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How to Attract Talent? Field-Experimental Evidence on Emphasizing Flexibility and Career Opportunities in Job Advertisements

Larissa Fuchs[1]
Matthias Heinz[2]
Pia Pinger[3]
Max Thon[4]

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[1]University of Cologne, Email: larissa.fuchs@wiso.uni-koeln.de
[2]University of Cologne, Email: heinz@wiso.uni-koeln.de
[3]University of Cologne & IZA, Email: pinger@uni-koeln.de
[4]University of Cologne, Email: m.thon@wiso.uni-koeln.de

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How to attract talent? Field-experimental evidence on emphasizing flexibility and career opportunities in job advertisements*

Larissa Fuchs, Matthias Heinz, Pia Pinger, Max Thon**

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Abstract

We conduct a randomized controlled trial (RCT) with a leading technology firm to study how highlighting flexibility and career advancement in job advertisements causally affects the applicant pool. Highlighting career advancement increases the number of applications from men for entry-level positions and attracts additional applicants with strong qualifications and a good fit, which in turn leads to more interview invitations. By contrast, highlighting flexibility increases applications from both women and men at the entry level but provides limited evidence of attracting higher-quality or better-fit applicants. A complementary survey experiment among STEM students shows how job advertisements shape beliefs about the firm's job characteristics and work environment. Overall, our results show that the amenities firms choose to highlight can powerfully influence both the size and characteristics of their applicant pool.

JEL Codes*: M51, M52, D22*

Keywords*: hiring, field experiments, job advertisements, gender*

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**Larissa Fuchs: University of Cologne, Matthias Heinz: University of Cologne, CEPR, Max Planck Institute for Research on Collective Goods, Pia Pinger: University of Cologne, CEPR, IZA, Max Planck Institute for Research on Collective Goods, Max Thon: University of Cologne, University of Zurich. Corresponding author: Pia Pinger, pia.pinger@uni-koeln.de, University of Cologne, Universitätsstraße 22, D-50931 Cologne, Germany.

1. Introduction

How can firms attract talented workers? Answering this question requires understanding how individuals decide which jobs to apply for. Earnings are an important factor in this decision, but workers typically consider many other job characteristics as well. These include, for example, the job's location, flexibility, career and personal development opportunities, as well as a firm's culture. The decision to apply thus depends on (i) the workers' preferences for these job characteristics and (ii) their beliefs about these characteristics at a particular job or firm. Preferences for job characteristics vary greatly across individuals (Ashraf et al. 2020), particularly between women and men (Wiswall and Zafar 2018, Le Barbanchon et al. 2021). While some workers are drawn to dynamic and challenging environments, others place greater emphasis on flexibility. These preferences are shaped by how people perceive jobs - perceptions that firms can actively influence. Job advertisements, in particular, are a powerful tool through which firms can shape beliefs about work and attract different types of applicants.[1]

In job advertisements, firms not only inform potential candidates about the existence of a vacancy, but also send signals about the job's characteristics and the working environment at the firm (Del Carpio and Guadalupe 2022, Delfino 2024, Hsu and Tambe 2025, Card et al. 2024, Burn, Firoozi, Ladd, and Neumark forthcoming). These signals may lead potential applicants to perceive a job as more attractive and can help firms attract more talented workers, a key strategic resource in today's knowledge-driven economy (Coff 1997, Bapna et al. 2013, Le Barbanchon et al. 2023), where many firms report skilled labor shortages.[2] Besides, if highlighting certain job characteristics leads to a better alignment between workers' preferences and job attributes, it may also improve the overall matching process and job satisfaction among workers (Ferreira and Taylor 2011). The

[1] Job advertisements remain one of the most important ways for professionals to learn about vacancies at firms. In 2018, job boards accounted for half of all job applications and contributed to 30 percent of successful hires (Jobvite 2019a,b).

[2] See, for instance, Marjenko et al. (2021) or ManpowerGroup (2024).

type of information emphasized in job advertisements is therefore of critical importance for firms, for workers, and for the quality of the worker–firm match.

In this paper, we study how job characteristics highlighted in a firm's job advertisement affect the applicant pool along dimensions such as size, quality, gender, and fit, as well as the beliefs of young professionals. We conduct an RCT within the German unit of one of Europe's largest technology firms, which employs approximately 3,000 workers. We randomized the job characteristics highlighted in all STEM vacancies newly posted by the firm over a 12-month period. Specifically, we posted each job advertisement three times, applying a sequence of treatments randomized at 10-day intervals: In one instance, we emphasized the firm's high level of job flexibility (the *flexibility* treatment); in another, we highlighted opportunities for career advancement, including skill development and wage growth (the *career* treatment); and in the third instance, we did not emphasize either characteristic (the *control* treatment).

We focus on flexibility and career advancement for two reasons: (i) both play a major role for the perceived attractiveness of jobs (Mas and Pallais 2017, Wiswall and Zafar 2018, He et al. 2021, Hsu and Tambe 2025) and (ii) in-depth pre-RCT interviews carried out among the firm's managers, workers, and workers' representatives revealed that flexibility and career advancement are two distinctive features of the jobs offered at the study firm.

Our study is grounded in a conceptual framework that informs the empirical analysis. In this framework, potential applicants derive utility from a combination of job-specific ability and job characteristics, such as job flexibility and career advancement. Highlighting specific job characteristics (the treatment) is interpreted as a signal that leads to an updating of beliefs concerning the attractiveness of the job (the mechanism), thereby influencing the likelihood of applying (the outcome). Based on this framework, we derive several empirical predictions, which we test in our study. First, both treatments should increase the total number of applications, with a larger effect expected for entry-level positions (which require no work experience) than for professional-level positions (which demand work experience). The rationale is that, while the signal increases perceived job attractiveness for all applicants, its communicative value is greater for entry-level candidates. Second, the *flexibility* (*career*) treatment is expected to increase the number of female (male) applicants relatively more than that of male (female) applicants. Third, if job preferences are correlated with worker productivity or background characteristics (Nekoei 2022, Emanuel and Harrington 2024), we also expect variation in applicant characteristics, an aspect we assess in an exploratory manner. Finally, both treatments should lead to a positive shift in beliefs about the expected levels of job flexibility and career advancement.

In our RCT, we find large treatment effects for entry-level positions, though not for professional-level ones: For entry-level positions, we observe an increase in applications of 35 percent for the *career* and of 44 percent for the *flexibility* treatment, respectively. The effects are driven by men in the *career*, and women and men in the *flexibility* treatment.

While these results show that highlighting certain characteristics increases job attractiveness among young professionals, what employers ultimately care about is not necessarily the size of the applicant pool, but the number of top candidates applying for a position (Del Carpio and Guadalupe 2022). Our dataset is unique in that it covers the universe of applications, including detailed CV information, firm ratings, and records of interview invitations. Leveraging these comprehensive data, we find that young professionals in the *career* treatment (i) are more likely to have graduated from higher-ranked universities, (ii) are more frequently rated as a good fit by the department's operational managers, and (iii) are invited to interviews more often.[3] These results show that the *career* treatment attracts more applicants who are both highly qualified and well-matched to the firm's needs. In contrast, the *flexibility* treatment we find no or weak evidence for an increase of the number of high-quality or well-fitting applicants, but there is no evidence of a decline in applicant quality.

[3] We also find that candidates in the *career* treatment treatment are offered a job more often. However, we abstain from putting too much emphasis on this finding, as the number of observations is relatively small.

To analyze whether belief-updating is indeed the underlying mechanism that drives the observed increase in applications for entry-level positions, we supplement our RCT data with survey-experimental evidence from 2,000 STEM students. Each survey experiment was conducted concurrently with a job posting and targeted participants whose educational backgrounds aligned with the requirements of the respective job advertisement. We find that both treatments significantly shifted beliefs about job and workplace characteristics by 12–14 percent of a standard deviation. Notably, while the *career* treatment *improved* beliefs regarding career-advancement opportunities, it concurrently *reduced* expectations about workplace flexibility.

We move beyond existing work in at least three respects. First, we provide evidence that the mere highlighting content in job advertisements can substantially influence both the size and characteristics of the applicant pool, even without introducing any new information. This evidence complements work where researchers experimentally manipulate job ads or recruitment messages in domains such as, e.g., the posted wage and career benefits (Dal Bó et al. 2013, Ashraf et al. 2020, Belot et al. 2022), stereotyped language (Del Carpio and Fujiwara 2023, Burn, Firoozi, Ladd, and Neumark forthcoming), job flexibility (He et al. 2021), role-models (Del Carpio and Guadalupe 2022, Delfino 2024), listed qualifications (Abraham et al. 2024), or expected success at the job (Delfino 2024).[4] It also relates to a literature exploiting large-scale regulatory changes to show that a removal of an employer's gender preferences in job ads increased applications from the previously non-preferred gender (Kuhn and Shen 2023) and to more gender-neutral hiring outcomes (Card et al. 2024).

Our second contribution is that we can study the characteristics of all actual job applicants who applied over the course of one year, including their quality and fit as assessed by company ratings. This allows us to examine which individuals respond to a specific job amenity and to analyze potential quality tradeoffs that arise when job preferences correlate with worker productivity or

[4] For papers studying the importance of job ads based on observational data, see Marinescu and Wolthoff (2020), Chaturvedi et al. (2025).

background characteristics (Nekoei 2022, Emanuel and Harrington 2024). For example, Del Carpio and Guadalupe (2022) show that reducing gender stereotypes can adversely affect worker selection. In our setting, we can study how different treatments affect applications by gender and by geographic origin. We can also investigate both objective and subjective evaluation criteria, including the firm's rating of applicant fit.[5]

Regarding our third contribution, we study not only actual applicants but also belief formation in a broad pool of potential applicants. This allows us to examine how individuals update their beliefs about job characteristics and about the working environment more generally. We consider a wide set of attributes, including child care provision, flexible work arrangements, the work environment, and the composition of co-workers. The employer-branding literature (Lievens and Slaughter 2016) highlights that such belief changes are informative about which characteristics employees value. Our findings therefore help firms understand how changes in job advertisements shape perceived attractiveness and influence the expectations of potential applicants.

Finally, what sets our paper apart from existing studies we can experimentally study the impact of job ads on the number of applications, the applicant pool, the quality of applicants, applicant beliefs, and potential drawbacks all in one coherent "real-life" setting. In this respect, our approach offers a holistic view of the types of considerations that matter for firm decision-making: from publishing the job ad to hiring a suitable candidate.

As regards all four contributions, our paper also relates to, and connects, studies investigating application, sorting, and hiring decisions more generally, in particular as regards preferences of both employers and employees. Research shows that preferences differ across different types of employees, most prominently women and men (Wiswall and Zafar 2018, Ashraf et al. 2020, Coffman et al. 2024, Vattuone 2024). Firms also differ in their preferences for certain candidates, as becomes evident when companies react to signals and subtle cues on CVs when selecting candidates (Heinz and

[5]For evidence on how job advertisements affect the on the job outcomes of newly hired workers see Delfino (2024) and Card et al. (2024) for firm level outcomes.

Schumacher 2017, Hoffman et al. 2018, Stans et al. 2025). If firms knew about the preferences of their preferred "types" of workers, they could make strategic use of that knowledge and provide - as well as highlight in their recruiting initiatives - those job characteristics. If successful, such firm strategies could improve the matching process, increase firm productivity, and reduce turnover.

The remainder of the paper is organized as follows. In the next section, we present a conceptual framework that guides our empirical analysis. In Section 3, we present the study setup including the description of our study firm, the design of our treatments, and our data. Section 4 presents the results of the field experiment in terms of its effects on the number and quality of applications, both overall and by experience and gender. Section 5 explores the belief-related mechanisms underlying these effects, using data from a complementary survey experiment. Section 6 concludes.

2. Conceptual framework and empirical predictions

How does highlighting job flexibility or career advancement in job ads affect potential applicants' beliefs, expected job utility, and application decisions? In the following, we discuss a conceptual framework that guides our empirical analysis. It illustrates how a change in the content of job ads might affect workers' application behavior. The framework is inspired by Delfino (2024) and is formalized in Appendix A.

In our framework, an individual considers applying for a job advertised by a single firm. The individual chooses to apply if the expected utility from the job exceeds the (fixed) utility of an outside or alternative option. Potential applicants derive utility from the immediate wage payment, the individual returns to ability, and the expected level of flexibility and career-advancement opportunities provided by the firm. Ex-ante, individuals are uncertain about the job's flexibility and career-advancement opportunities but hold beliefs about both. Additionally, we allow for these beliefs to be correlated. This implies that some applicants may believe that these two characteristics are unrelated (no trade-off), while some others might think that career advancement comes at the cost of flexibility (a negative trade-off) or that career advancement requires flexibility (a positive trade-off).[6] To derive hypotheses about heterogeneities in application decisions in response to reading a job ad, which either highlights flexibility or career advancement, we consider workers who differ (i) in terms of their prior beliefs and (ii) in terms of their preferences for flexibility and career advancement.

To accommodate differences in belief updating, we distinguish between individuals with and without previous work experience. We assume that the distributions of prior beliefs differ across these workers. Longer activity in the labor market arguably comes with better networks and, consequently, greater knowledge of the industry and firms.[7] In our framework, this translates into the assumption that experienced applicants hold a more precise and weakly more positive belief about the exact level of flexibility and career-advancement opportunities offered by the firm.[8] We assume that, when potential candidates read a job ad which highlights flexibility or career advancement, they receive a positive signal about either of these job characteristics, leading them to update their beliefs about that characteristic positively. More positive beliefs, in turn, increase the expected utility derived from the job and raise the likelihood of applying. Since professional-level applicants already hold more precise and more positive beliefs about the level of flexibility and career advancement offered by the firm, their expected utility gain from the signal should be smaller than for entry-level applicants.

As regards differential preferences, it is conceivable that the preferences for flexibility and career advancement differ systematically, in particular between female and male applicants. For example, Wiswall and Zafar (2018) find that women have a relatively higher willingness to pay for jobs with more flexibility, whereas men have a relatively higher willingness to pay for jobs with a higher

[6] In our survey among STEM students (see Section 5), we find that earnings, flexibility, and career advancement indeed play a major role for the perceived attractiveness of a job. This is consistent with previous studies (e.g., Wiswall and Zafar 2018).

[7] For instance, more experienced workers may receive information through better co-worker networks (Glitz 2017).

[8] All results continue to hold even if experienced workers' prior beliefs are slightly more negative than those of inexperienced workers, provided that the difference is not too large and the prior of experienced workers is sufficiently more precise. See the discussion around Proposition 1 in Appendix A for details.

potential for career-advancement opportunities. In line with these findings, we assume that women have a stronger relative preference for flexibility and males have a stronger relative preference for career advancement.[9] This translates to larger expected utility gains for women when they see a job ad highlighting flexibility, and larger gains for men when they see a job ad emphasizing career-advancement opportunities. Consequently, job ads that highlight flexibility (career advancement) should lead to a larger increase in applications from female (male) applicants.

