealed a marked aversion to those with career breaks – even if they possess identical skill sets to their consistently employed counterparts (Baert & Verhaest, 2019; Eriksson & Rooth, 2014; Kristal et al., 2023; Kroft et al., 2013). Specifically, employers are wary of hiring the (long-term) unemployed, presuming they are less productive, competent, and motivated (Bonoli, 2014; D'hert et al., 2024; Trzebiatowski et al., 2020; Van Belle et al., 2018). Furthermore, an inactivity-induced career hiatus seems to incur even harsher hiring penalties (D'hert et al., 2024; Dorsett & Lucchino, 2018; Weisshaar, 2018, 2021).

However, whilst the literature on unemployment scarring is extensive,[1] research on inactivity scarring is limited and for some of the five aforementioned subgroups even non-existent. More specifically, in their systematic literature review, D'hert et al. (2024) noted a lack of studies addressing discouraged applicants' hireability. They also found research on the hiring prospects of former caregivers to be scarce. Moreover, no study has examined the recruitment prospects of the different non-employed groups within one experimental framework, thus precluding a direct comparison of their hiring chances and associated stigma. These shortfalls likely reflect a traditional policy emphasis on re-employing the unemployed rather than on (re)integrating the inactive into the labour force (Baert, 2021; Brandolini & Viviano, 2018). The inactive represent a less visible portion of the population and have long been considered socio-culturally desirable (e.g. homemakers; Baert, 2021).

Our study pioneers the logical progression from the unemployment scarring literature to the inactivity scarring literature and is the first to incorporate all relevant inactivity-related work histories within one experimental framework.[2] In doing so, we investigate the demand-side challenges faced by individuals re-entering the labour force after inactivity.[3] More concretely, we map whether, why, and when employers rank candidates by their non-

[1] In this study, 'scarring' refers to demand-side scarring, focused on employers' attitudes towards the non-employed. Since this study comprises an experiment with recruiters assessing fictitious, experimentally controlled applicants, supply-side and institution-induced scarring effects are ruled out by design.

[2] Due to ecological validity concerns, we excluded early retirees, who have voluntarily left the workforce, making their return highly unlikely (Baert, 2021). Reactivating early retirees holds limited value; the focus lies instead on preventing early retirement (Barr, 2006). However, this issue is beyond the scope of the current study.

[3] In line with a strict interpretation, we consider inactive individuals to not be actively seeking employment. Therefore, by 'potential labour force', we refer to individuals who, after a period of inactivity, have regained the ability to participate in the workforce (Gammarano, 2019). For instance, a person on long-term sick leave may be temporarily unable to work but will eventually resume job-seeking activities upon recovery.

employment histories. Through a state-of-the-art vignette experiment, real-life recruiters evaluate fictitious applicants who randomly vary in their reasons for and periods of being out of work. Each non-employed applicant is assessed on hireability and productivity. These attributes are grounded in the two seminal theories related to unemployment scarring: human capital theory and signalling theory (as described in Section 2).

Our results reveal hireability disparities between the unemployed and inactive, as well as among the inactive subgroups. Employers rank the non-employed by work history in the following order: training breaks, caregiving gaps, health-related lapses and unemployment, and breaks due to discouragement. This ranking is closely mirrored in employers' perceptions of skill loss, productivity, trainability, and negative evaluations by other employers for each non-employment type, which predominantly supports our theoretical expectations. Additionally, recruitment prospects decline with longer non-employment durations, except for those in education or training, for whom longer breaks enhance recruitment chances. Also, male candidates face harsher penalties for career interruptions.

The remainder of this paper proceeds as follows. In Section 2, we introduce the theoretical background underpinning our hypotheses. We then outline our experimental design in Section 3. In Section 4, we analyse the data. Section 5 concludes the paper.

2. Theoretical background and hypotheses

Prior to presenting the experiment, we outline a theoretical basis for employers' tendency to use career hiatuses as a filter in resume screening. This background section hypothesises that different employment gaps evoke distinct employer reactions and perceptions. Our approach builds on the two seminal theories in the field of unemployment scarring: human capital theory and signalling theory, with the latter incorporating queuing theory and rational herding theory as specific applications.

Human capital theory argues that employers believe periods of non-employment hinder skill development and may even cause skill deterioration due to disuse (Acemoglu, 1995; Becker, 1962; Pissarides, 1992; Van Belle et al., 2018). According to this theory, hireability differences among job applicants with employment gaps should be indifferent to the nature of the career hiatus, except for those who were engaged in education or training during their break, which evidences ongoing skill accumulation (Albrecht et al., 1999; Becker, 1962; Dalle et al., 2024b; Picchio & van Ours, 2013).

Signalling theory, however, indicates that demand-side biases affecting non-employed job seekers vary by the type of employment lapse (Namingit et al., 2021; Sterkens et al., 2023; Weisshaar, 2018, 2021). This theory states that employers interpret specific resume characteristics (e.g. employment history) as proxies for unobservable dimensions of productivity (e.g. motivation) when making hiring decisions (Blanchard & Diamond, 1994; Connelly et al., 2011; Spence, 1973; Vishwanath, 1989). Thus, certain resume features can prompt employers to draw on commonly held stereotypes about individuals with similar characteristics (Blanchard & Diamond, 1994; Lockwood, 1991; Van Belle et al., 2018; Viswanath, 1989). In what follows, we discuss the stigmas often associated in the literature with non-occupational periods resulting from (i) unemployment, (ii) education or training, (iii) caregiving, (iv) long-term illness, and (v) discouragement in job seeking. In many cases, these stigmas were only raised theoretically in the literature, or (indirect) empirical evidence was found for a specific stigma related to a specific type of non-employment. We first lay out the theoretical puzzle below and then take the test empirically. Since the stigmas related to long-term unemployment have been studied most and unemployment is the logical counterpart of the four categories of inactivity, we apply signalling theory to unemployment first, then use it as a benchmark.

According to signalling theory, periods of unemployment often trigger stigmas of reduced productivity related to lower capabilities and traits, thereby 'scarring' unemployed applicants when compared to their currently employed counterparts (Pedulla, 2020; Spence, 1973; Vishwanath, 1989). From this perspective, (long-term) unemployment has been linked to perceptions of lower mental and social capabilities (Van Belle et al., 2018; Vishwanath, 1989). Concerning negative traits, unemployment has been linked to poor motivation, self-discipline, reliability, and flexibility (Atkinson et al., 1996; Bonoli, 2014; Pedulla, 2020; Van Belle et al., 2018). Furthermore, Van Belle et al. (2018) integrated two widely cited applications of signalling theory in their theoretical framework on demand-side unemployment scarring: queuing theory and rational herding theory. Drawing on queuing theory (Thurow, 1975), employers rank applicants based on their perceived ease of training. Again faced with incomplete information and based on observable characteristics, employers prioritise applicants who are expected to require the least training investment (Dalle et al., 2024b). Consequently, candidates who have spent time out of work may be viewed as less trainable than their employed counterparts (Shi & Wang, 2022; Van Belle et al., 2018) – a pattern similarly observed for applicants with less favourable school performance indicators (Di Stasio, 2014). Also related to signalling theory, rational herding theory posits that extended unemployment reinforces negative perceptions since recruiters may interpret prolonged joblessness as a sign of prior rejection by other employers (Banerjee, 1992; Bonoli & Hinrichs, 2012; Oberholzer-Gee, 2008; Van Belle et al., 2018). Based on each of these channels, a substantial disadvantage of long-term unemployment in the recruitment process is expected. This was also found in Van Belle et al. (2018), with particular stigma related to motivation, talent, and trainability.

Second, applicants with career breaks for education or training are typically assessed more favourably than those with unemployment gaps. This premium arises not only from their reduced susceptibility to skill erosion (consistent with human capital theory) but also because their commitment to skill development signals counter-stereotypical information, including increased motivation, intellectual ability, self-discipline, and flexibility – at least in comparison to unemployment (Dalle et al., 2024b; Kristal et al., 2023; Lockwood, 1991; Neumark, 2018; Weisshaar, 2021). Furthermore, queuing theory suggests these applicants are expected to be preferred since their engagement in training reflects an ability to rapidly absorb new information and adapt to workplace demands (Thurow, 1975). Their training-related absence from the labour market also provides a clear rationale for not seeking employment during this period, avoiding negative ability signals linked to rational herding.

Third, individuals who opted out of the workforce for caregiving purposes are often perceived as prioritising family over work, thereby signalling lower motivation, intellectual and social abilities, reliability, and flexibility when compared to the employed (Coltrane et al., 2013; Correll et al., 2007; Fernandez-Lozano, 2020; Petts et al., 2022; Sterkens et al., 2023; Van Borm & Baert, 2022; Weisshaar, 2018, 2021). However, it remains unclear how the intensity of these perceptions compares to those of the unemployed. Some scholars suggest that caregivers face greater penalties due to their violation of 'ideal worker' norms

(Weisshaar, 2018, 2021), whilst others report no significant differences in the evaluations of these applicant groups (Kristal et al., 2023; Tomlin, 2022).

Fourth, illness-related career gaps are also subject to disadvantageous treatment by employers when compared to those without career breaks since they raise concerns about intellectual and social abilities, reliability, and flexibility (Stergiou-Kita et al., 2016; Sterkens et al., 2023; van Beukering et al., 2022). For instance, individuals returning from sick leave are often assessed as less reliable due to an increased risk of future health-related relapses (Sterkens et al., 2023). However, the existing literature provides little clarity on the extent to which these health stigmas align with unemployment scarring.

Finally, applicants labelled as 'discouraged unemployed' are expected to elicit greater employer aversion than the merely 'unemployed' since this label explicitly confirms – and thus amplifies – the central stereotype of low motivation among the unemployed. Furthermore, since unemployed individuals with sufficient self-discipline typically manage to secure work eventually (Demazière, 2021), the discouraged are likely to be judged as deficient in self-discipline. Rational herding theory further underscores their adverse treatment, suggesting that employers may infer they have faced more frequent rejections than active job seekers (i.e. the unemployed), which in turn led to their demotivation in the job search process.

