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The Impact of Higher Education on Employer Perceptions

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The Impact of Higher Education on Employer Perceptions *

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Abstract

Do employers seek to attract individuals with more education because it enhances human capital or because it signals higher levels of pre-existing traits? We experimentally vary master's degree completion rates on applicant résumés and examine how this influences candidates' desirability and employer perceptions of their productive characteristics. Our findings show that while a completed master's degree increases desirability, an incomplete master's degree is perceived by human resource managers as less favorable than a bachelor's degree. This suggests that employers prefer candidates with higher education mainly because they view the degree as a signal of pre-existing productive traits. Consistent with this, employers perceive both cognitive and non-cognitive traits as stronger in master graduates but non-cognitive traits as weaker in master dropouts compared to bachelor's degree holders. Overall, perceived cognitive and non-cognitive traits play a larger role in determining a candidate's attractiveness than expertise. This paper thus provides causal evidence on the origins of the education premium.

Keywords: returns to education, beliefs, labor demand, labor productivity, signaling, wages
JEL-Codes: I23, I26, J23, J24, J31

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1 Introduction

Employers have an interest in hiring individuals who add value to their company. In this context, individuals with more education credentials are more attractive to employers, who reward them with higher wages and better employment prospects (see e.g. Ashenfelter and Ham, 1979; Card, 1999; Cunha et al., 2011; Falato and Milbourn, 2015; Piopiunik et al., 2017; Patrinos and Psacharopoulos, 2020; Altonji and Zhong, 2021; Cairó and Cajner, 2018). However, do employers seek to attract individuals with more education because it builds human capital or because it signals higher levels of pre-existing traits? Does a higher education certificate (or the lack thereof) prompt expectations about particular productive traits, acquired expertise, or candidate background? This paper provides causal answers to these questions by eliciting belief-related candidate judgment among employers in an experimental setting.

A substantial body of literature documents the causal effect of education on wages (Card, 2001; Moretti, 2004; Oreopoulos and Petronijevic, 2013; Gunderson and Oreopolous, 2020). However, the underlying reasons why employers value education remain a topic of ongoing debate. One explanation for the premium is that degree holders possess more human capital in the form of knowledge acquired during their studies (Becker, 1962; Schultz, 1963; Chevalier et al., 2004; Aryal et al., 2022). Alternatively, degrees may reflect productive but mostly pre-determined traits, such as IQ or personality traits, i.e., that relate to the psychic costs of studying and future employee productivity (Spence, 1973; Stiglitz and Weiss, 1990; Bedard, 2001; Chatterji et al., 2003; Caplan, 2018). Empirical models on the education premium typically incorporate years of schooling or education degrees (Mincer, 1974; Card, 2001), but provide little explicit evidence on *why* employers may seek workers with more education. Nonetheless, it is important for applicants, firms, and management to understand whether it is acquired expertise or other more fundamental traits that employers seek in higher-educated workers. This also holds importance for educational institutions, e.g., as regards the selection and promotion of students and graduates.

In this paper, we conduct a survey experiment among a large pool of human resource managers to assess employer's valuation of degree completion, as well as education-related beliefs about candidates' productive characteristics. Managers are randomly assigned three realistic résumés of fictitious applicants who have either completed, partly completed or not started a master's degree. Importantly, completed education is one of many varying résumé characteristics and it is *not* particularly emphasized to the managers. After reviewing each résumé, managers indicate the likelihood that their company would interview or hire the candidate, as well as the wage their company would most likely pay conditional on hiring. We then elicit managers' beliefs about each candidate's (i) expertise acquired at university, (ii) cognitive (trainability and IQ) traits, (iii) non-cognitive (perseverance, conscientiousness, commitment and emotional stability) traits, and (iv) socio-economic background. Cognitive and non-cognitive traits typically stabilize during childhood or adolescence whilst reliably predicting various behaviors throughout life (Hopkins and Bracht, 1975; Schuerger and Witt, 1989; Almlund et al., 2011; Cobb-Clark and Schurer, 2012). In line with this literature, we view these traits as mostly pre-determined. In contrast, we consider subject matter expertise as mostly acquired during one's studies.

Our analysis proceeds in three steps. First, we investigate how a degree (partially completed or completed) influences employer assessments of candidates' attractiveness. Second, we explore how employers' beliefs about candidates' acquired and pre-determined traits differ by educational attainment. Third, we decompose the education premium into belief-related mechanisms to understand the extent to which the elicited beliefs about latent traits can explain differences in candidate attractiveness.

First, we find that master's degree graduates are more desirable to employers than individuals with a bachelor's degree, as they have higher chances of being invited for an interview or offered a job and are proposed higher starting wages. On the contrary, an unfinished master's degree — even when all coursework has been successfully completed — makes candidates less desirable than those with only a bachelor's degree. This suggests that employers value higher education primarily as a signal of pre-existing skills rather than as an indicator of acquired human capital. Second, we show that, compared to holding a bachelor's degree, obtaining a master's degree increases employers' perceptions of a candidate's cognitive and non-cognitive traits, as well as their subject matter expertise. Dropouts, however, receive no credit for the expertise they gained while studying and are instead rated lower in terms of non-cognitive traits than individuals with only a bachelor's degree. Finally, we show that up to 75% of the education premium in interview and hiring probabilities can be attributed to differences in beliefs about candidates' characteristics, with cognitive and non-cognitive traits together accounting for a larger share than subject matter expertise. Taken together, this suggests that signaling traits plays a larger role than acquired expertise in determining candidates' desirability among employers.

This study contributes to several existing strands of literature. Methodologically, our work most closely relates to Heinz and Schumacher (2017) and Piopiunik et al. (2020), who also confront human resource managers with applicant résumés. Our study differs from these papers in that we focus on the causal effect of higher education credentials on candidate attractiveness. We further innovate by directly eliciting employer beliefs about a substantial number of unobserved candidate traits, thus speaking to a prominent literature that uses survey experiments to learn about economic expectations (Fuster and Zafar, 2023).

Our research further relates to literature using résumé-based audit studies to causally identify the importance of different worker characteristics. While audit studies have mainly been used to study racial or gender discrimination (Bertrand and Mullainathan, 2004; Oreopoulos, 2011; Kline et al., 2022; Ruffle and Shtudiner, 2015; Kang et al., 2016), they have also been employed to uncover how labor markets reward work experience, or type of educational institution (Deming et al., 2016; Lennon, 2021; Eriksson and Rooth, 2014; Farber et al., 2016; Nunley et al., 2016). For example, Deming et al. (2016) use an audit study to show that employers prefer applicants with degrees from public institutions over those with degrees from for-profits, and Gaulke et al. (2019) report no significant returns to a post-baccalaureate business certificate on the call-back rate. The most closely related study is Bennett

(2023), who conducts a correspondence study examining employers' responses to MBAs from less-selective universities and finds that candidates with MBAs receive no higher callback rates than those with only a bachelor's degree. In contrast to Bennett (2023), our fictitious applicants hold degrees from top-ranked universities and have less than one year of work experience, which may explain why we find a significantly positive effect of a master's degree on the probability of being invited for an interview. At present, no audit studies exist that compare the effects of partially completed degrees with those of fully completed degrees.

We chose an experimental approach over an audit study approach for three reasons: First, as our goal is to assess how human resource managers evaluate résumés with different levels of (non-)completed education, there is little concern about systematic biases that relate to norms or rules on how education "should" be assessed. While stereotypical assessments based on gender, race, or socio-economic status are viewed as discriminatory (and in some instances even illegal), it is commonly acceptable to evaluate a candidate based on their obtained educational credentials.[1] Second, since systematic biases are not a strong concern, we could choose a design that does not rely on deception.[2] Third, by relying on a survey experiment, we can study outcomes beyond call-back probabilities including beliefs about hiring probabilities, wages and – most importantly – a large vector of candidate characteristics. Yet, arguably, employers may behave differently when they know they are being studied or when they lack sufficient incentives. To address these concerns, we have taken several steps. Most notably, we (i) engaged human resource (HR) managers through a professional business partner company that acted as a "firewall" between the data collection and research teams, and (ii) explicitly tested the role of incentives within our framework in a supplementary data collection among individuals with hiring experience in Germany.

[1] In a supplementary data collection among individuals with hiring experience in Germany, we have explicitly asked respondents about the appropriateness of taking various factors into account when hiring. 93% reported that it was appropriate to take the level of education into account, but only 11% reported that gender should be a criterion in hiring (see Figure E.1).

[2] For a discussion of deception in audit studies, see Kessler et al. (2019).

By unveiling the underlying mechanisms behind the employer demand for higher education credentials, our findings speak to a large body of literature on the sources of returns to higher education, such as productivity differentials, sheepskin effects, human capital, or signaling (see, e.g., Weiss, 1995; Lange and Topel, 2006, for reviews). The corresponding empirical evidence on the relative importance of human capital versus signaling effects for (higher) education premia remains largely inconclusive (Patrinos and Psacharopoulos, 2020). While most recent studies find evidence in support of the human capital hypothesis (e.g., Layard and Psacharopoulos, 1974; Chevalier et al., 2004; Kroch and Sjoblom, 1994; Arteaga, 2018; Aryal et al., 2022) other findings are in line with important signaling effects (Hungerford and Solon, 1987; Jaeger and Page, 1996; Park, 1999; Bedard, 2001; Chatterji et al., 2003; Caplan, 2018; Hopkins, 2019). We contribute to this debate by examining employers' perceptions. Our experimental setup enables us to disentangle the effects of length of study from holding a degree on candidate attractiveness. Furthermore, it enables us to link attractiveness to employers' underlying beliefs about candidates' cognitive skills, non-cognitive skills, and expertise, providing insight into the relative importance of these traits. In this respect, our approach also aligns with a recent literature which argues that a richer and more flexible conceptualization of human capital is needed, comprising human capital dimensions that are often referred to as "soft-skills", "non-cognitive skills" or "higher-order skills" (Heckman and Rubinstein, 2001; Almlund et al., 2011; Deming, 2022; Edin et al., 2022; Deming and Silliman, 2024).

This literature on non-cognitive traits documents that in particular personality aspects related to conscientiousness and emotional stability prove valuable on the labor market (Almlund et al., 2011; Nyhus and Pons, 2005; Salgado, 1997). First, individuals with higher cognitive and non-cognitive traits are better at information processing and task completion. Second, these traits are both incentive-enhancing and related to intrinsic motivation, allowing employers to induce effort at lower costs (Bowles et al., 2001; Segal, 2012). Employers thus have an incentive to seek and interpret signals about cognitive and non-cognitive traits and to act upon these beliefs when selecting candidates.

Finally, this paper complements our own work focusing on students' expected returns to degree completion (Ehrmantraut et al., 2020) by focusing on the labor demand side.

The remainder of the paper is organized as follows. In section 2, we describe the sample recruitment procedure, survey design and main measures. Subsequently, section 3 describes our results for each of the three sub-questions and the robustness analysis. Finally, section 4 discusses our findings and concludes.

2 Study Design

2.1 Sample recruitment

Our survey experiment addresses human resource (HR) managers with real-life hiring responsibilities.[3] HR managers are a target group that hold strong interest for research on the labor market returns to education but are usually difficult to reach. To engage this group of professionals from a wide variety of industries, we drew on the same sample of top-level German HR managers whose judgment also provides the basis for the most well-known employer-based German university ranking ("Wirtschaftswoche Hochschulranking"). We include HR managers who 1) work for companies with at least ten employees, 2) are actively involved in hiring and 3) regularly hire business majors. The latter criteria is a prerequisite for our experimental set-up (see subsection 2.3).

HR managers were approached by a business partner company. The professional agency ensured that the quality of our data was very high. The agency that collected the data applied strict screening standards. They automatically excluded participants who took less than 4 minutes to complete the survey. They also excluded respondents who did not provide sensible answers to the open-ended questions. Based on these criteria, 485 HR managers were included in the sample. In our main analysis, we focus on respondents who filled in reasonable values for prospective

[3]The pre-registration of our survey experiment can be accessed at https://osf.io/tupw3.

wage offers, leaving us with a sample of 433 individuals (see Appendix C for more details on our cleaning procedure).[4] On average, participants took 10.5 minutes to finish the survey and participation was incentivized by a one-time fixed payment. We took several measures to ensure high data quality: (i) at no point in time were HR managers informed about the purpose of the study or asked to focus specifically on candidates' educational attainment; (ii) all respondents were approached during work hours and in their role as HR professionals to ensure truthful and unbiased evaluations; and (iii) the research team never interacted directly with the managers to reduce the risk of potential researcher demand effects. For descriptive statistics on the managers, the companies for which they work, and their hiring process, see Appendix table F.1.

2.2 Higher education system in Germany

The Bologna Process, launched in 1999 by 29 European countries and later adopted by 49 countries, aimed to harmonize higher education across Europe through a standardized three-tier system of bachelor's, master's, and doctoral degrees. The bachelor's degree, typically the first stage of higher education, takes three years to complete and is designed to prepare graduates either for direct entry into the workforce or for further study in a master's program. A master's degree builds upon the bachelor's, usually requiring an additional two years. As of 2022, the European Union had 18.8 million tertiary education students, with 59% enrolled in bachelor's programs and 29.4% pursuing master's degrees (Eurostat, 2024).

Germany began implementing this system in 2000, resulting in a substantial expansion of bachelor's and master's programs. During this time there has been a substantial rise in higher education participation in Germany. The proportion of a birth cohort entering higher education grew from 33% in 2000 to over 55% (Statistisches Bundesamt, 2024). Obtaining a master's degree is very common. Of those earning a bachelor's degree, approximately 45% continue on to pursue a master's degree (Statistisches Bundesamt, 2023). However, dropout rates for master's programs

[4] In the robustness section, we test the sensitivity of our results to sample selection.

are significant, with around 21% leaving their studies before completion (Heublein et al., 2022).

2.3 Applicant profiles

Each employer in our sample was asked to evaluate three hypothetical applicant profiles.[5] We presented a respective applicant's résumé, after which the employer answered several questions about her perception of the candidate (see subsection 2.4). The information on applicant résumés was displayed as realistically as possible. The layout was standardized, to ease screening and to avoid distraction or inference that may come from using different fonts or alignment of information. As many firms use online forms to collect applicant information, one may think of this standardized résumé information as output generated by one of these information systems. While all applicants are business majors, their profiles experimentally vary in terms of completed education, personal information, and work experience. We chose business majors because most companies hire business graduates irrespective of the type of industry. Moreover, business studies is the most relevant major in the German context, as it is by far the most popular field of study. In the academic year 2022/2023 there were 237,581 students — 8.1% of the total student population — enrolled in business studies, compared to, e.g., 143,582 students in informatics, the second most popular field of study. All applicant information displayed on the résumés was randomized at the respondent level (see Appendix B for more details).

Education - Our main characteristic of interest is the applicants' level of higher education obtained. Importantly, employers were not in any way primed or asked to focus on applicant education, and completed education was simply one of many résumé characteristics. We randomly vary between four education levels: (i) having only a bachelor's degree, denoted as Bsc.; (ii) having a bachelor's degree plus having completed 25% of a master studies (30 ECTS); denoted as Bsc.+25; (iii) having a

[5] Employers were asked to evaluate three applicant profiles, as evaluating four profiles was not feasible within the time constraints set by the professional agency.

bachelor's degree plus having completed 75% of a master studies (90 ECTS), denoted as Bsc.+75; or (iv) having completed a master's degree (120 ECTS), denoted as Msc.[6] Each respondent received three résumés.[7]

Résumé design might matter for candidate attractiveness (Kristal et al., 2023). In particular, applicants might highlight degree completion in different ways on their résumé. To realistically convey (ii) and (iii), our résumé designs follow online recommendations on presenting university drop-out.[8] Our aim was to draw on the same information as real-life applicants (see figures B.1 - B.4 for the résumé designs). Recent work shows that around one third of applicants omit information about partially completed schooling in the US (Kreisman et al., 2021). If this evidence extends to European labor markets, our results about dropouts are informative only for the 70% of applicants who disclose this information.

In addition, we vary grades corresponding to the 10th, 50th and 90th percentile of the actual GPA distribution of a large sample of German university students who studied (business) economics and successfully graduated, to cover a substantial range of educational performance. Finally, we vary the university where students obtained their degree, using three top-rated universities for the subject of business administration, namely Universities of Cologne, Frankfurt, and Munich, all of which, are well-renowned large public universities. The corresponding master programs are very similar in terms of student selection and degree quality.

Work Experience - While in many countries, including the US, it is common for business graduates to start working after obtaining a bachelor's degree and before starting a master's degree or MBA program, this is rarely the case in Germany. Instead, most master students enter the program right after completing their bachelor's

[6]The choice of 30 and 90 ECTS is based on the course structure at German universities, which implies that credits are generally awarded in blocks. Besides, students most likely drop out having finished the ECTS of a full semester, which leads to the division in 25% blocks, as master studies in Germany have four semesters. Especially the last semester generally comprises writing a thesis worth 30 credits. It is thus unrealistic to leave university without a diploma while having obtained more than 90 ECTS.

[7]We chose these four educational levels because many positions in business are open to both bachelor and master graduates, with qualifications from both levels being widely accepted.

[8]The résumés convey that applicants with an unfinished master's degree are not in the process of finishing the degree, but instead left university with no intention to return.

degree. To mimic this institutional feature, résumés only include work experience in the form of an internship (in one of three fields: sales, project management or controlling). We vary not only the field of work but also the length and type of internship and the company name.

Variation of other résumé items - In order to create realistic applicant résumés, we vary multiple other characteristics across the three résumés that each HR manager evaluated. Using résumés with varying characteristics ensured that educational completion did not play an overly prominent role on each résumé. Such characteristics relate to the applicants' language skills, free-time activities, IT skills and secondary school grade. Further, the applicants differ in terms of gender – indicated by the name of the applicant – and age. The applicants' years of birth slightly differ to avoid gaps on the résumé when presenting different lengths of education. For more details on the creation of the résumés and the different components, see subsection B.1 in the Appendix and the corresponding table B.1.

2.4 Candidate attractiveness and beliefs

To elicit perceived candidates' attractiveness[9] and traits, we ask employers to imagine they want to fill an entry-level job at their firm. The respective entry-level job is randomly chosen to be a position either in project management or controlling (each with a 50% probability). We use two fields of specialization that most hiring employers are familiar with irrespective of the industry and that are often filled with applicants who have a background in business administration. We vary the type of entry level position to investigate whether this affects degree returns or beliefs about expertise or traits. Controlling arguably requires more study-specific knowledge, while project management might be more demanding in terms of non-cognitive traits.

[9]We refer to candidate attractiveness as the combination of the three hiring outcomes. This may not fully reflect the attractiveness of the candidate, as the perceived probability of accepting the job may be negatively correlated with attractiveness and in turn may affect the hiring outcomes. We therefore test for these relationships in Section 3.5.

To measure hiring outcomes, we ask the employers to answer the following questions for each applicant profile:

1. What is the likelihood that you would invite [*applicant name*] for a job interview? (0-100%)

2. Conditional on satisfactory performance in the interview, what is the likelihood that you would offer [*applicant name*] a job? (0-100%)

3. Which gross yearly salary excluding bonus payments would you offer [*applicant name*]? (in Euro)

The questions correspond to the different steps of the hiring process, allowing us to investigate whether (not) having a degree matters at the initial step and whether it continues to matter in later stages. Each question is designed to be understood as conditional on the previous step(s) being fulfilled. The invitation probability represents the employer's initial impression of the résumé, indicating their interest in meeting the applicant. The probability of an offer is conditional on the candidate having been invited and having performed satisfactorily in the interview. Finally, the wage offer is conditional on having invited and offered the candidate the job.[10]

Additionally, we aim to understand the underlying traits employers associate with a (unfinished) degree and seek when hiring a candidate. On the one hand, for education to function as relevant proxy information, these traits should positively relate to candidate productivity and negatively relate to the (psychic) cost of studying (Weiss, 1995). Existing studies offer an indication of important traits in this context. First, in the employer learning literature cognitive measures such as IQ and trainability are often considered relevant measures of productivity, while also being imperative for educational attainment (see e.g. Thurow, 1975; Farber and Gibbons, 1996; Altonji and Pierret, 2001; Lange, 2007; Di Stasio, 2014; Arcidiacono et al., 2010; Aryal et al., 2022). Second, non-cognitive traits are shown to be predictive

[10]In Germany, there are no universal hiring or wage-setting rules, apart from the legal minimum wage. However, some firms have internal rules, such as fixed entry-level wages or a strict preference for master's degrees. This heterogeneity in internal rules is addressed in the robustness section.

for both educational and labor market outcomes, with conscientiousness and emotional stability being the most important ones (Heineck and Anger, 2010; Mueller and Plug, 2006; Nyhus and Pons, 2005; Almlund et al., 2011; Heckman et al., 2021). Moreover, grit may be especially relevant in our context where some applicants left without a degree. Grit is defined as "perseverance and passion for long-term goals" and correlated with both education and employment outcomes (Duckworth et al., 2007; Duckworth and Quinn, 2009). However, as grit is a concept that is potentially unknown to employers, we use the terms perseverance and commitment instead.[11] On the other hand, employers may seek subject matter knowledge acquired during studying (henceforth called expertise), in line with the predictions from human capital models (Becker, 1962; Chevalier et al., 2004). Finally, there is evidence of students from more advantaged socio-economic backgrounds experiencing higher labor market returns, while also facing lower costs of education (see e.g. Björklund and Salvanes, 2011; Solon, 1999). Moreover, individuals from lower socio-economic backgrounds often face systematic disadvantages in hiring processes (Belmi et al., 2023).