The above framework yields several empirical predictions about the effects of job ads that emphasize either flexibility or career advancement: 1) both should increase the number of applications due to positive belief-updating, but 2) the increase should be larger for entry-level than for professional-level positions, as applicants for entry-level positions are less familiar with the industry and firm and thus hold less precise priors about flexibility and career-advancement opportunities; 3) highlighting flexibility (career) should lead to a stronger increase in applications for women (men) than men (women), reflecting gender differences in preferences.

The framework does not yield predictions about the expected change in applicant quality, demographic characteristics or the skill set sought by the firm. How the treatments affect the nature of the applicant pool ultimately depends on the correlation of the workers' characteristics and productivity with their workplace preferences. We will investigate this in an exploratory manner. In the next section, we discuss the experimental design.

3. RCT implementation and data

The study firm. We conducted an RCT in collaboration with one of Europe's largest technology firms, a multinational semiconductor company that generated approximately 11 billion EUR in revenue in 2021 and employed around $60,000$ workers. The firm operates in an industry that

[9] We also investigate this using data collected from our survey experiment. We ask about preferences for various job characteristics and find similar gender differences. The results are presented in Appendix G.

experienced strong growth in demand in the past and is expected to grow further in the future according to industry experts (see, e.g., Burkacki et al. 2022).

For our project, we collaborate with one of the firm's units, which is situated in a rural area in Germany, around 100 km away from the next urban center and big university. In 2021, the unit employed $3,000$ workers with a mean tenure of 12 years. Workers earned a monthly wage of around $5,300$ EUR, which is about 30% higher than the German average wage (German Federal Statistical Office 2025). The majority of employees have a high education level, most of them in the field of STEM, specifically in engineering, manufacturing, construction, computer science, mathematics, or physics. The share of female STEM workers in the unit - about 20% - is roughly equivalent to the share of female graduates in STEM fields from German universities (OECD 2024) and to the share of females working in the technology industry (Bitkom Research 2023). Recently the unit won a prestigious award for being an attractive employer. For simplicity, we will refer the firm's unit as "firm" or "study firm" in the following text.

The firm produces semiconductors, particularly for electric cars, trains, wind turbines, solar panels, and heat pumps. In the years preceding our RCT, it experienced strong growth in product demand, and top management expects this growth to continue in the future. Between 2011 and 2021, this growth led to a roughly 50% increase in the workforce, creating a continuous need for new hires. Recruiting STEM workers is a major challenge for the firm. Although the firm advertised vacancies internationally on many different job boards, engaged in cooperation with many local institutions (e.g., schools, employment agencies), and attended regional and university job fairs, the overall number of applications for jobs in the firm is fairly low. For each advertised position, the firm receives on average only 12 applications. In preparation for our RCT, we discussed possible ways to increase the number of applications with the management and quickly agreed to focus on how positions are advertised. After all, job ads are among the most important instruments to attract applicants and current research (see, e.g., Del Carpio and Guadalupe 2022, Delfino 2024, Burn, Firoozi, Ladd, and Neumark forthcoming) provides evidence about the important role their content can play for application decisions.

Treatment motivation. To investigate how highlighting flexibility and career advancement in job ads affects application behavior, we had to ensure that these characteristics were indeed met at the study firm. To gain a comprehensive understanding of the firm's distinctive job characteristics, we conducted in-depth discussions with unit executives, senior HR and diversity managers, the workers' council, and both recently hired and long-term employees. Nearly all participants highlighted flexibility and career advancement as two key distinguishing features of jobs at the firm. They consistently reported that the firm provides a lot of flexibility, such as the opportunity to work full-time or part-time, and that job-sharing arrangements are fairly common. The local municipality offers a sufficient number of day-care spots with affordable care fees.[10] Employees generally describe the workplace culture at the firm as family-friendly. For example, workers report that it is widely accepted within the company culture to leave early, work from home when children are sick, or make use of flexible working hours. According to the HR office, it is common practice to find individualized solutions for new employees with caregiving responsibilities. Due to rapid growth in the past as well as good future growth prospects, workers also state that the firm offers ample opportunities for career advancement, skill development, and wage growth, and that new leadership roles are created regularly.[11]

The literature reports that flexibility and growth opportunities are two job characteristics for which workers have a high willingness to pay, in particular women for flexibility and men for increasing earnings (Wiswall and Zafar 2018, Mas and Pallais 2020, He et al. 2021). The fact that i) flexibility and ii) opportunities for career advancement, skill development and wage growth are distinctive job characteristics at our study firm thus provides us with the unique opportunity to

[10] In Germany, the demand for day care for young children far exceeds supply; the estimated shortfall for children aged one and younger is 24% (Alt et al. 2017). As a result, securing day care remains a major challenge for many young parents.

[11] Fox (2009), Brown and Medoff (1989), Groshen (1991), and Idson and Oi (1999) show that firm growth and wage growth within firms are highly correlated.

examine how highlighting these workplace attributes in job ads affects the applicant pool for jobs in a "real-world" setting.

Design of the recruiting process and the treatment. The study firm's recruiting process consists of six steps. In the first step, operational managers from the department that has a vacancy inform the unit's HR office about the title of the position and provide a description of the job and the set of skills that an "ideal" candidate should possess (e.g., length and type of work experience, technical skills). In the second step, the HR office creates the job ad and, in the third step, posts the job ad on the firm's homepage as well as on different job boards, the main ones being Indeed, LinkedIn, and local job boards. As a general rule, the firm posts all job ads for at least 30 days, as the vast majority of candidates apply within this period of time. In the fourth step, operational managers from the department with the vacancy screen all applications, assess how well each candidate fits the skill requirements defined in step 1, and classify applicants as either fitting or not fitting the outlined criteria.[12] In the fifth step, operational managers and a representative from the HR office select candidates and conduct job interviews with the applicants; according to the firms' HR policies, the firm aims to interview around 20% of the applicants. Finally, following the job interviews, the operational managers and the representative from the HR office select the candidate who receives a job offer, and the HR office negotiates with the candidate. In our RCT, the recruiting process remains unchanged except for one modification: after the HR office creates the job ad (step two), but before it is published (step three), we implement our treatment.

All job ads in the entire tech company have a similar design. Figure 1 shows a fictitious sample of a job ad of the study firm's unit. The content was generated via OpenAI (2024) based on all job ads that our study firm posted during our RCT in the control group.[13] In the *Job title and teaser* section at the top of the job ad, the study firm presents the title of the job and provides a superficial description of the advertised job in a teaser text. The *Job description* provides a summary of the

[12] A small number of applicants are screened out immediately after the arrival of the application by the HR office, e.g., because key application documents are missing. Those applications are not included in our dataset.

[13] The font, color, and pictures are manually altered to preserve the firm's anonymity.

job and outlines the specific tasks in bullet points. The *Your profile* section summarizes the job requirements. The *At a glance* section lists the general conditions of the specific job (e.g., the desired start date, contract type). The *Why us?* section provides a description of the study firm, the *Benefits* section provides a long list of employee benefits and workplace attributes (e.g., flexible working hours, sabbatical options, healthcare programs, employer-funded pension plans). All parts of the job ads are individualized for each job, except for the *Benefits* section, which is the same for all vacancies in the tech company. Thus, before our RCT, all job ads posted by the study firm already referred to flexibility and opportunities for career advancement, but as they were mentioned as part of a long list with many other employee benefits and workplace attributes, they were not emphasized.

In our RCT, the basic design of the jobs ads in the control group is the same as before. Our treatments consist of two statements, one of which (or none) was randomly shown as the last sentence in the *Job title and teaser* section of the job ad. In our *flexibility* treatment, the statement reads as follows:

FLEXIBILITY is very important to us! Together we look for individual solutions, so that your job does not get in the way of your personal life.

The statement highlights the opportunity for flexibility at the study firm in a very general way, without referring to specific dimensions of flexibility (such as flexible working hours, working from home, or day care availability). We decided on a general statement, as preferences for different dimensions of flexibility likely differ between potential applicants, and the way flexible working conditions can be arranged by the firm varies across jobs. In the career treatment, the statement is also rather general and reads as follows:

GROWTH is very important to us! With us, you not only grow personally, but also your salary.

As the treatments are included in the job ads' teaser text, and as the words "flexibility" and "growth" are written in caps, it is likely that potential applicants notice them. In Section 5, we show that the treatments indeed affect young professionals' respective beliefs about the jobs' flexibility and career-advancement opportunities, and how people interpret the rather general statements. A sample ad showing the *career* and the *flexibility* treatment is presented in Appendix B.

Figure 1: Sample job ad

Empowering.
Innovation.
Sustainability.
Together.

Product Development Engineer (w/m/div)

Ready to lead the future of power semiconductor innovation?
As a Product Development Engineer, you'll transform groundbreaking ideas into high-volume production realities. Join our team and elevate your career by shaping the next generation of advanced technology.

FLEXIBILITY is very important to us! Together we look for individual solutions, so that your job does not get in the way of your personal life.

Job description

We are looking for a skilled Product Development Engineer to join our dynamic team, focused on creating cutting-edge power semiconductor modules.

- Develop mechanical details and functionalities for both new and existing product packages and families.
- Ensure that the latest research and cutting-edge technologies are incorporated into designs and systems, while optimizing for cost efficiency.

Your Profile

You are a highly motivated and enthusiastic engineer who is passionate about technology and enjoys analyzing complex technical relationships.

You are best equipped for this task if you have:

- A University degree in mechanical engineering, mechatronics, automation technology, or a related field of study.
- Experience with tools such as Autodesk Inventor, 3D CAD systems, and the Vault database, along with metrology software for tolerance analysi.

At a Glance

Location:	City (Country)
Job ID:	XXXXXXX
Start Date:	20XX-XX-XX
Entry Level:	0-1 years
Contract:	Full time
Job sharing:	Possible

Apply to this position online by following the URL and entering the Job ID in our job search.

Job ID: XXXXX
Homepage Company

Why us?

As a global leader in semiconductor solutions for power systems and IoT, we drive innovation in green energy, clean mobility, and smart IoT. Join us in making life easier, safer, and greener.

Are you in?

Contact:
First name Last name
Talent Attraction Manager

Company logo

Benefits

- Opportunities for coaching, mentoring, and networking; training offerings and structured development planning; possibility for international assignments; various career paths: Project Management, Technical Ladder, Management, and Individual Contributor; flexible working hours with trust-based flexitime; opportunities to work from home; openness to part-time work (including during parental leave); sabbatical options; holiday childcare; social counseling and company doctor services; health and preventive care programs; cafeteria; insurance offerings at attractive rates; continued salary in case of illness; employer-funded company pension plan; openness to flexible transition into retirement; performance bonus; accessibility across the entire site; possibility to work remotely from abroad (within the EU).

Notes: This figure presents a fictitious sample of a job ad of the study firm. It was created manually, but the content was generated via OpenAI (2024) based on input from real job ads of the study firm. All details (e.g., wording, font, color) were modified to keep the anonymity of the study firm.

Randomization. To study the effects of highlighting job characteristics in job advertisements, we randomize treatments within job ads rather than across them. Given the heterogeneity of the advertised positions in our RCT, this within-ad randomization - implemented over a rolling 10-day window per ad - enhances statistical power and improves the precision of our estimates (Bellemare et al. 2014).[14] We chose a 10-day duration for each of the three treatment conditions, as the firm posts all job ads for a minimum of 30 days and the vast majority of applications are submitted within this time frame.[15]

Specifically, our randomization procedure is as follows: After the job ad is created by the unit's HR office (step 2 of the recruiting process), a random draw determines the treatment, i.e., to include either the *control*, *flexibility*, or *career* teaser text. The job ad is then posted in this version for ten days. After ten days, one of the two remaining treatments is randomly selected, and from day 11 to 20 the same job ad is posted with a teaser text corresponding to the respective treatment. Finally, from day 21 to 30, the same job ad is posted with a teaser text corresponding to the remaining treatment condition. Each job ad is thus posted sequentially under each treatment condition.[16] As we cannot measure the exact time of the treatment switch – some job boards implemented the treatment switch within seconds, while others need a few hours –, we exclude the day of the treatment switch and the day immediately after (days 10, 11, 20, 21).[17]

The randomization and posting of the job ads were carried out by a freelancer, who was employed as an external employee by the study firm and paid by the research team. The freelancer strictly followed the randomization schedule provided by the research team. The freelancer was not involved in any other tasks of the HR office, and the HR office employees were not informed of the treatment

[14] List (2025) provides an overview of the advantages and disadvantages of within- versus between-subject randomization. Since each ad runs for 30 days and treatments are applied in randomized order across a one-year period, concerns about panel imbalance and temporal instability are mitigated. We assess potential spillover effects in Appendix D.

[15] We have outlined in our pre-registration that we only include applications arriving in the first 30 days after the job ad is posted in our analyses. Note that, in this period of time, the total number of applications is slightly larger in the first compared to the last ten days. For some job ads, the firm posts the job ad longer when it does not find suitable candidates within 30 days.

[16] In Section Appendix B, we present in Table B.6 the distribution of job ads by period and treatment.

[17] Including days 11 and 21 yields qualitatively similar results, see Section Appendix D.

assignment for each time period.[18] All job ads for vacancies requiring a STEM background that were first posted between the beginning of October 2022 and the end of September 2023 were part of the RCT.

Research ethics. Our research project was approved by the firm's workers' council and by the Ethics Committee of the Faculty of Management, Economics, and Social Sciences of the University of Cologne (reference: 220022MT). We pre-registered our RCT – including the main outcome variables (total number of application; applicants' gender, job experience, quality, fit, success in the hiring process, and place of residence) – with the American Economic Association (AEA-RCTR-0010433). Moreover, we set up a privacy-protection process to ensure that the research team did not gain access to any personal data.

Data. Our dataset comprises information on 105 job ads, for which the firm received a total of 1,583 applications. For each application, our dataset includes the date of application, anonymized data from the applicant's CV (including gender, university of graduation, municipality of residence (if available)), the applicant's fit with the criteria outlined in the job ad according to the operational managers of the department has an open vacancy, the decision whether a candidate is interviewed and whether she/he receives an offer, internal justification by the HR office why an interviewed candidate is rejected, and whether a candidate finally accepts a job offer. Summary statistics are provided in Appendix B. Among employees hired on positions that were part of the RCT, we also collected data through in-depth interviews on commuting distances, and personal expectations regarding wages, career benefits, and flexibility a few months after they started working in the firm.

[18] As a safeguard for the RCT, we checked every day during the RCT that the "correct" job ad was posted online on each platform. We detected three inconsistencies in terms of a missing treatment switch when scheduled over the 12-month treatment periods on all platforms, and we immediately changed the treatment to the correct one.

4. Results

In this section, we first analyze the impact of our treatments on the daily number of applications (Section 4.1). Consistent with the empirical predictions outlined in Section 2, we disaggregate the effects by job experience level (entry vs. professional positions) and applicant gender. Second, we examine whether the treatments affect applicant quality and fit (Section 4.2).