Grounded in these theoretical rationales, we first hypothesise that among individuals with periods of non-employment, applicants engaged in education or training during these periods will be rated most favourably regarding recruitment chances (H1a), whereas those categorised as discouraged unemployed will be rated least favourably (H1b). However, the literature does not provide sufficient theoretical foundations for applicants with caregiving gaps or long-term sickness absences to predict their hiring prospects relative to those of the unemployed. Second, related to human capital theory, we expect the perceptions of skill loss to be rated similarly across all groups, except for those who were in education or training (H2). Third, building on signalling theory, we anticipate that individuals with training periods will be rated higher than the other groups on the associated productivity perceptions (H3a), whereas the discouraged unemployed are expected to face the most severe penalties (H3b). In line with the aforementioned literature in general and with Van Belle et al. (2018) in particular, we will test the following productivity-related capabilities and traits: (i) motivation, (ii) intellectual abilities, (iii) social abilities, (iv) self-discipline, (v) reliability, and (vi) flexibility. Fourth, regarding queuing theory, applicants who were in education or training are expected to be rated higher than the unemployed in terms of expected trainability (**H4**). Fifth, in the context of rational herding theory, we hypothesise that applicants with training breaks, caregiving gaps, and illness-related lapses will be rated more favourably than the unemployed and the discouraged in terms of perceived rejection by other employers (**H5a**), with the discouraged receiving a lower evaluation than the unemployed (**H5b**).

Beyond the reason for being out of work, based on the literature, we identify two key moderators at the candidate level that can further alter unemployment and inactivity scarring: non-employment duration and gender.

First, longer employment gaps are expected to strengthen employers' perceptions of reduced skills, motivation, ability, and trainability (Arulampalam et al., 2000; Bonoli & Becker, 1964; D'hert et al., 2024; Hinrichs, 2012; Lockwood, 1991; Van Belle et al., 2018; Vishwanath, 1989). Hence, we anticipate that non-employment duration negatively impacts both hireability and perceptions linked to human capital, signalling, and queuing theory. However, longer career breaks are expected to indicate greater skill and ability accumulation for those engaged in education or training, resulting in a less outspoken interaction with non-employment duration (**H6**).

Second, concerning gender, empirical evidence suggests men typically face harsher penalties for career breaks since these are less common among men and thus more visibly conflict with ideal worker norms (Albrecht et al., 1999; Baert et al., 2016; Eriksson & Rooth, 2014; Van Borm & Baert, 2022). This disadvantage is expected to be particularly pronounced for men who opt out of the workforce for caregiving purposes (**H7**) since prior research has suggested that they are penalised more severely than female opt-outers (Albrecht et al., 1999; Wayne & Cordeiro, 2003; Weisshaar, 2018).

3. Experiment

To investigate whether, why, and when hiring prospects vary with job candidates' periods of non-employment, we conducted a factorial survey experiment – a method widely used to study behavioural intentions in specific decision-making processes (Auspurg & Hinz, 2014; Baert, 2018; Eriksson & Kristensen, 2014; Jasso, 2006; Sterkens et al., 2023; Van Belle et al., 2018). Over the past decade, this method has increasingly been employed to examine demand-side unemployment scarring effects and elucidate employers' reasoning within this context (McDonald, 2019; Shi & Di Stasio, 2022; Shi et al., 2018; Van Belle et al., 2018). Our study expands this approach to address inactivity scarring.

In studying employers' screening preferences, a vignette experiment tasks respondents with evaluating brief, carefully crafted profiles of hypothetical job applicants (i.e. vignettes) whose relevant characteristics (i.e. vignette factors) vary across predetermined categories (i.e. vignette levels) (Atzmüller & Steiner, 2010; Auspurg & Hinz, 2014). Hence, supply-side scarring effects due to job seekers' behaviour are ruled out by design.

A vignette experiment offers several methodological advantages. First, vignette studies enhance ecological validity relative to traditional surveys: varying the vignette characteristics obscures the study's objective, thereby reducing socially desirable responses and yielding more genuine reactions from participants (Auspurg & Hinz, 2014). Second, the internal validity of this method is superior to that of non-experimental methods since precise control over experimental manipulations minimises correlations among dimensions and facilitates causal interpretations of how these factors shape participants' judgements (Atzmüller & Steiner, 2010; Auspurg & Hinz, 2014; Sterkens et al., 2021, 2023; Van Belle et al., 2018). Therefore, this approach avoids unobserved variables that might bias outcome estimates, thus ensuring more accurate interpretations (Neumark, 2018). Additionally, unlike correspondence studies, vignette experiments are useful for gaining insights into the motivations related to employers' decisions (Auspurg & Hinz, 2024; Van Belle et al., 2018), which is one of this study's objectives.

3.1. Vignette design

Each participant was presented with profiles of five unique fictitious non-employed applicants, structured as tabulated vignettes.[4] These hypothetical profiles described applicants according to three key vignette factors: (i) reason for being out of work, (ii) duration of being out of work, and (iii) gender. All vignette factors and their respective levels are outlined in Table A1 of the Appendix and discussed below.

First, the focal vignette factor in this study is the reason for the non-occupational period, which comprised five levels: unemployment, participation in education or training, caregiving responsibilities for children or other family members, long-term illness, and discouragement due to the perceived unavailability of jobs. As outlined in the introduction, these categories were informed by established classifications of inactive individuals provided by Baert (2021) and the ILO (2016).

Second, beyond the reason for not working, the fictitious candidates within our experiment also differed in their non-employment duration. We opted for a quasi-continuous distribution to prevent the number of possible vignettes from inflating. As a result, duration was operationalised as five intervals (expressed in months): [1–2], [3–5], [6–11], [12–23], and [24–36]. After assigning an employment duration level to a participant, a random number from the interval was presented. This factor is pivotal to the study's design since it facilitates an investigation into whether inactivity scarring – akin to unemployment scarring – aggravates with prolonged periods of joblessness and whether the advantage for those in training amplifies over time. Following the experimental designs of Kroft et al. (2013) and Van Belle et al. (2018), the non-occupational period ranged from 1 to 36 months.

Third, as the final factor, each fictitious applicant was assigned a gender (male or female). Our literature review in Section 2 indicated that gender may moderate the hireability of candidates with employment gaps, suggesting that men with career breaks have lower recruitment chances than women, with this effect being more pronounced for men with care-related hiatuses.

The intersection of these three levels yielded a vignette universe of 50 (2 x 5 x 5) unique

[4] Following Auspurg and Hinz (2014), tabular vignettes were selected over textual vignettes for their superior fit in decision-making tasks, especially in evaluating hypothetical resumes against multiple criteria.

vignettes. These were allocated across 10 decks, each containing exactly one instance of each non-employment reason. Respondents were randomly assigned to one of these decks to enhance internal validity and optimise design efficiency (Auspurg & Hinz, 2014). The sequence of the vignettes within each deck was also randomised to mitigate order effects.

3.2. Data collection

Our experimental data were acquired through a web-based survey administered to professional recruiters in Flanders, the Dutch-speaking region of Belgium.[5] A total of 163 recruiters completed the survey, yielding 815 observations, since each recruiter evaluated five fictitious non-employed applicants. By using a sample of recruiters involved in real-life hiring processes, we strengthened the external validity of our experiment – specifically its participant validity. Recruiters were contacted through Belgium's largest job website, the Public Employment Agency of Flanders (PEAF; Delbeke, 2019), via invitations to recruiters' email addresses associated with vacancies deemed relevant to the study.

These vacancies varied by skill level, which allowed us to assess whether employers perceive non-employment differently depending on the type of job being applied for. The current literature on unemployment scarring lacks consensus on this issue. On the one hand, Eriksson and Rooth (2014) found that (long-term) unemployment mainly impacts hiring prospects for low- and medium-skilled jobs since highly-skilled candidates often have longer lapses due to searching for premium positions, with their skill level serving as a clearer productivity signal than a period of unemployment. On the other hand, Bonoli (2014) argued that unemployment is less critical for low-skilled jobs since productivity signals carry less weight for these jobs. We included jobs requiring varying intellectual, social, and technological skills to test which perspectives apply across different non-employment histories. The crossing of these three levels led to a selection of eight jobs.[6] This range of job

[5] The web-based survey was programmed in Qualtrics and conducted from July to December 2023 and February to April 2024.

[6] Combining the three skill levels (i.e. intellectual, social, and technological skills) in a (8x3) matrix, we identified the following eight jobs from the O*NET database as having the best fit: (i) order picker, (ii) CNC machine operator, (iii) telemarketer, (iv) telecommunications equipment installer, (v) cytogenetic technologist, (vi) computer programmer, (vii) insurance sales agent, and (viii) architect. Further details on job characteristics and descriptions are provided in Appendix Table A2.

types also further improves the generalisability of our experiment across different job markets, thus enhancing external validity.

3.3. Experimental procedure

Participants were guided through the experiment in four stages: (i) introduction, (ii) instructions, (iii) experimental evaluation, and (vi) post-experimental questionnaire. First, the introduction provided general information (e.g. the study concerns recruiting processes) and practical details (e.g. the survey will take approximately 10 minutes). Participants were also presented with a consent form outlining their rights and the confidential processing of their data. Upon confirming consent, participants proceeded to the second stage.

In the second stage of the experiment, participants were supplied with a description of one of the eight job vacancies (see Appendix Table A2), along with detailed instructions. They were informed that a fictitious human resources colleague had preselected candidates who formally met the roles' specific requirements (e.g. educational degree), differing by only a few characteristics summarised by this colleague. Participants were instructed to evaluate the candidates for possible interview selection, with no limit on the number of applicants they could shortlist.