We ask each employer to judge candidate characteristics compared to the entire cohort of recently graduated business students along the dimensions of trainability and IQ (cognitive traits), commitment, perseverance, conscientiousness and emotional stability (non-cognitive traits), subject matter expertise, and socio-economic status. Employers evaluate each trait on a scale from -100 to 100, where positive (negative) values mean the candidate scores above (below) average.[12]

3 Results

3.1 How does education shape candidate attractiveness?

In a first step, we assess how educational differences translate into candidate attractiveness to confirm the existence and magnitude of education premia in our data.

[11] Although grit is correlated with conscientiousness it has additional predictive power, especially when focusing on perseverance (Credé et al., 2017).

[12] For a complete overview of our survey questions, please see Appendix A.

Figure 1, presents the raw averages of the three main employment outcomes for each: a bachelor's degree (Bsc.), a bachelor's degree but dropped out after obtaining 25% or 75% of additional master credits (30 or 90 ECTS in the European system), and a completed master's degree (Msc.). Comparing these educational levels helps to disentangle the impact of length of study from the effect of holding a degree. A series of t-tests is conducted to assess whether the differences between the Bsc. and the other education scenarios are significantly different from zero. The figure shows that for the master completers, all outcomes are significantly better. Employers thus "reward" a completed master's degree during all steps of the hiring process. However, while the outcomes for the first two bachelor scenarios are similar, the invitation and offer probabilities are lower for Bsc.+75%. In particular, the probability of being invited to a job interview is significantly reduced, and the "penalty" of dropping out shortly before degree completion is, in absolute terms, more than half as large as the "gain" from completing one's degree.[13] In addition, we estimate the returns to education as follows:

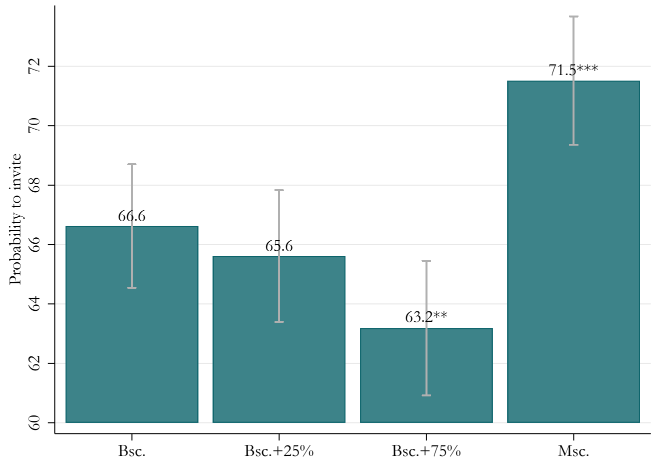
$$Y_{i,m} = \alpha + \beta_{25}\, Bsc.25_i + \beta_{75}\, Bsc.75_i + \beta_{Msc.}\, Msc._i + \beta_X\, X_i + \gamma_m + \epsilon_{i,m}, \quad (1)$$

where $Y_{i,m}$ is a respective measure of candidate attractiveness (invitation probability, offer probability, potential wage) for applicant profile i assessed by employer m. X_i is a vector of control variables comprising all randomized résumé elements: gender, age, high school GPA, university, GPA of the last obtained degree, internship fit to job vacancy, internship firm, internship duration, languages, personal interests and IT skills. The employer fixed effect is represented by γ_m and captures employer traits and the type of job (controlling or project management). The coefficients of interest are $\beta_{Bsc.25}$, $\beta_{Bsc.75}$ and $\beta_{Msc.}$, which yield the return to education with respect to the baseline of obtaining a bachelor's degree.

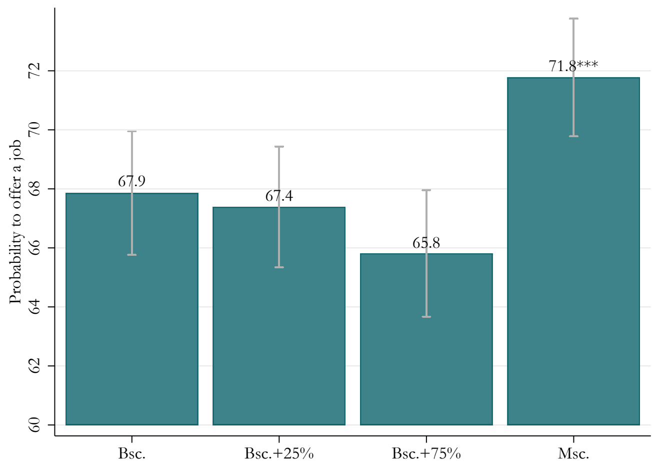
The results are presented in columns 2, 4 and 6 of table 1. Controlling for other résumé items and including employer fixed effects only slightly reduces the effect sizes

[13]The corresponding regression estimates are presented in columns 1, 3 and 5 of table 1.

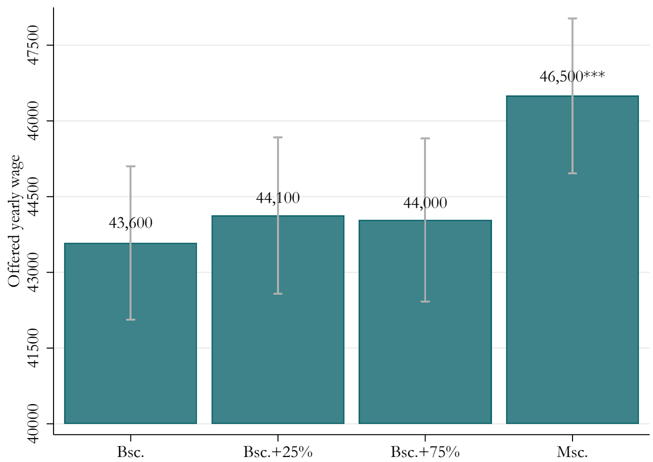
Figure 1: Candidate attractiveness by educational completion



(a) Invitation probability



(b) Probability of offering a job



(c) Prospective wages

Notes: The figure displays the average invitation probability (Panel A), the probability of offering a job (Panel B), and the prospective wage (Panel C) by educational achievement. The stars indicate significance from a series of two-sides t-tests, that compare the average of having obtained a Bsc. only with the respective averages of each of the other scenarios. Error bars indicate 95% confidence intervals.

Table 1: Candidate attractiveness by educational completion

	Base Bsc.					
	(1)	(2)	(3)	(4)	(5)	(6)
	Pr. to invite	Pr. to invite	Pr. to offer	Pr. to offer	Log wage	Log wage
Bsc.+25%	-1.010	-0.492	-0.467	0.361	0.011	-0.001
	(1.311)	(1.238)	(1.255)	(1.170)	(0.015)	(0.008)
Bsc.+75%	-3.435**	-2.302*	-2.042	-0.831	0.007	0.000
	(1.391)	(1.267)	(1.347)	(1.241)	(0.015)	(0.008)
Msc	4.897***	4.486***	3.920***	3.601***	0.070***	0.048***
	(1.233)	(1.169)	(1.228)	(1.179)	(0.016)	(0.008)
N	1299	1299	1299	1299	1299	1299
Ind. FE	No	Yes	No	Yes	No	Yes

Notes: All columns show coefficients that are estimates from a linear regression, with columns 2, 4 and 6 including employer FEs and control variables. White robust standard errors clustered at the respondent level are displayed in parentheses. The data are unbalanced as employers randomly receive and assess three out of four possible education scenarios. Bsc. only serves as a baseline estimate. Control variables comprise the randomized résumé elements: gender, age, high school GPA, university, GPA of the last obtained degree, internship fit to job vacancy, internship firm, internship duration, languages, personal interests and IT skills. ***, **, * indicate significance at the 1, 5 and 10% level, respectively.

and significance of the coefficients.[14] Obtaining a master's degree over a bachelor's degree increases the probability of being invited by 4.5 percentage points (6.6%), but dropping out shortly before degree completion reduces it by 2.3 percentage points (3.5%).

Hence, even conditional on academic performance, successfully obtaining (a large) part of the credits from a master's degree reduces labor market prospects when compared to a bachelor's degree if a candidate drops out of university. The signaling value of an unfinished degree thus seems to outweigh any human capital effects arising from successfully completing a large portion of the coursework. Leaving university with completed coursework but no degree thus seems to be perceived as a negative signal by employers.

There are several (non-exclusive) explanations for this finding. First, employers might not believe in human capital accumulation if no degree was obtained. Second, not finishing a degree might be associated with adverse non-cognitive traits,

[14]See table F.2 in Appendix F for the coefficients of all other résumé items.

outweighing any positive human capital effects. The marginally negative effect size in columns 1 and 2 of table 1 supports this presumption. The smaller – and insignificant – negative coefficients for candidates who left after finishing 25% of the course material suggest that the negative signal of dropping out increases with time spent in the degree program. Third, human capital in the form of expertise might not be valued by employers. We further investigate these hypotheses in subsection 3.2.

3.2 Education effects on employer beliefs

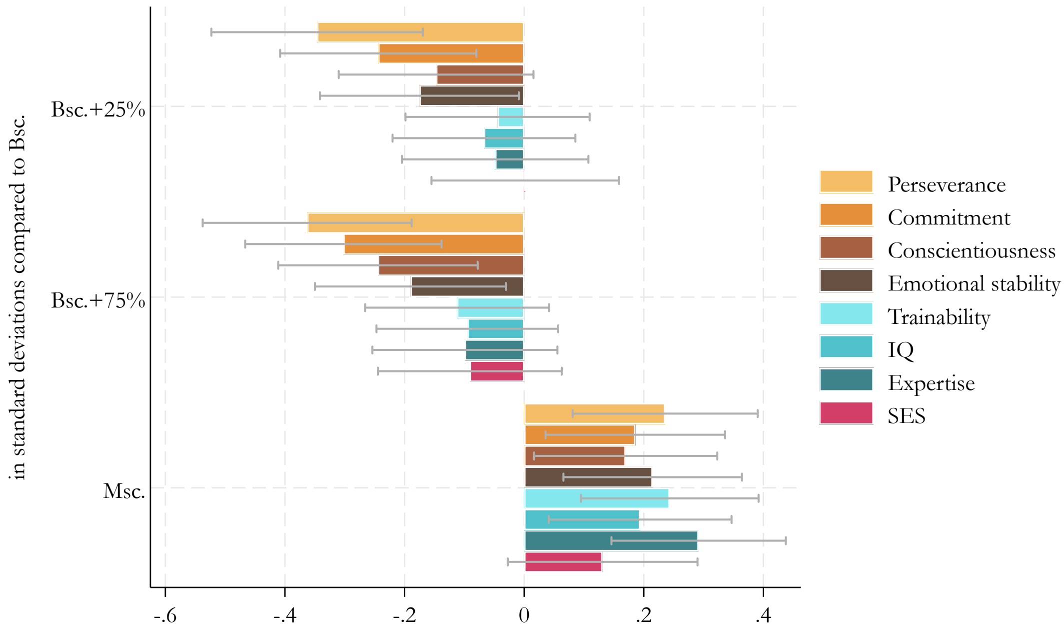
In this section, we investigate the underlying mechanisms by assessing how education affects employer beliefs about candidate characteristics. In line with economic theory, we distinguish between (i) mostly pre-determined productive traits such as cognitive (trainability and IQ) and non-cognitive traits (commitment, perseverance, conscientiousness and emotional stability) related to the psychic costs of studying (Spence, 1973; Stiglitz and Weiss, 1990; Bedard, 2001; Chatterji et al., 2003; Caplan, 2018), and (ii) accumulated human capital in the form of subject matter expertise (Becker, 1962; Schultz, 1963; Mincer, 1974; Chevalier et al., 2004; Aryal et al., 2022). Besides, we assess beliefs about socio-economic status as a proxy for family support and financial constraints.

Figure 2 displays mean differences in employer beliefs about Bsc.+25%, Bsc.+75%, and Msc. candidates compared to Bsc. candidates, where all trait scores are standardized using the respective Bsc. distributions. Error bars indicate 95% confidence intervals.[15]

We observe several patterns. First, starting but not finishing a master's degree induces a downward shift in beliefs regarding non-cognitive traits when compared to having obtained a bachelor's degree only. The negative effect is particularly strong for perseverance and commitment but also apparent for conscientiousness and emotional stability. For Bsc.+75% candidates, these effect sizes amount to over 19% of a standard deviation for emotional stability and over 30% of a standard deviation

[15]See table F.3 for the corresponding averages and p-values. See figure F.2 for a version of the plot that summarizes the trait scores into non-cognitive traits, cognitive traits and expertise.

Figure 2: Employer beliefs by educational completion



Notes: The figure displays standardized differences in trait scores of the Bsc. +25%, Bsc. +75%, and Msc. scenarios compared to the Bsc. scenario, with all scores being standardized with respect to the Bsc. distributions. The gray bars indicate 95% confidence intervals.

for perseverance and commitment. Second, regarding cognitive traits and expertise, the differences between Bsc. and Bsc.+25% or Bsc.+75% candidates are not statistically significant. However, there is a large and statistically significant difference in all traits when comparing the Bsc.+75% to the master candidates. In particular, the number of study credits completed does not prompt employers to believe in higher accumulated expertise. Third, master graduates score significantly higher on all trait dimensions compared to bachelor graduates, with effect sizes amounting to 17-30% of a standard deviation. In particular, master graduates are perceived to perform better in terms of trainability (24% of a standard deviation), and expertise (29% of a standard deviation) compared to bachelor graduates. Perceived socio-economic status is positively (but not significantly) affected by Msc. attainment.

We now turn to the question whether employers hold correct beliefs about the traits of individuals from different educational groups. As there are no readily available datasets that contain information on the above traits as well as measures of master dropout, we have conducted a follow-up survey on degree completion among individuals who formerly participated in a large student survey in Germany (Fachkraft 2030). The data contains high quality measures of IQ, emotional stability, and conscientiousness, as well as socio-economic status.[16] For both employer beliefs and actual traits, we standardize the scores relative to the bachelor scenario and categorize them into cognitive traits (IQ), non-cognitive traits (emotional stability and conscientiousness), and socio-economic background. When comparing these scores side by side in Figure D.1, the results are strikingly similar, with the only notable exception being a slight overestimation of the non-cognitive skills of master's degree holders compared to bachelor's. We interpret this as evidence that employers on average hold surprisingly accurate beliefs. It also speaks to the quality of our data.

The findings in this section improve our understanding in several respects. First, adverse beliefs about non-cognitive traits of Bsc.+25% and Bsc.+75% candidates substantiate the notion that leaving university without a degree is perceived as a negative signal about pre-determined non-cognitive traits. Moreover, the fact that

[16] See Appendix D for a detailed description of the data and available measures.

employers do not acknowledge subject matter expertise in Bsc.+25% and Bsc.+75% candidates indicates that human capital effects in the form of subject matter expertise are closely tied to the signal of obtaining a degree. Finally, obtaining a degree serves as a positive signal about both pre-determined cognitive and non-cognitive traits *and* acquired expertise.

Arguably respondents may view cognitive and non-cognitive traits as partly malleable and believe they can be improved through studying. However, reductions in candidate attractiveness and perceived traits at intermediate levels of master's completion — even in the presence of good grades — are only consistent with an interpretation that views these traits as mostly pre-determined.

3.3 Beliefs and candidate attractiveness

We now explore how much of the differences in candidate attractiveness for bachelor's, unfinished master's degree, and master's degree holders is associated with differences in beliefs about the candidates' expertise, (non-)cognitive traits, and socio-economic status, respectively. To assess the relative importance of the elicited belief mechanisms, we make additional assumptions to be able to present candidate attractiveness as a function of productive traits. We then use this function to conduct a mediation analysis with the aim of providing suggestive evidence on how any of the significant differences in candidate attractiveness by educational attainment relate to employer beliefs about candidate characteristics.

Assuming that candidate attractiveness ($Y_{i,d}$) is a function of a candidate's productive characteristics, where beliefs about these characteristics vary by randomly assigned degree completion, candidate i's market attractiveness – when degree assignment is set to "treated" ($d = 1$) for Msc. or Bsc.+75% or "control" ($d = 0$) for Bsc. – is written as:

$$Y_{i,d} = \kappa_d + \alpha_d^C C_{i,d} + \alpha_d^N N_{i,d} + \alpha_d^E E_{i,d} + \alpha_d^{SES} SES_{i,d} + \alpha_d^U U_{i,d} + \epsilon_{i,d}, \quad d \in \{0,1\}, \quad (2)$$

where $Y_{i,d}$ represents attractiveness as measured by the invitation and offer probabilities and wages offered, respectively. κ_d is an intercept and α_d^C and α_d^N are vectors, denoting the effects of beliefs about cognitive and non-cognitive ability. Similarly, α_d^E and α_d^{SES} are scalar parameters for the effect of beliefs about expertise acquired at university and socio-economic background. Moreover, α_d^U is a vector denoting the effect of several unobserved factors ($U_{i,d}$). Finally, ϵ_i denotes an error term that here is assumed to be independent of the mechanisms and pre-determined variables.

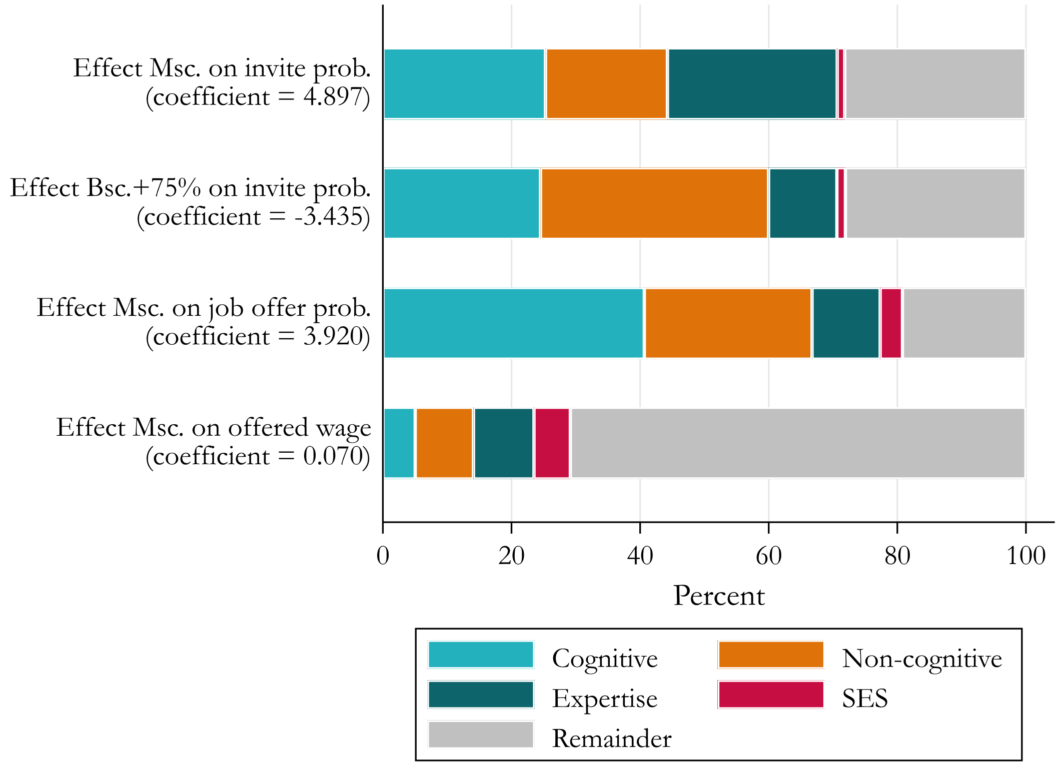
Random assignment of résumé characteristics in terms of degree finalization ensures that the treatment effects on attractiveness and belief mechanisms are easily computed (displayed in Figures 1 and 2). The following decomposition will now assess the relative importance of each belief mechanism on all of the significant differences in candidate attractiveness (as displayed by Figure 1), thus bringing our results full circle. We make two assumptions: first, we assume that the impact of each trait on labor market outcomes is the same across educational groups, i.e. $\alpha_0^C = \alpha_1^C$, $\alpha_0^N = \alpha_1^N$ etc.; and second, we assume that the unobserved traits (U) are statistically independent from observed belief mechanisms (C, N, E, and SES) conditional on the random assignment of résumés.[17] Prior research (e.g. Heckman et al., 2013) shows that under these assumptions the effect of belief mechanisms can be decomposed into:

$$\begin{aligned}\underbrace{\mathbb{E}[Y_1 - Y_0]}_{\text{Attractiveness}} \quad = \quad & \underbrace{\tau_1 - \tau_0}_{\text{Unexplained}} + \underbrace{\alpha^C\ \mathbb{E}[C_1 - C_0]}_{\text{Cognitive}} + \underbrace{\alpha^N\ \mathbb{E}[N_1 - N_0]}_{\text{Non-cognitive}} + \\ & \underbrace{\alpha^E\ \mathbb{E}[E_1 - E_0]}_{\text{Expertise}} + \underbrace{\alpha^{SES}\ \mathbb{E}[SES_1 - SES_0]}_{\text{SES}}, \end{aligned} \tag{3}$$

where $\tau_d = \kappa_d + \sum_{j \in J_U} \alpha_d^j\ \mathbb{E}[U_d^j]$, such that $\tau_1 - \tau_0$ captures the contribution of treatment-induced changes in a number of J_U unmeasured mechanism variables.