4.1. Does highlighting flexibility and career advancement in job ads attract more applicants?

We start out by estimating the causal effect of highlighting flexibility and career advancement on the number of daily applications. Since each job ad was posted under three different treatment conditions (*control*, *flexibility*, *career*), our data follow a panel structure that allows us to exploit variation within each of the 105 job ads over a period of 30 days. We rely on the following linear specification:

$$y_{it} = \beta_{ca} Career_{it} + \beta_f Flexibility_{it} + \alpha_i + \lambda_t + \epsilon_{it}, \tag{1}$$

where y_{it} denotes the number of applications received for job ad i on day t. The variables $Flexibility_{it}$ and $Career_{it}$ are dichotomous and equal to one if job ad i was posted under the *flexibility* or *career* treatment on day t. The time index t denotes the number of days since the job ad first went online, excluding day t and day $t+1$ of the treatment switch.[19] The variable λ_t accounts for time fixed effects, α_i denotes the individual job ad fixed effect, and ϵ_{it} denotes the error term. To derive our main results, we rely on OLS fixed-effects regressions but also present Poisson fixed-effects

[19]In Appendix D, we present also an estimation including all observations. The results are similar.

estimations due to the count-level nature of the dependent variable.[20] All standard errors are clustered on job-ad level.[21]

Panel A of Table 1 presents the results of OLS estimations and Panel B the corresponding results of Poisson estimations.[22] As shown in Column 1, we observe no statistically significant average treatment effect on the total number of applications.

Our conceptual framework predicts that the treatment mostly affects the application decisions of workers with no or limited work experience. To test this, we distinguish between entry-level and professional-level positions. This serves as a meaningful proxy for applicant experience, as 50% of applicants to entry-level positions have less than 0.5 years of work experience, compared to 4 years for professional-level positions (and 75% of applicants to entry-level positions have less than 3 years of work experience, compared to 10 years for professional-level positions, see Appendix B for details). As shown in Column 2, we find that both treatments significantly increase the number of applications for entry-level jobs. The size of the effect is economically meaningful. We present relative effect sizes as percentages, denoted by $\Delta_{ca}\%$ and $\Delta_{f}\%$ (see Panel A).[23] The *flexibility* treatment increases the number of daily applications by approximately 44% (0.172 per day, Panel A). The *career* treatment is estimated to increase the applications by approximately by 34% (0.137 per day, Panel A). When extrapolating these point estimates to a full 30-day period, this implies that the *flexibility* treatment increases the total number of applications by approximately five, and the *career* treatment by four applications. As shown in Column 5, we find no statistically significant effects for professional-level positions.

[20]Specifically, due to overdispersion and the presence of inflated zeros, we rely on the Poisson Pseudo Maximum Likelihood estimator. The estimation is implemented in Stata using the *ppmlhdfe* command from the *ppml* package; see Correia et al. (2020).

[21]Although the number of clusters is in an acceptable range to rely on standard clustering methods, we also present the p-value of wild bootstrapped standard errors (see Cameron et al. 2008) in the last two rows of additional statistics for the OLS estimations.

[22]Panel B is based on a slightly different number of observations than Panel A due to the well-known separation problem in non-linear models. This occurs, for example, when there is insufficient variation in the number of applications across treatment periods. Since such observations do not contribute identifying information, they can be safely excluded (Correia et al. 2020).

[23]These are derived by dividing the estimate by the control mean and multiplying by 100.

Table 1: Effect on the number of applications

	No. of applications						
	All	Entry-level			Senior-level		
	All (1)	All (2)	Female (3)	Male (4)	All (5)	Female (6)	Male (7)
Panel A: OLS estimation							
Career	0.016	0.133*	0.000	0.133*	-0.030	-0.007	-0.023
	(0.034)	(0.078)	(0.025)	(0.072)	(0.033)	(0.017)	(0.029)
Flexibility	0.091	0.172**	0.052***	0.121*	0.060	0.006	0.054
	(0.087)	(0.067)	(0.018)	(0.061)	(0.119)	(0.026)	(0.096)
Control mean	0.374	0.386	0.063	0.323	0.368	0.075	0.293
$\Delta_{ca}\%$	4.2%	34.5%	0.0%	41.2%	-8.2%	-9.3%	-7.8%
$\Delta_{f}\%$	24.3%	44.5%	82.5%	37.5%	16.3%	8.0%	18.4%
p-val $H_0: \ \beta_f = \beta_{ca}$	0.344	0.565	0.012	0.843	0.410	0.396	0.433
Bootstrap p-val $H_0: \ \beta_{ca} = 0$	0.640	0.082	0.982	0.056	0.334	0.750	0.400
Bootstrap p-val $H_0: \ \beta_{f} = 0$	0.426	0.010	0.008	0.048	0.866	0.908	0.802
Observations	2727	829	829	829	1896	1896	1896
No. of Clusters	105	32	32	32	73	73	73
Panel B: Poisson estimation							
Career	0.095	0.327**	0.026	0.365**	0.026	-0.093	0.029
	(0.088)	(0.162)	(0.434)	(0.161)	(0.120)	(0.254)	(0.118)
Flexibility	0.141	0.455***	0.690**	0.397**	-0.004	-0.205	0.039
	(0.108)	(0.147)	(0.322)	(0.163)	(0.162)	(0.203)	(0.182)
IR career	1.10	1.39	1.03	1.44	1.03	0.91	1.03
IR flexibility	1.15	1.58	1.99	1.49	1.00	0.81	1.04
p-val $H_0: \ \beta_f = \beta_{ca}$	0.629	0.276	0.028	0.803	0.802	0.610	0.948
Observations	2490	827	569	827	1662	908	1610
No. of Clusters	96	32	24	32	64	35	62

Notes: This table shows the impact of the treatments on the number of applications received per day. Column 1 shows the effect for all job ads, Columns 2 to 4 (5 to 7) for entry-level (professional-level) positions. Columns 1,2, and 5 show the results for all applicants, while Columns 3 and 6 (4 and 7) show the results for female (male) applicants only. The estimates in Panel A are obtained using standard OLS fixed-effect regressions; the respective marginal effects need to be interpreted in terms of the change in the number of applications per day. The estimates in Panel B are obtained using a Poisson Pseudo Maximum Likelihood estimator. All specifications include job-ad and time fixed effects. Standard errors clustered on job-ad level are reported in parentheses. For Panel A, the first two rows of additional statistics show relative treatment effects in percent, derived by dividing the estimate by the control mean and multiplying by 100. For Panel B, the first two rows of additional statistics present the incidence ratios of the estimators. The incidence ratio is the exponential of the coefficient (e^{β_j}) and is interpreted as the factor by which the average of the dependent variable approximately changes upon belonging to a specific treatment group. $(IR-1) \times 100\%$ thus gives an estimate that is directly comparable to the $\Delta\%$ reported in Panel A. The third row of additional statistics of Panel A and B shows the p-value from a test of $\beta_f = \beta_{ca}$. The fourth and fifth row of additional statistics for Panel A show the p-values from wild bootstrapped clustered standard errors (Cameron et al. 2008). Panel B is based on a slightly different number of observations than Panel A due to the well-known separation problem in non-linear models. This occurs, for example, when there is insufficient variation in the number of applications across treatment periods. Since such observations do not contribute identifying information, they can be safely excluded (Correia et al. 2020). Standard errors presented with the point estimates are clustered on job-ad level. $^{*}< 0.1$, $^{**}< 0.05$, $^{***}< 0.01$

As outlined in our conceptual framework, due to differential preferences we expect that women respond more strongly to the *flexibility* treatment and men to the *career* treatment. Indeed, as shown in Column 3, the daily number of female applicants for entry-level positions increases in our *flexibility* treatment by 82% (0.052 per day, Panel A), while the *career* treatment yields no effect; the number of male applicants increases by 37% (0.121 per day, Panel A) under the *flexibility* treatment and by 41% (0.133 per day, Panel A) under the *career* treatment. For professional-level positions, we find no significant effects for either gender.

The Poisson regressions in Panel B of Table 1 confirm these findings. In fact, the reported incidence ratios (IRs) when converted to percent changes in application counts ($[\text{IR} - 1] \times 100\%$) closely correspond to the percent changes in daily applications ($\Delta\%$) as estimated from the OLS models. Moreover, as shown in Appendix D, the main findings are the same in a number of further robustness checks. In particular, to test for spillover effects, we also include lagged treatment variables in our main regression and find no evidence that spillovers significantly affect the magnitude of our estimated treatment coefficient.

Taken together, we find that our treatments have a strong effect on the size of the applicant pool for entry-level positions. However, what employers ultimately care about is not necessarily the size of the applicant pool, but the number of top candidates applying for a position. Although our conceptual framework does not generate predictions regarding applicant quality, the richness of our data, with detailed information on individual applicants, allows us to investigate this question in an exploratory manner. For this analysis, we focus on applicants to entry-level positions.

4.2. Does highlighting flexibility and career advancement in job ads attract more applicants with a high quality and fit?

The above results serve as a proof of the concept that highlighting certain amenities can be an effective tool for firms to increase the number of applications. Emphasizing specific job characteristics in job ads may nevertheless be undesirable for a firm if it leads to a surge in low-quality applications, or worse, if it lowers the overall quality of the applicant pool. This could arise, for example, if preferences for these amenities are negatively correlated with applicant quality, or if highlighting them attracts individuals whose qualifications or skill sets are a poor match for the advertised position (Nekoei 2022). However, assessing applicant quality requires detailed data on the characteristics of all applicants, a type of information that is generally not available to researchers. Our dataset is unique in that it includes detailed data from all applicants (e.g., their CVs) submitted to the firm as part of their applications as well as internal firm ratings assessing how well each candidate fits to the set of skills that an "ideal" candidate should possess for the advertised position. We use these data to examine the impact of our treatments on applicant caliber, drawing on (i) degrees from selective universities as an objective proxy for applicant quality, (ii) the firm's own candidate ratings as a measure of perceived fit, and (iii) information whether a respective candidate was invited for a job interview.

Applicant quality. As a proxy for overall applicant quality, we use the prestige of the applicant's graduating university. This choice is motivated by the observation that graduates from highly ranked, selective institutions are generally perceived as more attractive hires, reflecting both the competitive admissions standards of these universities and the more highly perceived quality of education they provide (Dale and Krueger 2002, Chetty et al. 2020, Weinstein 2025). We classify individuals as "top graduates" if they hold a degree from a German U15 or TU9 university.[24] The U15 comprises Germany's leading comprehensive research universities, while the TU9 consists of the country's top technical universities. Both groups are widely recognized for their academic selectivity and research intensity and consistently rank among the top institutions in national and international comparisons (for detailed information, see Appendix B). In our control group, 18.44% of applicants meet this criterion.

[24]The firm rarely receives any applications from top universities outside of Germany.

When we estimate Equation 1 using the number of top graduates as the outcome variable, we find that the *career* treatment leads to a statistically significant increase of 0.053 applicants per day (see Column 1 of Table 2). The magnitude of the coefficient implies that the number of highly qualified applicants nearly doubles (see $\Delta_{ca}\%$). For the *flexibility* treatment, we observe positive effects as well, but they are not statistically significant.

Applicant fit. To measure how well an applicant fits a given position, we use the rating provided by the operational managers of the department within the firm seeking to fill the vacancy. Prior to posting a job ad, the responsible manager in that department specifies a set of required skills for the position. For example, during our RCT, hiring managers sought candidates with skills such as 'knowledge of implementing ML-based solutions', 'expertise in the calculation and simulation of power electronic circuits', or 'background knowledge of silicon material technology.'

All applications received by the firm are assessed by the lead manager or other representatives of the relevant department to determine whether the applicant meets the required skill set. In the control group, 25% of applicants are rated as a "good fit".

When we re-estimate equation 1 using the number of applicants assessed as a good fit as the outcome variable, we find that the *career* treatment leads to a significant increase of 0.062 applicants per day (see Column 2 in Panel A of Table 2). The magnitude of the coefficient implies that the number of highly qualified applicants increases by roughly 56% (OLS with p-val=0.045). For the *flexibility* treatment, we find positive but statistically insignificant effects (Panel A). However, we find a weakly statistically significant effect of 67% for the Poisson estimation (Panel B).

Interview invitations. The firm invites top candidates from the applicant pool to an interview. While approximately 20% of applicants are invited overall, 70% of applicants who are both highly qualified and assessed as a "good fit" by the hiring department's managers are invited for an interview, supporting the validity of our proxies for applicant quality and fit. When we re-estimate

Table 2: No. of applications

	Application outcomes		
	Applicant quality (1)	Applicant fit (2)	Interview invitation (3)
Panel A: OLS estimation			
Career	0.053*	0.062**	0.067*
	(0.029)	(0.030)	(0.036)
Flexibility	0.024	0.053	0.039
	(0.026)	(0.033)	(0.028)
Control mean	0.057	0.110	0.085
Δ_{ca}%	93.0%	56.4%	78.8%
Δ_{f}%	53.3%	48.2%	45.9%
p-val $H_0: \ \beta_f = \beta_{ca}$	0.256	0.799	0.360
Bootstrap p-val $H_0: \ \beta_{ca} = 0$	0.070	0.042	0.082
Bootstrap p-val $H_0: \ \beta_f = 0$	0.316	0.138	0.154
Observations	829	829	829
No. of Clusters	32	32	32
Panel B: Poisson estimation			
Career	0.649*	0.511**	0.530*
	(0.361)	(0.260)	(0.302)
Flexibility	0.377	0.512*	0.342
	(0.405)	(0.267)	(0.240)
IR career	1.91	1.67	1.70
IR flexibility	1.46	1.67	1.41
p-val $H_0: \ \beta_f = \beta_{ca}$	0.359	0.997	0.388
Observations	595	545	645
No. of Clusters	25	22	25

Notes: This table shows the impact of the treatments on the number of applications received per day. Column 1 shows the effect on the number of applicants graduating from Germany's top 24 universities (either U15 or T9, see Appendix B for details). Column 2 reports the effect on the number of applicants assessed as a good fit by the hiring department's managers. Column 3 shows the effect for the number of applicants who were invited for an interview. The estimates in Panel A are obtained using standard OLS fixed-effect regressions; the respective marginal effects need to be interpreted in terms of the change in the number of applications per day. For Panel A, the first two rows of additional statistics show relative treatment effects in percent, derived by dividing the estimate by the control mean and multiplying by 100. The fourth and fifth row of additional statistics for Panel A show the p-values from wild bootstrapped clustered standard errors (Cameron et al. 2008). The estimates in Panel B are obtained using a Poisson Pseudo Maximum Likelihood estimator. For Panel B, the first two rows of additional statistics present the incidence ratios of the estimators. The incidence ratio is the exponential of the coefficient (e^{β_j}) and is interpreted as the factor by which the average of the dependent variable approximately changes upon belonging to a specific treatment group. $(IR - 1) \times 100\%$ thus gives an estimate that is directly comparable to the $\Delta\%$ reported in Panel A. The third row of Panel A and the third row of Panel B of additional statistics show the p-value from a test of $\beta_f = \beta_{ca}$. Panel B is based on a slightly different number of observations than Panel A due to the well-known separation problem in non-linear models. This occurs, for example, when there is insufficient variation in the number of applications across treatment periods. Since such observations do not contribute identifying information, they can be safely excluded (Correia et al. 2020). Standard errors presented with the point estimates are clustered on job-ad level. $^{*}< 0.1$, $^{**}< 0.05$, $^{***}< 0.01$

equation 1 using the number of interviewed applicants as an outcome variable, we observe that the *career* treatment results in a significant increase of 0.067 ($p - val = 0.072$) applicants per day (see Column 3 in Panel A of Table 2). The magnitude of the coefficient implies that the number of highly qualified applicants increases by roughly 79% (see Δ_{ca}%). For the *flexibility* treatment, we find positive but insignificant effects.