During the third stage of the survey, participants were provided with five tabulated candidate profiles with randomly varied characteristics (in line with Appendix Table A1). Guided by these profiles, participants expressed their hiring recommendations by rating the likelihood of (i) inviting the candidate for a job interview (i.e. a proximal hiring outcome) and (ii) hiring the candidate for the job (i.e. a distal hiring outcome) on an 11-point Likert scale, in line with similar recent research (Dalle et al., 2024a; Sterkens et al., 2023; Van Belle et al., 2018). These outcomes facilitate the identification of hireability variations across non-employed candidates (H1a, H1b, H6, H7). Next, participants were prompted to evaluate these fictitious applicants across 11 perception variables linked to the four theories outlined in Section 2. First, we incorporated three statements associated with human capital theory (H2), scoring the candidate on (i) deterioration in general skills, (ii) decline in social skills, and (iii) awareness of technological evolutions (Oberholzer-Gee, 2018; Van Belle et al., 2018). Second, participants assessed six statements related to signalling theory (H3a, H3b), asking participants whether they believed the candidate possessed a sufficient level of the following capabilities and traits: (i) motivation, (ii) intellectual abilities, (iii) social abilities, (iv) self-discipline, (v) reliability, and (vi) flexibility to perform properly in the job (Sterkens et al., 2023; Van Belle et al., 2018; Van Borm & Baert, 2022; Weisshaar, 2018). Third, in line with queuing theory (H4), participants were probed on the candidate's level of perceived trainability (Di Stasio, 2014; Van Belle et al., 2018). Fourth, participants indicated whether they believed that the candidate had often been rejected by other employers – a statement linked to rational herding theory (H5a, H5b; Oberholzer-Gee, 2008; Van Belle et al., 2018). The outcomes of these perception variables provide insights into how recruiters assess applicants differently based on their type of career break. All statements are detailed, signal by signal, in Appendix Table A3.

Fourth, to conclude the survey, a post-experimental questionnaire gathered participant characteristics to be utilised within robustness checks. On the one hand, seven personal characteristics were collected: (i) gender (male, female, or other), (ii) age (open question), (iii) educational degree (primary degree, secondary degree (vocational, technical, or general), or tertiary degree (bachelor's, master's, or doctorate)), (iv) involvement in selection decisions (less than yearly, yearly, semesterly, monthly, weekly, or daily), (v) experience in selection decisions (less than 1 year, 1 to 5 years, more than 5 years), (vi) experience in selection decisions for the presented vacancy (11-point response scale), and (vii) occupational level (junior, senior, or managerial). On the other hand, to test the experiment's outcome for social desirability bias, participants' tendencies towards socially desirable answers were questioned using Steenkamp et al.'s (2010) widely applied scale, which includes 10 statements for egoistic response tendencies (ERT; $\alpha = 0.631$) and 10 statements for moralistic response tendencies (MRT; $\alpha = 0.717$).[7] For additional robustness checks, we surveyed familiarity with the 'unemployed' and 'inactive' terminology by asking if participants reviewed these applicants' profiles during the experiment (yes or no). Participants also rated the difficulty of the vignette decisions (11-point scale) and the realism of the fictitious candidate profiles (11-point scale).

[7] Internal consistency (measured using Cronbach's alpha) for the ERT scale is subpar; however, this statistic aligns with Steenkamp et al. (2010), who documented values between 0.49 and 0.79. Whilst the scales originally attained only moderate levels of internal consistency, such scores remain acceptable for research purposes.

3.4. Data description

Descriptives on the 163 participating recruiters (Appendix Table A4) reveal that the majority were women (63.8%) and people with a tertiary degree (86.5%), with an average age of 41. To test representativeness (i.e. population validity), we compared our sample's descriptive statistics with those of Belgian recruiters in the most recent European Social Survey, showing a similar gender distribution, educational profile, and average age.[8] Furthermore, 44.8% of participants were engaged in hiring decisions at least daily, 62.6% had more than 5 years of recruitment experience, and the majority reported above-average familiarity with the vacancies presented in the experiment (sample average: 6.822; scale midpoint: 5.000). Most participants make hiring decisions from a managerial position (66.9%).

Furthermore, our respondents scored slightly above average on the ERT (sample average: 4.623) and MRT (sample average: 4.150) scales, given that the averages of these scales were equal to 4. The vast majority recognised that they had judged both an unemployed (90.2% selected 'yes') and an inactive candidate (93.3% selected 'yes'). They also found the vignette decisions to be moderately difficult (sample average: 4.914; scale midpoint: 5.000) and rated the candidate profiles as relatively realistic (sample average: 6.012; scale midpoint: 5.000).

4. Results

Here, we report the results of our vignette experiment. First, we cover career gap effects on both interview and hiring probability (Subsection 4.1; H1a, H1b). Second, we examine the productivity perceptions recruiters form based on the different non-occupational reasons (Subsection 4.2; H2, H3a, H3b, H4, H5a, and H5b). Third, we assess the heterogeneity in the relationship between the different reasons for being out of work and the corresponding interview and hiring probabilities (Subsection 4.3; H6, H7)

[8] In line with Sterkens et al. (2021), we retrieved Belgian data from the most recent wave of the ESS (2023) for the following ISCO-08 codes: 1212 (Human resource managers), 2423 (Personnel and careers professionals), 3333 (Employment agents and contractors) and 4416 (Personnel clerks).

4.1. Effects of various career hiatus explanations on hiring chances

To examine whether recruiter preferences differ among the non-employed, we conducted multivariate regressions investigating whether applicants with a training break were preferred over others (H1a) and whether the discouraged were penalised most severely (H1b). Additionally, this approach enabled us to determine the relative rankings of former full-time caregivers and the previously ill. The interview and hiring probabilities served as the dependent variables, whilst the applicant's reason for being out of work (i.e. unemployment, education or training, care of family, own illness, or discouragement) was the primary independent variable. Unemployment was used as the reference situation, with controls for the other candidate characteristics as well as the job and participant characteristics. Furthermore, standard errors were adjusted for clustering of the observations at the participant level since each participant evaluated five fictitious candidates. Pairwise *F*-tests were employed to assess whether outcomes differed significantly across non-employment reasons. The multivariate regressions for both interview and hiring probability are presented in Table 1.

< Table 1 about here >

Our results reveal a distinct ordering among the applicants, accounting for all candidate, job, and participant characteristics. This ranking supports hypotheses (H1a) and (H1b), as detailed in the theoretical background (see Section 2), and successfully positions former full-time caregivers and the previously ill relative to the other non-employed applicants.

Compared to the unemployed, those engaged in education or training enjoy notable recruitment benefits, with a 14.81 ($p < 0.001$) percentage point higher interview likelihood and a 16.37 ($p < 0.001$) percentage point higher chance of being hired.[9] These represent the highest hireability scores among all applicant groups, as verified by pairwise *F*-tests for equality (all significant at the $p < 0.001$ level). This result supports our hypothesis (H1a) that those in education or training are preferred over all other non-employed applicants. Similarly, the recruitment chances of those who neither worked nor actively sought employment (i.e. the discouraged unemployed) are consistent with our theoretical

[9] Measured on a 0 to 10 scale, regression coefficients are converted to percentage point differences relative to the reference category when multiplied by 10.

expectations outlined in Section 2 (**H1b**). Recruiters heavily penalise their lack of job search activity, decreasing interview probability by 12.18 ($p < 0.001$) percentage points and hiring prospects by 8.73 ($p < 0.001$) percentage points when compared to active job seekers. Relative to all other non-employed applicants, the discouraged unemployed perform markedly worse, with all pairwise *F*-tests confirming these differences at the $p < 0.001$ level.

For the other types of career breaks, where our theoretical background did not propose a clear ranking relative to the unemployed, our results indicate that candidates with caregiving-related employment hiatuses are favoured over the unemployed. They exhibit higher probabilities for both interviews (β = 1.013, $p < 0.001$) and hiring (β = 1.066, p = 0.001). On the other hand, for applicants with health-related lapses, recruiters' hireability assessments are comparable to those of the unemployed.

Since pairwise comparisons between the hireability outcomes of the different non-employed applicants (i.e. *F*-tests for equality) were all significant at the $p < 0.001$ level, a clear recruitment ranking emerges across unemployed and inactive applicants. A break due to education or training ranks highest with the strongest positive effect, followed by a care-related hiatus, both of which are perceived more favourably than unemployment. A sickness leave ranks close to an unemployment lapse, whilst a gap due to discouragement occupies the lowest rank in the hierarchy.

To verify our results' robustness, we first re-ran the linear regressions whilst excluding the top 5% of participants scoring highest on the ERT (i.e. 16 participants) and MRT scales (i.e. 11 participants). The outcomes of this robustness check are presented in Appendix Table A5. Second, additional checks (i) excluded participants who reported seeing neither an unemployed nor an inactive candidate in the presented vignettes – indicating potential inattention or unfamiliarity with terminology; (ii) excluded the top 10% of participants who believed that the vignette decisions were challenging; and (iii) excluded the top 10% who perceived the vignettes as unrealistic. Third, we re-estimated our results using ordered logistic regressions. None of these robustness checks altered the main effects from the complete, unrestricted sample. Full results are available upon request.

Beyond the reason for non-employment, the duration of the lapse itself strongly shapes job prospects: each additional month out of work lowers interview and hiring chances by 0.56 ($p < 0.001$) and 0.41 ($p < 0.001$) percentage points, respectively. This finding aligns with previous studies on the impact of unemployment duration on candidate evaluations (Dalle et al., 2024a; D'hert et al., 2024; Eriksson & Rooth, 2014; Kroft et al., 2013; Van Belle et al., 2018). Additionally, career breaks tend to impose greater penalties on men than women ($\beta = -0.259$, $p = 0.080$ for interview and $\beta = -0.336$, $p = 0.005$ for hiring probability), again confirming previous research (Baert et al., 2016; Eriksson & Rooth, 2014; Weisshaar, 2018).

4.2. Signals of various career hiatus explanations

To clarify why recruiters' judgements of non-employed applicants vary by reason (H2, H3a, H3b, H4, H5a, and H5b), we probed participants' perceptions of each type of hiatus. Employing the multivariate regressions from Subsection 4.1, we substituted hireability outcomes with the 11 candidate perception variables discussed in Subsection 3.3. The results for these perceptions are presented below, organised according to their respective theoretical frameworks. All findings remain robust under the aforementioned checks.