[17] The first assumption can be relaxed by allowing for different parameters or including interaction terms, whereby doing so yields very similar results.

Figure 3: Decomposition of differences in candidate attractiveness



Notes: The figure shows the decomposition of the significant differences in candidate attractiveness (see the effect sizes in brackets). See equation 3 for details on the decomposition. The traits are grouped in four categories: cognitive skills (trainability and IQ), non-cognitive skills (perseverance, commitment, conscientiousness and emotional stability), expertise and SES. The bars represent how much of the difference between the Bsc. scenario versus the Msc. degree scenario (bars 1, 3, 4) and the Bsc.+75% scenario (bar 2) can be explained by the traits. The remainder reflects the sum of the unexplained part and the negative coefficients (see table F.4).

The results of this decomposition analysis are displayed graphically in Figure 3, with the traits being grouped together as cognitive ability, non-cognitive ability, expertise and SES for readability.[18]

The figure shows that for the probabilities of both inviting a candidate and offering them a job, the included traits can explain up to 75% of the variation in significant differences discussed in section 3.1. Subject matter expertise, cognitive ability and non-cognitive ability all make up for a significant share of the differences between

[18] Appendix table F.4 shows all separate coefficients and t-statistics. As few coefficients have a (insignificant) negative sign, the "remainder" in Figure 3 reflects the sum of the unexplained part and the negative coefficients. This practice eases the interpretation of the figure, while the difference is negligible due to the small effect sizes of the negative coefficients.

Bsc. and Msc., as well as between Bsc. and Bsc.+75% completion. Depending on the precise difference in candidate attractiveness, the relative importance of the traits varies, but overall, the share of differences ascribed to mostly pre-determined traits (cognitive and non-cognitive) consistently exceeds that of expertise.

Both differences in perceived (non-)cognitive traits (45%) and perceived expertise (27%) offer an important explanation why master's degree holders are more likely to be invited to an interview. In contrast, the reduced likelihood of being invited to a job interview after leaving university with only 75% of the course work completed, is mainly explained by differences in perceived non-cognitive abilities. The perceived importance of non-cognitive skills in the decision to drop out is consistent with Heckman and Rubinstein (2001), who highlight the central role of non-cognitive skills in educational attainment decisions. Together, non-cognitive and cognitive abilities account for around 60% of the observed difference, while the share of the variation captured by expertise becomes insignificant. The attractiveness of Msc. candidates with respect to the job offering probability can be predominantly explained by differences in ascribed cognitive ability. Together, (non-)cognitive traits explain over 70% of the difference. In contrast to the invite probability of Msc. candidates, expertise becomes insignificant in explaining the offer probability, which might be due to the offer probability being conditioned on strong interview performance.

Overall, the importance of expertise in explaining differences in invite probabilities between master's and bachelor's degree holders aligns with human capital theories. However, expertise only explains 27% of the difference. Meanwhile the dominant role of cognitive and non-cognitive abilities, particularly for candidates with incomplete degrees, in explaining differences in attractiveness provides evidence that is in line with signaling theory. For all three cases, the difference in invitation and offering probabilities remaining after controlling for candidates' traits – i.e. the unexplained difference – is statistically insignificant.

At the end of the survey, employers were asked whether they perceive (not) finishing a degree as a (lack of) proof for expertise or as a (negative) signal for character traits. Figure F.3 displays the distribution of responses. Consistent with the decomposition results, over 60% of employers view a completed degree as both a signal of character traits and a demonstration of expertise. Approximately 20% lean towards associating it primarily with character traits, and another 20% with human capital. In contrast, less than 15% of individuals view dropping out mainly as a lack of human capital, as opposed to a lack of character traits, which plays a role for 85% of respondents. This finding is also supported by the responses to the open-ended question about their association with not completing a degree. About 47% explicitly stated that they perceived dropping out as a negative signal about non-cognitive traits, most of them mentioning a lack of perseverance and commitment.

For the difference in log wages offered between bachelor's and master's degree holders i.e., in the final step of the hiring process – the picture is different. Here, a larger part of the difference remains unexplained, and none of the traits display a statistically significant effect on the wage difference. A potential reason for this finding could be that the wage offered is tied mostly to education and previous experience, which leaves less room for interpretation. Alternatively, since wages were assessed conditional on the hiring decision, employers may no longer consider initially perceived skills at this stage. Given that the wage offer follows a positive hiring decision—likely influenced by a successful interview—employers may assume that any initial concerns based on the résumé have already been resolved.

3.4 The role of incentives

The responses in our main survey were obtained from a specialized sample of professional human resource managers which implied, in our case, that responses could not be incentivized. Given the high data quality, we view this as a minor concern. After all, there is no reason to believe that human resource managers give biased responses when reflecting on a candidate's obtained educational qualifications. This might also explain why it is common practice to assess beliefs and expectations about educational returns or other non-political domains in a non-incentivized manner (see e.g. Wiswall and Zafar, 2021; Haaland et al., 2023).

Yet, to rule out that incentives matter in our setting, we investigate whether they systematically change the relative evaluation of applicant profiles by educational level. To this end, we conducted a complementary experiment via the online platform Prolific.[19] The additional survey was targeted at individuals living in Germany that have experience in hiring. The final sample consists of 269 observations.[20]

The complementary study closely follows the design of the main study, with three main differences: participants were shown four applicant profiles, one for each level of education, participants were asked to provide beliefs about how the HR managers in the main study perceived the candidates, and participants were incentivized for two of the four applicant profiles. Each applicant profile corresponded to an applicant profile rated by a hiring manager in the main study. Respondents were then asked what they thought the HR manager's answers were to the hiring questions, as well as to the questions about expertise, cognitive traits, non-cognitive traits, and socio-economic background. For two of the four applicant profiles, participants' ratings were incentivized, with substantial rewards based on how closely their responses matched those of the hiring managers.[21] Which of the two profiles was incentivized was randomized.

To assess whether incentives systematically change the relative evaluation of candidates by educational level, we regress each hiring outcome and each trait on the educational level of the applicant profile and its interaction with the presence or absence of incentives. In the regression we control for person fixed effects as well as other résumé items that were used as control variables in the main study.[22] Figure 4 shows the coefficients of interest, i.e., the effect of incentives on the evaluation of candidates for the different educational levels compared to the bachelor scenario. Error bars indicate 95% confidence intervals.

The results show that there are no significant differences in the assessment of candidates with an unfinished or finished master's degree compared to candidates with a bachelor's degree when they are incentivized. This applies both to the assessment

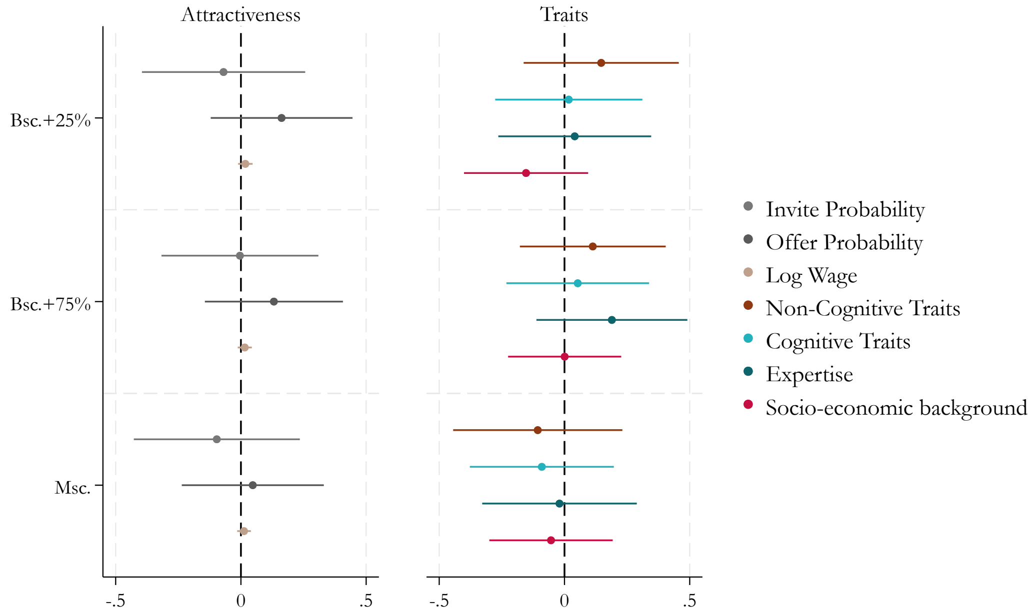
[19]The pre-registration of the complimentary experiment can be accessed at https://osf.io/5ez7h.

[20]Our registration plan prioritized participants with hiring experience. As we successfully recruited a sufficient number of such participants, we report results exclusively for this group. See Appendix E for a detailed description of the sample and the cleaning procedure.

[21]Incentives in total corresponded to more than twice the amount paid out for mere survey participation.

[22]See table E.2 for the full regression table.

Figure 4: Evaluation of applicant profiles by incentive



Notes: The figure shows the effect of incentives on the standardized differences in attractiveness and trait scores of Bsc. +25%, Bsc. +75%, and Msc. scenarios relative to the Bsc. scenario, with all scores standardized relative to the Bsc. distributions. Each standardized score was regressed on level of education and its interaction with whether the profile was incentivized, controlling for individual fixed effects and all other résumé items used as controls in the main study. Non-cognitive traits (perseverance, commitment, conscientiousness, emotional stability) and cognitive traits (trainability, IQ) are the equally weighted averages of z-scores of its components. The z-scores are calculated by subtracting the Bsc. scenario mean and dividing by the Bsc. scenario standard deviation.

of attractiveness and to the assessment of the traits of the candidate. When disaggregating non-cognitive traits into perseverance, commitment, conscientiousness and emotional stability, there exist two effects that are borderline significant at the 10% level. These effects do not seem to be systematic, but simply a random result of the number of coefficients we are testing.[23] We, therefore, conclude that incentives do not systematically change the relative evaluation by educational level. The idea that incentives do not play a significant role in our setting is supported by the responses to an additional question in the survey about the appropriateness of taking various factors into account when hiring. Around 93% of respondents said that it was appropriate to take into account the level of education, while only 5-11% said that it was appropriate to take into account gender or socio-economic background (see Figure E.1).

Incentives do seem to matter slightly when it comes to the precision of beliefs. For each hiring outcome and each trait, the absolute deviation from the hiring managers' original responses decreases when incentives are provided, although this is only significant for a single outcome (see Table E.3). Incentives might thus slightly increase attention and the precision of estimated coefficients. However, they do not lead to biased estimates in a sense that they change the direction or magnitude of the relative scores assigned to applicant profiles.

We now address the question of how individuals in the complementary study assess HR-managers' beliefs, when compared to the HR managers' assessments in the main sample and examine whether the qualitative findings from the main study can be replicated. To this end, we compute for each résumé the deviation of responses in the complementary survey to those in the original survey of HR managers and regress this measure on the educational level. This analysis allows us to determine whether the relative assessment by educational level differs. Respondents in the follow-up survey provide assessments that are qualitatively similar to those of the HR managers, but somewhat larger in size (see Table E.4). For example, candidates

[23]The two effects that are significant at the 10% level are that Commitment is evaluated higher for Bsc.+30% in comparison to Bsc. and that Emotional stability is evaluated slightly lower for Msc. in comparison to Bsc. when the profiles are incentivized.

with a master's degree are perceived as even more likely to be invited to an interview or offered a job compared to candidates with only a bachelor's degree. This is mainly because master's degree holders are attributed even greater advantages in traits such as perseverance, intelligence, and expertise. Similarly, candidates who dropped out are seen as even less likely to be invited to an interview compared to those with a bachelor's degree. Notably, the differences in non-cognitive traits are perceived as significantly larger in the complementary survey.

3.5 Heterogeneities and robustness checks

To assess the generalizability and robustness of these results, we conduct several additional analyses. First, we explore the importance of grades obtained during (unfinished) Msc. studies for candidate attractiveness. Existing research shows that a better GPA can result in higher (immediate) wage returns (Hansen et al., 2024). However, in our context this may not necessarily be true, given that leaving university while having a high GPA may be perceived as an even worse signal of non-cognitive skills. We find that having a higher GPA is advantageous for Bsc.+25% and Msc. candidates, while for Bsc.+75% candidates the opposite is true. However, we lack statistical power to further investigate these patterns (see table F.5 in the Appendix).

Next, we turn to high school GPA. In all scenarios it is advantageous to have a better high school GPA. In the bachelor scenario, the probability of being invited increases the most with high school GPA. For each of the other scenarios, this effect of high school GPA on the probability of being invited becomes less pronounced. It seems that additional signals, such as dropping out or completing a master's degree, reduce the importance of high school GPA as a source of information (see table F.6). We find the same pattern in beliefs about cognitive and non-cognitive traits as well as expertise (see figure F.4).

It has been shown that signals about skills can be interpreted differently depending on gender (Sarsons, 2022; Bohren et al., 2019). In our setting, we see no significant gender differences in the perceived attractiveness of candidates in any of the scenarios (see table F.7). Regarding beliefs about traits and expertise, women are on average perceived to have higher trait scores and expertise in the bachelor scenario. For cognitive and non-cognitive traits this male-female difference is slightly statistically significant.[24] This is reversed in the dropout scenarios, where women are believed to have in particular lower cognitive skills and expertise after dropping out, although these differences are not significant. In the master's scenario, there are virtually no differences in the assessment of skills by a candidate's gender (see figure F.4).

Two other aspects that may create heterogeneities in the attractiveness of an educational degree are the type of job and size of a firm. In our setup, employers are hiring for a job in either controlling or project management. Since controlling requires more course-specific knowledge, additional study credits might matter more for controlling jobs. Similarly, larger companies may rely more on degrees, as they have more streamlined hiring processes. However, the results neither display significant differences in the return to study credits between the two types of jobs nor by firm size (see tables F.8 and F.9 in the Appendix).

Further, employer characteristics may matter for their assessment of candidates with varying rates of educational degree completion. In particular, there might be important differences by employer expertise. We thus regress employers' beliefs of candidates' traits on an interaction term with categories for the number of years of work experience. The results show that more experienced employers place less value on a Msc. degree when assessing a candidate's level of cognitive ability (see table F.10 in the Appendix). Hence, it seems that more experienced employers are less likely to downward shift their beliefs about cognitive abilities when a candidate did not finish the degree.

Next, we test the sensitivity of our findings by re-running our analyses while imposing alternative specifications. First, we check whether loosening or tightening our sample restrictions alters our results. We thus relax the wage restrictions and include all respondents in one specification, whereas in another we add the requirement that respondents spent more than seven minutes answering the survey. Second, we test

[24] The difference is significant at $p = 0.095$ for non-cognitive and at $p = 0.04$ for cognitive traits.

whether the results are driven by a company's wage-setting policy. For this purpose, we drop respondents whose company has a hiring rule in place that favors master's degree holders. Third, we investigate the influence of the Covid-19 pandemic, by splitting the sample between below- versus above-median beliefs on how much the pandemic changed the hiring requirements of a respective company.

We ran these alternative specifications for all three main analyses (see Appendix tables F.11, F.12 and F.13). The findings show that the statistical significance and economic interpretation of our main estimates remain robust.

Finally, we analyze the robustness of our results to the inclusion of the perceived probability of accepting a job offer. This variable could be correlated with perceived outside options, which might be inferred from résumé items such as grades or prior experience, and could thus influence a candidate's hiring perspective.

Regressing the perceived probability of acceptance on all résumé items reveals that perceived acceptance is primarily driven by factors that relate to how committed a candidate is to start working, such as having dropped out of university, having completed a master's degree, or having completed longer internships. In addition, HR managers perceive candidates with better high school grades as more likely to accept the job (see Appendix table F.14).

Controlling for the perceived probability of accepting a job offer in the main specification shows that it has a significantly positive effect on all hiring outcomes, but that including it as an explanatory variable does not change the main results. If anything, the relative assessment by educational completion becomes even more pronounced (see Appendix table F.15).

4 Conclusion

This study opens the black box of why higher education is desirable to employers and provides new evidence on the human capital and signaling roles of higher education. After randomly varying master's degree attainment on applicant résumés, we elicit candidate attractiveness in terms of interview probability, job offer probability, and wages, as well as employer beliefs about eight productivity-related candidate characteristics, such as cognitive and non-cognitive traits, and subject matter expertise, all of which have been shown to relate to the psychic cost of education and labor market productivity.

Our findings confirm that a master's degree increases candidate attractiveness. All else being equal, candidates who have completed a master's degree are 4.5 percentage points (6.6%) more likely to be offered a job interview than candidates with a bachelor's degree. The size of this effect is roughly similar to the effect of having a migration background (Kaas and Manger, 2012; Weichselbaumer, 2020). Moreover, degree completion increases the likelihood of receiving an offer by 3.6 percentage points (5%) and earnings potentials by 4.8%. More importantly, however, our findings show that an incomplete masters' degree is treated as less valuable by employers than a bachelor's degree, even if a large part of the program has been completed successfully. Having completed nearly all coursework, but not having obtained a master's degree, results in a reduced invitation probability of 2.3 percentage points (3.5%) compared to not having started the master's at all.

In a second step we investigated the belief-related mechanisms behind these effects. Our results show that having completed a master's degree improves employers' perceptions of a candidate's cognitive and non-cognitive traits and expertise by around 20% of a standard deviation when compared to a candidate who just completed a bachelor's degree. However, successfully studying but not finishing a master's degree, as opposed to not even starting, significantly reduces employers' perceptions about non-cognitive traits by up to 35% of a standard deviation. Hence, even though these candidates show scholastic aptitude, they still face limited opportunity due to perceived deficits in non-cognitive traits (Heckman et al., 2011).

These findings hold significance regarding the human capital and signaling values of higher education. Previous research on the debate of signaling versus human capital as explanations for the education premium mostly stems from observational data with measures of actual academic ability or exogenous variation in education curricular or years of schooling (e.g., Arteaga, 2018; Aryal et al., 2022). Our results complement these findings by providing first causal evidence that completing education positively shapes employer beliefs about cognitive and non-cognitive traits, as well as expertise. A decomposition analysis unveils that the positive change in beliefs in response to degree completion arises mainly from the positive signal about pre-existing traits and to a lesser extent from the human capital enhancing effect of education. Importantly, subject matter expertise is only valued when combined with a degree, indicating that employers devalue the human capital enhancing aspect of education if this is not documented with a degree certificate. The human capital part of education thus seems invariably intertwined with the degree signal and difficult for employers to separate.

On the contrary, dropping out is mostly perceived as a negative signal about (pre-existing) non-cognitive traits. It has a strong and negative effect on employer beliefs about these traits. An individual who has dropped out after completing 75% of her degree for example is perceived almost 60% of a standard deviation less perseverant and committed than someone who completes the degree, even if her grades while studying were very good. Such a person would thus need to provide *much* additional positive information about herself to make up for this malus.

Due to the specific setup of our study, the magnitude of our results is not directly comparable to the results from audit or quasi-experimental studies, as employers looked at each résumé separately and in the absence of competition from other applicants. Moreover, wages, for example, were reported conditional on having successfully completed a job interview. It is therefore conceivable that in real hiring situations with many competitors for one position, effects are more pronounced and future work may ascertain whether this is indeed the case.

Moreover, to the extent that different types of educational credentials differentially influence employers' perceptions of candidates' underlying traits, the evidence presented in this paper may help explain important heterogeneities in the returns to higher education (Gunderson and Oreopolous, 2020; Altonji et al., 2012). Additional evidence on differential belief updating by degree or field could provide valuable insights that inform this literature.

Prospective research may also extend our analysis by investigating whether the anticipation of employer beliefs affects the enrollment decisions of prospective students, possibly in conjunction with self-perceived abilities and risk preferences. Incorporating students' and employers' beliefs into models of educational decision-making thus seems a promising avenue for future research that could enhance our understanding of student enrollment, dropout, degree completion and employer-employee matching.