The results presented from Poisson regressions in Panel B of Table 2 largely confirm these results. In general, improvements in applicant quality appear to be primarily driven by male applicants, that is, by the type of candidates attracted by the career treatment. For the *flexibility* treatment, we only find weak evidence for an increase of applicants with a good fit.

In our dataset, we also observe which candidates receive a job offer (which almost all candidates accept). We see that the firm hires relatively more applicants from the *career* treatment (47% of hired applicants were in the career treatment group, while 26.5% were in the *flexibility* or *control* groups). However, given the relatively small number of observations, we do not place strong emphasis on these findings.

Main result 1: *Consistent with our framework, job ads targeting workers with little or no experience show strong treatment effects. Female applications rise 82% under the* ***flexibility*** *treatment, while the* ***career*** *treatment has no effect. For men, applications increase by about 40% under both treatments. The* ***career*** *treatment attracts more highly qualified applicants assessed as a good fit, leading to more interview invitations, whereas for the* ***flexibility*** *treatment we find no significant effect on high-quality applicants and only weak evidence of an increase in applicants with a good fit.*

5. Mechanisms: Belief-updating among potential entry-level applicants

We have shown that highlighting career advancement or flexibility increases the number of applications for entry-level positions and improves (or at least does not worsen) the quality of the applicant pool. What explains these effects? As outlined in our conceptual framework, the most plausible mechanism is belief updating: Highlighting job amenities serves as a signal to potential applicants about the nature of the position and the working environment, inducing them to revise their beliefs accordingly. As it is impossible to measure beliefs of (potential) applicants in our hiring data, we assess this mechanism using complementary evidence from a survey experiment with STEM students, i.e., who closely resemble the firm's target population for entry-level positions. We then provide evidence that alternative mechanisms are unlikely to explain our findings.

5.1. Young professionals' beliefs about the job and the work environment

Our RCT targets young professionals who recently graduated in STEM fields. To assess how our treatments shape beliefs about job characteristics and the working environment among entry-level workers, we ran a concurrent survey experiment with STEM students. We selected STEM students because they will soon enter the labor market and closely resemble the population our firm targets with entry-level ads.

Each time the study firm posted an entry-level job ad, we launched a lab session for our online survey experiment and invited STEM students who met the educational requirements of the vacancy. This approach allowed us to conduct the survey experiment in "real time", aligning it with the firm's actual recruitment period for the advertised position.[25] We collected responses from 2,014 STEM students across twelve economic laboratories in Germany and Austria.[26] Due to differences in administrative procedures, the labs became available on a rolling basis throughout

[25] To ensure the survey experiment did not influence the main RCT results, e.g., by artificially increasing application numbers, we gave participants the option to contact the firm and apply for the job right after completing the survey. Only three participants did so, and we excluded them from our main analysis.

[26] For detailed information on the labs, subject pool, and survey design, see Appendix F.

the RCT. For each job ad, we recruited at least 45 participants from at least two different labs. Because of limitations in participant availability, the survey included only 20 entry-level positions from the RCT. We selected job ads based solely on lab availability, a sufficiently large participant pool, and the timing of the job ad's posting relative to lab availability. Participants received a fixed fee of 25 Euros for completing the survey.

In the online survey, we showed participants a job ad from our RCT. We randomized whether the teaser text of the job ad was from the *control*, the *flexibility*, or the *career* treatment. We informed participants about the name of the firm and that the job ad was for a "real" vacancy currently posted by the company.[27] We then elicited participants' beliefs about the job's characteristics by asking them about the expected work-life balance, opportunities for flexible scheduling, the possibility of working from home, childcare support, a family-friendly workplace, the possibility of avoiding overtime, provision of a high income, prospects for salary growth, opportunities for salary negotiation, career-advancement opportunities, and how challenging the job tasks were.[28] Participants rated how accurately these job characteristics described the presented job at the study firm on a scale from 0 (does not apply at all) to 10 (fully applies).

To test our conceptual framework's prediction that highlighting flexibility and career advancement in job ads affects young professionals' beliefs, we create a composite score for *flexibility conditions*, which encompasses expected work-life balance, flexible scheduling, opportunities to work from home, childcare support, avoidance of overtime, and family-friendly job characteristics, and a score for *career advancement*, which comprises a good salary, possibility of salary growth, career-advancement opportunities, the level of challenge of the individual job tasks, and the opportunity

[27] To avoid confounding across lab locations, we removed the information about the workplace location and asked participants to assume that the the place of work was within a reasonable commuting distance from their current residence.

[28] The job characteristics are based on Ronen (1994) and have been applied in previous studies, e.g., Gill et al. 2023. We also asked participants in our survey to rate the expected attractiveness of the job location, opportunities for part-time work, the necessity of work-related travel, and job security. We exclude these items in the following analysis because the location was not mentioned in the survey, opportunities for part-time work and the necessity of work-related travel were explicitly stated in the job ad, and job security is generally high for permanent positions in Germany. In Appendix G, we present the results for these excluded items.

for regular salary negotiations. The composite scores for each category consist of the normalized sum of the ratings for the items within that category. We estimate an equation similar to (1) with the outcome variables being the two composite scores.[29] As shown in Table 3 A, the *flexibility* treatment increases the composite score for *flexibility* by about 0.123 standard deviations, while producing small and noisy point estimates close to zero for *career advancement*. The *career* treatment, in turn, raises the composite score for *career advancement* by 0.141 standard deviations, but reduces the *flexibility* score by 0.105 standard deviations.

While it is reassuring and consistent with our initial hypotheses that the treatments induce potential entry-level candidates to update their beliefs about flexibility and career advancement, this alone does not reveal how exactly these beliefs are revised. Furthermore, examining belief-updating across different dimensions allows us to assess what specific job characteristics individuals associate with flexibility and career advancement. In the next step, we thus identify the *exact* job characteristics individuals associate with workplace flexibility and career advancement. We estimate an equation similar to (1), using each job characteristic item as outcome variable. The results are presented in Columns 1-11 of Table 3 B. We find that the *flexibility* treatment significantly increases beliefs about flexible scheduling, better work-life balance, and opportunities to work from home. While the point estimates for childcare opportunities, family-friendly workplace, and the possibility to avoid overtime are positive as well, they are not statistically significant. The *career* treatment positively shifts beliefs about salary growth and salary-negotiation opportunities; for career-advancement opportunities, we find a positive point estimate, which is close to being statistically significant. Regarding the underlying correlation of flexibility and career-advancement beliefs, we also find that the *career* treatment negatively affects the expected work-life balance and beliefs about employer support in organizing childcare.

[29]We include as control variables gender, high-school GPA, migration background, university degree, family status, and job-ad and lab fixed effects. In Appendix F, we provide a detailed descriptions of the variables. We also show that our main qualitative results are the same when we exclude the control variables and when we generate factors using principal component analysis.

Table 3: Treatment effects on beliefs

Table A: Scores	*Belief scores*	
	Composite score: Flexibility conditions (1)	Composite score: Career advancement (2)
Career	-0.105**	0.141**
	(0.046)	(0.055)
Flexibility	0.123***	-0.021
	(0.042)	(0.051)
Bootstrap p: $\beta_{ca} = 0$	0.04	0.02
Bootstrap p: $\beta_f = 0$	0.01	0.70
Observations	2014	2014
No. Clusters	20	20

Table B: All outcomes	*Beliefs single items*										
	Work-life balance						Career benefits				
	Flex sched. (1)	WB balance (2)	HO (3)	CC (4)	Family (5)	Overtime (6)	Salary (7)	Career (8)	Sal. growth (9)	Challenge (10)	Nego. (11)
Career	-0.019	-0.134**	-0.022	-0.077*	-0.073	-0.096	0.005	0.110	0.308***	0.025	0.073*
	(0.052)	(0.058)	(0.058)	(0.043)	(0.050)	(0.060)	(0.046)	(0.067)	(0.049)	(0.075)	(0.041)
Flexibility	0.127**	0.097**	0.103*	0.044	0.048	0.065	-0.030	-0.042	0.012	-0.000	-0.018
	(0.053)	(0.039)	(0.057)	(0.043)	(0.056)	(0.051)	(0.044)	(0.050)	(0.059)	(0.059)	(0.052)
Bootstrap p: $\beta_{ca} = 0$	0.73	0.03	0.73	0.09	0.19	0.13	0.90	0.11	0.00	0.76	0.09
Bootstrap p: $\beta_f = 0$	0.03	0.02	0.09	0.32	0.40	0.23	0.51	0.40	0.83	0.99	0.74
Observations	2014	2014	2014	2014	2014	2014	2014	2014	2014	2014	2014
No. Clusters	20	20	20	20	20	20	20	20	20	20	20

Notes: Table A shows the impact of the treatments on the beliefs about job characteristics. Composite flex adds up beliefs about flexibility, work-life balance, oportunities to work from home, childcare support, family-friendly workplace culture, and expected overtime avoidance. Composite career adds up beliefs about expected salary, career opportunities, salary growth, degree of challenge of the tasks, and the possibility to negotiate salary increases regularly. The outcome variables are standardized, thus the marginal effects need to be interpreted in terms of standard deviations. Table B shows the impact of the treatments on the single belief-items. The outcomes are standardized, thus the marginal effects need to be interpreted in terms of standard deviations. All regressions include job ad and lab fixed-effects, and control variables, which include gender, high-school GPA, migration background, university degree, and family status. Standard errors clustered on job-ad level are reported in parentheses. The first two rows of additional statistics show the p values from wild bootstrapped clustered standard errors (Cameron et al. 2008). $^{*}< 0.1$, $^{**}< 0.05$, $^{***}< 0.01$

In response to the job-ad signal, potential applicants might update their beliefs not only about the respective job, but also about the broader work environment. As part of the survey, we also elicited participants' beliefs about the expected share of co-workers with particular personal or character traits. Specifically, we focus on the perceived share of direct colleagues who (i) are female, (ii) have a family, (iii) prioritize career over family, (iv) are eager to advance their careers, and (v) earn a high income.[30] When we re-estimate equation (1), using each of the believed shares as outcome variables, we observe that the *flexibility* treatment increases the expected share of female colleagues by 0.8 standard deviations and the *career* treatment increases the share of workers who are eager to make a career by 0.1 standard deviations compared to the *control* group (see Table G.20 in Appendix G for detailed results).

Main result 2: *STEM students adjust their beliefs in response to the treatments. The* ***flexibility*** *treatment raises expectations of flexible schedules, better work-life balance, opportunities to work from home, and more female colleagues. The* **career** *treatment raises expectations of salary growth, negotiation opportunities, and a career-oriented workplace, but lowers expectations of work-life balance indicating a perceived trade-off between career advancement and quality of life. These results support our framework: Highlighting job amenities shifts young professionals' beliefs, helping to explain treatment effects among workers with little or no experience.*

5.2. Can our results be explained by alternative mechanisms?

Aside from belief-updating, several alternative explanations may account for differences in treatment effects between entry-level and professional-level positions. Below, we discuss potential alternative mechanisms.

[30]We also elicited the share of colleagues with a STEM degree and over a particular age as distraction items. We present the results for these items in Appendix G.

Do preferences for job characteristics vary with age? A potential alternative explanation for our main finding could be that individuals' job preferences vary with age, i.e., that our findings arise because younger individuals place considerably more weight on flexibility and career advancement. Several pieces of evidence suggest that this explanation is unlikely. First, among the STEM students who participated in our survey experiment, we find that the participants' preferences remain stable between ages 25 and 30 (see Appendix G, and note that the mean age of applicants is 31). Second, we calculate the mean age of the applicants for each professional-level position in the control group and rerun our baseline regression focusing only on professional-level positions for which the average age of the applicants is below the median age (< 33 years). As shown in Appendix E, we find no statistically significant treatment effects for this subsample of professional-level positions in our RCT, although the age distribution among applicants for this subset of positions is statistically the same as for the entry-level positions; however, the large majority of the applicants in the former group have little or no labor-market experience, compared to a median of three years of work experience in the latter group. Third, to explain our findings with differences in age would require assuming that women's and men's preferences for flexibility would *decline* when they are between their mid-20s and early 30s (i.e., right before women and men in Germany on average have their first child).[31] Along these same lines, one would have to assume that men's preferences for career advancement decline with age. We consider it unlikely that women's and men's job preferences change i) to a large extent ii) in such heterogeneous ways iii) within a few years, and iv) at this stage of life.[32]

Do potential applicants obtain additional information? One might wonder whether our main results are driven not by the highlighting of job characteristics, but rather by the simple

[31] In Germany, mothers were on average 30.4, and fathers 34.7 years old when their first child was born (Willführ and Klüsener 2024).

[32] Another finding that supports belief-updating as the most likely mechanism is that we see treatment effects only among individuals with no or limited work experience who do not live in the vicinity of the firm's location. Individuals who live further away from the firm are arguably much less likely to know the firm from hearsay or have direct personal connections to employees of the firm. Detailed results are presented in Section Appendix E.3.

provision of additional information about job amenities. However, flexibility and career advancement are mentioned in all job ads, regardless of treatment assignment; our intervention merely emphasizes these aspects more prominently, limiting their informational content. Moreover, in the *career* treatment, we observe effects among men, but not among women, while the *flexibility* treatment influences application behavior for both genders. These heterogeneous effects are difficult to reconcile with a mere increase in the amount of information provided. Finally, job-ad length varies substantially across departments (e.g., some hiring departments in the firm provide more detailed job descriptions than others), yet we find no correlation between the length of a job ad and the number of applications in the control group (see Appendix E).

Is the labor market for professional-level positions too small to generate measurable treatment effects in our RCT? Another potential explanation for the large treatment effects we observe for entry-level, but not professional-level, positions is that the labor market for the former is larger and attracts applicants with more potential. Several pieces of evidence suggest that this is not the driver behind our findings. First, most of the positions advertised by the company were successfully filled within a short period of time. This holds both historically (75% over the last 10 years) and during our RCT (80%). Second, as shown in Table 1, we observe not only no increase in the absolute number of applications for professional-level positions, but also that the *relative* size of the point estimates is much smaller than the effect sizes estimated for entry-level positions. Third, we conduct an additional analysis in which we restrict the sample of professional-level positions to those with an above-median average number of daily applicants (i.e., > 0.2) and re-estimate equation 1. The results, presented in Appendix E, again show no significant treatment effects for this subsample.