< Table 2 about here >

Table 2 summarises the impacts of the various reasons for being out of work on recruiter perceptions.[10] Concerning the statements related to human capital theory, we first found variation in perceptions of skill loss across nearly all non-employed groups (most pairwise *F*-tests reach significance at the $p < 0.001$ level). These results challenge our hypothesis (H2) that human capital loss is perceived similarly for former caregivers, the previously ill, the unemployed, and the discouraged. More specifically, recruiters attribute additional social skill loss and technological delays to the discouraged unemployed vis-à-vis the other non-employed ($p < 0.05$ for all comparisons), which aligns with their low recruitment prospects (as detailed in Subsection 4.1). Similarly, human capital perceptions of former caregivers correspond to their higher hiring probabilities when compared to the (discouraged) unemployed: they are considered to be at a significantly ($p < 0.01$) lower risk of general skill decay, social skill decay, and technological freeze. Applicants with illness-related lapses are also considered less prone to being outdated with technologies than the (discouraged) unemployed (*p*-values are significant at the $p < 0.05$ level). Second, aligning with our

[10] Job and participant characteristics are not presented for conciseness and limited relevance, as these variables yielded few significant results, similar to Table 1. The full tables are available upon request.

hypothesis (H2), those in training are perceived as having the strongest human capital among all the non-employed. Recruiters view them as less susceptible to general skill loss, social skill loss, and technological stagnation (nearly all *p*-values show significance with $p < 0.001$). These perceptions are consistent with their top-ranked recruitment outcomes (reported in Subsection 4.1).

Turning to signalling theory, our results reflect our hypotheses (H3a and H3b) and reveal a clear ranking among the different non-employed applicant groups based on productivity-related signals. This ranking closely mirrors the recruitment assessments presented in Subsection 4.1: across all these productivity-related signals, those in education or training score the highest, followed by former caregivers, the previously ill, the unemployed, and finally, the discouraged. Below, we detail productivity signals by non-employment type.

Applicants with an employment break related to education or training received higher ratings across all perceptions than the other non-employed applicants (supporting H3a). The *p*-values associated with the coefficients comparing education or training with unemployment, as well as those associated with the *F*-tests comparing education or training with the other inactivity conditions, indicate that those in education or training are highly significantly seen as more motivated, intellectually capable, socially adept, self-disciplined, reliable, and flexible. Consistent with their higher recruitment prospects, our findings highlight that training periods convey counter-stereotypical information (Dalle et al., 2024b; Kristal et al., 2023; Lockwood, 1991; Weisshaar, 2021).

Similarly, the productivity perceptions of non-employed individuals who were discouraged from job seeking fit our hypothesis (H3b). As theoretically expected, they were rated the lowest in terms of motivation and self-discipline when compared to the other groups. Furthermore, they also score poorly across all other productivity estimations, including intellectual and social know-how, reliability, and flexibility. Again, all *p*-values for the coefficients comparing discouragement and unemployment and *F*-tests for the comparison between the inactive groups are highly significant. Evidently, disclosing a lack of effort in job searching triggers highly negative productivity perceptions.

For applicants with caregiving pauses, the literature has not established how the productivity signals associated with such breaks compare to those of other non-employed groups. However, our findings indicate that caregiving pauses are judged significantly more positively than those of the previously ill, the unemployed, and the discouraged. Caregivers are thought to be more motivated, intellectually capable, self-disciplined, and reliable. Interestingly, their social ability scores are on par with those of individuals in education or training, indicating that caregivers are perceived as highly sociable. However, their perceived flexibility is rated much lower and does not differ significantly between caregivers, the unemployed, and the previously ill. This finding likely reflects assumptions about ongoing caregiving duties – a bias commonly associated with mothers (Correll et al., 2007). Hence, contrary to previous findings by Weisshaar (2018, 2021), which suggested that opting out for care violates 'ideal worker' norms, our results show no such penalty. Instead, recruiters seem to regard caregiving as relevant experience, as Tomlin (2022) suggested.

Next, applicants with an inactivity period due to illness score significantly higher on all productivity perceptions versus the unemployed and the discouraged. Despite their inability to work or job search, they are perceived as more motivated, with higher intellectual and social abilities. They also receive higher ratings for self-discipline, reliability, and flexibility. However, these results contrast with their recruitment chances, which do not significantly differ from those of the unemployed. This discrepancy may stem from illness being less linked to an applicant's abilities, instead prompting concerns about potential health-related costs, as Sterkens et al. (2023) argued.

In the context of the specific applications of signalling theory – i.e. queuing theory and rational herding theory – our findings fully support the hypotheses (H4, H5a, and H5b). First, consistent with queuing theory, those who pursued education or training during their break score significantly higher on trainability (in line with H4), the construct operationalising this theory. Furthermore, recruiters also differentiate other non-employed applicants based on this theory. Those with caregiving breaks and sickness-related leaves rank higher than the unemployed on the trainability scale; however, they do not differ significantly from one another. The discouraged unemployed again receive lower ratings than the unemployed.

Second, regarding rational herding theory, we find that those with training, caregiving, and illness-related breaks are perceived as having experienced fewer rejections by other employers when compared to the (discouraged) unemployed (confirming H5a). Additionally, significant differences also emerge among these three groups: even without engaging with recruiters during their break, those in training are thought to have faced the fewest rejections from other recruiters, followed by former caregivers, and the previously ill. Discouraged unemployed applicants are assessed as the most prone to refusals by other employers – a result that echoes our expectations (H5b).

Concerning the other candidate characteristics, our findings partially support our theoretical background in Section 2. Indeed, all recruiter perceptions over the four theories worsen with increasing gap duration, yet men are not consistently judged more negatively following a career break. Most results for gender are only marginally significant, although men with career gaps are viewed as less self-disciplined than women (β = −0.448, $p < 0.001$).

4.3. Heterogeneity in the relationship between various career hiatus explanations and hiring chances

To examine how the specific stigmas associated with different non-employment types vary by duration and gender (H6 and H7), we broadened our benchmark regressions with interaction terms. In specifications (1) and (3) of Table 3, we added interactions between the non-employment reasons and both duration and gender for interview and hiring probability. Specifications (2) and (4) extend this analysis by including interaction terms with job and participant characteristics.

< Table 3 about here >

For the interactions with non-employment duration, we find that the longer this duration is, the more positively training periods affect interview (β = 0.083, $p = 0.001$) and hiring (β = 0.071, $p < 0.001$) probabilities relative to the unemployed and controlled for (interactions with) other characteristics. This premium applies to the first 36 months of the training period (i.e. the maximum duration examined in this experiment), beyond which no conclusions can be drawn. For the remaining reasons, no interaction effect with duration emerges, indicating that the biases against these candidates evolve comparably to those for unemployment over time. Thus, whilst hiring prospects are inversely related to duration for most career breaks, education stands as the sole explanation not penalised by longer durations, potentially signalling skill acquisition, which is in line with hypothesis (H6). This interaction effect persists across all the robustness checks mentioned in Subsection 4.1.

Upon examining the interaction between gender and career break reason, we find no significant results, with the exception that caregiving gaps, when compared to periods of unemployment, are less detrimental for men (β = 0.825, p = 0.080). However, this effect is only marginally significant for hiring probability. This finding contrasts with our expectations (H7) and Weisshaar's (2018) results, indicating that men receive greater disapproval for such gaps but aligns with research on employer aversion toward parents, where mothers face adverse treatment whilst fathers do not (Correll et al., 2007; El Haj et al., 2024).

Although no theoretical rationale supports anticipating interaction effects at other levels, we conducted secondary analyses to explore interactions between the employment break histories and job and participant characteristics. This absence of theoretical grounding is mirrored in our results, which indicate that hiring decision levels are not significantly influenced by any other job or participant characteristics. Results are available upon request.

5. Conclusion

Raising the employment rate is a core ambition for European governments to safeguard social security systems, prioritising the activation of unemployed and inactive individuals. Although current research extensively documents the scarring effects of unemployment on hiring prospects, employers' assessments of other non-employed applicants (e.g. former caregivers or the previously ill) remain understudied. Given their potential as a substantial untapped labour resource, it is essential to understand the demand-side biases they encounter in hiring processes. The current research advances the unemployment scarring literature by extending it to inactivity scarring. We employed a state-of-the-art factorial survey experiment in which genuine recruiters evaluated fictitious candidates who varied in their reasons for being out of work. Recruiters assessed contact and hiring probability and evaluated 11 theoretically relevant signals. This experimental approach allows for the detection of heterogeneity in employers' hiring preferences across distinct non-employed subgroups and offers insights into the productivity-related signals recruiters associate with these employment hiatuses. This is the first study to incorporate all relevant non-employed groups within a single experimental framework, thereby enabling a direct comparison of their recruitment chances and the associated stigma.

Our study shows employers use non-employment histories as a sorting tool to rank applicants. More concretely, such applicants are ranked in descending order as follows: (i) those with education or training breaks, (ii) former caregivers, (iii) the previously ill and the unemployed, and last, (vi) the discouraged. These hireability outcomes closely correspond with employers' perceptions of each non-employed group. Training breaks are perceived most positively, receiving the highest ratings for skills, motivation, intellectual abilities, self-discipline, reliability, flexibility, trainability, and minimal rejection by other employers. Care-related gaps rank second, excelling in terms of perceived social skills but failing on flexibility perceptions, presumably due to concerns about potential scheduling conflicts with family responsibilities. Illness-induced inactivity ranks third, eliciting more favourable perceptions than unemployment; however, health-related concerns likely limit their hiring rates. Discouragement-based unemployment triggers the most severe productivity stigma. Overall, hiring prospects are inversely related to non-employment durations, except for those engaged in education or training, since prolonged non-employment periods further reinforce their advantage over the unemployed. Additionally, men are more prone to hiring penalties, potentially due to more substantial deviations from ideal worker norms.