References

Almlund, Mathilde, Angela Lee Duckworth, James Heckman, and Tim Kautz, "Personality Psychology and Economics," in "Handbook of the Economics of Education," Vol. 4, Elsevier, 2011, pp. 1–181.

Altonji, Joseph G. and Charles R. Pierret, "Employer Learning and Statistical Discrimination," *The Quarterly Journal of Economics*, 2001, *116* (1), 313–350.

_ **and Ling Zhong**, "The Labor Market Returns to Advanced Degrees," *Journal of Labor Economics*, 2021, *39* (2), 303–360.

Altonji, Joseph G, Erica Blom, and Costas Meghir, "Heterogeneity in Human Capital Investments: High School Curriculum, College Major, and Careers," *Annu. Rev. Econ.*, 2012, *4* (1), 185–223.

Arcidiacono, Peter, Patrick Bayer, and Aurel Hizmo, "Beyond Signaling and Human Capital: Education and the Revelation of Ability," *American Economic Journal: Applied Economics*, October 2010, *2* (4), 76–104.

Arteaga, Carolina, "The Effect of Human Capital on Earnings: Evidence from a Reform at Colombia's Top University," *Journal of Public Economics*, 2018, *157*, 212–225.

Aryal, Gaurab, Manudeep Bhuller, and Fabian Lange, "Signaling and Employer Learning with Instruments," *American Economic Review*, 2022, *112* (5), 1669–1702.

Ashenfelter, Orley and John Ham, "Education, Unemployment, and Earnings," *Journal of Political Economy*, 1979, *87* (5, Part 2), S99–S116.

Becker, Gary S, "Investment in Human Hapital: A Theoretical Analysis," *Journal of Political Economy*, 1962, *70* (5, Part 2), 9–49.

Bedard, Kelly, "Human Capital versus Signaling Models: University Access and High School Dropouts," *Journal of Political Economy*, 2001, *109* (4), 749–775.

Belmi, Peter, Kelly Raz, Margaret Neale, and Melissa Thomas-Hunt, "The Consequences of Revealing First-Generational Status," *Organization Science*, 2023.

Bennett, Christopher T., "Labor Market Returns to MBAs from Less-Selective Universities: Evidence from a Field Experiment during COVID-19," *Journal of Policy Analysis and Management*, 2023, *42* (2), 525–551.

Bertrand, Marianne and Sendhil Mullainathan, "Are Emily and Greg More Employable than Lakisha and Jamal? A Field Experiment on Labor Market Discrimination," *American Economic Review*, 2004, *94* (4), 991–1013.

Björklund, Anders and Kjell G. Salvanes, "Education and Family Background: Mechanisms and Policies," in Eric A. Hanushek, Stephen Machin, and Ludger Woessmann, eds., *Handbook of the Economics of Education*, Vol. 3, Elsevier, 2011, chapter 03, pp. 201–247.

Bohren, J. Aislinn, Alex Imas, and Michael Rosenberg, "The Dynamics of Discrimination: Theory and Evidence," *American Economic Review*, 2019, *109* (10).

Bowles, Samuel, Herbert Gintis, and Melissa Osborne, "Incentive-Enhancing Preferences: Personality, Behavior, and Earnings," *American Economic Review*, 2001, *91* (2), 155–158.

Cairó, Isabel and Tomaz Cajner, "Human Capital and Unemployment Dynamics: Why More Educated Workers Enjoy Greater Employment Stability," *The Economic Journal*, 2018, *128* (609), 652–682.

Caplan, Bryan, *The Case Against Education: Why the Education System is a Waste of Time and Money*, Princeton University Press, 2018.

Card, David, "The Causal Effect of Education on Earnings," in "Handbook of Labor Economics," Vol. 3, Elsevier, 1999, pp. 1801–1863.

_ , "Estimating the Return to Schooling: Progress on Some Persistent Econometric Problems," *Econometrica*, 2001, *69* (5), 1127–1160.

Chatterji, Monojit, Paul T Seaman, and Larry D Singell Jr, "A Test of the Signalling Hypothesis," *Oxford Economic Papers*, 2003, *55* (2), 191–215.

Chevalier, Arnaud, Colm Harmon, Ian Walker, and Yu Zhu, "Does Education Raise Productivity, or Just Reflect it?," *The Economic Journal*, 2004, *114* (499), F499–F517.

Cobb-Clark, Deborah A and Stefanie Schurer, "The Stability of Big-Five Personality Traits," *Economics Letters*, 2012, *115* (1), 11–15.

Credé, Marcus, Michael C Tynan, and Peter D Harms, "Much Ado About Grit: A Meta-Analytic Synthesis of the Grit Literature," *Journal of Personality and Social Psychology*, 2017, *113* (3), 492.

Cunha, Flavio, Fatih Karahan, and Ilton Soares, "Returns to Skills and the College Premium," *Journal of Money, Credit and Banking*, 2011, *43*, 39–86.

Deming, David J, "Four Facts about Human Capital," *Journal of Economic Perspectives*, 2022, *36* (3), 75–102.

_ **and Mikko I Silliman**, "Skills and Human Capital in the Labor Market," 2024. National Bureau of Economic Research Working Paper no. 32908.

Deming, David J., Noam Yuchtman, Amira Abulafi, Claudia Goldin, and Lawrence F. Katz, "The Value of Postsecondary Credentials in the Labor Market: An Experimental Study," *American Economic Review*, 2016, *106* (3), 778–806.

Duckworth, Angela L, Christopher Peterson, Michael D Matthews, and Dennis R Kelly, "Grit: Perseverance and Passion for Long-Term Goals.," *Journal of Personality and Social Psychology*, 2007, *92* (6), 1087.

Duckworth, Angela Lee and Patrick D Quinn, "Development and Validation of the Short Grit Scale (GRIT–S)," *Journal of Personality Assessment*, 2009, *91* (2), 166–174.

Edin, Per-Anders, Peter Fredriksson, Martin Nybom, and Björn Öckert, "The Rising Return to Noncognitive Skill," *American Economic Journal: Applied Economics*, 2022, *14* (2), 78–100.

Ehrmantraut, Laura, Pia Pinger, and Renske Stans, "The Expected (Signaling) Value of Higher Education," 2020. IZA Discussion Paper no. 13729.

Eriksson, Stefan and Dan-Olof Rooth, "Do Employers Use Unemployment as a Sorting Criterion When Hiring? Evidence from a Field Experiment," *American Economic Review*, 2014, *104* (3), 1014–1039.

Eurostat, "Tertiary Education Statistics," 2024. https://ec.europa.eu/eurostat/statistics-explained/index.php?title=Tertiary_education_statistics[Accessed: 2025-02-12].

Falato, A. and T. Milbourn, "Which Skills Matter in the Market for CEOs? Evidence from Pay for CEO Credentials," *Management Science*, 2015, *61* (12), 2845–2869.

Farber, Henry S and Robert Gibbons, "Learning and Wage Dynamics," *The Quarterly Journal of Economics*, 1996, *111* (4), 1007–1047.

_ , Dan Silverman, and Till Von Wachter, "Determinants of Callbacks to Job Applications: An Audit Study," *American Economic Review*, 2016, *106* (5), 314–18.

Fuster, Andreas and Basit Zafar, "Survey Experiments on Economic Expectations," in "Handbook of Economic Expectations," Elsevier, 2023, pp. 107–130.

Gaulke, Amanda, Hugh Cassidy, and Sheryll Namingit, "The Effect of Post-Baccalaureate Business Certificates on Job Search: Results from a Correspondence Study," *Labour Economics*, 2019, *61*, 101759.

Goldberg, Lewis R., John A. Johnson, Herbert W. Eber, Robert Hogan, Michael C. Ashton, C. Robert Cloninger, and Harrison G. Gough, "The International Personality Item Pool and the Future of Public-Domain Personality Measures," *Journal of Research in Personality*, 2006, *40* (1), 84–96.

Gunderson, Morley and Philip Oreopolous, "Returns to Education in Developed Countries," in "The Economics of Education," Elsevier, 2020, pp. 39–51.

Haaland, Ingar, Christopher Roth, and Johannes Wohlfart, "Designing Information Provision Experiments," *Journal of Economic Literature*, 2023, *61* (1), 3–40.

Hansen, Anne Toft, Ulrik Hvidman, and Hans Henrik Sievertsen, "Grades and Employer Learning," *Journal of Labor Economics*, 2024, *42* (3), 659–682.

Heckman, James J and Yona Rubinstein, "The Importance of Noncognitive Skills: Lessons from the GED Testing Program," *American Economic Review*, 2001, *91* (2), 145–149.

_ , John Eric Humphries, and Nicholas S Mader, "The GED," in "Handbook of the Economics of Education," Vol. 3 Elsevier 2011, pp. 423–483.

_ , Tomáš Jagelka, and Timothy D Kautz, "Some Contributions of Economics to the Study of Personality," in "Handbook of Personality: Theory and Research," Vol. 4 The Guilford Press 2021, pp. 853–892.

Heckman, James, Rodrigo Pinto, and Peter Savelyev, "Understanding the Mechanisms through Which an Influential Early Childhood Program Boosted Adult Outcomes," *American Economic Review*, 2013, *103* (6), 2052–2086.

Heineck, Guido and Silke Anger, "The Returns to Cognitive Abilities and Personality in Germany," *Labour Economics*, 2010, *17* (3), 535–546.

Heinz, Matthias and Heiner Schumacher, "Signaling Cooperation," *European Economic Review*, 2017, *98*, 199–216.

Heublein, Hutzsch, and Schmelzer, "Die Entwicklung der Studienabbruchquoten in Deutschland," 2022. Deutsches Zentrum für Hochschul- und Wissenschaftsforschung.

Hopkins, Ed, "College as a Signal of Self-Control: Self-Control Preferences in a High Temptation Environment," 2019. University of Edinburgh Working Paper.

Hopkins, Kenneth D. and Glenn H. Bracht, "Ten-Year Stability of Verbal and Nonverbal IQ Scores," *American Educational Research Journal*, 1975, *12* (4), 469–477.

Hungerford, Thomas and Gary Solon, "Sheepskin Effects in the Returns to Education," *The Review of Economics and Statistics*, 1987, *69* (1), 175–177.

Jaeger, David A. and Marianne E. Page, "Degrees Matter: New Evidence on Sheepskin Effects in the Returns to Education," *The Review of Economics and Statistics*, 1996, *78* (4), 733–740.

Kaas, Leo and Christian Manger, "Ethnic Discrimination in Germany's Labour Market: A Field Experiment," *German Economic Review*, 2012, *13* (1), 1–20.

Kang, Sonia K, Katherine A DeCelles, András Tilcsik, and Sora Jun, "Whitened Résumés: Race and Self-Presentation in the Labor Market," *Administrative Science Quarterly*, 2016, *61* (3), 469–502.

Kessler, Judd B., Corinne Low, and Colin D. Sullivan, "Incentivized Resume Rating: Eliciting Employer Preferences without Deception," *American Economic Review*, 2019, *109* (11), 3713–44.

Kline, Patrick, Evan K Rose, and Christopher R Walters, "Systemic Discrimination Among Large U.S. Employers," *The Quarterly Journal of Economics*, 2022, *137* (4), 1963–2036.

Kreisman, Daniel, Jonathan Smith, and Bondi Arifin, "Labor Market Signaling and the Value of College: Evidence from Resumes and the Truth," *Journal of Human Resources*, 2021.

Kristal, Ariella S, Leonie Nicks, Jamie L Gloor, and Oliver P Hauser, "Reducing Discrimination against Job Seekers with and without Employment Gaps," *Nature Human Behaviour*, 2023, *7* (2), 211–218.

Kroch, Eugene A. and Kriss Sjoblom, "Schooling as Human Capital or a Signal: Some Evidence," *Journal of Human Resources*, 1994, *29* (1), 156–180.

Lange, Fabian, "The Speed of Employer Learning," *Journal of Labor Economics*, 2007, *25* (1), 1–35.

_ **and Robert Topel**, "The Social Value of Education and Human Capital," *Handbook of the Economics of Education*, 2006, *1*, 459–509.

Layard, Richard and George Psacharopoulos, "The Screening Hypothesis and the Returns to Education," *Journal of Political Economy*, 1974, *82* (5), 985–998.

Lennon, Conor, "How Do Online Degrees Affect Labor Market Prospects? Evidence from a Correspondence Audit Study," *ILR Review*, 2021, *74* (4), 920–947.

Mincer, Jacob A, "Schooling and Earnings," in "Schooling, Experience, and Earnings," NBER, 1974, pp. 41–63.

Moretti, Enrico, "Workers' Education, Spillovers, and Productivity: Evidence from Plant-Level Production Functions," *American Economic Review*, 2004, *94* (3), 656–690.

Mueller, Gerrit and Erik Plug, "Estimating the Effect of Personality on Male and Female Earnings," *Industrial and Labor Relations Review*, 2006, *60* (1), 3–22.

Nunley, John M, Adam Pugh, Nicholas Romero, and R Alan Seals Jr, "College Major, Internship Experience, and Employment Opportunities: Estimates from a Résumé Audit," *Labour Economics*, 2016, *38*, 37–46.

Nyhus, Ellen K and Empar Pons, "The Effects of Personality on Earnings," *Journal of Economic Psychology*, 2005, *26* (3), 363–384.

Oreopoulos, Philip, "Why Do Skilled Immigrants Struggle in the Labor Market? A Field Experiment with Thirteen Thousand Resumes," *American Economic Journal: Economic Policy*, 2011, *3* (4), 148–71.

_ **and Uros Petronijevic**, "Making College Worth It: A Review of the Returns to Higher Education," *The Future of Children*, 2013, *23* (1), 41–65.

Park, Jin Heum, "Estimation of Sheepskin Effects Using the Old and the New Measures of Educational Attainment in the Current Population Survey," *Economics Letters*, 1999, *62* (2), 237–240.

Patrinos, Harry Anthony and George Psacharopoulos, "Returns to Education in Developing Countries," in "The Economics of Education," Elsevier, 2020, pp. 53–64.

Piopiunik, Marc, Franziska Kugler, and Ludger Wößmann, "Einkommenserträge von Bildungsabschlüssen im Lebensverlauf: Aktuelle Berechnungen für Deutschland," *ifo Schnelldienst*, 2017, *70* (7), 19–30.

_ **, Guido Schwerdt, Lisa Simon, and Ludger Woessmann**, "Skills, Signals, and Employability: An Experimental Investigation," *European Economic Review*, 2020, *123.*

Raven, John C. and John H. Court, *Raven's Progressive Matrices and Vocabulary Scales*, Oxford Psychologists Press, 1998.

Ruffle, Bradley J and Ze'ev Shtudiner, "Are Good-Looking People More Employable?," *Management Science*, 2015, *61* (8), 1760–1776.

Salgado, Jesus F, "The Five Factor Model of Personality an Job Performance in the European Community," *Journal of Applied Psychology*, 1997, *82* (1), 30.

Sarsons, Heather, "Interpreting Signals in the Labor Market: Evidence from Medical Referrals," September 2022. https://drive.google.com/file/d/1YQFZbY-Y0iRtmH06zOK6J9cSn9tgSVUi/view[Accessed: 2025-02-14].

Schuerger, James M and Anita C Witt, "The Temporal Stability of Individually Tested Intelligence," *Journal of Clinical Psychology*, 1989, *45* (2), 294–302.

Schultz, Theodore W, *The Economic Value of Education*, Columbia University Press, 1963.

Seegers, Philipp, Jan Bergerhoff, Stephan Hartmann, and Anne Knappe, "Fachkraft 2020: 5. und 6. Erhebung zur wirtschaftlichen und allgemeinen Lebenssituation der Studierenden in Deutschland.," 2016.

Segal, Carmit, "Working When No One Is Watching: Motivation, Test Scores, and Economic Success," *Management Science*, 2012, *58* (8), 1438–1457.

Solon, Gary, "Intergenerational Mobility in the Labor Market," in Orley C. Ashenfelter and David Card, eds., *Handbook of Labor Economics*, Vol. 3, Elsevier, 1999, chapter 29, pp. 1761–1800.

Spence, Michael, "Job Market Signaling," *The Quarterly Journal of Economics*, 1973, pp. 355–374.

Stasio, Valentina Di, "Education as a Signal of Trainability: Results from a Vignette Study with Italian Employers," *European Sociological Review*, 2014, *30* (6), 796—-809.

Statistisches Bundesamt, "Bildung und Kultur / Studienverlaufsstatistik," 2023. https://www.statistischebibliothek.de/mir/receive/DEHeft_mods_00149171[Accessed: 2025-02-12].

_ , "Entwicklung der Studienanfängerquote in Deutschland von 2000 bis 2023," 2024. https://de.statista.com/statistik/daten/studie/72005/umfrage/entwicklung-der-studienanfaengerquote/[Accessed: 2025-02-12].

Stiglitz, Joseph and Andrew Weiss, "Sorting Out the Differences Between Signaling and Screening Models," *Mathematical Models in Economics*, 1990, pp. 1–34.

Thurow, Lester C, *Generating Inequality*, Basic Books, 1975.

Weichselbaumer, Doris, "Multiple Discrimination against Female Immigrants Wearing Headscarves," *ILR Review*, 2020, *73* (3), 600–627.

Weiss, A, "Human Capital vs. Signaling Explanation of Wages and Sorting Models of Education and Training," *Journal of Economic Perspectives*, 1995, *9* (4), 133–154.

Wiswall, Matthew and Basit Zafar, "Human Capital Investments and Expectations about Career and Family," *Journal of Political Economy*, 2021, *129* (5), 1361–1424.

Appendix

A Questionnaire

A.1 Intro

Thank you for participating in our survey!

By participating, you support a research project about current labor market and hiring processes, which is conducted under the direction of Prof. Pia Pinger at the Universities of Cologne, Bonn, and Rotterdam.

Your answers will be treated confidentially and in accordance with European data protection regulations. The results of the survey will be presented in aggregated form only.

Answering the questionnaire takes about 10 minutes.

A.2 General Questions

Are you currently employed?

- Yes
- No

Which of the following areas do you work in?

- Human resources development
- Personnel recruitment
- Personnel strategy/personnel planning
- Labor law

- Compensation management
- Other personnel areas
- Other areas except personnel

How many employees does your company have in Germany?

- Fewer than 10 employees
- 10 to 49
- 50 - 100
- 101 - 500
- 501 - 1000
- 1,001 - 2,000
- More than 2,000

For which of the following areas do you recruit employees in your company?

- Commercial
- Technical
- IT
- Natural sciences
- Humanities
- Other

A.3 Main part

In the following, the main part of the survey begins.

Your expert opinion is of great importance for our research project. We would therefore like to ask you to give your answers as if you were conducting a real hiring process.

Imagine you are looking for a new employee for an entry-level position in your company in [controlling/project management].

In the following, we will ask you about your assessments of three applicants.

For this purpose, please assume that all of the information that we do not give you about the applicant profiles is identical between the applicants. For better comparability, we present the applicant data in a uniform and simplified form.

In the first part of the survey, we ask you to give your assessment of the candidate for each of the three candidate profiles.

By clicking on the Next button, you will see the first candidate profile.

Here, the résumé of applicant 1, 2 or 3 is shown (see Appendix B for examples and details).

Imagine that there is an entry-level position to be filled in the area of [controlling/project management].

How do you rate the likelihood that you would invite [name] to an interview for the described entry-level position in your company?

0% 100%

Suppose that [name] was invited for an interview. Assuming a good performance and a positive impression, how likely do you think it is that [name] would receive an offer for the described entry-level position in your company?

0% 100%

How would you rate the likelihood that [name] would accept an offer from your company?

0% 100%

What salary (annual salary in Euro for a full-time position, excluding special benefits such as bonuses) would you offer [name] for the described entry-level position in your company?

Based on the information from the above résumé, how would you rate [name] compared to other graduates of a business degree program in terms of the following traits. Negative numbers indicate below-average and positive numbers above-average skills.

Trainability

Much lower learning ability (-100) / Much higher learning ability (+100)

-100 +100

Intelligence

Much lower intelligence (-100) / Much higher intelligence (+100)

-100 +100

Expertise

Much lower study-specific knowledge (-100) / Much higher study-specific knowledge (+100)

-100 +100

Perseverance

Much lower perseverance (-100) / Much higher perseverance (+100)

-100 +100

Commitment

Much lower commitment (-100) / Much higher commitment (+100)

-100 +100

Conscientiousness

Much lower conscientiousness (-100) / Much higher conscientiousness (+100)

-100 +100

Emotional stability

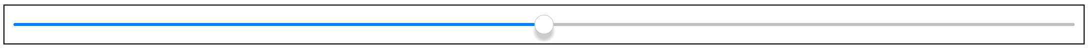
Much lower emotional stability (-100) / Much higher emotional stability (+100)

-100 +100

Social origin

Much less privileged social origin (-100) / Much more privileged social origin (+100)

-100 +100



A.4 Stated preferences

Imagine receiving an application from someone who left college during her last semester, i.e., just before earning a master's degree (but without a degree). Please write in a few words what you associate with this?