Does the higher negotiability of professional roles limit the value of highlighted job characteristics? For professional-level positions it is more common to negotiate individual employment conditions with employees (e.g., wages) compared to entry-level positions (Seidel et al. 2000). This may explain why potential applicants for professional-level positions do not respond to our treatment, as they anticipate that flexibility and career advancement are typically negotiated at the offer stage. In our setup, only 12% percent of the professional-level (and 100 percent of the entry-level) positions are paid based on collective bargaining agreements.[33] For those types of positions, there is almost no leeway for adjustments (e.g. wage increases); in contrast, the firm and the applicant have considerable scope of negotiation for jobs that are not based on collective bargaining agreements. When we rerun our analyses excluding job ads for positions outside of the collective bargaining agreement, we find no significant treatment effects either, indicating that differences in negotiability are unlikely to explain our main finding.

5.3. Potential side effects of changes in the applicants' beliefs

A potential side effect of highlighting flexibility and career benefits in job ads could be that applicants form expectations that the study firm cannot meet. For example, it could be that the *flexibility* treatment encourages job seekers to ask for working conditions that are legally, organizationally, or for safety reasons impossible to implement (e.g., to work night shifts in an office job, or to bring a pet to the workplace). With respect to our *career* treatment, it could be that applicants' expected wages are disproportionately high (e.g., because the treatment attracts more ambitious or qualified applicants). However, for most jobs in our study firm, wage adjustments are difficult, as the wages are based on collective bargaining agreements. Instead, wages usually rise as individuals advance on the career ladder.

There are several pieces of evidence that suggest that potential side effects of our intervention are unlikely to be significant. First, the HR office systematically documents the reasons why an interviewed applicant does not receive a job offer. During the RCT, only one out of 217 interviewed

[33] In Germany, collective bargaining agreements categorize jobs in different pay scales mainly based on the required qualifications, required work experience, and responsibility. Before a job ad is published by our study firm, the HR office decides about the categorization of the position.

candidates was rejected due to an unreasonable wage request (we and the HR department do not know whether this applicant was part of the *career* treatment). According to the HR documentation, this candidate was, however, the only one whose rejection was potentially related to our treatments. Second, nearly all applicants who received a job offer accepted it. Third, nearly all employees hired into positions covered by our RCT stated in our in-depth interviews that their personal expectations regarding wages, career benefits, and flexibility were fully met (for details, see Appendix H).[34]

6. Conclusion

In the rapidly expanding technology sector, where highly-skilled human capital represents a key strategic asset, firms face substantial challenges in attracting new talent (Coff 1997, Bapna et al. 2013, Del Carpio and Guadalupe 2022). Based on an RCT at one of Europe's largest tech firms, we show that emphasizing flexibility and career-advancement opportunities in job advertisements significantly increases the number of applications for entry-level positions. Specifically, highlighting career advancement attracts more applications from men, while emphasizing flexibility increases application numbers among both women and men.

Our dataset is unique because it covers the complete universe of applications and includes detailed information on CVs, firm ratings, and interview invitations. These data allow us to show that the increase in applications did not come at the expense of applicant quality or fit. Highlighting career advancement opportunities expanded the pool of high quality candidates and increased the number of applicants who matched the advertised positions. At the same time, highlighting flexible work arrangements strongly attracted in particular female applicants. Taken together, our results suggest that firms may face a trade off between attracting more diverse applicants through flexible work amenities and attracting high quality male applicants through career focused information.

[34]We conducted the in-depth interviews with the first 68 employees hired for RCT-related vacancies; 36 workers participated.

More broadly, emphasizing specific job amenities appears to be an effective and cost efficient way to increase the number of strong applications, offering a useful tool in the continuing "war for talent".

We complemented our RCT with a survey experiment with STEM students to examine the belief-related mechanisms behind our main treatment effects, assessing how highlighting flexibility or career advancement affects young professionals' beliefs and expectations about job characteristics. Highlighting flexibility in job ads shifts beliefs towards a better work-life balance, while highlighting career-advancement opportunities leads young professionals to expect higher career benefits and a less favorable work-life balance. They also update beliefs about the working environment: When flexibility is highlighted, they expect the share of female colleagues to be higher, while career advancement leads to increases in the expected share of colleagues eager to make a career. Our results thus unveil the importance of job ads in shaping applicants' beliefs about job characteristics, the workforce, and the working environment with potential implications for a firm's employer reputation.

Our findings also provide important insights into how highlighting job characteristics can shape the selection of workers into jobs. First, we show that seemingly minor changes in job advertisements can substantially influence applicant behavior. This suggests the presence of significant information frictions in the labor market for entry-level jobs (see, e.g., Pissarides 2011, Belenzon and Tsolmon 2016). These effects are especially striking given that the choice of a first job can have long-lasting consequences for an individual's career (Kahn 2010). Second, by highlighting job amenities, rather than explicitly targeting or excluding specific types of workers, we show that small changes to conventional job ads can significantly influence the applicant pool (Flory et al. 2015, Kuhn and Shen 2023). This connects the survey-based literature on preferences for job attributes (Wiswall and Zafar 2018) with the literature on worker selection into firms (see, e.g., Nekoei 2022, Gill et al. 2023, DeVaro et al. 2024). Third, the fact that entry-level and professional-level workers, as well as male and female applicants, reacted differently to the same information provides novel evidence on the heterogeneity of worker preferences and belief-updating in a real-world setting (Del Carpio and Guadalupe 2022, Belot et al. 2022).

Our findings demonstrate that firms can attract specific demographic groups through small, targeted modifications to their job advertisements. It is likely that ongoing technological advances will soon allow firms to target job advertisements even to individual candidates. Our findings suggest that such personalized targeting could be highly effective in attracting suitable applicants. Combining the insights from our study with recent developments in the optimal treatment assignment literature (see, e.g., Kasy and Sautmann 2021, Opitz et al. 2025) may open up new avenues for hiring strategies with far-reaching implications for labor-market search and matching.

While our study setup and dataset enable us to measure the causal effect of the content of job ads not only on the quantity, but also on the quality and fit of the applicants, a limitation is that we cannot assess the impact of our treatments on long-term worker and firm-level outcomes. For example, one could expect that the greater number of high-quality applications will increase firm performance and that the larger number of applicants who fit the advertised positions will lead to a reduction in personnel turnover.[35] We hope that our results may inspire further research on job ads, applicants quality, and on-the-job outcomes.

[35] According to the HR office, the strongest predictor of turnover in our firm is whether employees reside in the region where the firm is located, which inspired us to measure in our in-depth interviews the commuting distances of workers hired during the RCT. 97% of the workers reported a commuting distance of 30 kilometers or less, suggesting that at least an increase in personnel turnover among the newly-hired candidates in the treatment group is unlikely. In line with this, two years after the RCT, the HR office informed us that the personnel turnover among newly hired workers in the last years did not increase.

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Online Appendix for: How to attract talent? Field-experimental evidence on emphasizing flexibility and career opportunities in job advertisements

January 7, 2026

Appendix A. Conceptual framework

In this section of the Appendix, we present the formal model serving as a basis for the empirical predictions discussed in Section 2.

Preferences and beliefs

Assume that potential applicants are characterized by (i) belonging to a group g of experienced workers denoted by E or inexperienced workers denoted by I, such that $g \in \{E, I\}$, and by (ii) having a fixed preference for job flexibility denoted by π_w^f and career advancement denoted by π_w^{ca}, where $w \in \{F, M\}$ denotes the gender. Additionally, each potential applicant has a job-specific ability denoted by α_i. We assume that workers decide between applying for a job at our target firm or an outside offer, the utility of which we denote by $\bar{U}_g$, and that it depends on previous work experience g, but is otherwise constant. The utility of a job at the target firm is a function of immediate wage returns denoted by m, returns to job-specific ability denoted by δ_g, and utility from job flexibility and from career-advancement opportunities:

$$U_{g,w,i} = m_{w,g} + \delta_g \alpha_i + \pi_w^f \tilde{\theta}_g^f + \pi_w^{ca} \tilde{\theta}_g^{ca}. \tag{2}$$

The job-specific ability, α_i, might arbitrarily correlate with gender-specific workplace preferences for flexibility π_w^f and career advancement π_w^{ca}. The utility component $\pi_w^f \tilde{\theta}_g^f$ formalizes that applicants derive utility from workplace flexibility which is linear in their beliefs about flexibility in a particular job. We assume that $\pi_w^f \in [0, \infty)$, meaning that – all else equal – individuals prefer working under flexible working conditions, but are heterogeneous in this preference. Similarly, the utility component $\pi_w^{ca} \tilde{\theta}_g^{ca}$ describes an applicant's utility from career advancement and shows a preference for career advancement of $\pi_w^{ca} \in [0, \infty)$.

Potential applicants are ex-ante uncertain about (i) the exact workplace flexibility and (ii) the career-advancement potential at the firm. Their priors for θ^f and θ^{ca} are normally distributed with

$\tilde{\theta}_g^f \sim N\left(\bar{\theta}_g^f, \tau_g^{f-1}\right)$ and $\tilde{\theta}_g^{ca} \sim N\left(\bar{\theta}_g^{ca}, \tau_g^{ca-1}\right)$. Thus, before agents of group g obtain any additional information from the job ads, they have a prior $\tilde{\theta}_g^f$ with mean $\bar{\theta}_g^f$ and precision τ_g^f about the provided workplace flexibility and a prior $\tilde{\theta}_g^{ca}$ with mean $\bar{\theta}_g^{ca}$ and precision τ_g^{ca} about the provided career-advancement opportunities. Additionally, applicants have a belief about the correlation between provided flexibility and career advancement. More formally, applicants have a common fixed and exogenously given belief $\tilde{\rho}$ about the correlation coefficient of their priors, $\tilde{\theta}_g^f$ and $\tilde{\theta}_g^{ca}$. Moreover, we assume that $\tilde{\theta}_E^f \perp \tilde{\theta}_I^f$ and $\tilde{\theta}_E^{ca} \perp \tilde{\theta}_I^{ca}$, i.e., the prior beliefs about workplace flexibility for experienced and inexperienced workers are statistically independent.

For our further analysis, we make two assumptions.

Assumption 1. We assume that, on average, more experienced workers hold strictly more precise ex-ante beliefs about the provided workplace flexibility and career opportunities at the job.

Formally, Assumption 1 translates into $\tau_E^f > \tau_I^f$ and $\tau_E^{ca} > \tau_I^{ca}$. The assumption that inexperienced workers have less accurate beliefs is motivated by the observation that more experienced workers have better networks (see, e.g., Glitz 2017) and are likely, overall, to be more informed about the labor market in their specific sector (due to already occurred learning in the past). This corresponds to assuming that they are better informed about the working conditions provided by the firm.

Secondly, we assume the following.

Assumption 2. We assume that female applicants have a higher preference for job flexibility than males and that male applicants have a higher preference for career-advancement opportunities than females.

Formally, Assumption 2 translates into $\pi_F^f > \pi_M^f$ and $\pi_M^{ca} > \pi_F^{ca}$ and is motivated by the findings of Wiswall and Zafar (2018).

The effect of highlighting flexibility and career advancement in job ads

Before the job ad is posted, individuals know their job-specific ability α_i, their preferences for flexibility π_w^f, and career advancement π_w^{ca}. In expectation, their prior beliefs about flexibility amount to $\bar{\theta}_g^f$, and their beliefs about career-advancement opportunities amount to $\bar{\theta}_g^{ca}$.

The employer posts job ads that either (a) contain no information about flexibility or career advancement (*control treatment*) (b) contain information about flexible working conditions (*flexibility treatment*), or (c) contain information about potential career-advancement opportunities (*career treatment*). We interpret our treatments as information treatments, which serve as a positive signal to potential applicants and result in belief-updating of their priors regarding flexibility and career advancement provided by the firm. The signal s depends on the realization with $s \in \{s_c, s_f, s_{ca}\}$ while $s_f \sim N(\theta^f, \tau^{s_f-1})$ and $s_{ca} \sim N(\theta^{ca}, \tau^{s_{ca}-1})$. As the signal is positive, it holds that $\theta^f > \bar{\theta}_E^f$, $\theta^f > \bar{\theta}_I^f$, $\theta^{ca} > \bar{\theta}_E^{ca}$, and $\theta^{ca} > \bar{\theta}_I^{ca}$. We interpret θ^f and θ^{ca} as the true level of flexibility and career-advancement opportunities provided by the firm. The signal s_c is assumed to be completely uninformative.[36]

After observing the signal, we assume that applicants update their beliefs. Due to the normality assumption regarding the distributions, the posterior beliefs denoted by $\hat{\theta}$ are a weighted average of the priors and signals (Bachmann et al. 2022). The posterior for θ^f upon observing s^f is given by:

$$\hat{\theta}_g^f(\tilde{\theta}_g^f, s_f) = \frac{\tilde{\theta}_g^f \tau_g^f + \tau^{s_f} s_f}{\tau_g^f + \tau^{s_f}} \tag{3}$$

The posterior for θ^{ca} upon observing s^{ca} is given by:

$$\hat{\theta}_g^{ca}(\tilde{\theta}_g^{ca}, s_{ca}) = \frac{\tilde{\theta}_g^{ca} \tau_g^{ca} + \tau^{s_{ca}} s_{ca}}{\tau_g^{ca} + \tau^{s_{ca}}} \tag{4}$$

[36] This only holds due to the exogenous nature of the signals.