From a practical perspective, our results highlight that clarifying career breaks on a resume may prove advantageous for hiring prospects, which aligns with previous non-employment scarring studies (Eriksson & Rooth, 2014; Namingit et al., 2021). Candidates who paused their careers to pursue education or training should highlight this since employers perceive such breaks as a valid non-employment reason, antidoting the stigma of unemployment. In any case, pursuing training during a period of inactivity is a beneficial strategy, and even signalling a willingness to engage in training can have a positive impact on hiring chances (Dalle et al., 2024b). Hence, it is pertinent for policymakers to facilitate upskilling initiatives for formerly non-employed individuals as they re-enter the job market. Similarly, employers also value caregiving gaps, particularly for their association with social skills, which supports Tomlin's (2022) perspective that caregiving reflects relevant experience. However, these applicants should anticipate potential employer concerns regarding reduced flexibility. For illness-related gaps, employers' hiring reluctance is likely to revolve around health implications rather than perceived productivity deficits. Following Sterkens et al. (2021, 2023), candidates should aim to alleviate these concerns by indicating full recovery or regained resilience on their resumes, for instance. Finally, employers exhibit limited sympathy for applicants who refrained from job seeking due to perceived job market mismatches, making it advisable to omit such reasons from a resume. However, preventing discouragement should be the primary focus to maintain job seekers' hireability. Targeted policy interventions, such as job search assistance programmes, have proven effective in achieving this goal (Card et al., 2010). This recommendation is consistent with previous research highlighting that swift transitions into employment are most effective in mitigating unemployment scarring (D'hert et al., 2024).

However, our experimental setup is not without research limitations. First, concerns about the ecological validity of results obtained in a laboratory versus a field setting may arise, given the hypothetical nature of the former. We sought to mitigate this limitation by withholding the study's true objective from participants; however, some may have inferred its purpose due to the limited number of candidate characteristics. Additionally, participants were prompted to make realistic trade-offs resembling actual hiring decisions. Whilst the potential for socially desirable response patterns existed, we addressed this issue by incorporating a social desirability scale for robustness checks, thereby demonstrating that excluding this scale's highest-scoring respondents did not impact our results. However, future studies could include a broader range of candidate characteristics to better obscure the study's goal and achieve higher ecological validity. Second, claiming causality for the effects of the signalling variables on employers' decisions is not possible since these signals were not randomly assigned. Consequently, we did not conduct a mediation analysis. Notably, future field experiments could determine whether these signals genuinely drive employers' decision-making processes regarding the non-employed. Third, our design employed rather limited definitions for the different reasons for inactivity. For instance, for applicants with illness-related lapses, specifying the type of illness may yield different results. Certain health conditions (e.g. AIDS) may be perceived as being within an individual's control, placing blame on the individual and associating them with negative traits; while other illnesses (e.g. cancer) are viewed as beyond one's control and are likely to elicit fewer negative perceptions (Deacon, 2006; Karren & Sherman, 2013; Krug et al., 2019; Norlander et al., 2020). Similar effects could pertain to different training or caregiving contexts. Therefore, future research should further distinguish different scenarios within specific inactive subgroups to determine their influence on employers' decisions and perceptions.

References

Acemoglu, D. (1995). Public policy in a model of long-term unemployment. *Economica*, *62*(246), 161–178. https://doi.org/10.2307/2554901

Albrecht, J. W., Edin, P. A., Sundström, M., & Vroman, S. B. (1999). Career interruptions and subsequent earnings: A reexamination using Swedish data. *Journal of Human Resources*, *32*(2), 294–311. https://doi.org/10.2307/146347

Arulampalam, W., Booth, A. L., & Taylor, M. P. (2000). Unemployment persistence. *Oxford Economic Papers*, *52*(1), 24–50. https://doi.org/10.1093/oep/52.1.24

Atkinson, J., Lesley, G., & Meager, N. (1996). Employers, recruitment and the unemployed. The Institute for Employment Studies. https://www.employment-studies.co.uk/system/files/resources/files/325.pdf

Atzmüller, C., & Steiner, P. M. (2010). Experimental vignette studies in survey research. *Methodology*, *6*(3), 128–138. https://doi.org/10.1027/1614-2241/a000014

Auspurg, K., & Hinz, T. (2014). *Factorial survey experiments*. SAGE.

Ayllón, S. (2013). Unemployment persistence: Not only stigma but discouragement too. *Applied Economics Letters*, *20*(1), 67–71. https://doi.org/10.1080/13504851.2012.681020

Aysun, U., Bouvet, F., & Hofler, R. (2014). An alternative measure of structural unemployment. *Economic Modelling*, *38*, 592–603. https://doi.org/10.1016/j.econmod.2014.02.009

Baert, S. (2018). Hiring a gay man, taking a risk? A lab experiment on employment discrimination and risk aversion. *Journal of Homosexuality*, *65*(8), 1015–1031. https://doi.org/10.1080/00918369.2017.1364950

Baert, S. (2021). The iceberg decomposition: A parsimonious way to map the health of labour markets. *Economic Analysis and Policy*, *69*, 350–365. https://doi.org/10.1016/j.eap.2020.12.012

Baert, S., De Visschere, S., Schoors, K., Vandenberghe, D., & Omey, E. (2016). First depressed, then discriminated against? *Social Science and Medicine*, *170*, 247–254. https://doi.org/10.1016/j.socscimed.2016.06.033

Baert, S., & Verhaest, D. (2019). Unemployment or overeducation: Which is a worse signal to employers? *De Economist*, *167*(1), 1–21. https://doi.org/10.1007/s10645-018-9330-2

Banerjee, A. (1992). A simple model of herd behavior. *The Quarterly Journal of Economics*, *107*(3), 797–817. https://doi.org/10.2307/2118364

Barr, N. (2006). Pensions: Overview of the issues. *Oxford Review of Economic Policy*, *22*(1), 1–14. https://doi.org/10.1093/oxrep/grj001

Becker, G. S. (1962). Human capital: A theoretical analysis. *Journal of Political Economy*, *70*(5), 9–49. http://www.jstor.org/stable/1829103

Blanchard, O. J., & Diamond, P. (1994). Ranking, unemployment duration, and wages. *Review of Economic Studies*, *61*, 417–434. https://doi.org/10.2307/2297897

Bonoli, G. (2014). Employers' attitudes towards long-term unemployed people and the role of activation in Switzerland. *International Journal of Social Welfare*, *23*(4), 421–430. https://doi.org/10.1111/ijsw.12086

Bonoli, G., & Hinrichs, K. (2012). Statistical discrimination and employers' recruitment: Practices for low-skilled workers. *European Societies*, *14*(3), 338–361. https://doi.org/10.1080/14616696.2012.677050

Brandolini, A., Viviano, E. (2018). Measuring employment and unemployment. *IZA World of Labor*, *445*. https://doi.org/10.15185/izawol.445

Calvó-Armengol, A., & Jackson, M. O. (2004). The effects of social networks on employment and inequality. *American Economic Review*, *94*(3), 426–454. https://doi.org/10.1257/0002828041464542

Card, D., Kluve, J., & Weber, A. (2010). Active labour market policy evaluations: A meta-analysis. The Economic Journal, 120(548), 452–477. https://doi.org/10.1111/j.1468-0297.2010.02387.x

Clark, A., Georgellis, Y., & Sanfey, P. (2001). Scarring: The psychological impact of past unemployment. *Economica*, *68*(270), 221–241. https://doi.org/10.1111/1468-0335.00243

Coltrane, S., Miller, E.C., DeHaan, T. and Stewart, L. (2013). Fathers and the flexibility stigma. *Journal of Social Issues*, *69*, 279–302. https://doi.org/10.1111/josi.12015

Connelly, B. L., Certo, S. T., Ireland, R. D., & Reutzel, C. R. (2011). Signalling theory: A review and assessment. *Journal of Management*, *37*(1), 39–67. https://doi.org/10.1177/0149206310388419

Correll, S. J., Benard, S., & Paik, I. (2007). Getting a job: Is there a motherhood penalty? *American Journal of Sociology*, *112*(5), 1297–1338. https://doi.org/10.1086/511799

Dalle, A., Verhofstadt, E., & Baert, S. (2024a). The subsidy trap: Explaining the unsatisfactory effectiveness of hiring subsidies for the senior unemployed. *Journal of Economic Behavior & Organization*, *227*, 106713. https://doi.org/10.1016/j.jebo.2024.106713

Dalle, A., Wybo, T., Baert, S., & Verhaest, D. (2024b). Age discrimination, apprenticeship training and hiring: Evidence from a scenario experiment (IZA Discussion Paper, No. 17225). https://ssrn.com/abstract=4929062

Deacon, H. (2006). Towards a sustainable theory of health-related stigma: Lessons from the HIV/AIDS literature. *Journal of Community & Applied Social Psychology*, *16*(6), 418–425. https://doi.org/10.1002/casp.900

Delbeke, K. (2019, October 9). VDAB blijft kampioen van jobzoektocht. *De Standaard*. https://www.standaard.be/cnt/dmf20191009_04654119

Demazière, D. (2021). Job search success among the formerly-unemployed: paradoxically, a matter of self-discipline. *Critical Policy Studies*, *15*(2), 192–208. https://doi.org/10.1080/19460171.2020.1746372

D'hert, L., Baert, S., & Lippens, L. (2024). Unemployment, inactivity, and hiring chances: A systematic review and meta-analysis (IZA Discussion Paper, No. 17141). http://dx.doi.org/10.2139/ssrn.4898321

Di Stasio, V. (2014). Education as a signal of trainability: Results from a vignette study with Italian employers. *European Sociological Review*, *30*(6), 796–809. https://doi.org/10.1093/esr/jcu074

Dorsett, R., & Lucchino, P. (2018). Young people's labour market transitions: The role of early experiences. *Labour Economics*, *54*, 29–46. https://doi.org/10.1016/j.labeco.2018.06.002

El Haj, M., Baert, S., Van Ootegem, L., Verhofstadt, E., & Lippens, L. (2024). Fertility, pregnancy, and parenthood discrimination in the labour market: A systematic review (IZA Discussion Paper, No. 17435). http://dx.doi.org/10.2139/ssrn.5015032