Do you prefer an applicant with a master's degree over an applicant with a bachelor's degree in the selection process for a controlling/project management position?

- Yes, a master's degree is used for pre-selection.
- Yes, there is an internal company rule that makes a master's degree a mandatory requirement in the hiring process.
- Yes, because:
- No.

What do you associate with a degree? In your view, is it more a proof of learned study content or rather a signal of certain character traits?

- Exclusively character traits
- Rather character traits
- Both equally
- Rather study content

- Exclusively study content

What do you associate with dropping out of university? Do you see it more as a lack of proof of learned study content or more as a negative signal about a candidate's character traits?

- Exclusively character traits
- Rather character traits
- Both equally
- Rather study content
- Exclusively study content

A.5 Background information

Finally, we have a few statistical questions about you and your company so that we can better evaluate your answers. This information will also be treated confidentially and will only be evaluated anonymously.

How much work experience do you have?

- 0 - 5 years
- 6 - 15 years
- 16 - 25 years
- 26 - 35 years
- More than 35 years

How many applications do you receive on average for a typical entry-level controlling/project management position in your company?

What is the average salary (annual gross amount in Euro excluding individual bonuses or benefits) for an entry-level position in controlling/project management in your company with a business administration background?

Is it common practice for company to pay a performance-related bonus for an entry-level position in controlling/project management?

- ○ Yes
- ○ No

What is the relative share of variable salary/bonus of total salary?

Very low share of variable salary (0%) / Very high share of variable salary (100%)

0% 100%

How much leeway do you have for salary negotiations (base salary and bonuses) with applicants who receive a job offer for an entry-level position in controlling/project management in your company?

There is no room for negotiation (0%) / Free negotiations possible (100%)

0% 100%

Have selection criteria for applicants in your company changed as a result of Covid-19?

No differences compared to before Covid (0%) / Large differences compared to before Covid (100%)

0% 100%

Do you have any comments regarding this survey? Is there anything special that we should know about the hiring process at your company?

Thank you for your participation and support of our research project!

B Applicant profiles

B.1 Variation of résumé components

For each hypothetical candidate, a one-page résumé is presented to the HR manager, comprising twenty components (see table B.1 for all items). The different components are randomized at the applicant level for each HR manager separately, with the exception of all time-related variables (indicated with an asterisk in table B.1). The résumé items that comprise a date (e.g. information on education obtained) depend on the randomly chosen accomplished university education to create a coherent and synchronized picture in one résumé. Below, we provide a detailed description of the variation that we include in the résumés, with the exception of the variation related to education, which is described in section 2.3.

Demographics - The gender of the applicant is indicated by the name on the résumé, with randomly half of the names being male and half being female. To avoid associations with socio-economic status, we make use of common German first and last names for the respective age cohort. In addition, there is a slight variation in the age of the applicants, which is indicated by the birth date on the résumé. There is a maximum two-year age difference between applicants, corresponding to the different lengths of educational pathways and internship lengths. Hence, all time-related variables are adjusted to avoid gaps in the résumé. This implies – for instance – that an applicant who only obtained a bachelor's degree is always slightly younger than an applicant with a master's degree. Although this implies that we cannot disentangle a potential age effect from the degree effect, we believe that this résumé design is suitable for several reasons. First of all, it is the most realistic set-up, where bachelor graduates are on average younger than master graduates. Second, previous research has not shown age effects in terms of the desirability of university graduates (Piopiunik et al., 2020).

Other variation - Other variation in the résumés is related to the applicant's language skills, free-time activities, IT skills and secondary school grade. With respect to the latter, we again looked at the actual distribution of high-school GPAs and vary grades corresponding to the 10th, 50th and 90th percentile. The free-time activities are gender neutral and comprise one sport and one other activity such as drawing or playing an instrument. With respect to languages skills, all applicants are German natives and speak English fluently. Besides, they have either basic or good skills in Spanish or French as a third language. Similarly, for IT skills, each applicant is excellent in Microsoft Office and has basic knowledge of one other statistical program. It is important to note, that these individual characteristics are not the main focus of this study but rather serve the purpose of making the résumés as realistic as possible.

Table B.1: Overview résumé components

Component	Options			
Gender	Female	Male		
First name (male)	Lukas	Maximilian		
First name (female)	Johanna	Lena		
Last name	Schneider	Weber	Becker	Fischer
Date of birth∗	3.9.1999	12.7.1998	24.6.1997	11.8.1997
High-school degree∗	2018	2017	2016	2016
High-school GPA	1.6	2.4	3.3	
University education∗	bachelor's degree	bachelor's degree & master's studies (30 ects)	bachelor's degree & master's studies (90 ects)	bachelor's degree & master's degree
Institution	University of Cologne	University of Frankfurt	University of Munich	
Bachelor GPA	1.5	2.3	3.2	
Master GPA	1.4	2.0	2.7	
Bachelor start & end date∗	Start: 2018; End: July 2021	Start: 2017; End: July 2020	Start: 2016; End: September 2019	Start: 2016; End: August 2019
Master start & end date∗	n.a.	Start: 2020; End: 2021	Start: 2019; End: 2021	Start: 2019; End: September 2021
Internship area	Sales	Project management	Auditing	
Internship employer	Windmoeller & Hoelscher, Lengerich	FACT, Muenster	MVI Proplant, Wolfsburg	
Internship year∗	2021	2020	2019	2019
Internship length	3 months	5 months	9 months	
Languages	German (native), English (fluent), Spanish (good)	German (native), English (fluent), French (basic)	German (native), English (fluent), Spanish (basic)	
Personal interests	Biking, choir	Swimming, drawing	Running, guitar	
IT skills	Microsoft Office (excellent), R (basic)	Microsoft Office (excellent), SPSS (basic)	Microsoft Office (excellent), Stata (basic)	

Notes: This table shows all components that are randomized on the résumés. The components marked by an ∗ are fixed within an applicant profile to ensure that there are no gaps in the timeline.

B.2 Examples of résumés

Figure B.1: Example of applicant with a Bsc. degree

Maximilian Becker
geb. 03/09/99

SCHULBILDUNG

Allgemeine Hochschulreife Abiturnote 3.3	2018

STUDIENLEISTUNGEN

Bachelorabschluss Betriebswirtschaftslehre 180/180 ECTS erreicht Goethe-Universität Frankfurt Abschlussnote: 3.2 Abschlussdatum: Juli 2021	2018 - 2021

ARBEITSERFAHRUNG

Praktikum Projektmanagement (9 Monate) FACT, Münster	2021

SPRACHEN

Deutsch: Muttersprache
Englisch: fließend
Französisch: Grundkenntnisse

IT KENNTNISSE

Microsoft Office (sehr gut), Stata (Grundkenntnisse)

PERSÖNLICHE INTERESSEN

Schwimmen, Zeichnen

Notes: Figure B.1 shows an example of a résumé of an hypothetical applicant with a Bsc. degree.

Figure B.2: Example of applicant with a Msc. degree

Maximilian Fischer
geb. 11/08/97

SCHULBILDUNG

Allgemeine Hochschulreife Abiturnote 3.3	2016

STUDIENLEISTUNGEN

<u>Masterabschluss Betriebswirtschaftslehre</u> 120/120 ECTS erreicht Goethe-Universität Frankfurt Abschlussnote: 1.4 Abschlussdatum: September 2021	2019 – 2021
<u>Bachelorabschluss Betriebswirtschaftslehre</u> 180/180 ECTS erreicht LMU München Abschlussnote: 1.5 Abschlussdatum: August 2019	2016 – 2019

ARBEITSERFAHRUNG

Praktikum Sales (9 Monate) FACT, Münster	2019

SPRACHEN

Deutsch: Muttersprache
Englisch: fließend
Spanisch: gut

IT KENNTNISSE

Microsoft Office (sehr gut), SPSS (Grundkenntnisse)

PERSÖNLICHE INTERESSEN

Laufen, Gitarre

Notes: Figure B.2 shows an example of a résumé of an hypothetical applicant with a Msc. degree.

Figure B.3: Example of applicant with a Bsc.+25% degree

Lukas Schneider
geb. 12/07/98

SCHULBILDUNG

Allgemeine Hochschulreife 2017
Abiturnote 2.4

STUDIENLEISTUNGEN

Bachelorabschluss Betriebswirtschaftslehre
180/180 ECTS erreicht 2017 – 2020
LMU München
Abschlussnote: 1.5
Abschlussdatum: Juli 2020

Sonstige Leistungen:

Masterstudium Betriebswirtschaftslehre (nicht abgeschlossen)
Erstes Semester (30/120 ECTS) absolviert 2020 – 2021
LMU München
Durchschnittsnote: 2.7
Exmatrikulation: 2021

ARBEITSERFAHRUNG

Praktikum Controlling (5 Monate) 2020
Windmöller & Hölscher, Lengerich

SPRACHEN

Deutsch: Muttersprache
Englisch: fließend
Spanisch: Grundkenntnisse

IT KENNTNISSE

Microsoft Office (sehr gut), R (Grundkenntnisse)

PERSÖNLICHE INTERESSEN

Laufen, Gitarre

Notes: Figure B.3 shows an example of a résumé of an hypothetical applicant who dropped out after attaining 25% (i.e. 30 ECTS) of a Msc. degree.

Figure B.4: Example of applicant with a Bsc.+75% degree

Lena Weber

geb. 24/06/97

SCHULBILDUNG

Allgemeine Hochschulreife 2016
Abiturnote 1.6

STUDIENLEISTUNGEN

Bachelorabschluss Betriebswirtschaftslehre
180/180 ECTS erreicht 2016 – 2019
Universität zu Köln
Abschlussnote: 2.3
Abschlussdatum: September 2019

Sonstige Leistungen:

Masterstudium Betriebswirtschaftslehre (nicht abgeschlossen)
Kursphase (90/120 ECTS) absolviert 2019 – 2021
Goethe-Universität Frankfurt
Durchschnittsnote: 1.4
Exmatrikulation: 2021

ARBEITSERFAHRUNG

Praktikum Sales (3 Monate) 2019
MVI Proplant, Wolfsburg

SPRACHEN

Deutsch: Muttersprache
Englisch: fließend
Spanisch: gut

IT KENNTNISSE

Microsoft Office (sehr gut), SPSS (Grundkenntnisse)

PERSÖNLICHE INTERESSEN

Rennrad, Chor

Notes: Figure B.4 shows an example of a résumé of an hypothetical applicant who dropped out after attaining 75% (i.e. 90 ECTS) of a Msc. degree.

C Data cleaning procedure

When designing the survey, we bounded most answer ranges to fit feasible possibilities. For example, for the interview and hiring probabilities, it is only possible to fill in values between 0 and 100. When asking respondents the wage that they would offer the candidate, the following message shows up when they fill in an amount below €10,000 or above €99,000: please check your entry and confirm it by clicking next.[25] However, it is possible for respondents to ignore the message and fill in any amount that they deem appropriate.

As this may create noise in the answers that we observe, we clean the wage variable as follows. First, we check whether the wages that a respondent filled in are consistent across applicants and with the reported average starting wage of their firm (36 observations are dropped due to inconsistent relative wages). We also check whether respondents may have misunderstood the question and filled in the wage per month instead of year. For values between €1,400 and €12,500, we assume they meant monthly wages, in which case the value is multiplied by 12 (30 respondents or roughly 7% of the sample). Finally, we drop all respondents whose yearly wage value is below €17,000 or above €150,000 (16 observations are dropped due to implausible absolute wages). The lower bound of €17,000 originates from the minimum full-time salary mandated by German law, while the upper bound comes from an online search of the highest starting salaries in Germany.

Overall, 484 employers completed the survey. After the cleaning procedure described above, we are left with 433 respondents who answered questions about 1,299 applicants.

[25] Original text: *Bitte überprüfen Sie Ihre Eingabe und bestätigen Sie diese mit dem Weiter-Button.*

D Traits of actual candidates

We assess if human resource managers hold correct beliefs about the characteristics of dropout and master students as compared to bachelor students using actual survey data containing information on degree completion as well as measures of conscientiousness, emotional stability, IQ, and socio-economic status. To this end we use data from the German student study 'Fachkraft 2030".[26] The original data, containing measures of personality traits, IQ and SES were collected in September 2014 and March 2015. A follow-up survey to assess final educational outcomes of these students was collected in January 2023. The data contain around 450 observations for parental socio-economic status, and around 390 observations for the measures of personality traits and IQ. 78% of the sample have completed a bachelor's degree, 13% have obtained master's degree, and 9% have dropped out from their master studies after having obtained a bachelor's degree.

D.1 Measures

Students' conscientiousness and emotional stability were assessed using the respective parts of the 50 item IPIP test (Goldberg et al., 2006). IQ was measured based on ten items from a Raven-type matrix IQ test (Raven and Court, 1998). For socio-economic status we construct a score combining information on maternal and paternal levels of education, as well as a student's migrant status. Importantly, all measures were collected in 2014 and 2015, i.e., while students were enrolled, such that they are unaffected by later job performance or career trajectories.

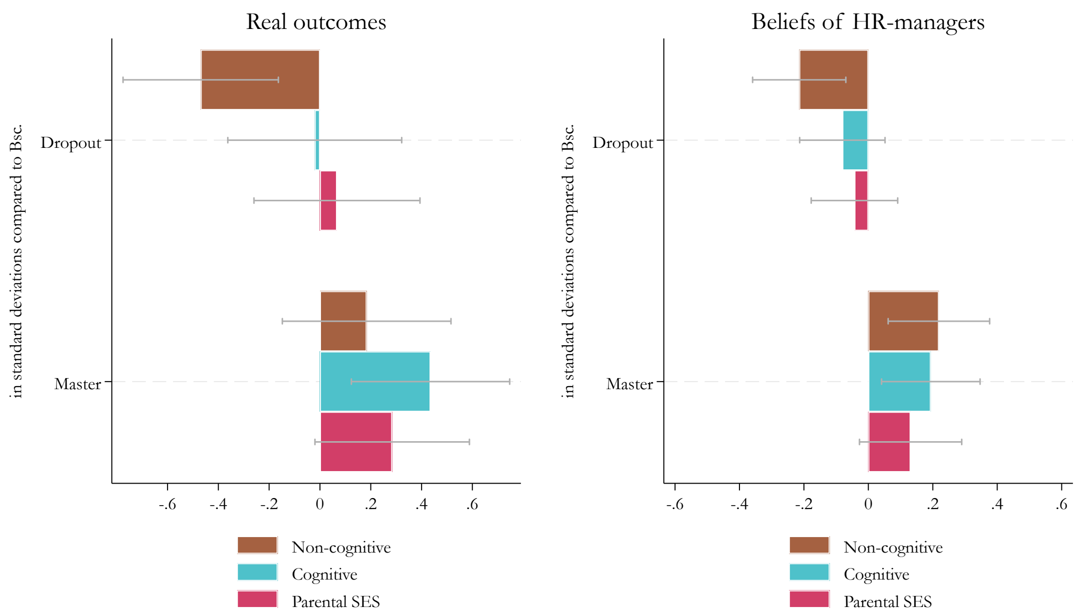
D.2 Results

Figure D.1 compares actual trait scores (left panel) by educational level with HR managers' beliefs (right panel). For both actual traits and employer beliefs, we standardize the scores relative to the bachelor scenario in their respective samples, making them directly comparable. We categorize the scores into cognitive traits

[26] See Seegers et al. (2016) for more information.

(IQ), non-cognitive traits (emotional stability and conscientiousness), and socio-economic background. Qualitatively, the differences in actual traits are surprisingly similar to the beliefs held by the HR managers. HR managers seem to only slightly overestimate the non-cognitive traits of master's degree holders compared to bachelor's degree holders. Overall, however, the findings in this section indicate that employers hold remarkably accurate beliefs about candidates' characteristics.

Figure D.1: Actual trait differences and beliefs about trait differences by educational completion



Notes: The figure displays real differences (left panel) and employer beliefs about differences (right panel) in trait scores among dropouts and master's degree holders compared to bachelor's degree holders. The gray bars indicate 95% confidence intervals. Non-cognitive traits (Conscientiousness, Emotional stability), Cognitive traits (IQ) and SES are indices, more specifically the equally weighted averages of z-scores of its components. The z-scores are calculated by subtracting the Bsc. scenario mean and dividing by the Bsc. scenario standard deviation. The indices are then again normalized, i.e. divided by the Bsc. scenario standard deviation.

E Role of incentives

We investigate whether the introduction of incentives in our setting systematically changes the main results. To do this, we conducted an additional experiment on the online platform Prolific in October 2024. Subjects with hiring experience were prioritized through a pre-screening process on Prolific. They were only eligible to participate if they lived in Germany and were fluent in German. Subjects received a fixed payment of €4 upon successful completion of the survey.

E.1 Design

The design closely followed that of the main study. The three main differences are that each participant was shown four instead of three candidate profiles, that participants were asked about their beliefs about how the HR managers of the main study perceived these candidates, and that participants were incentivized for two of the four candidate profiles.

Each participant was shown four fictitious applicant profiles and we elicited their beliefs about how HR managers perceived these applicants. The four profiles differed in terms of the applicant's level of education. For each participant, one profile was randomly selected for each educational level, corresponding to an applicant profile rated by a HR manager in the main study. The order in which they received the applicant profiles of different educational levels was randomized. They were asked what they thought the HR manager's answers were to the hiring questions as well as to the questions about expertise, cognitive traits, non-cognitive traits, and socio-economic background. In the end, all participants were asked the same questions about their personal views and background information.

For two out of the four applicant profiles, participants' evaluations were incentivized, with rewards based on how closely their responses matched the HR manager's actual evaluation. Which of the two profiles was incentivised was randomised. If their response differed by less than 5 percentage points (€2500 for wages) from the HR manager's actual response, they received an additional €5.

E.2 Sample description

Based on the criteria described above, we were able to collect 334 responses who, according to Prolific, had hiring experience. The data cleaning procedure is similar to the main study. 24 responses were removed because the absolute or relative wages are nonsensical. Another 41 responses were removed because they answered that they had no hiring experience, although they were pre-screened for this, which leads us to believe that they are inattentive. This leaves a final sample size of 269.[27] Respondents in the final sample spent an average of 16 minutes completing the survey. The descriptive statistics of the sample are displayed in Table E.1.

Table E.1: Descriptive statistics of Prolific sample

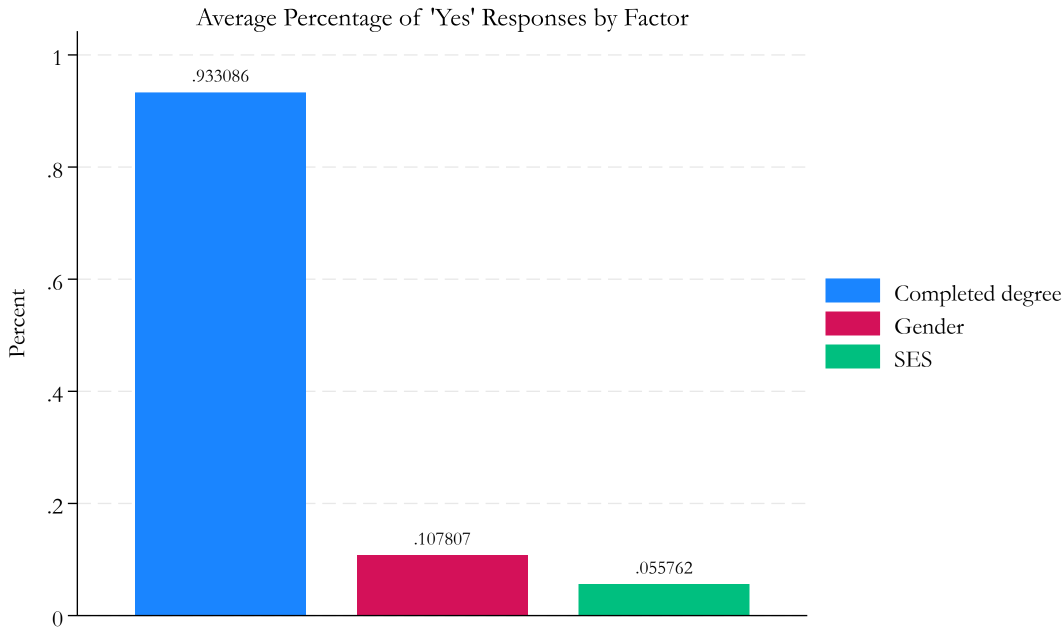
	mean	sd
Gender (sample share)		
Female	0.33	0.47
Male	0.66	0.47
Divers	0.01	0.11
Age (sample share)		
18-34	0.54	0.50
34-54	0.41	0.49
55+	0.05	0.21
Education (sample share)		
High school degree or less	0.24	0.43
Bachelor's degree or more	0.76	0.43
Years of experience (sample share)		
0-5	0.38	0.49
6-15	0.40	0.49
16-25	0.14	0.35
26-35	0.06	0.24
35+	0.02	0.15
Occupation (sample share)		
Business, Finance, and Administration	0.23	0.42
Sales and Service	0.09	0.28
Applied sciences and Manufacturing	0.25	0.44
Research and Education	0.18	0.38
Medicine and Health Care	0.06	0.24
Other	0.19	0.40
Observations	269	

Notes: The table shows the sample mean and standard deviation for several characteristics of the Prolific sample.