Due to the belief about the correlation of priors for flexibility and career-advancement opportunities $\tilde{\rho}$, individuals can also learn about θ^f (θ^{ca}) when observing s^{ca} (s^f). Note that this learning solely occurs via learning about the posterior for $\hat{\theta}^{ca}$ ($\hat{\theta}^f$). Applicants then infer via updating the conditional expectation of θ^f (θ^{ca}) given new information about θ^{ca} (θ^f). The respective posteriors can then be inferred by $\hat{\theta}_g^f = \mathbb{E}[\theta_g^f \mid s^{ca}] = \mathbb{E}[\mathbb{E}[\theta_g^f \mid \theta_g^{ca}] \mid s^{ca}]$ and, similarly, for $\hat{\theta}_g^{ca} = \mathbb{E}[\theta_g^{ca} \mid s^f] = \mathbb{E}[\mathbb{E}[\theta_g^{ca} \mid \theta_g^f] \mid s^f]$. Relying on the expressions of conditional expectations of two normal random variables (DeGroot 2005, Bachmann et al. 2022), we get

$$\mathbb{E}[\theta_g^f \mid s^{ca}] = \tilde{\theta}_g^f + \tilde{\rho}\sqrt{\frac{(\tau_g^f)^{-1}}{(\tau_g^{ca})^{-1}}}\left(\hat{\theta}_g^{ca} - \tilde{\theta}_g^{ca}\right) = \tilde{\theta}_g^f + \tilde{\rho}\sqrt{\frac{\tau_g^{ca}}{\tau_g^f}}\left(\hat{\theta}_g^{ca} - \tilde{\theta}_g^{ca}\right) \tag{5}$$

and,[37]

$$\mathbb{E}[\theta_g^{ca} \mid s^f] = \tilde{\theta}_g^{ca} + \tilde{\rho}\sqrt{\frac{(\tau_g^{ca})^{-1}}{(\tau_g^f)^{-1}}}\left(\hat{\theta}_g^f - \tilde{\theta}_g^f\right) = \tilde{\theta}_g^{ca} + \tilde{\rho}\sqrt{\frac{\tau_g^f}{\tau_g^{ca}}}\left(\hat{\theta}_g^f - \tilde{\theta}_g^f\right) \tag{6}$$

Next, we can plug in the posterior $\hat{\theta}^{ca}$ derived in (4) into (5) as well as the posterior $\hat{\theta}^f$ derived in (3) into (6). This yields the final expressions for the posteriors,

$$\hat{\theta}_g^f(\tilde{\theta}_g^{ca}, \tilde{\theta}_g^f, s_{ca}) = \tilde{\theta}_g^f + \tilde{\rho} \cdot \sqrt{\frac{\tau_g^{ca}}{\tau_g^f}} \cdot \frac{\tau^{s_{ca}}(s_{ca} - \tilde{\theta}_g^{ca})}{\tau^{s_{ca}} + \tau_g^{ca}} \tag{7}$$

and

$$\hat{\theta}_g^{ca}(\tilde{\theta}_g^f, \tilde{\theta}_g^{ca}, s_f) = \tilde{\theta}_g^{ca} + \tilde{\rho} \cdot \sqrt{\frac{\tau_g^f}{\tau_g^{ca}}} \cdot \frac{\tau^{s_f}(s_f - \tilde{\theta}_g^f)}{\tau^{s_f} + \tau_g^f} \tag{8}$$

[37] In particular, $\mathbb{E}[x|y] = \mathbb{E}[x] + \frac{Cov[x,y]}{V[x]}(y - \mu_y)$. In our context and in the case of Bayesian updating, $\mathbb{E}[x]$ corresponds to the prior about flexibility $\tilde{\theta}_g^f$, then $\frac{COV[x,y]}{V[x]}$ needs to be replaced by $Cov[\tilde{\theta}_g^f, \tilde{\theta}_g^{ca}] = \tilde{\rho}\sqrt{(\tau_g^f)^{-1}}\sqrt{(\tau_g^{ca})^{-1}}$, and $V[x]$ corresponds to $V[\tilde{\theta}_g^{ca}] = (\tau^{ca})^{-1}$. Given that we make use of the information given by the signal, y corresponds to the realized value, i.e., the posterior $\hat{\theta}_g^{ca}$, while $\mathbb{E}[y]$ corresponds to the prior $\tilde{\theta}_g^{ca}$. Plugging in these expressions into (5), yields expression (7). With the exact similar approach, we can derive (8).

Note that whether applicants use information provided via s_f to update their prior $\tilde{\theta}_g^{ca}$ and equally the information provided via s_{ca} to update their prior $\tilde{\theta}_g^f$ depends on their beliefs about potential trade-offs. In case $\tilde{\rho} = 0$, the right-hand side of (8) and (7) collapses to the respective prior beliefs. Since the *control treatment* does not contain information about flexibility or career-advancement opportunities, such job ads do not shift agents' priors.

Applicant i applies to the job if $U_{g,w,i} > \bar{U_g}$; thus, it is reasonable to assume that each increase of $U_{g,w,i}$ translates into a higher likelihood to apply. The average treatment effect of the *flexibility treatment* depending on group membership g and the belief about the trade-off $\tilde{\rho}$ can thus be described as $\Delta U|s_f(w,g,\tilde{\rho}) = E[U_{g,w} \mid s_f] - E[U_{g,w} \mid s_c] = E[U_{g,w} \mid s_f] - E[U_{g,w}]$, and the treatment effect of the *career treatment* can be described as $\Delta U|s_{ca}(w,g,\tilde{\rho}) = E[U_{g,w} \mid s_{ca}] - E[U_{g,w} \mid s_c] = E[U_{g,w} \mid s_{ca}] - E[U_{g,w}]$. We can explicitly formulate both expressions as

$$\Delta U|s_f(w,g,\tilde{\rho}) = \frac{\tau^{s_f}}{\tau_g^f + \tau^{s_f}}(\theta^f - \bar{\theta}_g^f) \cdot \left(\pi_w^f + \pi_w^{ca}\sqrt{\frac{\tau_g^f}{\tau_g^{ca}}}\tilde{\rho}\right) \tag{9}$$

$$\Delta U|s_{ca}(w,g,\tilde{\rho}) = \frac{\tau^{s_{ca}}}{\tau_g^{ca} + \tau^{s_{ca}}}(\theta^{ca} - \bar{\theta}_g^{ca}) \cdot \left(\pi_w^{ca} + \pi_w^f\sqrt{\frac{\tau_g^{ca}}{\tau_g^f}}\tilde{\rho}\right) \tag{10}$$

Given our previous discussion, we can now analyze the expected utility change in more detail. Considering (9) and (10), we observe that both expressions are positive if $\tilde{\rho}$ is not too small or, more precisely, if $\tilde{\rho} > -\frac{\pi_w^f}{\pi_w^{ca}} \cdot \sqrt{\frac{\tau^{ca}}{\tau^f}}$ holds.

So far, we have assumed that the precision of prior beliefs is strictly larger for group E compared to group I. If we additionally assume that the average of the prior belief for group E is weakly more positive than for group I, i.e., $(\theta^f - \bar{\theta}_g^f)$ and $(\theta^{ca} - \bar{\theta}_g^{ca})$, we find that the expected increase in utility and therefore increase in likelihood to apply is larger for group E compared to group I. This can be motivated similarly to the assumption regarding precision. As experienced applicants have more experience with the industry overall, it is likely that they are better informed due to learning in the past (i.e., have on average a prior belief closer to the true value). This leads to Proposition 1, which serves as a basis for the empirical predictions discussed in Section 2.

Proposition 1. *If $\tilde{\rho}$ is not too small, both treatments increase on average the total number of applications. If $\theta^f > \bar{\theta}^f_E \geq \bar{\theta}^f_I$ holds, the increase is on average larger for applicants from group $g = I$ than from group $g = E$.*

Note that we may also predict a similar heterogeneity with respect to the increase of applications across groups in case $\theta^f > \bar{\theta}^f_E \geq \bar{\theta}^f_I$ does not hold. However, if this condition fails, the differences in precision parameters across groups must be relatively large enough compared to the difference in mean priors.

Considering (9) and (10) further, we observe that π^f_w enters (9) positively while π^{ca}_w enters (10) positively as well. Thus, the larger both are, the larger the total expected utility change upon s_f and s_{ca} respectively. Due to the assumed differences in gender preferences, it holds that $\pi^f_F > \pi^f_M$ and $\pi^{ca}_M > \pi^{ca}_F$, and thus the increases following the flexibility signal are expected to be larger for female applicants, while the expected increases following the career-advancement signal are expected to be larger for male applicants. This finding leads to Proposition 2 and serves as a basis for the empirical predictions in Section 2.

Proposition 2. *It holds that $\Delta U|s_f(g, \tilde{\rho}) > \Delta U|s_{ca}(g, \tilde{\rho})$ for $w = F$, i.e., female applicants, and $\Delta U|s_f(g, \tilde{\rho}) < \Delta U|s_{ca}(g, \tilde{\rho})$ for $w = M$, i.e., male applicants.*

In this Appendix, we present supplementary material for the RCT. In particular, we present summary statistics in Appendix B.1, descriptive graphics, and summary statistics showing the distribution of age and work experience of applicants in Appendix B.2, the distribution of treatments by period in Appendix B.3, as well as the job ads presented in Section 3 for the control and career-advancement treatment in Appendix B.4.

Appendix B.1. Summary statistics

Table B.4: Summary statistics: Daily application data by required experience and treatment

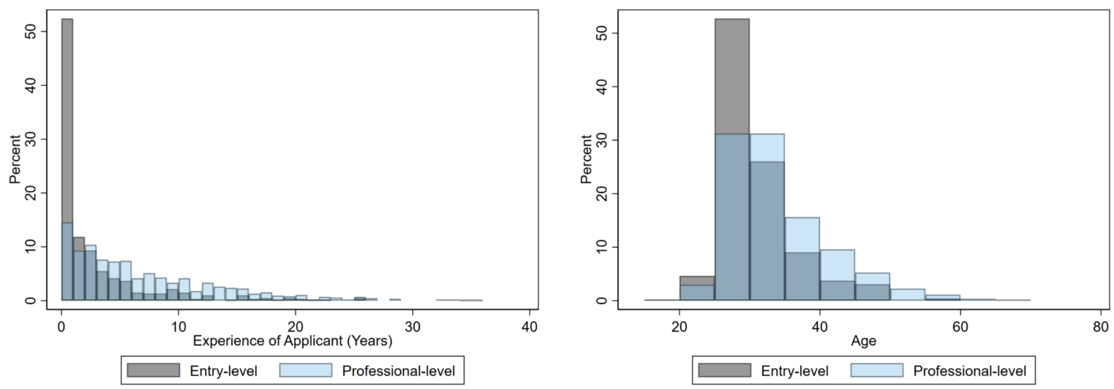
	Entry-level positions						**Professional-level positions**					
	Control		Career		Flexibility		Control		Career		Flexibility	
Variable	Mean	SD	Mean	SD	Mean	SD	Mean	SD	Mean	SD	Mean	SD
A. Number of applicants												
Total	0.387	0.667	0.480	0.849	0.506	0.823	0.368	0.999	0.315	0.821	0.427	2.169
Male applicants	0.323	0.583	0.422	0.765	0.399	0.721	0.293	0.821	0.251	0.634	0.343	1.655
Female applicants	0.064	0.245	0.058	0.289	0.106	0.320	0.075	0.318	0.064	0.323	0.084	0.581
B. Quality and fit												
Top university	0.057	0.247	0.105	0.361	0.077	0.267	0.045	0.237	0.054	0.320	0.062	0.396
Good fit	0.110	0.366	0.163	0.433	0.150	0.397	0.116	0.395	0.103	0.375	0.059	0.249
Interview	0.085	0.304	0.144	0.382	0.117	0.344	0.072	0.287	0.054	0.247	0.038	0.192
C. Region of residence												
Germany w/o state	0.149	0.404	0.238	0.553	0.238	0.498	0.147	0.574	0.127	0.430	0.198	1.253
State	0.114	0.329	0.144	0.372	0.117	0.355	0.110	0.346	0.095	0.392	0.110	0.494
Abroad	0.124	0.390	0.098	0.332	0.154	0.427	0.111	0.414	0.092	0.358	0.119	0.607
Observations	282		277		273		639		629		630	

Notes: This table shows summary statistics for the average daily number of applicants by the level of required experience for the job and treatment. In A., Number of applicants, we present the total number of applicants, male applicants and female applicants. In B., we present the daily number of applicants graduating from a top university (*Top university*, as defined in Appendix C), the ones rated with a good fit by the hiring department (*good fit*, as defined in Section 4.2), and the ones invited for an interview. In C., we show the number of daily applicants by region of residence. In particular, we distinct between applicants living in the (federal) state in which the firm is located (*State*), applicants living in Germany, but not in the state of the firm's location (*Germany w/o state*), and applicants living abroad (*Abroad*).

Appendix B.2. Distributions of age and work experience

Figure B.2

(a) Distribution of work experience (b) Distribution of age



Notes: Figure B.2a presents the distribution of the applicants' work experience in years for entry- and professional-level positions. For 0.4% (5 out of 1209) of the workers, we have no information about their corresponding work experience. Figure B.2b presents the distribution of applicants' age for entry- and professional-level positions. For 32% (386 out of 1209) of the workers we have no information about their age.

Appendix B.3. Randomization

Table B.6: Distribution of treatments by period

Period	Control	Flexibility	Career	Total
Day 1–10	42	31	32	105
Day 11–20	29	46	30	105
Day 21–30	34	28	43	105
Total	105	105	105	-

Notes: This table shows the distribution of job ads across three treatments (Control, Flexibility, Career) and periods (Days 1–10, 11–20, 21–30). The total sample consists of 105 job ads.

Table B.5: Descriptive statistics by experience level

	Overall	**Entry-level**	**Professional-level**
FT work experience (years)			
Mean	4.59	2.20	6.32
Std. Dev.	5.85	3.84	6.42
Min	0	0	0
25th pct	0	0	1.5
Median	2	0.5	4
75th pct	7	3	10
Max	36	25	33
N	1,204	506	698
Age (years)			
Mean	31.84	30.05	33.36
Std. Dev.	6.69	5.25	7.38
Min	21	23	21
25th pct	27	27	28
Median	30	29	31
75th pct	34	32	37
Max	66	56	66
N	823	379	444

Notes: This table presents summary statistics of applicants full-time work experience and age. Column 1 shows the statistics for all applicants, Column 2 for applicants to entry-level positions, and Column 3 for professional-level positions.

Appendix B.4. Job ads

Figure B.3: Sample job ad - Career

Empowering.
Innovation.
Sustainability.
Together.

Product Development Engineer (w/m/div)

Ready to lead the future of power semiconductor innovation?
As a Product Development Engineer, you'll transform groundbreaking ideas into high-volume production realities. Join our team and elevate your career by shaping the next generation of advanced technology.

GROWTH is very important to us! With us, you do not only grow personally, but also your salary.

Job description

We are looking for a skilled Product Development Engineer to join our dynamic team, focused on creating cutting-edge power semiconductor modules.

- Develop mechanical details and functionalities for both new and existing product packages and families.
- Ensure that the latest research and cutting-edge technologies are incorporated into designs and systems, while optimizing for cost efficiency.

Your Profile

You are a highly motivated and enthusiastic engineer who is passionate about technology and enjoys analyzing complex technical relationships.

You are best equipped for this task if you have:

- A University degree in mechanical engineering, mechatronics, automation technology, or a related field of study.
- Experience with tools such as Autodesk Inventor, 3D CAD systems, and the Vault database, along with metrology software for tolerance analysi.

At a Glance

Location:	City (Country)
Job ID:	XXXXXXX
Start Date:	20XX-XX-XX
Entry Level:	0-1 years
Contract:	Full time
Job sharing:	Possible

Apply to this position online by following the URL and entering the Job ID in our job search.

Job ID: XXXXX
Homepage Company

Why us?

As a global leader in semiconductor solutions for power systems and IoT, we drive innovation in green energy, clean mobility, and smart IoT. Join us in making life easier, safer, and greener.

Are you in?

Contact:
First name Last name
Talent Attraction Manager

Company logo

Benefits

- Opportunities for coaching, mentoring, and networking; training offerings and structured development planning; possibility for international assignments; various career paths: Project Management, Technical Ladder, Management, and Individual Contributor; flexible working hours with trust-based flexitime; opportunities to work from home; openness to part-time work (including during parental leave); sabbatical options; holiday childcare; social counseling and company doctor services; health and preventive care programs; cafeteria; insurance offerings at attractive rates; continued salary in case of illness; employer-funded company pension plan; openness to flexible transition into retirement; performance bonus; accessibility across the entire site; possibility to work remotely from abroad (within the EU).