Eriksson, S., & Rooth, D.-O. (2014). Do employers use unemployment as a sorting criterion when hiring? Evidence from a field experiment. *American Economic Review*, *104*(3), 1014–1039. https://doi.org/10.1257/aer.104.3.1014

Eriksson, T., & Kristensen, N. (2014). Wages or fringes? Some evidence on trade-offs and sorting. *Journal of Labor Economics*, *32*(4), 899–928. https://doi.org/10.1086/676662

Feist, L. (2024). Imbalances between supply and demand: Recent causes of labour shortages in advanced economies (ILO Working Paper, No. 115). https://www.econstor.eu/bitstream/10419/296583/1/1888716649.pdf

Fernandez-Lozano, I., González, M. J., Jurado-Guerrero, T., & Martínez-Pastor, J. I. (2020). The hidden cost of flexibility: A factorial survey experiment on job promotion. *European Sociological Review*, *36*(2), 265–283. https://doi.org/10.1093/esr/jcz059

Gammarano, R. (2019). *Persons outside the labour force: How inactive are they really?* ILOSTAT. https://ilostat.ilo.org/persons-outside-the-labour-force-how-inactive-are-they-really/

Goodger, S., & Makay., M. (2024). *Employment policy*. European Parliament. https://www.europarl.europa.eu/factsheets/en/sheet/54/employment-policy

Hainmueller, J., Hangartner, D., & Yamamoto, T. (2015). Validating vignette and conjoint survey experiments against real-world behavior. *Proceedings of the National Academy of Sciences*, *112*(8), 2395–2400. https://doi.org/10.1073/pnas.1416587112

Harasty, C., & Ostermeier, M. (2020). Population ageing: Alternative measures of dependency and implications for the future of work (ILO Working Paper, No. 5). https://www.ilo.org/sites/default/files/wcmsp5/groups/public/@ed_emp/documents/publication/wcms_747257.pdf

ILO. (2016). *Key indicators of the labour market* (9th ed.). International Labour Organization. https://webapps.ilo.org/wcmsp5/groups/public/---dgreports/---stat/documents/publication/wcms_498929.pdf

ILO. (2024a). *Labour force participation rate by sex and age (annual)*. International Labour Organization. https://rshiny.ilo.org/dataexplorer15/?lang=en&segment=indicator&id=EAP_2WAP_SEX_AGE_RT_A

ILO. (2024b). *World employment and social outlook: Trends 2024*. International Labour Organization. https://www.ilo.org/publications/flagship-reports/world-employment-and-social-outlook-trends-2024

Jasso, G. (2006). Factorial survey methods for studying beliefs and judgments. *Sociological Methods & Research*, *34*(3), 334–423. https://doi.org/10.1177/0049124105283121

Karren, R., & Sherman, K. (2013). Layoffs and unemployment discrimination: A new stigma. *Journal of Managerial Psychology*, *27*(8), 848–863.

Keane, M. P., & Wolpin, K. I. (1997). The career decisions of young men. *Journal of Political Economy*, *105*(3), 473–522. https://doi.org/10.1086/262080

Kristal, A. S., Nicks, L., Gloor, J. L., & Hauser, O. P. (2023). Reducing discrimination against job seekers with and without employment gaps. *Nature Human Behaviour*, *7*(2), 211–218. https://doi.org/10.1038/s41562-022-01485-6

Kroft, K., Lange, F., & Notowidigdo, M. J. (2013). Duration dependence and labor market conditions: Evidence from a field experiment. *The Quarterly Journal of Economics*, *128*(3), 1123–1167. https://doi.org/10.1093/qje/qjt015

Krug, G., Drasch, K., & Jungbauer-Gans, M. (2019). The social stigma of unemployment: Consequences of stigma consciousness on job search attitudes, behaviour and success. *Journal for Labour Market Research*, *53*(1), 1–27. https://doi.org/10.1186/s12651-019-0261-4

Lockwood, B. (1991). Information externalities in the labour market and the duration of unemployment. *The Review of Economic Studies*, *58*(4), 733–753. https://doi.org/10.1111/1468-0297.00666

McDonald, P. (2019). How factorial survey analysis improves our understanding of employer preferences. *Swiss Journal of Sociology*, *45*(2), 237–260. https://doi.org/10.2478/sjs-2019-0011

Namingit, S., Blankenau, W., & Schwab, B. (2021). Sick and tell: A field experiment analyzing the effects of an illness-related employment gap on the callback rate. Journal of *Economic Behavior & Organization*, *185*, 865–882. https://doi.org/10.1016/j.jebo.2020.09.033

National Center for O*NET Development. (n.d.). *O*NET OnLine*. Retrieved January 22, 2023, from https://www.onetonline.org/

Neumark, D. (2018). Experimental research on labor market discrimination. *Journal of Economic Literature*, *56*(3), 799–866. https://doi.org/10.1257/jel.20161309

Norlander, P., Ho, G. C., Shih, M., Walters, D. J., & Pittinsky, T. L. (2020). The role of psychological stigmatization in unemployment discrimination. *Basic and Applied Social Psychology*, *42*(1), 29–49. https://doi.org/10.1080/01973533.2019.1689363

OECD. (2024). *Employment Outlook 2024*. Organisation for Economic CO-operation and Development. https://www.oecd.org/en/publications/oecd-employment-outlook-2024_ac8b3538-en.html

Pedulla, D. S. (2020). *Making the cut: Hiring decisions, bias, and the consequences of nonstandard, mismatched, and precarious employment*. Princeton University Press. https://psycnet.apa.org/record/2020-08078-000

Petts, R. J., Mize, T. D., & Kaufman, G. (2022). Organizational policies, workplace culture, and perceived job commitment of mothers and fathers who take parental leave. *Social Science Research*, *103*, 102651. https://doi.org/10.1016/j.ssresearch.2021.102651

Picchio, M., & Van Ours, J. C. (2013). Retaining through training even for older workers. *Economics of Education Review*, *32*, 29–48. https://doi.org/10.1016/j.econedurev.2012.08.004

Pissarides, C. A. (1992). Loss of skill during unemployment and the persistence of employment shocks. *The Quarterly Journal of Economics*, *107*(4), 1371–1391. https://doi.org/10.2307/2118392

Shi, L. P., & Di Stasio, A. V. (2022). Finding a job after unemployment—education as a moderator of unemployment scarring in Norway and German-speaking Switzerland. *Socio-Economic Review*, *20*(3), 1125–1149. https://doi.org/10.1093/ser/mwaa056

Shi, L. P., Imdorf, C., Samuel, R., & Sacchi, S. (2018). How unemployment scarring affects skilled young workers: Evidence from a factorial survey of Swiss recruiters. *Journal for Labour Market Research*, *52*(1), 7. https://doi.org/10.1186/s12651-018-0239-7

Shi, L. P., & Wang, S. (2022). Demand-side consequences of unemployment and horizontal skill mismatches across national contexts: An employer-based factorial survey experiment. *Social Science Research*, 104. https://doi.org/10.1016/j.ssresearch.2021.102668

Spence, M. (1973). Job market signalling. *The Quarterly Journal of Economics*, *87*(3), 355–374. https://doi.org/10.2307/1882010

Stergiou-Kita, M., Pritlove, C., & Kirsh, B. (2016). The “Big C”—stigma, cancer, and workplace discrimination. *Journal of Cancer Survivorship*, *10*, 1035–1050. https://doi.org/10.1007/s11764-016-0547-2

Sterkens, P., Baert, S., Rooman, S., & Derous, E. (2021). As if it weren’t hard enough already: Breaking down hiring discrimination following burnout. *Economics & Human Biology*, *43*, 101050. https://doi.org/10.1016/j.ehb.2021.101050

Sterkens, P., Sharipova, A., & Baert, S. (2023). Disclosing the 'Big C': What does cancer survivorship signal to employers? *The European Journal of Health Economics*, 25(4), 671–688. https://doi.org/10.1007/s10198-023-01618-2

Thurow, L. C. (1975). *Generating inequality: Mechanisms of distribution in the U.S. economy*. Basic Books.

Tomlin, B. (2022). Maternity breaks: Unemployment spells or relevant experience? *Journal of Economic Behavior & Organization*, *198*, 673–681. https://doi.org/10.1016/j.jebo.2022.04.015

Trzebiatowski, T. M., Wanberg, C. R., & Dossinger, K. (2020). Unemployed needn't apply: Unemployment status, legislation, and interview requests. *Journal of Management*, *46*(8), 1380–1407. https://doi.org/10.1177/0149206318823952

Van Belle, E., Di Stasio, V., Caers, R., De Couck, M., & Baert, S. (2018). Why are employers put off by long spells of unemployment? *European Sociological Review*, *34*(6), 694–710. https://doi.org/10.1093/esr/jcy039

van Beukering, I. E., Smits, S. J. C., Janssens, K. M. E., Bogaers, R. I., Joosen, M. C. W., Bakker, M., van Weeghel, J., & Brouwers, E. P. M. (2022). In what ways does health related stigma affect sustainable employment and well-being at work? A systematic review. *Journal of Occupational Rehabilitation*, *32*, 365–379. https://doi.org/10.1007/s10926-021-09998-z

Van Borm, H., Baert, S. (2022) Driving in the minds of recruiters: What triggers gender stereotypes in hiring? (IZA Discussion Paper, No. 15261). http://dx.doi.org/10.2139/ssrn.4114837

Vishwanath, T. (1989). Job search, stigma effect, and escape rate from unemployment. *Journal of Labor Economics*, *7*(4), 487–502. https://doi.org/10.1086/298218

Wayne, J. H., & Cordeiro, B. L. (2003). Who is a good organizational citizen? Social perception of male and female employees who use family leave. *Sex Roles*, *49*(5), 233–246. https://doi.org/10.1023/A:1024600323316

Weisshaar, K. (2018). From opt out to blocked out: The challenges for labor market re-entry after family-related employment lapses. *American Sociological Review*, *83*(1), 34–60. https://doi.org/10.1177/0003122417752355

Weisshaar, K. (2021). Employment lapses and subsequent hiring disadvantages: An experimental approach examining types of discrimination and mechanisms. *Socius*, *7*. https://doi.org/10.1177/23780231211019861

Declarations

Ethics approval and consent to participate

Participants were informed about the general aim of the study. Due to the nature of the experiment, participants could not be a priori informed about the study's exact objective. Consent to use the participants' data for research purposes was obtained prior to the start of the experiment.