[27] Our registration plan only prioritized participants with hiring experience. As we successfully recruited a sufficient number of such participants, we report results exclusively for this group.

E.3 Results

Figure E.1: Appropriateness to consider factor when making hiring decisions



Notes: The figure shows the distribution of responses to the question of whether it is appropriate to consider a degree, gender or socio-economic background when making a hiring decision.

Table E.2: Heterogeneity by incentive

	Attractiveness			Traits							
	(1) Prob. to invite	(2) Prob. to offer	(3) Log Wage	(4) Perseverance	(5) Commitment	(6) Conscient.	(7) Emotional stab.	(8) Trainability	(9) IQ	(10) Expertise	(11) SES
Bsc.+25%	-3.338	-3.446*	0.010	-27.365***	-20.533***	-12.847***	-12.445***	-5.321	-2.330	-1.902	1.413
	(2.356)	(2.050)	(0.012)	(4.456)	(3.804)	(3.224)	(3.309)	(3.635)	(3.064)	(3.711)	(2.558)
Bsc.+75%	-3.138	-2.131	0.025*	-25.431***	-16.815***	-12.888***	-9.529***	-4.972	-2.157	-5.094	-1.738
	(2.383)	(2.038)	(0.013)	(4.006)	(3.470)	(3.389)	(3.213)	(3.534)	(3.038)	(3.881)	(2.642)
Msc	11.838***	10.735***	0.100***	22.534***	10.955***	11.634***	13.145***	14.090***	12.230***	20.964***	8.986***
	(2.521)	(2.094)	(0.013)	(4.260)	(3.716)	(3.492)	(3.358)	(3.697)	(3.239)	(3.818)	(2.564)
Incentivized	2.603	0.431	-0.008	-2.040	-0.245	5.131	4.136	0.402	-0.397	-1.230	1.590
	(2.457)	(2.183)	(0.014)	(4.236)	(3.583)	(3.529)	(3.497)	(3.683)	(3.162)	(3.948)	(2.844)
Bsc.+25%*Incentivized	-1.565	3.531	0.024	4.553	10.018*	0.679	2.111	1.402	-0.209	1.555	-5.224
	(3.739)	(3.125)	(0.020)	(6.347)	(5.407)	(5.020)	(5.335)	(5.612)	(4.919)	(5.876)	(4.289)
Bsc.+75%*Incentivized	-0.086	2.863	0.021	7.263	5.919	0.937	-0.603	2.534	1.038	7.172	0.026
	(3.593)	(3.043)	(0.019)	(6.239)	(5.584)	(5.075)	(5.059)	(5.357)	(4.810)	(5.800)	(3.906)
Msc.*Incentivized	-2.171	1.030	0.017	-1.461	1.681	-3.413	-9.264*	-4.444	-1.651	-0.752	-1.830
	(3.802)	(3.130)	(0.019)	(7.040)	(6.118)	(5.586)	(5.348)	(5.638)	(4.717)	(5.941)	(4.262)
N	1076	1076	1076	1076	1076	1076	1076	1076	1076	1076	1076
Ind. FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Controls (other)	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes

Standard errors in parentheses

* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Notes: All columns show coefficients that are estimates from a linear regression, including participant FEs and control variables. White robust standard errors clustered at the respondent level are displayed in parentheses. Incentivized is a dummy variable that equals 1 if the participant received incentives for this applicant profile. Bsc. completion serves as a baseline estimate. Control variables comprise the randomized résumé elements: age, high school GPA, university, GPA of the last obtained degree, internship fit to job vacancy, internship firm, internship duration, languages, personal interests and IT skills. ***, **, * indicate significance at the 1, 5 and 10% level, respectively.

Table E.3: Absolute deviation from HR manager responses by incentive

	Attractiveness			Traits							
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)
	Prob. to invite	Prob. to offer	Wage	Perseverance	Commitment	Conscient.	Emotional stab.	Trainability	IQ	Expertise	SES
Incentivized	-0.087	-0.092	-0.002	-0.072	-0.078	-0.122**	-0.058	-0.082	-0.066	-0.081	-0.045
	(0.056)	(0.056)	(0.049)	(0.062)	(0.063)	(0.058)	(0.060)	(0.059)	(0.054)	(0.058)	(0.057)
N	1076	1076	1076	1076	1076	1076	1076	1076	1076	1076	1076
Ind. FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes

Standard errors in parentheses

* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Notes: All columns show coefficients that are estimates from a linear regression, including participant FEs. White robust standard errors clustered at the respondent level are displayed in parentheses. The dependent variable is the absolute deviation of the participant's response from the response of the hiring manager who rated the exact same profile in the main study. Incentivized is a dummy variable that equals 1 if the participant received incentives for this applicant profile. Non incentivized profiles serve as a baseline estimate. ***, **, * indicate significance at the 1, 5 and 10% level, respectively.

Table E.4: Deviation from HR manager responses by education level

	Attractiveness			Traits							
	(1) Prob. to invite	(2) Prob. to offer	(3) Wage	(4) Perseverance	(5) Commitment	(6) Conscient.	(7) Emotional stab.	(8) Trainability	(9) IQ	(10) Expertise	(11) SES
Bsc.+25%	-0.142*	-0.036	0.075	-0.393***	-0.212**	-0.243***	-0.152*	-0.145*	-0.103	-0.110	-0.047
	(0.079)	(0.079)	(0.064)	(0.101)	(0.095)	(0.087)	(0.086)	(0.084)	(0.073)	(0.080)	(0.080)
Bsc.+75%	-0.089	-0.044	0.063	-0.374***	-0.195**	-0.151*	-0.113	-0.125*	-0.083	-0.070	0.048
	(0.076)	(0.073)	(0.066)	(0.090)	(0.086)	(0.084)	(0.080)	(0.072)	(0.068)	(0.075)	(0.074)
Msc	0.202**	0.335***	0.040	0.227***	0.124	0.078	-0.011	0.082	0.134*	0.199***	0.064
	(0.082)	(0.078)	(0.069)	(0.076)	(0.078)	(0.082)	(0.075)	(0.077)	(0.075)	(0.074)	(0.075)
N	1076	1076	1076	1076	1076	1076	1076	1076	1076	1076	1076
Ind. FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes

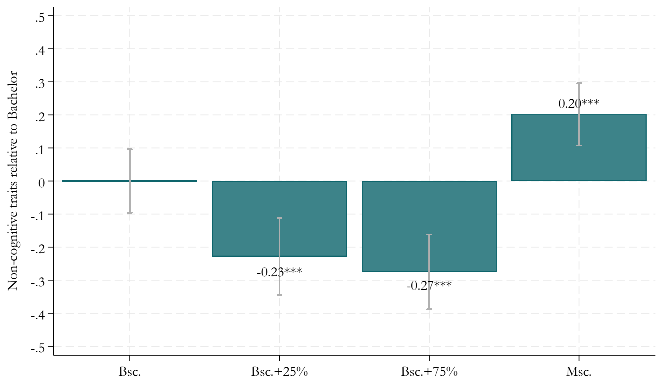
Standard errors in parentheses

* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

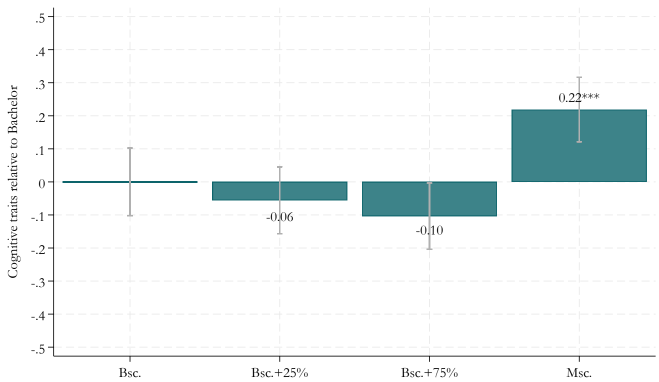
Notes: All columns show coefficients that are estimates from a linear regression, including participant FEs. White robust standard errors clustered at the respondent level are displayed in parentheses. The dependent variable is the deviation of the participant's response from the response of the hiring manager who rated the exact same profile in the main study. Non incentivized profiles serve as a baseline estimate. ***, **, * indicate significance at the 1, 5 and 10% level, respectively.

F Additional figures and tables

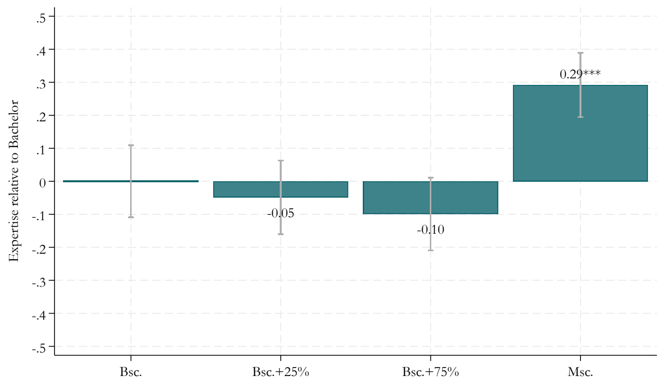
Figure F.1: Employer beliefs by educational completion



(a) Non-cognitive traits



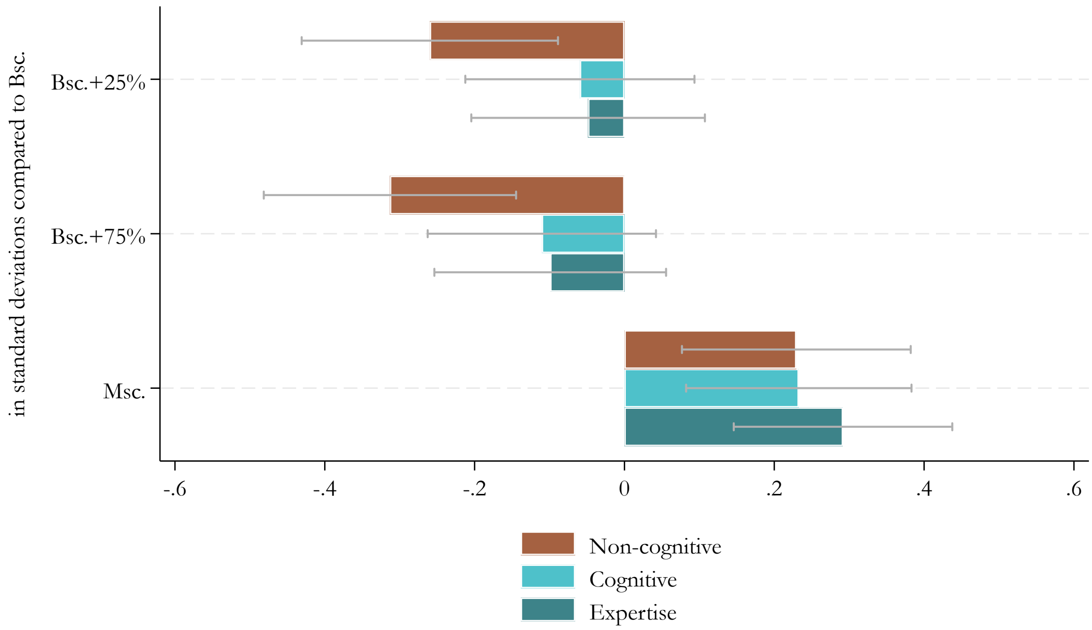
(b) Cognitive traits



(c) Expertise

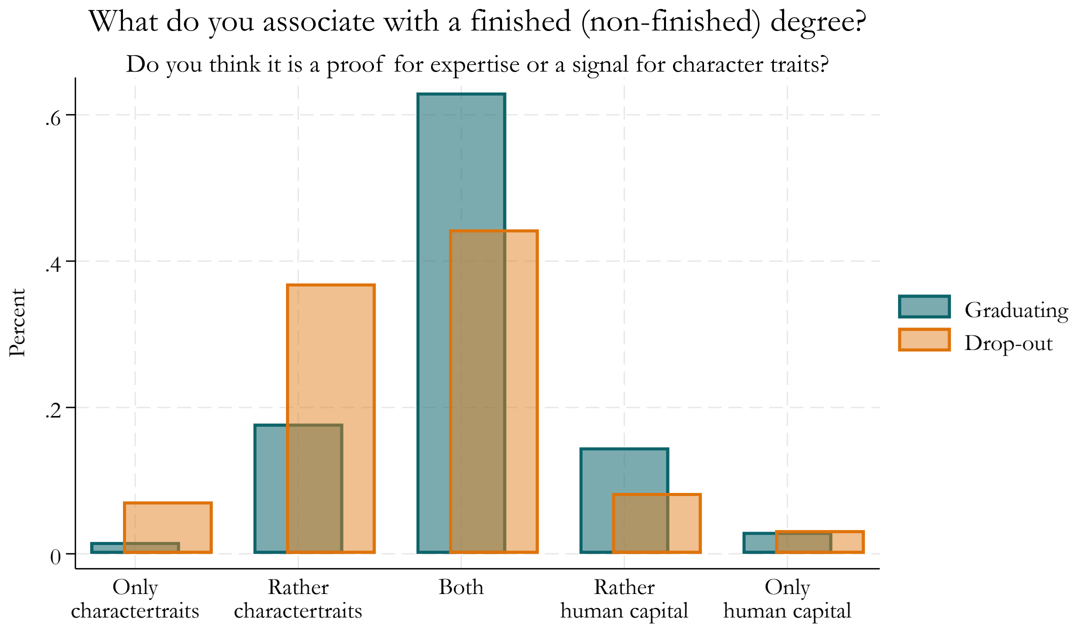
Notes: The figure displays the employer beliefs about average non-cognitive traits (Panel A), cognitive traits (Panel B), and expertise (Panel C) by educational achievement relative to the Bsc. scenario. The stars indicate significance from a series of two-sides t-tests, that compare the average of having obtained a Bsc. only with the respective averages of each of the other scenarios. Error bars indicate 95% confidence intervals. Non-cognitive traits (Perseverance, Commitment, Conscientiousness, Emotional stability), Cognitive traits (Trainability, IQ) and Expertise are the equally weighted averages of z-scores of its components. The z-scores are calculated by subtracting the Bsc. scenario mean and dividing by the Bsc. scenario standard deviation.

Figure F.2: Employer beliefs by educational completion - Grouped



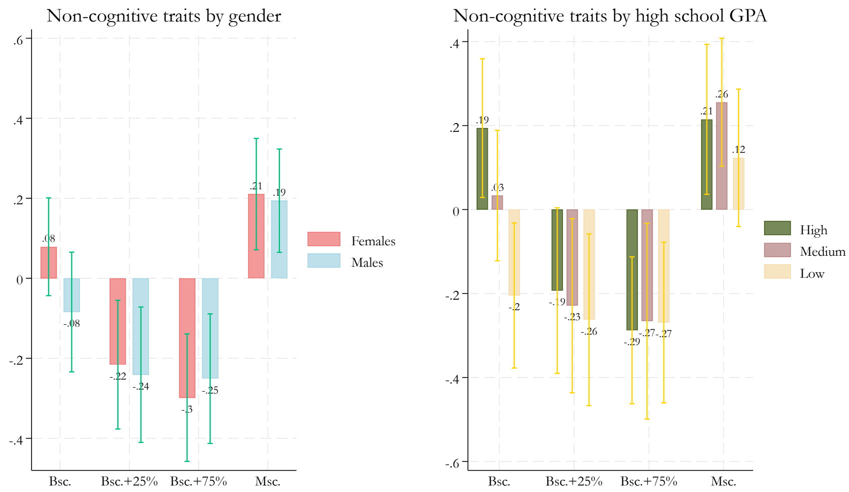
Notes: The figure displays standardized differences in non-cogntive traits, cognitive traits and expertise of the Bsc. +25%, Bsc. +75%, and Msc. scenarios compared to the Bsc. scenario, with all scores being standardized with respect to the Bsc. distributions. The gray bars indicate 95% confidence intervals. Non-cognitive traits (Perseverance, Commitment, Conscientiousness, Emotional stability), Cognitive traits (Trainability, IQ) and Expertise are the equally weighted averages of z-scores of its components. The z-scores are calculated by subtracting the Bsc. scenario mean and dividing by the Bsc. scenario standard deviation.

Figure F.3: Character traits vs. Human capital

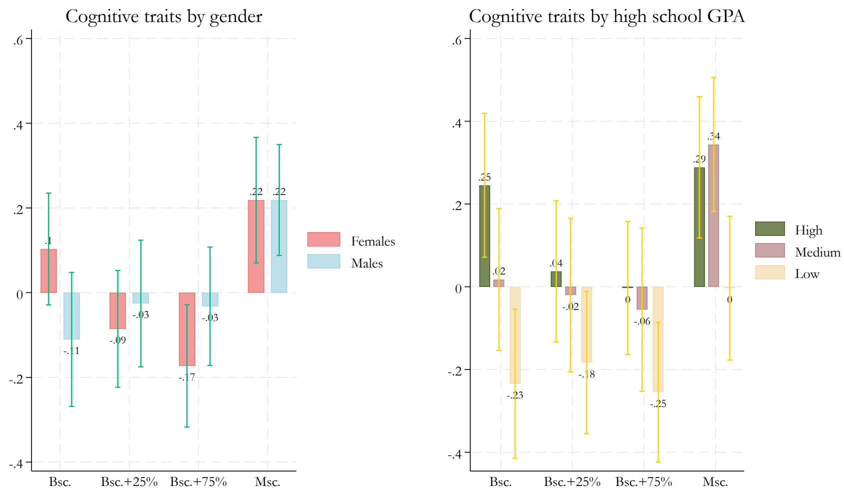


Notes: The figure shows the distribution of answers to the question of whether (not) finishing a degree is (lack of) proof for expertise or a (negative) signal for character traits. The paired t-test shows that finishing a degree is equally associated with a signal for character traits and proof for expertise while not finishing a degree is significantly more associated with a signal for character traits.

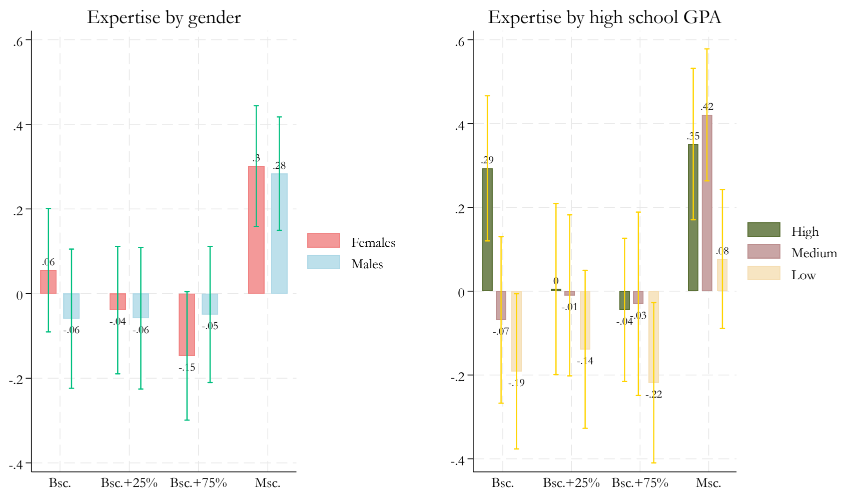
Figure F.4: Employer beliefs by educational completion split by gender and high school GPA



(a) Non-cognitive traits



(b) Cognitive traits



(c) Expertise

Notes: The figure displays the employer beliefs about average non-cognitive traits (Panel A), cognitive traits (Panel B), and expertise (Panel C) by educational achievement relative to the Bsc. scenario. The plots on the left display beliefs split by gender and the plots on the right display beliefs split by high school GPA. Error bars indicate 95% confidence intervals.

Table F.1: Descriptive statistics of employers

	Mean	St.dev.
Years of experience (sample share)		
0-5	0.12	0.32
6-15	0.45	0.50
16-25	0.26	0.44
26-35	0.15	0.36
35+	0.03	0.17
Firm size (sample share)		
10 - 49	0.09	0.28
50 - 100	0.10	0.30
101 - 500	0.33	0.47
501 - 1000	0.23	0.42
1001 - 2000	0.12	0.33
2000+	0.13	0.34
Average number of applicants	42.79	65.56
Average company starting wage (in Euro)	42740.36	17114.47
Bonus paid on top of base salary (sample share)	0.37	0.48
Change in hiring due to Covid-19 (0-100)	34.49	30.74
Observations	433	

Notes: The table shows the sample mean and standard deviation for several characteristics of HR managers and the firms for which they work.