Notes: This figure presents a fictitious sample of a job ad of the study firm. It is created manually, but the content is generated via OpenAI (2024) based on input of real job ads of the study firm. All details (e.g., wording, font, color) are changed to keep the anonymity of the study firm.

Figure B.4: Sample job ad - Control

Empowering.
Innovation.
Sustainability.
Together.

Product Development Engineer (w/m/div)

Ready to lead the future of power semiconductor innovation?
As a Product Development Engineer, you'll transform groundbreaking ideas into high-volume production realities. Join our team and elevate your career by shaping the next generation of advanced technology.

Job description

We are looking for a skilled Product Development Engineer to join our dynamic team, focused on creating cutting-edge power semiconductor modules.

- Develop mechanical details and functionalities for both new and existing product packages and families.
- Ensure that the latest research and cutting-edge technologies are incorporated into designs and systems, while optimizing for cost efficiency.

Your Profile

You are a highly motivated and enthusiastic engineer who is passionate about technology and enjoys analyzing complex technical relationships.

You are best equipped for this task if you have:

- A University degree in mechanical engineering, mechatronics, automation technology, or a related field of study.
- Experience with tools such as Autodesk Inventor, 3D CAD systems, and the Vault database, along with metrology software for tolerance analysi.

At a Glance

Location:	City (Country)
Job ID:	XXXXXXX
Start Date:	20XX-XX-XX
Entry Level:	0-1 years
Contract:	Full time
Job sharing:	Possible

Apply to this position online by following the URL and entering the Job ID in our job search.

Job ID: XXXXX
Homepage Company

Why us?

As a global leader in semiconductor solutions for power systems and IoT, we drive innovation in green energy, clean mobility, and smart IoT. Join us in making life easier, safer, and greener.

Are you in?

Contact:
First name Last name
Talent Attraction Manager

Company logo

Benefits

- Opportunities for coaching, mentoring, and networking; training offerings and structured development planning; possibility for international assignments; various career paths: Project Management, Technical Ladder, Management, and Individual Contributor; flexible working hours with trust-based flexitime; opportunities to work from home; openness to part-time work (including during parental leave); sabbatical options; holiday childcare; social counseling and company doctor services; health and preventive care programs; cafeteria; insurance offerings at attractive rates; continued salary in case of illness; employer-funded company pension plan; openness to flexible transition into retirement; performance bonus; accessibility across the entire site; possibility to work remotely from abroad (within the EU).

Notes: This figure presents a fictitious sample of a job ad of the study firm. It is created manually, but the content is generated via OpenAI (2024) based on input of real job ads of the study firm. All details (e.g., wording, font, color) are changed to keep the anonymity of the study firm.

Appendix C. University rankings

This Appendix presents information about the used university rankings for the analysis in Section 4.2. The U15 universities are an association of the fitfteen leading universities with a strong research tradition. They are the most renowned and internationally visible institutions in the German academic system (German U15 e.V. 2025). The TU9 is an alliance of nine leading German universities of technology. They define themselves as renowned for world-class research and education in engineering and natural sciences, close collaboration with industry, and fostering innovation from basic research to real-world applications (TU9 – German Universities of Technology e. V. 2025).

Table C.7: German U15 and TU9 universities

University	Network	THE 2025	Gov't (M€)*	DFG (M€)*	EU (M€)*
U15 only					
Free University of Berlin	U15	104	211.5	296.8	55.0
Humboldt University of Berlin	U15	84	221.6	267.2	46.2
University of Bonn	U15	89	84.9	293.7	49.6
Goethe University Frankfurt	U15	201-250[2]	68.4	198.3	24.8
University of Freiburg	U15	128	116.8	287.8	31.2
University of Göttingen	U15	121	82.2	232.5	19.0
University of Hamburg	U15	132	106.5	270.6	57.5
Heidelberg University	U15	47	106.4	307.5	58.0
University of Cologne	U15	157	58.7	266.2	23.9
Leipzig University	U15	—	84.7	153.4	12.5
Johannes Gutenberg University Mainz	U15	251-300[2]	65.6	182.0	18.1
LMU Munich	U15	38	117.7	335.1	69.3
University of Münster	U15	188	71.4	237.8	25.2
University of Tübingen	U15	100	134.8	285.5	43.8
University of Würzburg	U15	163	67.0	170.9	16.9
TU9 only					
TU Berlin	TU9	140	170.7	152.7	32.1
TU Braunschweig	TU9	501-600[2]	128.8	108.5	14.2
TU Darmstadt	TU9	160	152.2	154.4	37.5
TU Dresden	TU9	160	281.8	265.0	52.5
Leibniz University Hannover	TU9	351-400[2]	157.9	187.0	26.9
Karlsruhe Institute of Technology	TU9	166	275.9	211.7	61.7
University of Stuttgart	TU9	251-300[2]	210.8	188.3	30.4
Both U15 & TU9					
RWTH Aachen University	U15 & TU9	92	412.4	324.6	50.4
TUM – Technical University of Munich	U15 & TU9	26	304.7	333.4	113.1

Notes: This table presents a list of the universities, their belonging to the respective association (U15 and/or T9) in Column 2, their ranking in the Times Higher Education ranking 2025 in Column 3, the amount of research and development funding from German governmental institutions in Column 4, the amount of third-party funding received by the German research foundation in Column 5, and the amount of funding received via Horizon Europe in Column 6. *All funding data are sourced from the German Research Foundation (DFG) (2025).
[2] Universities in this range(s) share the same ranking band with multiple other institutions, and an exact position is not assigned.

In this Subsection, we present the main results including all days as observations in D.8, show that spillover effects do not pose an identification threat in Appendix D.2, , and repeat the analyses on the qualification and fit of applicants using shares as outcome variables in Appendix D.3.

Appendix D.1. Inclusion of all days

We re-estimate equation 1 including all days as observations. We present results of an OLS estimation in Table D.8 and Poisson estimates in Table D.9. The Poisson estimation is implemented in Stata using the *ppmlhdfe* command from the *ppml* package; see Correia et al. (2020).

Table D.8: Effect on the number of applications - All days - OLS

	No. of applications - OLS						
	All	Entry-level			Senior-level		
	All (1)	All (2)	Female (3)	Male (4)	All (5)	Female (6)	Male (7)
Career	0.016	0.134*	0.010	0.124*	-0.032	-0.004	-0.028
	(0.031)	(0.074)	(0.023)	(0.069)	(0.029)	(0.014)	(0.025)
Flexibility	0.074	0.140**	0.036*	0.104*	0.048	0.007	0.042
	(0.081)	(0.064)	(0.019)	(0.058)	(0.110)	(0.024)	(0.089)
p-val $H_0: \ \beta_f = \beta_{ca}$	0.452	0.925	0.100	0.733	0.449	0.526	0.452
Bootstrap p-val $H_0: \ \beta_{ca} = 0$	0.612	0.078	0.668	0.066	0.240	0.832	0.224
Bootstrap p-val $H_0: \ \beta_f = 0$	0.566	0.034	0.082	0.084	0.914	0.884	0.876
Control mean	0.374	0.390	0.069	0.321	0.368	0.075	0.292
Observations	3149	959	959	959	2190	2190	2190
No. of Clusters	105	32	32	32	73	73	73

Notes: This table shows the impact of the treatments on the number of applications received per day including all days as observations. Column 1 shows the effect for all job ads, Columns 2 to 4 (5 to 7) for entry-level (professional-level) positions. Columns 1,2, and 5 show the results for all applicants, while Columns 3 and 6 (4 and 7) show the results for female (male) applicants only. The estimates are obtained using standard OLS fixed-effect regressions; thus, the marginal effects need to be interpreted in terms of the change in the number of applications per day. All specifications include job-ad and time fixed effects. Standard errors clustered on job-ad level are reported in parentheses. The first two rows of additional statistics show bootstrap estimates of the relative treatment effects in percent. The third row of additional statistics shows the p-value from a test of $\beta_f = \beta_{ca}$. The fourth and fifth row of additional statistics show the p-values from wild bootstrapped clustered standard errors (Cameron et al. 2008). Standard errors presented with the point estimates are clustered on job-ad level. $^{*}< 0.1$, $^{**}< 0.05$, $^{***}< 0.01$

Table D.9: Effect on the number of applications - All days - Poisson estimation

	No. of applications - Poisson						
	All	Entry-level			Senior-level		
	All (1)	All (2)	Female (3)	Male (4)	All (5)	Female (6)	Male (7)
Career	0.083	0.312**	0.215	0.331**	-0.003	-0.056	-0.011
	(0.081)	(0.157)	(0.343)	(0.158)	(0.102)	(0.240)	(0.102)
Flexibility	0.108	0.362***	0.497**	0.331**	-0.028	-0.149	0.000
	(0.106)	(0.137)	(0.250)	(0.150)	(0.152)	(0.174)	(0.171)
p-val $H_0: \beta_f = \beta_{ca}$	0.795	0.667	0.159	0.997	0.843	0.662	0.939
IR career	1.09	1.37	1.24	1.39	1.00	0.95	0.99
IR flexibility	1.11	1.44	1.64	1.39	0.97	0.86	1.00
Control mean	0.374	0.390	0.074	0.301	0.368	0.078	0.292
Observations	2939	959	671	959	1980	1200	1920
No. of Clusters	96	32	32	32	68	68	68

Notes: This table shows the impact of the treatments on the number of received applications per day including all days as observations. Column 1 shows the effect for all job ads, Column 2 (3) for entry-level (professional-level) positions. The estimates are obtained using a Poisson Pseudo Maximum Likelihood estimator. All specifications include job ad and time fixed effects. The incidence ratios of the estimators are presented as additional statistics in the regression table. The incidence ratio is the exponential of the coefficient and is interpreted as the factor by which the average of the dependent variable approximately changes upon belonging to a specific treatment group. Standard errors clustered on job-ad level are reported in parentheses. The first row of additional statistics shows the p-value from a test of the linear hypothesis that the treatment effects are equal in magnitude.
$^{*}< 0.1$, $^{**}< 0.05$, $^{***}< 0.01$

Appendix D.2. Spillover

We investigate potential spillover effects that may arise if applicants are exposed to multiple treatment conditions over time. Such spillovers could lead to a downward bias in our main estimates. So far, to alleviate this concern, we excluded the day of the treatment switch and the following day in our main analysis. In order to examine spillovers further, we conduct two additional sets of analyses. (i) We re-estimate our main regression model with interaction terms for each 10-day period. The results, presented in Column 1 of Table D.10, show no evidence of strong time trends in the treatment effects. This suggests the absence of spillovers, as such effects should manifest in changing treatment impacts over time. (ii) We re-estimate the main model including lagged treatment variables. Column 2 of Table D.10 show that the point estimates remain stable when accounting for lagged treatments. Also, neither lag is statistically significant. This provides strong evidence that spillovers do not meaningfully impact the size or significance of our main treatment effects.

Table D.10: Robustness - Time heterogeneity and lags for entry-level positions

	No. of applications - OLS	
	(1)	(2)
Career	0.225	0.120
	(0.168)	(0.088)
Flexibility	0.237	0.215**
	(0.159)	(0.080)
Career×Day 11-20	-0.091	
	(0.236)	
Career×Day 21-30	-0.179	
	(0.200)	
Flexibility×Day 11-20	-0.178	
	(0.192)	
Flexibility×Day 21-30	-0.017	
	(0.268)	
Lag1 Career		-0.049
		(0.081)
Lag1 Flexibility		0.115
		(0.080)
Control mean	0.39	0.39
Observations	829	829
No. of Clusters	32	32

Notes: This table shows the impact of the treatments on the number of received applications per day. The estimates are obtained using standard OLS fixed-effect regressions; thus, the marginal effects need to be interpreted in terms of change in the number of applications per day. All specifications include job ad and time fixed-effects. Column 1 includes interactions of the treatment dummies with time-period dummies. More precisely, we interact each treatment dummy with a dummy being equal to one for treatment days 11 to 20, and one being equal to one for treatment days 21 to 30. Column 2 includes the first lag for the *flexibility* treatment and the *career* treatment. These dummies are equal to one in case in the period before the current treatment period either the *flexibility* or the *career* treatment was online. Standard errors clustered on job-ad level are reported in parentheses.
$^{*}< 0.1$, $^{**}< 0.05$, $^{***}< 0.01$

Appendix D.3. Effects on the composition of the applicant pool

We present the results presented in Table 2 using shares instead of absoulte numbers as outcome variable in Table D.11.

Table D.11: Results - Quality and fit of applicants in shares

	Share of applications - OLS		
	Applicant qualification	Applicant fit	Interview invitation
	(1)	(2)	(3)
Career	0.032	0.035	0.048
	(0.020)	(0.026)	(0.032)
Flexibility	0.014	0.034	0.020
	(0.020)	(0.028)	(0.023)
Bootstrap p-val $H_0: \beta_{ca} = 0$	0.104	0.198	0.154
Bootstrap p-val $H_0: \beta_f = 0$	0.430	0.280	0.392
Control mean	0.026	0.085	0.065
Observations	829	829	829
No. of Clusters	32	32	32

Notes: This table shows the impact of the treatments on the share of applications received per day. Column 1 shows the effect on the share of applicants graduating from Germany's top 24 Universities (either U15 or T9, see Appendix B for details). Column 2 shows the effect on the share of applicants, who the HR office evaluated with a good fit. Column 3 shows the effect for the number of applicants who got invited for an interview. The estimates are obtained using standard OLS fixed-effect regressions; thus, the marginal effects need to be interpreted in terms of change in the number of applications per day. All specifications include job-ad and time fixed effects. Standard errors clustered on job-ad level are reported in parentheses. The first row of additional statistics shows the p-value from a test of a linear hypothesis that the treatment effects are equal in magnitude. The second and third row of additional statistics show the p values from wild bootstrapped clustered standard errors (Cameron et al. 2008). Standard errors presented with the point estimates are clustered on job-ad level. $^{*}< 0.1$, $^{**}< 0.05$, $^{***}< 0.01$

Appendix E. Alternative mechanisms

In this Appendix, we present several analyses, which are discussed in Section 5.2. We present treatment effects for professional-level positions with relatively young applicants in Appendix E.1, the treatment effects for professional-level positions with many applicants in Appendix E.2, and treatment effects by region of residence of the applicants in Appendix E.3.