Data and code availability

Data and code are available at https://osf.io/sgp9c.

Declaration of competing interest

The authors declare that they have no competing interests.

Funding

We acknowledge financial support from FWO (Research Foundation – Flanders) under grant number G073924N. In addition, Louis Lippens acknowledges funding from FWO under grant number 12AM824N.

CRediT authorship contribution statement

Liam D'hert: Conceptualisation, Methodology, Formal analysis, Investigation, Data curation, Writing – original draft, Writing – review & editing; **Louis Lippens**: Conceptualisation, Methodology, Investigation, Writing – review & editing; **Stijn Baert**: Conceptualisation, Methodology, Writing – review & editing, Supervision, Project administration, Funding acquisition.

Tables

Table 1. Regression results with interview and hiring probability as outcome variables

	Interview probability	Hiring probability
A. CANDIDATE CHARACTERISTICS		
Gender (ref. = Female)		
Male	−0.259† (0.147)	−0.336** (0.118)
Duration of being out of work (c.)	−0.056*** (0.006)	−0.041*** (0.005)
Reason for being out of work (ref. = Unemployment)		
Education or training	1.481*** (0.208)	1.637*** (0.186)
Care of family	1.013*** (0.205)	1.066*** (0.175)
Own illness	0.127 (0.223)	0.297 (0.189)
Discouragement	−1.218*** (0.219)	−0.872*** (0.182)
B. JOB CHARACTERISTICS		
Level of intellectual skills (ref. = Low)		
High	−0.029 (0.280)	−0.040 (0.232)
Level of social skills (ref. = Low)		
High	0.492† (0.291)	0.208 (0.231)
Level of technological skills (ref. = Low)		
High	−0.143 (0.290)	−0.109 (0.234)
C. PARTICIPANT CHARACTERISTICS		
Gender (ref. = Female)		
Male	−0.282 (0.323)	−0.339 (0.250)
Age (c.)	0.009 (0.015)	−0.006 (0.012)
Educational degree (ref. = Secondary education)		
Tertiary education	−0.073 (0.303)	−0.365 (0.289)
Involvement in selection decisions (ref. = Less than daily)		
Daily	−0.298 (0.322)	−0.294 (0.252)
Experience in selection decisions (ref. = Less than 5 years)		
More than 5 years	0.355 (0.333)	0.112 (0.276)
Experience in selection decisions for the presented vacancy (c.)	0.060 (0.051)	0.054 (0.039)
Occupation (ref. = Employee)		
Manager	−0.328 (0.367)	−0.151 (0.320)

Table 1. Regression results with interview and hiring probability as outcome variables (continued)

	Interview probability	Hiring probability
D. ADDITIONAL PARAMETERS AND DIAGNOSTICS		
F-tests for equality (*p*-value)		
Education or training and Care of family	0.000	0.000
Education or training and Own illness	0.000	0.000
Education or training and Discouragement	0.000	0.000
Care of family and Own illness	0.000	0.000
Care of family and Discouragement	0.000	0.000
Own illness and Discouragement	0.000	0.000

Notes. The following abbreviations are used: c. (continuous variable) and ref. (reference category). The outcome variable ranges from 0 (i.e. definitely no interview or hire) to 10 (i.e. definitely an interview or hire). The presented statistics are coefficient estimates, and their standard errors are in parentheses. Standard errors are corrected for the clustering of observations at the participant level. Intercepts are omitted. Significances are indicated as *** when $p < .001$, ** when $p < .01$, * when $p < .05$, and † when $p < .10$. The sample comprises 815 observations.

Table 2. Regression results with the perceptions as outcome variables

	Human capital theory			Signalling theory
	General skill loss	Social skill loss	Not up to date with technologies	Motivation
A. CANDIDATE CHARACTERISTICS				
Gender (ref. = Female)				
Male	−0.086 (0.161)	−0.051 (0.130)	−0.316* (0.129)	−0.241† (0.125)
Duration of being out of work (c.)	−0.042*** (0.008)	−0.028*** (0.006)	−0.062*** (0.007)	−0.036*** (0.006)
Reason for being out of work (ref. = Unemployment)				
Education or training	1.204*** (0.226)	0.965*** (0.193)	1.947*** (0.202)	1.632*** (0.202)
Care of family	0.662** (0.218)	0.677*** (0.182)	0.681** (0.194)	1.070*** (0.176)
Own illness	0.409† (0.215)	0.285 (0.174)	0.493* (0.205)	0.773*** (0.190)
Discouragement	−0.229 (0.230)	−0.455* (0.193)	−0.717*** (0.185)	−1.342*** (0.204)
B. JOB CHARACTERISTICS				
Included	Yes	Yes	Yes	Yes
C. PARTICIPANT CHARACTERISTICS				
Included	Yes	Yes	Yes	Yes
D. ADDITIONAL PARAMETERS AND DIAGNOSTICS				
F-tests for equality (*p*-value)				
Education or training and Care of family	0.004	0.084	0.000	0.000
Education or training and Own illness	0.001	0.000	0.000	0.000
Education or training and Discouragement	0.000	0.000	0.000	0.000
Care of family and Own illness	0.158	0.021	0.232	0.036
Care of family and Discouragement	0.000	0.000	0.000	0.000
Own illness and Discouragement	0.000	0.000	0.000	0.000

Table 2. Regression results with the perceptions as outcome variables (continued)

	Signalling theory			
	Intellectual abilities	Social abilities	Self-discipline	Reliability
A. CANDIDATE CHARACTERISTICS				
Gender (ref. = Female)				
Male	−0.195† (0.100)	−0.190† (0.104)	−0.448*** (0.109)	−0.211† (0.117)
Duration of being out of work (c.)	−0.024*** (0.004)	−0.020*** (0.005)	−0.029*** (0.005)	−0.030*** (0.005)
Reason for being out of work (ref. = Unemployment)				
Education or training	1.300*** (0.162)	1.149*** (0.148)	2.096*** (0.216)	1.509*** (0.186)
Care of family	0.990*** (0.134)	1.278*** (0.149)	1.499*** (0.182)	1.197*** (0.168)
Own illness	0.657*** (0.134)	0.485** (0.148)	0.810*** (0.189)	0.516** (0.174)
Discouragement	−0.477** (0.147)	−0.879*** (0.150)	−1.021*** (0.180)	−0.544** (0.171)
B. JOB CHARACTERISTICS				
Included	Yes	Yes	Yes	Yes
C. PARTICIPANT CHARACTERISTICS				
Included	Yes	Yes	Yes	Yes
D. ADDITIONAL PARAMETERS AND DIAGNOSTICS				
F-tests for equality (*p*-value)				
Education or training and Care of family	0.000	0.256	0.000	0.033
Education or training and Own illness	0.000	0.000	0.000	0.000
Education or training and Discouragement	0.000	0.000	0.000	0.000
Care of family and Own illness	0.002	0.000	0.000	0.000
Care of family and Discouragement	0.000	0.000	0.000	0.000
Own illness and Discouragement	0.000	0.000	0.000	0.000

Table 2. Regression results with the perceptions as outcome variables (continued)

	Signalling theory	Queuing theory	Rational herding theory
	Flexibility	Trainability	Rejection
A. CANDIDATE CHARACTERISTICS			
Gender (ref. = Female)			
Male	−0.079 (0.116)	−0.099 (0.117)	−0.293† (0.164)
Duration of being out of work (c.)	−0.038*** (0.005)	−0.036*** (0.006)	−0.044*** (0.008)
Reason for being out of work (ref. = Unemployment)			
Education or training	1.471*** (0.186)	1.730*** (0.199)	2.465*** (0.253)
Care of family	0.173 (0.187)	0.648*** (0.162)	1.642*** (0.235)
Own illness	0.311† (0.168)	0.444** (0.162)	0.527* (0.229)
Discouragement	−0.654*** (0.180)	−0.721*** (0.173)	−0.872*** (0.225)
B. JOB CHARACTERISTICS			
Included	Yes	Yes	Yes
C. PARTICIPANT CHARACTERISTICS			
Included	Yes	Yes	Yes
D. ADDITIONAL PARAMETERS AND DIAGNOSTICS			
F-tests for equality (*p*-value)			
Education or training and Care of family	0.000	0.000	0.000
Education or training and Own illness	0.000	0.000	0.000
Education or training and Discouragement	0.000	0.000	0.000
Care of family and Own illness	0.361	0.161	0.000
Care of family and Discouragement	0.000	0.000	0.000
Own illness and Discouragement	0.000	0.000	0.000

Notes. The following abbreviations are used: c. (continuous variable) and ref. (reference category). The outcome variable ranges from 0 (e.g. not motivated) to 10 (e.g. very motivated). The results for job and participant characteristics are included but not shown for conciseness; the full table is available upon request. The presented statistics are coefficient estimates, and their standard errors are in parentheses. Standard errors are corrected for the clustering of observations at the participant level. Intercepts are omitted. Significances are indicated as *** when p < .001, ** when p < .01, * when p < .05, and † when p < .10. The sample comprises 815 observations.