Table F.2: Employment outcomes by all résumé items

	Base Bsc.		
	(1) Prob. to invite	(2) Prob. to offer	(3) Log Wage
Bsc.+25%	-0.492	0.361	-0.001
	(1.238)	(1.170)	(0.008)
Bsc.+75%	-2.302*	-0.831	0.000
	(1.267)	(1.241)	(0.008)
Msc	4.486***	3.601***	0.048***
	(1.169)	(1.179)	(0.008)
Interns. type fits	1.593*	1.497*	0.005
	(0.879)	(0.819)	(0.006)
Male	-1.041	-0.225	0.005
	(0.895)	(0.871)	(0.006)
High-school grade	2.969***	2.691***	0.012***
	(0.603)	(0.581)	(0.004)
GPA highest degree	3.569***	3.282***	0.014***
	(0.743)	(0.679)	(0.005)
Uni Munich (Bsc.)	1.510	0.131	0.005
	(1.016)	(0.921)	(0.006)
Uni Cologne (Bsc.)	-0.424	-1.629*	-0.001
	(0.986)	(0.982)	(0.007)
Uni Munich (Msc.)	1.249	2.112**	0.004
	(0.997)	(0.955)	(0.007)
Uni Cologne (Msc.)	0.201	0.005	-0.005
	(1.081)	(1.006)	(0.007)
5 months interns.	-0.033	0.760	0.006
	(1.023)	(1.003)	(0.007)
9 month interns.	0.680	0.796	0.012*
	(1.009)	(0.955)	(0.007)
Firm II	-0.143	-0.202	0.001
	(0.991)	(0.977)	(0.006)
Firm III	-0.411	-0.954	0.002
	(1.041)	(0.948)	(0.007)
Spanish basic	-0.751	0.069	0.009
	(1.032)	(0.959)	(0.007)
Spanish good	1.326	1.052	0.017**
	(1.004)	(0.957)	(0.007)
SPSS skills	0.919	0.550	0.008
	(0.958)	(0.925)	(0.007)
Stata skills	0.542	0.946	0.007
	(1.018)	(0.945)	(0.006)
Personal interests II	0.384	0.780	-0.004
	(1.040)	(0.976)	(0.007)
Personal interests III	1.827*	0.664	0.000
	(1.011)	(0.943)	(0.007)
N	1299	1299	1299
Ind. FE	Yes	Yes	Yes

Notes: All columns show coefficients that are estimates from a linear regression, including employer FEs. White robust standard errors clustered at the respondent level are displayed in parentheses. The data are unbalanced as employers randomly receive and assess résumés corresponding to three out of four education scenarios. Having obtained only a Bsc. serves as a baseline estimate. See table B.1 for the default category for each of the variables. ***, **, * indicate significance at the 1, 5 and 10 percent level, respectively.

Table F.3: T-tests of employer beliefs by educational completion

	Bsc.+25%		Bsc.+75%		Msc.	
	Dif.	P-value	Dif.	P-value	Dif.	P-value
Perseverance	-0.346***	0.000	-0.363***	0.000	0.236***	0.003
Commitment	-0.244***	0.004	-0.302***	0.000	0.186**	0.015
Conscientiousness	-0.147*	0.076	-0.244***	0.004	0.170**	0.030
Emotional stability	-0.175**	0.039	-0.190**	0.020	0.215***	0.005
Trainability	-0.045	0.570	-0.112	0.152	0.243***	0.001
IQ	-0.067	0.388	-0.095	0.220	0.194**	0.013
Expertise	-0.049	0.541	-0.099	0.209	0.292***	0.000
SES	0.002	0.982	-0.091	0.245	0.131	0.105

Notes: The table displays standardized differences in trait scores of the Bsc. +25%, Bsc. +75%, and Msc. compared to a Bsc., with all scores being standardized with respect the Bsc. distributions. ***, **, * indicate significance at the 1, 5 and 10% level, respectively.

Table F.4: Decomposition of differences in candidate attractiveness

	Msc.			Bsc.+75%
	(1)	(2)	(3)	(4)
	Pr. to invite	Pr. to offer	Log wage	Pr. to invite
Difference with Bsc.	4.897**	3.920**	0.070**	-3.435*
	(1.524)	(1.468)	(0.023)	(1.561)
Explained	3.484***	3.111***	0.007	-2.445*
	(0.956)	(0.935)	(0.005)	(1.089)
Unexplained	1.413	0.809	0.063**	-0.991
	(1.221)	(1.171)	(0.024)	(1.186)
Explained				
Trainability	1.332**	1.101*	-0.009	-0.694
	(0.492)	(0.440)	(0.006)	(0.498)
Intelligence	-0.064	0.611	0.005	-0.170
	(0.222)	(0.331)	(0.005)	(0.169)
Expertise	1.324**	0.446	0.008	-0.375
	(0.483)	(0.363)	(0.006)	(0.314)
Perseverance	0.677	0.822*	0.002	-1.476**
	(0.365)	(0.380)	(0.005)	(0.505)
Commitment	0.053	0.149	-0.001	-0.000
	(0.204)	(0.220)	(0.003)	(0.289)
Conscientiousness	0.183	0.128	0.002	0.315
	(0.240)	(0.200)	(0.004)	(0.263)
Emotional stability	0.039	-0.000	0.005	-0.091
	(0.252)	(0.217)	(0.004)	(0.181)
Socioeconomic background	-0.059	-0.146	-0.005	0.047
	(0.120)	(0.135)	(0.004)	(0.089)
Observations	645	645	645	642

Notes: The table shows the coefficients of the decomposition of the significant differences in candidate attractiveness shown in columns 1, 3 and 5 of table 1. See equation 3 for details on the decomposition. The t statistics are displayed in parentheses. ***, **, * indicate significance at the 1, 5 and 10% level, respectively.

Table F.5: Heterogeneous effects on employment outcomes by GPA

	(1) Prob. to invite	(2) Prob. to offer	(3) Log Wage
Bsc.+25%	0.411	0.437	0.003
	(1.862)	(1.782)	(0.014)
Bsc.+75%	-3.937**	-2.507	-0.003
	(1.852)	(1.694)	(0.011)
Msc	5.937***	5.817***	0.060***
	(1.862)	(1.885)	(0.012)
Bsc.+25% * High GPA	0.155	1.776	0.013
	(2.542)	(2.366)	(0.018)
Bsc.+25% * Low GPA	-4.091	-3.471	-0.036**
	(2.595)	(2.316)	(0.018)
Bsc.+75% * High GPA	1.877	1.393	0.006
	(2.663)	(2.406)	(0.017)
Bsc.+75% * Low GPA	2.706	3.153	-0.002
	(2.567)	(2.366)	(0.017)
Msc. * High GPA	1.848	-1.115	-0.021
	(2.444)	(2.424)	(0.016)
Msc. * Low GPA	-3.783	-3.318	-0.007
	(2.569)	(2.413)	(0.015)
N	1299	1299	1299
Ind. FE	Yes	Yes	Yes
Controls (other)	Yes	Yes	Yes

Notes: All columns show coefficients that are estimates from a linear regression, including employer FEs and control variables. White robust standard errors clustered at the respondent level are displayed in parentheses. High GPA is defined as the top 10th percentile of the grade distribution, while low GPA is set at the 90th percentile, both compared to the median GPA. Bsc. completion serves as a baseline estimate. Control variables comprise the randomized résumé elements: gender, age, high school GPA, university, internship fit to job vacancy, internship firm, internship duration, languages, personal interests and IT skills. ***, **, * indicate significance at the 1, 5 and 10% level, respectively.

Table F.6: Heterogeneous effects on employment outcomes by high school GPA

	(1) Prob. to invite	(2) Prob. to offer	(3) Log Wage
Bsc.+25%	9.287	-4.560	-0.066*
	(5.670)	(5.458)	(0.039)
Bsc.+75%	-0.226	-2.882	-0.033
	(6.097)	(5.639)	(0.038)
Msc	13.035**	4.585	0.034
	(6.569)	(6.334)	(0.040)
High school GPA	4.978***	2.052	0.001
	(1.576)	(1.547)	(0.011)
Bsc.+25%*High school GPA	-3.828*	1.935	0.026*
	(2.219)	(2.097)	(0.015)
Bsc.+75%*High school GPA	-0.853	0.820	0.013
	(2.329)	(2.149)	(0.015)
Msc*High school GPA	-3.368	-0.350	0.006
	(2.456)	(2.400)	(0.015)
N	1299	1299	1299
Ind. FE	Yes	Yes	Yes
Controls (other)	Yes	Yes	Yes

Standard errors in parentheses

* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Notes: All columns show coefficients that are estimates from a linear regression, including employer FEs and control variables. White robust standard errors clustered at the respondent level are displayed in parentheses. High school GPA takes on three different values, where higher values represent a better grade. Bsc. completion serves as a baseline estimate. Control variables comprise the randomized résumé elements: gender, age, university, GPA of the last obtained degree, internship fit to job vacancy, internship firm, internship duration, languages, personal interests and IT skills. ***, **, * indicate significance at the 1, 5 and 10% level, respectively.

Table F.7: Heterogeneous effects on employment outcomes by gender

	(1) Prob. to invite	(2) Prob. to offer	(3) Log Wage
Bsc.+25%	-0.191	0.414	-0.004
	(1.895)	(1.713)	(0.012)
Bsc.+75%	-3.182*	-1.226	0.009
	(1.928)	(1.744)	(0.013)
Msc	3.762*	4.380**	0.056***
	(2.015)	(1.858)	(0.013)
Male	-1.667	-0.037	0.011
	(2.040)	(1.986)	(0.013)
Bsc.+25%*Male	-0.616	-0.126	0.007
	(3.210)	(2.904)	(0.019)
Bsc.+75%*Male	1.744	0.839	-0.017
	(2.988)	(2.752)	(0.021)
Msc.*Male	1.428	-1.447	-0.016
	(3.196)	(2.981)	(0.020)
N	1299	1299	1299
Ind. FE	Yes	Yes	Yes
Controls (other)	Yes	Yes	Yes

Standard errors in parentheses

* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Notes: All columns show coefficients that are estimates from a linear regression, including employer FEs and control variables. White robust standard errors clustered at the respondent level are displayed in parentheses. Male is a dummy variable that turns 1 if the applicant profile showed a male name. Bsc. completion serves as a baseline estimate. Control variables comprise the randomized résumé elements: age, high school GPA, university, GPA of the last obtained degree, internship fit to job vacancy, internship firm, internship duration, languages, personal interests and IT skills. ***, **, * indicate significance at the 1, 5 and 10% level, respectively.

Table F.8: Heterogeneous effects on employment outcomes by job profile

	(1) Prob. to invite	(2) Prob. to offer	(3) Log Wage
Bsc.+25%	-0.907	-0.553	-0.012
	(1.782)	(1.585)	(0.013)
Bsc.+75%	-0.655	-0.723	0.006
	(1.637)	(1.608)	(0.012)
Msc	4.693***	3.796**	0.042***
	(1.630)	(1.625)	(0.011)
Bsc.+25%*Controlling	0.986	1.913	0.023
	(2.508)	(2.345)	(0.017)
Bsc.+75%*Controlling	-3.129	-0.196	-0.011
	(2.575)	(2.460)	(0.017)
Msc.*Controlling	-0.402	-0.429	0.011
	(2.335)	(2.304)	(0.015)
N	1299	1299	1299
Ind. FE	Yes	Yes	Yes
Controls (other)	Yes	Yes	Yes

Notes: All columns show coefficients that are estimates from a linear regression, including employer FEs and control variables. White robust standard errors clustered at the respondent level are displayed in parentheses. The "controlling" dummy indicates whether the hypothesized vacancy is within the area of controlling or project management. The data are unbalanced as employers randomly receive and assess three out of four possible résumés. Bsc. only serves as a baseline estimate. Control variables comprise the randomized résumé elements: gender, age, high school GPA, university, GPA of the last obtained degree, internship fit to job vacancy, internship firm, internship duration, languages, personal interests and IT skills. ***, **, * indicate significance at the 1, 5 and 10% level, respectively.

Table F.9: Heterogeneous effects on employment outcomes by firm size

	(1) Prob. to invite	(2) Prob. to offer	(3) Log Wage
Bsc.+25%	-1.306	-1.058	-0.005
	(1.461)	(1.473)	(0.011)
Bsc.+75%	-1.832	-0.662	0.002
	(1.577)	(1.575)	(0.011)
Msc	3.664**	2.103	0.042***
	(1.460)	(1.516)	(0.010)
Bsc.+25%*Firm size	0.002	0.003	0.000
	(0.002)	(0.002)	(0.000)
Bsc.+75%*Firm size	-0.001	-0.000	-0.000
	(0.002)	(0.002)	(0.000)
Msc.*Firm size	0.002	0.003	0.000
	(0.002)	(0.002)	(0.000)
N	1299	1299	1299
Ind. FE	Yes	Yes	Yes
Controls (other)	Yes	Yes	Yes

Notes: All columns show coefficients that are estimates from a linear regression, including employer FEs and control variables. White robust standard errors clustered at the respondent level are displayed in parentheses. Firm sizes measures the number of employees at the company for which the employer works. The Bsc. only serves as a baseline estimate. Control variables comprise the randomized résumé elements: gender, age, high school GPA, university, GPA of the last obtained degree, internship fit to job vacancy, internship firm, internship duration, languages, personal interests and IT skills. ***, **, * indicate significance at the 1, 5 and 10% level, respectively.

Table F.10: Heterogeneous effects on employer beliefs by experience

	(1) Perseverance	(2) Commitment	(3) Conscient.	(4) Emotional stab.	(5) Trainability	(6) IQ	(7) Expertise	(8) SES
Bsc.+25%	-0.209	-0.032	0.028	-0.246	0.280	0.217	0.180	0.191
	(0.216)	(0.171)	(0.201)	(0.209)	(0.213)	(0.193)	(0.188)	(0.182)
Bsc.+75%	-0.017	-0.140	-0.111	0.052	-0.051	0.109	0.112	0.098
	(0.209)	(0.203)	(0.199)	(0.174)	(0.196)	(0.172)	(0.221)	(0.157)
Msc	0.466**	0.404**	0.439**	0.219	0.460***	0.449***	0.338	0.255
	(0.185)	(0.198)	(0.185)	(0.184)	(0.158)	(0.146)	(0.210)	(0.168)
Bsc.+25%*Median-term exp.	-0.189	-0.264	-0.134	0.079	-0.281	-0.315	-0.252	-0.211
	(0.240)	(0.198)	(0.222)	(0.233)	(0.229)	(0.212)	(0.208)	(0.198)
Bsc.+25%*Long-term exp.	-0.030	-0.174	-0.235	0.127	-0.277	-0.238	-0.144	-0.180
	(0.251)	(0.201)	(0.225)	(0.235)	(0.232)	(0.212)	(0.207)	(0.197)
Bsc.+75%*Median-term exp.	-0.268	-0.162	0.018	-0.271	0.167	-0.079	-0.193	-0.107
	(0.238)	(0.224)	(0.221)	(0.199)	(0.213)	(0.196)	(0.241)	(0.173)
Bsc.+75%*Long-term exp.	-0.369	-0.176	-0.237	-0.242	-0.120	-0.268	-0.182	-0.270
	(0.241)	(0.234)	(0.229)	(0.202)	(0.221)	(0.196)	(0.240)	(0.178)
Msc.*Median-term exp.	-0.280	-0.302	-0.274	-0.111	-0.234	-0.359**	-0.121	-0.089
	(0.214)	(0.221)	(0.210)	(0.208)	(0.183)	(0.172)	(0.231)	(0.183)
Msc.*Long-term exp.	-0.231	-0.276	-0.372*	0.032	-0.313*	-0.356**	-0.082	-0.258
	(0.213)	(0.221)	(0.204)	(0.208)	(0.178)	(0.168)	(0.227)	(0.184)
N	1299	1299	1299	1299	1299	1299	1299	1299
Ind. FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Controls (other)	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes

Notes: All columns show coefficients that are estimates from a linear regression, including employer FEs and control variables. White robust standard errors clustered at the respondent level are displayed in parentheses. Median-term experience is defined as having worked in HR for five to fifteen years, while long-term experience is having more than fifteen years' experience, whereby both are compared to having less than five years' experience. The data are unbalanced as employers randomly receive and assess résumés corresponding to three out of the four scenarios. The Bsc. scenario serves as a baseline estimate. Control variables comprise the randomized résumé elements: gender, age, high school GPA, university, GPA of the last obtained degree, internship fit to job vacancy, internship firm, internship duration, languages, personal interests and IT skills. ***, **, * indicate significance at the 1, 5 and 10% level, respectively.

Table F.11: Robustness of employment outcomes by educational completion

	(1) Main	(2) All obs.	(3) Resp. time	(4) No rule	(5) Covid: low	(6) Covid: high
Panel A: Invite probability						
Bsc.+25%	-0.492	-0.496	0.019	-0.534	-1.786	0.485
	(1.238)	(1.145)	(1.397)	(1.322)	(1.811)	(1.719)
Bsc.+75%	-2.302*	-2.072*	-1.112	-2.381*	-2.105	-2.200
	(1.267)	(1.171)	(1.388)	(1.337)	(2.039)	(1.496)
Msc	4.486***	3.755***	5.186***	4.203***	4.733***	4.567***
	(1.169)	(1.123)	(1.359)	(1.295)	(1.702)	(1.645)
Panel B: Offer probability						
Bsc.+25%	0.361	0.816	0.771	0.154	-0.467	1.006
	(1.170)	(1.097)	(1.347)	(1.246)	(1.755)	(1.567)
Bsc.+75%	-0.831	-0.669	-0.021	-1.221	-1.632	0.128
	(1.241)	(1.168)	(1.337)	(1.266)	(1.891)	(1.596)
Msc	3.601***	3.790***	4.657***	3.376***	5.129***	2.485
	(1.179)	(1.136)	(1.353)	(1.262)	(1.771)	(1.595)
Panel C: Log wage						
Bsc.+25%	-0.001	-0.008	-0.004	0.002	-0.002	0.000
	(0.008)	(0.018)	(0.010)	(0.009)	(0.011)	(0.013)
Bsc.+75%	0.000	0.019	0.005	0.006	0.000	-0.000
	(0.008)	(0.017)	(0.009)	(0.009)	(0.010)	(0.013)
Msc	0.048***	0.074**	0.052***	0.051***	0.048***	0.048***
	(0.008)	(0.029)	(0.009)	(0.008)	(0.010)	(0.012)
N	1299	1449	906	1116	645	654
Ind. FE	Yes	Yes	Yes	Yes	Yes	Yes
Controls	Yes	Yes	Yes	Yes	Yes	Yes

Notes: All columns show coefficients that are estimates from a linear regression, including employer FEs and control variables. White robust standard errors clustered at the respondent level are displayed in parentheses. Column 1 shows the main specification. Column 2 includes all observations. Column 3 excludes individuals with a response time less than seven minutes. Column 4 excludes individuals whose company has a wage-setting policy favoring master's degree holders. Columns 5 and 6 split the sample by beliefs of how much Covid-19 changed hiring requirements. The data are unbalanced as employers randomly receive and assess résumés corresponding to three out of the four scenarios. The Bsc. scenario serves as a baseline estimate. Control variables comprise the randomized résumé elements: gender, age, high school GPA, university, GPA of the last obtained degree, internship fit to job vacancy, internship firm, internship duration, languages, personal interests and IT skills. ***, **, * indicate significance at the 1, 5 and 10% level, respectively.