Table 3. Regression results with interview and hiring probability as outcome variables: two-way interactions included

	Interview probability		Hiring probability	
	(1)	(2)	(3)	(4)
A. CANDIDATE CHARACTERISTICS				
Gender (ref. = Female)				
Male	−0.544 (0.396)	−0.563 (0.404)	−0.565† (0.319)	−0.550† (0.323)
Duration of being out of work (c.)	−0.088*** (0.018)	−0.091*** (0.020)	−0.058*** (0.013)	−0.061*** (0.014)
Reason for being out of work (ref. = Unemployment)				
Education or training	0.529 (0.343)	1.682 (1.077)	1.118*** (0.298)	1.671† (0.907)
Care of family	0.195 (0.473)	1.288 (1.186)	0.568 (0.366)	0.301 (0.969)
Own illness	−0.420 (0.478)	1.669 (1.285)	−0.158 (0.390)	0.191 (1.142)
Discouragement	−1.720** (0.523)	−0.778 (1.282)	−1.082** (0.400)	−2.262† (1.148)
B. JOB CHARACTERISTICS				
Included	Yes	Yes	Yes	Yes
C. PARTICIPANT CHARACTERISTICS				
Included	Yes	Yes	Yes	Yes

Table 3. Regression results with interview and hiring probability as outcome variables: two-way interactions included (continued)

	Interview probability		Hiring probability	
	(1)	(2)	(3)	(4)
D. ADDITIONAL PARAMETERS AND DIAGNOSTICS				
INTERACTIONS WITH CANDIDATE CHARACTERISTICS				
Gender (ref. = Female)				
Male x Education or training	−0.077 (0.491)	−0.103 (0.502)	−0.565 (0.400)	−0.613 (0.409)
Male x Care of family	0.722 (0.527)	0.836 (0.547)	0.780† (0.448)	0.825† (0.468)
Male x Own illness	0.106 (0.616)	0.051 (0.626)	0.197 (0.523)	0.157 (0.533)
Male x Discouragement	0.548 (0.669)	0.564 (0.695)	0.580 (0.511)	0.596 (0.521)
Duration of being out of work (c.)				
Duration x Education or training	0.079*** (0.022)	0.083** (0.024)	0.065*** (0.018)	0.071*** (0.019)
Duration x Care of family	0.036 (0.030)	0.039 (0.031)	0.007 (0.020)	0.010 (0.020)
Duration x Own illness	0.037 (0.028)	0.033 (0.030)	0.027 (0.022)	0.023 (0.024)
Duration x Discouragement	0.016 (0.030)	0.018 (0.033)	−0.008 (0.023)	−0.006 (0.024)
INTERACTIONS WITH JOB CHARACTERISTICS				
Included	No	Yes	No	Yes
INTERACTIONS WITH PARTICIPANT CHARACTERISTICS				
Included	No	Yes	No	Yes

Notes. The following abbreviations are used: c. (continuous variable) and ref. (reference category). The outcome variable ranges from 0 (i.e. definitely no interview or hire) to 10 (i.e. definitely an interview or hire). The results for job and participant characteristics are included but not shown for conciseness; the full table is available upon request. The presented statistics are coefficient estimates, and their standard errors are in parentheses. Standard errors are corrected for the clustering of observations at the participant level. Intercepts are omitted. Significances are indicated as *** when $p < .001$, ** when $p < .01$, * when $p < .05$, and † when $p < .10$. The sample comprises 815 observations.

Appendix A: Additional tables

Table A1. Vignette factors and corresponding levels used in the experimental materials

Vignette factors	Vignette levels
Gender	{Male, Female}
Duration of being out of work	{[1 to 2 months], [3 to 5 months], [6 to 11 months], [12 to 23 months], [24 to 36 months]}
Reason for being out of work	{Unemployment, Education or training, Caregiving responsibilities for children or other family members, Long-term illness, Discouragement due to perceived unavailability of jobs}

Notes. The factorial product of the vignette levels (i.e. 2x5x5) resulted in 50 possible combinations. Ten sets of five vignettes were drawn from this vignette universe and distributed at random to the recruiters, as described in Section 3.1. As a result, the vignette factors were nearly orthogonal.

Table A2. Job characteristics and descriptions used in the experimental materials

Jobs	Characteristics			Descriptions
	Level of intellectual skills	Level of social skills	Level of technological skills	
Order picker	Low	Low	Low	This employee is responsible for keeping track of all incoming and outgoing goods, checking and processing deliveries, and assembling orders.
CNC machine operator	Low	Low	High	This employee is responsible for performing machining operations, identifying machine malfunctions, and carrying out basic machine maintenance.
Telemarketer	Low	High	Low	This employee is responsible for contacting potential customers to inform them about the company's products and services, as well as completing follow-up documentation.
Telecommunications equipment installer	Low	High	High	This employee is responsible for installing telephone, television, and internet systems, troubleshooting installation issues, and informing customers about the operation of the systems.
Cytogenetic technologist	High	Low	Low	This employee is responsible for analysing biological specimens, interpreting and recording test results, and maintaining quality control.
Computer programmer	High	Low	High	This employee is responsible for writing, analysing, and reviewing computer software, performing revisions on existing software, and maintaining documentation related to the software.
Insurance sales agent	High	High	Low	This employee is responsible for creating customised insurance packages for clients, providing the necessary information about the features of the packages, and processing damage claims.
Architect	High	High	High	This employee is responsible for designing construction plans, consulting with clients to align them with their preferences, and managing construction projects.

Notes. As explained in Subsection 3.2, the characteristics of the selected jobs varied to enhance generalisability. The selected characteristics were intellectual skills, social skills, and technological skills. The selection of the jobs and their corresponding descriptions were based on the O*NET database, an application developed by the U.S. Department of Labor featuring occupational information on job characteristics for over 900 occupations (National Center for O*NET Development, n.d.).

Table A3. Statements used in the experimental materials

Outcomes and perceptions	Statements
A. OUTCOMES	
Interview probability	I would invite this candidate for a job interview for the job.
Hiring probability	I would hire this candidate for the job.
B. PERCEPTIONS	
Signalling theory	
Perceived motivation	I believe this candidate possesses a sufficient level of motivation to perform properly in the job.
Perceived intellectual abilities	I believe this candidate possesses a sufficient level of intellectual abilities to perform properly in the job.
Perceived social abilities	I believe this candidate possesses a sufficient level of social abilities to perform properly in the job.
Perceived self-discipline	I believe this candidate possesses a sufficient level of self-discipline to perform properly in the job.
Perceived reliability	I believe this candidate possesses a sufficient level of reliability to perform properly in the job.
Perceived flexibility	I believe this candidate possesses a sufficient level of flexibility to perform properly in the job.
Queuing theory	
Perceived trainability	I believe this candidate possesses a sufficient level of trainability to perform properly in the job.
Human capital theory	
Perceived general skill loss	I believe this candidate has developed a deterioration in general skills relevant to the job.
Perceived social skill loss	I believe this candidate has developed a deterioration in social skills relevant to the job.
Perceived technological up-to-dateness	I believe this candidate possesses sufficient awareness of the technological evolutions in the field to perform properly in the job.
Rational herding theory	
Perceived rejection of other employers	I believe this candidate has often been rejected by other employers.

Notes. This table outlines the statements about selection outcomes and perceptions presented to participants in the online experiment. Participants assessed each statement on an 11-point Likert scale, ranging from 0 ('strongly disagree') to 10 ('strongly agree').

Table A4. Description of participant characteristics

	Proportion (indicator variables) or mean (continuous and scale variables)
Gender	
Male	0.362
Female	0.638
Age (c.)	41.399 (0.889)
Educational degree	
Secondary education	0.135
Tertiary education	0.865
Involvement in selection decisions	
Less than daily	0.552
Daily	0.448
Experience in selection decisions	
Less than 5 years	0.374
More than 5 years	0.626
Experience in selection decisions for the presented vacancy (s.)	6.822 (0.271)
Occupation	
Employee	0.331
Manager	0.669
Response tendencies	
Egoistic response tendencies (s.)	4.623 (0.052)
Moralistic response tendencies (s.)	4.150 (0.050)
Comprehension and attention check: unemployed candidate	
Yes	0.902
No	0.098
Comprehension and attention check: inactive candidate	
Yes	0.933
No	0.067
Perception about the difficulty of the vignette decisions (s.)	4.914 (0.234)
Perception about the realism of the vignettes (s.)	6.012 (0.210)

Notes. The following abbreviations are used: c. (continuous variable) and s. (scale consisting of multiple items scored from 1 to 7 (for the response tendency variables) and from 0 to 10 (for the other scale variables)). Standard errors for the means of the continuous and scale variables are in parentheses. The sample comprises 163 participants.

Table A5. Robustness checks on regression results with interview and hiring probability as outcome variables

	Excluding the upper 5% on the ERT scale [N=799]		Excluding the upper 5% on the MRT scale [N=804]	
	Interview probability	Hiring probability	Interview probability	Hiring probability
A. CANDIDATE CHARACTERISTICS				
Gender (ref. = Female)				
Male	−0.168 (0.153)	−0.245* (0.119)	−0.254† (0.149)	−0.712† (0.390)
Duration of being out of work (c.)	−0.057*** (0.006)	−0.042*** (0.005)	−0.057*** (0.006)	−0.097*** (0.017)
Reason for being out of work (ref. = Unemployment)				
Education or training	1.481*** (0.200)	1.660*** (0.181)	1.475*** (0.213)	0.404 (0.333)
Care of family	1.010*** (0.201)	1.108*** (0.171)	1.032*** (0.213)	−0.017 (0.467)
Own illness	0.089 (0.228)	0.274 (0.185)	0.132 (0.230)	−0.597 (0.482)
Discouragement	−1.137*** (0.215)	−0.805*** (0.168)	−1.229*** (0.223)	−2.074*** (0.514)
B. JOB CHARACTERISTICS				
Included	Yes	Yes	Yes	Yes
C. PARTICIPANT CHARACTERISTICS				
Included	Yes	Yes	Yes	Yes

Notes. The following abbreviations are used: ERT (Egoistic Response Tendency), MRT (Moralistic Response Tendency), c. (continuous variable) and ref. (reference category). The outcome variable ranges from 0 (i.e. definitely no interview or hire) to 10 (i.e. definitely an interview or hire). The results for job and participant characteristics are included but not shown for conciseness; the full table is available upon request. The presented statistics are coefficient estimates, and their standard errors are in parentheses. Standard errors are corrected for the clustering of observations at the participant level. Intercepts are omitted. Significances are indicated as *** when p < .001, ** when p < .01, * when p < .05, and † when p < .10. The sample comprises 815 observations.