Table F.12: Robustness of employer beliefs by educational completion

	(1) Main	(2) All obs.	(3) Resp. time	(4) No rule	(5) Covid: low	(6) Covid: high
Panel A: Perseverance						
Bsc.+25%	-0.302***	-0.262***	-0.303***	-0.345***	-0.551***	-0.051
	(0.075)	(0.071)	(0.085)	(0.079)	(0.117)	(0.088)
Bsc.+75%	-0.295***	-0.273***	-0.243***	-0.370***	-0.498***	-0.102
	(0.075)	(0.072)	(0.084)	(0.077)	(0.121)	(0.088)
Msc	0.233***	0.203***	0.270***	0.227***	0.319***	0.159*
	(0.068)	(0.066)	(0.083)	(0.072)	(0.099)	(0.093)
Panel B: Commitment						
Bsc.+25%	-0.221***	-0.193***	-0.169**	-0.231***	-0.287***	-0.168*
	(0.066)	(0.063)	(0.076)	(0.068)	(0.102)	(0.086)
Bsc.+75%	-0.282***	-0.267***	-0.210***	-0.302***	-0.302***	-0.268***
	(0.068)	(0.065)	(0.075)	(0.070)	(0.110)	(0.080)
Msc	0.144**	0.115*	0.179**	0.141**	0.187**	0.093
	(0.063)	(0.062)	(0.074)	(0.067)	(0.093)	(0.085)
Panel C: Conscientiousness						
Bsc.+25%	-0.136**	-0.135**	-0.088	-0.153**	-0.163*	-0.128
	(0.065)	(0.061)	(0.072)	(0.067)	(0.096)	(0.088)
Bsc.+75%	-0.210***	-0.227***	-0.124	-0.259***	-0.230**	-0.188**
	(0.070)	(0.066)	(0.080)	(0.070)	(0.108)	(0.086)
Msc	0.156**	0.125**	0.248***	0.118*	0.210**	0.122
	(0.064)	(0.060)	(0.076)	(0.067)	(0.096)	(0.084)
Panel D: Emotional stability						
Bsc.+25%	-0.150**	-0.119*	-0.126*	-0.138*	-0.189*	-0.120
	(0.068)	(0.063)	(0.076)	(0.072)	(0.104)	(0.087)
Bsc.+75%	-0.169***	-0.193***	-0.083	-0.160**	-0.096	-0.227***
	(0.064)	(0.061)	(0.070)	(0.064)	(0.099)	(0.080)
Msc	0.178***	0.147**	0.197***	0.210***	0.231**	0.131
	(0.061)	(0.059)	(0.073)	(0.064)	(0.092)	(0.082)
N	1299	1449	906	1116	645	654
Ind. FE	Yes	Yes	Yes	Yes	Yes	Yes
Controls	Yes	Yes	Yes	Yes	Yes	Yes

Notes: All columns show coefficients that are estimates from a linear regression, including employer FEs and control variables. White robust standard errors clustered at the respondent level are displayed in parentheses. Column 1 shows the main specification. Column 2 includes all observations. Column 3 excludes individuals with a response time less than seven minutes. Column 4 excludes individuals whose company has a wage-setting policy favoring master's degree holders. Columns 5 and 6 split the sample by beliefs of how much Covid-19 changed hiring requirements. The data are unbalanced as employers randomly receive and assess résumés corresponding to three out of the four scenarios. The Bsc. scenario serves as a baseline estimate. Control variables comprise the randomized résumé elements: gender, age, high school GPA, university, GPA of the last obtained degree, internship fit to job vacancy, internship firm, internship duration, languages, personal interests and IT skills. ***, **, * indicate significance at the 1, 5 and 10% level, respectively.

Table F.12: Robustness of employer beliefs by educational completion (ctd.)

	(1) Main	(2) All obs.	(3) Resp. time	(4) No rule	(5) Covid: low	(6) Covid: high
Panel E: Trainability						
Bsc.+25%	0.029	0.033	0.066	-0.010	-0.051	0.092
	(0.061)	(0.057)	(0.068)	(0.063)	(0.092)	(0.083)
Bsc.+75%	-0.036	-0.045	0.024	-0.079	-0.101	0.010
	(0.063)	(0.059)	(0.071)	(0.063)	(0.099)	(0.077)
Msc	0.219***	0.211***	0.216***	0.201***	0.273***	0.172**
	(0.057)	(0.054)	(0.069)	(0.060)	(0.086)	(0.078)
Panel F: Intelligence						
Bsc.+75%	-0.032	-0.045	-0.000	-0.022	-0.099	0.009
	(0.060)	(0.057)	(0.067)	(0.062)	(0.085)	(0.087)
Bsc.+75%	-0.049	-0.054	0.024	-0.040	-0.092	-0.004
	(0.063)	(0.059)	(0.074)	(0.062)	(0.094)	(0.082)
Msc	0.131**	0.121**	0.175***	0.140**	0.085	0.181**
	(0.057)	(0.055)	(0.065)	(0.058)	(0.079)	(0.083)
Panel G: Expertise						
Bsc.+25%	0.001	0.005	0.018	-0.007	-0.029	0.009
	(0.065)	(0.061)	(0.069)	(0.068)	(0.095)	(0.086)
Bsc.+75%	-0.055	-0.063	0.028	-0.064	-0.074	-0.044
	(0.066)	(0.063)	(0.072)	(0.069)	(0.104)	(0.080)
Msc	0.245***	0.224***	0.302***	0.236***	0.293***	0.210***
	(0.061)	(0.057)	(0.070)	(0.067)	(0.090)	(0.080)
Panel H: SES						
Bsc.+25%	0.016	-0.000	0.063	0.023	-0.019	0.050
	(0.056)	(0.054)	(0.058)	(0.061)	(0.078)	(0.078)
Bsc.+75%	-0.070	-0.078	-0.001	-0.075	-0.070	-0.058
	(0.052)	(0.051)	(0.055)	(0.056)	(0.079)	(0.066)
Msc	0.101**	0.087*	0.167***	0.107**	0.155**	0.062
	(0.049)	(0.048)	(0.056)	(0.052)	(0.065)	(0.071)
N	1299	1449	906	1116	645	654
Ind. FE	Yes	Yes	Yes	Yes	Yes	Yes
Controls	Yes	Yes	Yes	Yes	Yes	Yes

Notes: All columns show coefficients that are estimates from a linear regression, including employer FEs and control variables. White robust standard errors clustered at the respondent level are displayed in parentheses. Column 1 shows the main specification. Column 2 includes all observations. Column 3 excludes individuals with a response time less than seven minutes. Column 4 excludes individuals whose company has a wage-setting policy favoring master's degree holders. Columns 5 and 6 split the sample by beliefs of how much Covid-19 changed hiring requirements. The data are unbalanced as employers randomly receive and assess résumés corresponding to three out of the four scenarios. The Bsc. scenario serves as a baseline estimate. Control variables comprise the randomized résumé elements: gender, age, high school GPA, university, GPA of the last obtained degree, internship fit to job vacancy, internship firm, internship duration, languages, personal interests and IT skills. ***, **, * indicate significance at the 1, 5 and 10% level, respectively.

Table F.13: Robustness of decomposition of candidate attractiveness

	Msc. - Prob. to invite						Msc. - Prob. to offer					
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)
	Main	All obs	Resp. time	No rule	Covid: low	Covid: high	Main	All obs	Resp. time	No rule	Covid: low	Covid: high
Difference with Bsc.	4.897***	4.798***	5.525***	4.415***	6.286***	3.560*	3.920***	4.784***	4.842***	3.260**	5.138**	2.772
	(1.524)	(1.444)	(1.814)	(1.640)	(2.351)	(1.931)	(1.468)	(1.412)	(1.740)	(1.581)	(2.177)	(1.957)
Explained	3.484***	3.506***	3.260***	2.872***	5.232***	2.066	3.111***	3.202***	2.772**	2.745***	4.932***	2.197*
	(0.956)	(0.917)	(1.187)	(1.009)	(1.524)	(1.268)	(0.935)	(0.906)	(1.137)	(0.964)	(1.466)	(1.264)
Unexplained	1.413	1.292	2.265	1.543	1.054	1.494	0.809	1.583	2.070	0.515	0.206	0.575
	(1.221)	(1.149)	(1.410)	(1.345)	(2.029)	(1.461)	(1.171)	(1.118)	(1.352)	(1.297)	(1.778)	(1.542)
Explained												
Train.	1.332***	1.206***	1.427**	1.045**	1.363	0.837	1.101**	0.955**	1.475**	0.981**	1.870*	0.589
	(0.492)	(0.428)	(0.672)	(0.485)	(0.926)	(0.642)	(0.440)	(0.378)	(0.698)	(0.467)	(0.975)	(0.471)
IQ	-0.064	0.114	0.235	-0.143	-0.008	0.081	0.611*	0.618**	0.563	0.346	-0.091	1.136*
	(0.222)	(0.202)	(0.266)	(0.241)	(0.438)	(0.247)	(0.331)	(0.312)	(0.369)	(0.296)	(0.397)	(0.686)
Expert.	1.324***	1.295***	1.146**	1.450***	1.727*	0.775	0.446	0.563*	-0.060	0.572	0.903	0.199
	(0.483)	(0.444)	(0.525)	(0.553)	(0.923)	(0.497)	(0.363)	(0.339)	(0.369)	(0.384)	(0.784)	(0.300)
Persev.	0.677*	0.794**	0.541	0.701*	2.537**	-0.031	0.822**	0.794**	0.868*	0.741*	2.170**	0.034
	(0.365)	(0.369)	(0.385)	(0.400)	(1.043)	(0.151)	(0.380)	(0.350)	(0.464)	(0.393)	(0.903)	(0.135)
Comm.	0.053	0.130	-0.145	0.010	-0.218	0.146	0.149	0.197	-0.038	0.197	0.214	0.079
	(0.204)	(0.196)	(0.240)	(0.187)	(0.485)	(0.200)	(0.220)	(0.206)	(0.233)	(0.223)	(0.503)	(0.172)
Consc.	0.183	0.052	0.084	0.075	0.400	0.088	0.128	0.118	0.024	0.026	0.238	0.052
	(0.240)	(0.196)	(0.317)	(0.171)	(0.647)	(0.208)	(0.200)	(0.186)	(0.295)	(0.165)	(0.577)	(0.131)
Emot.	0.039	-0.007	-0.068	-0.379	-0.622	0.222	-0.000	0.124	0.053	-0.008	-0.190	0.155
	(0.252)	(0.225)	(0.256)	(0.283)	(0.562)	(0.287)	(0.217)	(0.202)	(0.274)	(0.272)	(0.488)	(0.212)
SES	-0.059	-0.077	0.039	0.113	0.053	-0.051	-0.146	-0.166	-0.114	-0.108	-0.181	-0.047
	(0.120)	(0.122)	(0.139)	(0.138)	(0.265)	(0.146)	(0.135)	(0.138)	(0.146)	(0.130)	(0.244)	(0.134)
N	645	724	438	551	322	323	645	724	438	551	322	323

Notes: The table shows the coefficients of the decomposition of the significant differences in candidate attractiveness shown in columns 1 and 3 of table 1. Columns 1 and 7 show the main specification. Columns 2 and 8 include all observations. Columns 3 and 9 exclude individuals with a response time less than seven minutes. Columns 4 and 10 exclude individuals whose company has a wage-setting policy favoring master's degree holders. Columns 5, 6, 11 and 12 split the sample by beliefs of how much Covid-19 changed hiring requirements. See equation 3 for details on the decomposition. The t statistics are displayed in parentheses. ***, **, * indicate significance at the 1, 5 and 10% level, respectively.

Table F.13: Robustness of decomposition of candidate attractiveness (ctd.)

	Msc. - Log wage						Bsc.+75% - Prob. to invite					
	(1) Main	(2) All obs	(3) Resp. time	(4) No rule	(5) Covid: low	(6) Covid: high	(7) Main	(8) All obs	(9) Resp. time	(10) No rule	(11) Covid: low	(12) Covid: high
Difference with Bsc.	0.070***	0.112*	0.077***	0.077***	0.059**	0.078**	-3.435**	-2.531*	-2.432	-4.047**	-3.322	-3.494*
	(0.023)	(0.067)	(0.029)	(0.024)	(0.027)	(0.038)	(1.561)	(1.491)	(1.852)	(1.683)	(2.556)	(1.836)
Explained	0.007	0.038	0.009	0.008	0.016*	0.006	-2.445**	-2.189**	-1.748	-3.081***	-3.995**	-1.710
	(0.005)	(0.024)	(0.006)	(0.005)	(0.009)	(0.008)	(1.089)	(1.045)	(1.294)	(1.160)	(1.845)	(1.295)
Unexplained	0.063***	0.075	0.068**	0.069***	0.043	0.072*	-0.991	-0.343	-0.684	-0.966	0.673	-1.784
	(0.024)	(0.065)	(0.029)	(0.025)	(0.027)	(0.038)	(1.186)	(1.122)	(1.394)	(1.303)	(1.913)	(1.461)
Explained												
Train.	-0.009	-0.017	-0.006	-0.004	-0.010	-0.004	-0.694	-0.589	-0.741	-1.119**	-0.869	-0.556
	(0.006)	(0.020)	(0.006)	(0.005)	(0.010)	(0.005)	(0.498)	(0.462)	(0.738)	(0.557)	(0.784)	(0.657)
IQ	0.005	0.010	0.004	0.001	-0.002	0.008	-0.170	-0.151	-0.111	-0.161	-0.409	-0.043
	(0.005)	(0.017)	(0.005)	(0.004)	(0.006)	(0.007)	(0.169)	(0.169)	(0.187)	(0.177)	(0.473)	(0.113)
Expert.	0.008	0.001	0.007	0.010*	0.015	0.005	-0.375	-0.289	-0.163	-0.475	-0.376	-0.302
	(0.006)	(0.021)	(0.007)	(0.006)	(0.010)	(0.006)	(0.314)	(0.272)	(0.256)	(0.354)	(0.443)	(0.359)
Persev.	0.002	0.016	0.001	-0.001	0.005	0.002	-1.476***	-1.371***	-1.208**	-1.814***	-3.226***	-0.659
	(0.005)	(0.030)	(0.006)	(0.005)	(0.009)	(0.003)	(0.505)	(0.464)	(0.527)	(0.620)	(1.149)	(0.435)
Comm.	-0.001	0.044	-0.005	-0.000	0.006	-0.004	-0.000	-0.162	0.579	-0.039	0.486	-0.351
	(0.003)	(0.029)	(0.005)	(0.003)	(0.007)	(0.005)	(0.289)	(0.242)	(0.367)	(0.331)	(0.530)	(0.375)
Consc.	0.002	-0.029	0.008	0.001	0.004	0.000	0.315	0.414*	-0.020	0.553	0.539	0.176
	(0.004)	(0.020)	(0.007)	(0.003)	(0.009)	(0.002)	(0.263)	(0.251)	(0.241)	(0.356)	(0.495)	(0.304)
Emot.	0.005	0.030	0.001	0.005	0.005	0.002	-0.091	-0.081	-0.082	0.010	-0.162	0.095
	(0.004)	(0.022)	(0.005)	(0.005)	(0.007)	(0.004)	(0.181)	(0.157)	(0.149)	(0.187)	(0.248)	(0.321)
SES	-0.005	-0.018	-0.003	-0.003	-0.006	-0.002	0.047	0.041	-0.002	-0.037	0.022	-0.070
	(0.004)	(0.014)	(0.003)	(0.003)	(0.004)	(0.005)	(0.089)	(0.080)	(0.053)	(0.109)	(0.236)	(0.177)
N	645	724	438	551	322	323	642	714	454	554	315	327

Notes: The table shows the coefficients of the decomposition of the significant differences in candidate attractiveness shown in columns 1 and 5 of table 1. Columns 1 and 7 show the main specification. Columns 2 and 8 include all observations. Columns 3 and 9 exclude individuals with a response time less than seven minutes. Columns 4 and 10 exclude individuals whose company has a wage-setting policy favoring master's degree holders. Columns 5, 6, 11 and 12 split the sample by beliefs of how much Covid-19 changed hiring requirements. See equation 3 for details on the decomposition. The t statistics are displayed in parentheses. ***, **, * indicate significance at the 1, 5 and 10% level, respectively.

Table F.14: Employment outcomes (including probability of acceptance) by all résumé items

	Base Bsc.			
	(1) Prob. to invite	(2) Prob. to offer	(3) Log Wage	(4) Prob. to accept
Bsc.+25%	-0.492	0.361	-0.001	2.086*
	(1.238)	(1.170)	(0.008)	(1.124)
Bsc.+75%	-2.302*	-0.831	0.000	0.622
	(1.267)	(1.241)	(0.008)	(1.145)
Msc	4.486***	3.601***	0.048***	1.740*
	(1.169)	(1.179)	(0.008)	(1.018)
Interns. type fits	1.593*	1.497*	0.005	-0.021
	(0.879)	(0.819)	(0.006)	(0.794)
Male	-1.041	-0.225	0.005	0.226
	(0.895)	(0.871)	(0.006)	(0.792)
High-school GPA	2.969***	2.691***	0.012***	1.213**
	(0.603)	(0.581)	(0.004)	(0.512)
GPA highest degree	3.569***	3.282***	0.014***	0.470
	(0.743)	(0.679)	(0.005)	(0.639)
Uni Munich (Bsc.)	1.510	0.131	0.005	0.272
	(1.016)	(0.921)	(0.006)	(0.862)
Uni Cologne (Bsc.)	-0.424	-1.629*	-0.001	-1.463
	(0.986)	(0.982)	(0.007)	(0.907)
Uni Munich (Msc.)	1.249	2.112**	0.004	1.011
	(0.997)	(0.955)	(0.007)	(0.879)
Uni Cologne (Msc.)	0.201	0.005	-0.005	0.699
	(1.081)	(1.006)	(0.007)	(0.942)
5 months interns.	-0.033	0.760	0.006	1.898**
	(1.023)	(1.003)	(0.007)	(0.925)
9 month interns.	0.680	0.796	0.012*	2.913***
	(1.009)	(0.955)	(0.007)	(0.892)
Firm II	-0.143	-0.202	0.001	-0.688
	(0.991)	(0.977)	(0.006)	(0.894)
Firm III	-0.411	-0.954	0.002	-0.626
	(1.041)	(0.948)	(0.007)	(0.894)
Spanish basic	-0.751	0.069	0.009	-0.870
	(1.032)	(0.959)	(0.007)	(0.922)
Spanish good	1.326	1.052	0.017**	-0.491
	(1.004)	(0.957)	(0.007)	(0.853)
SPSS skills	0.919	0.550	0.008	0.985
	(0.958)	(0.925)	(0.007)	(0.903)
Stata skills	0.542	0.946	0.007	-0.549
	(1.018)	(0.945)	(0.006)	(0.812)
Personal interests II	0.384	0.780	-0.004	-0.521
	(1.040)	(0.976)	(0.007)	(0.870)
Personal interests III	1.827*	0.664	0.000	-0.824
	(1.011)	(0.943)	(0.007)	(0.884)
N	1299	1299	1299	1299
Ind. FE	Yes	Yes	Yes	Yes
Controls (other)	Yes	Yes	Yes	Yes

Notes: All columns show coefficients that are estimates from a linear regression, including employer FEs. White robust standard errors clustered at the respondent level are displayed in parentheses. The data are unbalanced as employers randomly receive and assess résumés corresponding to three out of four education scenarios. Having obtained only a Bsc. serves as a baseline estimate. See table B.1 for the default category for each of the variables. ***, **, * indicate significance at the 1, 5 and 10 percent level, respectively.

Table F.15: Employment outcomes (controlling for probability of acceptance) by all résumé items

	Base Bsc.		
	(1)	(2)	(3)
	Prob. to invite	Prob. to offer	Log Wage
Bsc.+25%	-1.236	-0.414	-0.005
	(1.193)	(1.084)	(0.008)
Bsc.+75%	-2.524**	-1.063	-0.001
	(1.203)	(1.158)	(0.008)
Msc	3.865***	2.955***	0.044***
	(1.106)	(1.101)	(0.007)
Interns. type fits	1.601*	1.505*	0.005
	(0.855)	(0.789)	(0.006)
Male	-1.122	-0.309	0.004
	(0.847)	(0.818)	(0.006)
High-school GPA	2.536***	2.240***	0.010**
	(0.578)	(0.551)	(0.004)
GPA highest degree	3.401***	3.107***	0.013***
	(0.719)	(0.639)	(0.005)
Uni Munich (Bsc.)	1.413	0.030	0.004
	(0.994)	(0.890)	(0.006)
Uni Cologne (Bsc.)	0.098	-1.085	0.002
	(0.930)	(0.898)	(0.006)
Uni Munich (Msc.)	0.888	1.736**	0.002
	(0.938)	(0.883)	(0.006)
Uni Cologne (Msc.)	-0.048	-0.254	-0.007
	(1.036)	(0.949)	(0.007)
5 months interns.	-0.711	0.055	0.002
	(0.976)	(0.926)	(0.007)
9 month interns.	-0.361	-0.286	0.006
	(0.953)	(0.891)	(0.006)
Firm II	0.103	0.053	0.003
	(0.938)	(0.911)	(0.006)
Firm III	-0.187	-0.721	0.003
	(0.996)	(0.907)	(0.007)
Prob. to accept	0.357***	0.371***	0.002***
	(0.059)	(0.054)	(0.000)
Spanish basic	-0.441	0.392	0.011*
	(0.984)	(0.898)	(0.006)
Spanish good	1.501	1.234	0.018***
	(0.963)	(0.911)	(0.006)
SPSS skills	0.567	0.184	0.006
	(0.919)	(0.873)	(0.006)
Stata skills	0.738	1.150	0.008
	(0.975)	(0.894)	(0.006)
Personal interests II	0.570	0.974	-0.003
	(0.984)	(0.921)	(0.006)
Personal interests III	2.122**	0.970	0.002
	(0.984)	(0.903)	(0.006)
N	1299	1299	1299
Ind. FE	Yes	Yes	Yes
Controls (other)	Yes	Yes	Yes

Notes: All columns show coefficients that are estimates from a linear regression, including employer FEs. White robust standard errors clustered at the respondent level are displayed in parentheses. The data are unbalanced as employers randomly receive and assess résumés corresponding to three out of four education scenarios. Having obtained only a Bsc. serves as a baseline estimate. See table B.1 for the default category for each of the variables. ***, **, * indicate significance at the 1, 5 and 10 percent level, respectively.