Appendix E.1. Effect for professional-level positions with young applicants

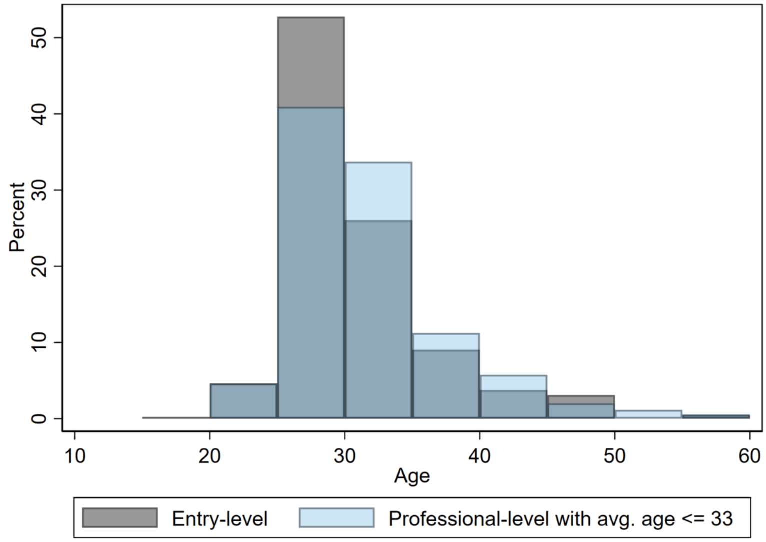
To provide suggestive evidence that a correlation of age and preferences for job characteristics is not the main driver of our results, we provide an analysis in which we restrict our sample to professional-level job ads with particularly young applicants. The median age of the average age of applicants by job ad for professional-level positions is 33. We now only consider only job ads where the average age of applicants is below the median. This matches in total to 28 job ads.

In Figure E.5, we show a histogram of the age of applicants for this group of job ads in blue and for the applicants to entry-level positions in gray. We cannot reject the Null that the two distributions are equal (e.g., a two-sample Kolmogorov–Smirnov yields a two-sided p-value of 0.231). With respect to the distributions, the median age is 29 for both entry-level positions and the chosen professional-level positions, and the mean ages are also very close (30.17 and 30.31).

In contrast, there is a substantial difference in full-time work experience between both groups. The applicants for entry-level positions show almost no prior experience, with a median of only 0.5 years and 75% of observations reporting 3 years or less. While the applicants to professional-level positions have a median of 3 years, with 75% of individuals having up to 6 years, and a substantially higher mean of 4.45 years (vs. 2.38 for entry-level applicants). This indicates that the two groups are similar in age, but differ meaningfully in their professional experience.

Table E.12 shows now the results of a re-estimation of equation 1 with the restricted sample of professional-level positions. We observe no significant treatment effects. This therefore provides

Figure E.5: Age distribution



Notes: This graph shows a histogram of the age of applicants to entry-level positions and professional-level positions for which the average age of applicants is below the median of 33. A two-sample Kolmogorov–Smirnov test checking for equality of distributions yields a two-sided p-value of 0.231.

Table E.12: Effect for professional-level positions with young applicants

	No. of applications - OLS
	Professional-level low age
Growth	0.093
	(0.111)
Flexibility	0.185
	(0.293)
Bootstrap p-val $H_0: \ \beta_{ca} = 0$	0.430
Bootstrap p-val $H_0: \ \beta_f = 0$	0.836
Observations	870
No. of Clusters	29

Notes: This table shows the impact of the treatments on the number of applications received per day. We restrict the sample to professional-level positions, where the average age (in years) of applicants is below the median. (< 33). The estimates are obtained using standard OLS fixed-effect regressions; thus, the marginal effects need to be interpreted in terms of the change in the number of applications per day. The specification includes job-ad and time fixed effects. The first two rows of additional statistics show the p-values from wild bootstrapped clustered standard errors (Cameron et al. 2008). Standard errors presented with the point estimates are clustered on job-ad level.
$^{*}< 0.1$, $^{**}< 0.05$, $^{***}< 0.01$

suggestive evidence that indeed labor-market experience is a main driver of the observed empirical patterns.

Appendix E.2. Effect for professional-level positions with relatively many applicants

We provide an analysis in which we restrict our sample to professional-level job ads with relatively many applicants. The median number of daily applicants for professional-level positions is 0.2. We now only consider job ads where the average number of daily applicants is above the median. This matches in total to 41 job ads.

Table E.13: Effect for popular professional-level positions

	No. of applications - OLS
	Senior-level popular ads
Career	-0.041
	(0.092)
Flexibility	0.087
	(0.254)
Bootstrap p-val $H_0: \ \beta_{ca} = 0$	0.774
Bootstrap p-val $H_0: \ \beta_f = 0$	0.946
Observations	1064
No. of Clusters	41

Notes: This table shows the impact of the treatments on the number of applications received per day. We restrict the sample to professional-level positions, where the average number of daily applicants is above the median (> 0.2). The estimates are obtained using standard OLS fixed-effect regressions; thus, the marginal effects need to be interpreted in terms of the change in the number of applications per day. The specification includes job-ad and time fixed effects. The first two rows of additional statistics show the p-values from wild bootstrapped clustered standard errors (Cameron et al. 2008). Standard errors presented with the point estimates are clustered on job-ad level.
$^{*}< 0.1$, $^{**}< 0.05$, $^{***}< 0.01$

Table E.13 now shows the results of a re-estimation of equation 1 with the restricted sample of professional-level positions. We observe no significant treatment effects. This therefore provides suggestive evidence that a lack of labor supply is not the main driver of the absence of treatment effects for professional-level positions.

Appendix E.3. Effects on the geographical dispersion of the applicant pool

We also investigate from which geographic area the firm receives the additional applications. Table E.14 shows the corresponding results. We use three different outcome variables, Colums 1 and 4 show the treatment effects for applicants living in the (federal) state in which the firm is located, Columns 2 and 5 show the treatment effects for applicants living in Germany, but not in the state of the firm's location, while Columns 3 and 6 show the treatment effects for applicants living abroad. Moreover, Columns 1 to 3 show the effect on the total number of applicants per day, while Columns 4 to 6 show the effect on the share of applications of the particular day belonging to the corresponding category.

We observe that the treatment effects for applicants living in the state of the firm and abroad are small and very noisy, while the estimated treatment effect for applicants living in Germany, but not in the firm's state of location is large and statistically significant. Hence, the increase in applications seems largely driven by this type of applicants. For the *flexibility* treatment, it accounts for $0.121/0.171 \approx 71\%$ of the new applicants and for the *career* treatment for $0.125/0.137 \approx 91\%$ of the newly generated applicants.

Table E.14: Effect on the number of applications by region of residence

	No. of applications - OLS		
	State (1)	Germany w/o state (2)	Abroad (3)
Career	0.041	0.119**	-0.026
	(0.038)	(0.048)	(0.027)
Flexibility	0.014	0.122***	0.040
	(0.034)	(0.042)	(0.042)
Bootstrap p-val $H_0: \ \beta_{ca} = 0$	0.270	0.014	0.352
Bootstrap p-val $H_0: \ \beta_f = 0$	0.666	0.006	0.356
Control mean	0.113	0.149	0.124
Observations	829	829	829
No. of Clusters	32	32	32

Notes: This table shows the impact of the treatments on the number of applications for entry-level positions received per day by region of residence. Column 1 shows the treatment effects on the number of applicants living in the state where the firm is located, and Column 2 on the number of applicants living in Germany, but not in the state of the firm, while Column 3 shows the treatment effects on the number of applicants living abroad. The estimates are obtained using standard OLS fixed-effect regressions; thus, the marginal effects need to be interpreted in terms of change in the number of applications per day. All specifications include job-ad and time fixed effects. Standard errors clustered on job-ad level are reported in parentheses. The first and second rows of additional statistics show the p values from wild bootstrapped clustered standard errors (Cameron et al. 2008).
$^{*}< 0.1$, $^{**}< 0.05$, $^{***}< 0.01$

Appendix E.4. Heterogeneity by word count

Table E.15 presents the correlation of the length of the job ad and application numbers for observations of the *control* group.

Table E.15: Correlation of information and applications (control group)

	No. of applications - OLS
Length job ad	0.000
	(0.000)
Mean dep. var.	0.393
Mean indep. var.	4767.137
Bootstrap p-val	0.536
Observations	866
No. of Clusters	99

Notes: This table shows an OLS estimate for the effect of the length of the job ad as a proxy for the amount of information on the job ad on the number of applications. We restrict the sample to control-group observations only. The estimates are obtained using standard OLS fixed-effect regressions; thus, the marginal effects need to be interpreted in terms of change in the number of applications per day. The specification includes time fixed effects. Standard errors clustered on job-ad level are reported in parentheses. The first row of additional statistics shows the p-value from a test of the linear hypothesis that the marginal effect is equal to zero relying on wild bootstrapped clustered standard errors (Cameron et al. 2008).
$^{*}< 0.1$, $^{**}< 0.05$, $^{***}< 0.01$

Appendix F. Experimental details: Survey

Summary statistics and descriptions

Table F.16 shows the distribution of participants in the survey experiment by lab location.

Table F.16: Survey - Laboratories and participants

Laboratory	Control	Flexibility	Career	Total Participants
RWTH Aachen	112	112	107	331
FU Berlin	161	166	160	487
University of Bonn	50	51	53	154
University of Hannover	39	38	37	114
University of Innsbruck	15	14	15	44
University of Cologne	81	82	78	241
KIT Karlsruhe	49	60	52	161
LMU Munich	79	79	82	240
TUM Munich	79	80	83	242
Total	665	682	667	2,014

Notes: This table shows the number of participants in our survey by laboratory and treatment.

Table F.17 shows definitions of used control variables.

Table F.17: Variable definitions

Variable	**Description**
Female	Dummy that equals 1 if the individual is female, 0 otherwise
Migration background	Dummy that equals 1 if at least one parent is born outside of Germany, 0 otherwise
University degree	Dummy that equals 1 if the individual is enrolled in a bachelor's program or has at least a bachelor's degree
Family status	Dummy that equals 1 if the individual has at least one child, 0 otherwise

Notes: This table presents the definitions of the control variables used in the regression analysis in Section 5 of the main text.

Table F.18 shows summary statistics of items elicitided as part of the survey experiment.

Table F.18: Summary statistics by treatment

	Control		Career		Flexibility	
Variable	Mean	SD	Mean	SD	Mean	SD
A. Background variables						
Female	0.426	0.495	0.373	0.484	0.374	0.484
At least Bachelor degree	0.602	0.490	0.559	0.497	0.532	0.499
Migration background	0.469	0.499	0.459	0.499	0.408	0.492
B. Beliefs about job characteristics						
Flexible work scheduling	6.266	2.149	6.180	2.142	6.500	2.184
Work-life balance	6.406	1.753	6.135	1.849	6.551	1.921
Childcare support	5.648	2.560	5.393	2.527	5.698	2.663
Family-friendly employer	6.720	2.061	6.553	2.107	6.789	2.016
Avoidance overtimes	4.347	2.172	4.132	2.263	4.447	2.270
Salary overall	6.723	1.789	6.721	1.710	6.645	1.831
Career benefits	6.937	1.804	7.132	1.684	6.849	1.846
Salary growth	6.451	1.853	7.031	1.782	6.460	1.964
Challenging tasks	7.241	1.868	7.289	1.811	7.238	1.825
Wage negotiation opportunities	5.666	2.004	5.793	2.104	5.600	2.038
C. Beliefs about working environment						
Share of colleagues...						
being female	33.101	13.333	33.862	12.948	33.843	13.595
with children	47.247	18.542	46.726	18.376	48.147	18.597
with high income	35.617	20.820	36.849	20.173	34.987	20.314
eager on making career	56.669	20.309	58.469	19.511	56.249	20.039
putting work over private life	39.192	21.033	39.331	21.140	37.739	20.755
Observations	665		667		682	

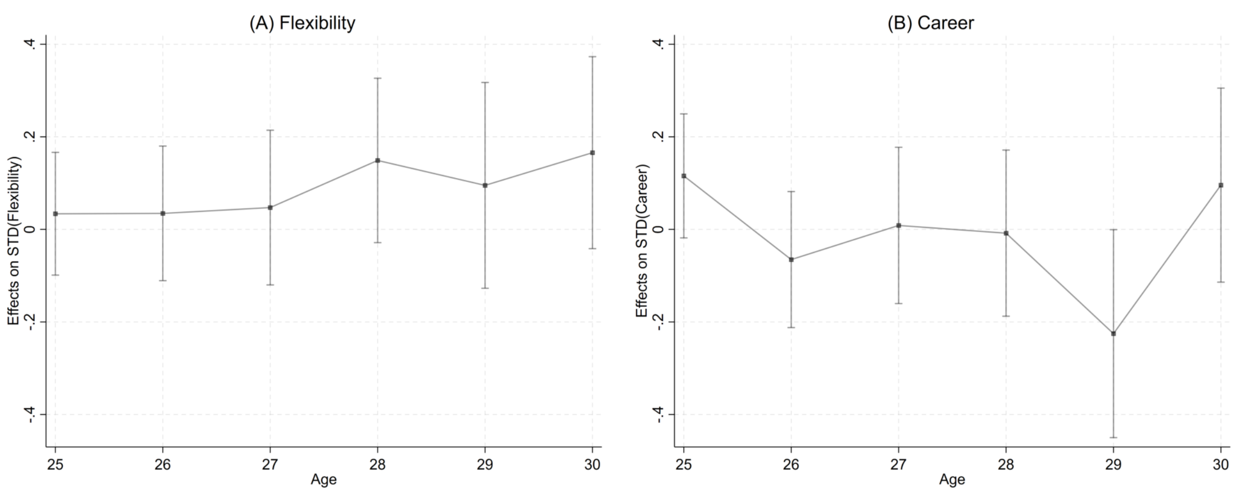
Notes: This table presents summary statistics by treatment status from the survey experiment. Panel A provides an overview of background variables. Panel B presents the items used in our analysis on how the treatments influenced expectations about job characteristics (see Section 5.1). Panel C focuses on the items used to evaluate how the treatments affected expectations regarding the working environment (see Section 5.1). A detailed description of the survey questions related to the items presented in this table can be found in Appendix G.

Appendix G. Further analyses: Survey

Preferences

Similar to the items described in Section Appendix F, we asked participants about their general preferences for job-flexibility conditions and career advancement. We measure these preferences via standardized composite scores of several items. In particular, we asked them to rate the importance of work-life balance, possibility for flexible scheduling, the possibility to work from home, childcare support, a family-friendly workplace, possibility to avoid overtime, provision of a high income, prospects of salary growth, salary-negotiation possibilities, career-advancement opportunities, and how challenging the tasks of the job are. Figure G.6 shows how these preferences vary with the age of participants for participants with an age between 25 and 30. Table G.19 shows regression results for both items and estimates the gender difference. The estimates show that women have relatively a stronger preference for flexible working conditions and a relatively weaker preference for career advancement.

Figure G.6: Preferences over age



Notes: The figure shows results from correlations regarding preferences for flexibility conditions and career advancement in a job with age. The composite scores are similar to the ones described in Appendix G, however, they relate to preferences in general and not beliefs about the shown job ad.

Table G.19: Gender differences in workplace preferences

	Composite scores preferences	
	Flexibility conditions	*Career advancement*
	(1)	(2)
Female	0.407***	-0.086*
	(0.044)	(0.045)
Observations	2014	2014
Controls	Yes	Yes

Notes: This table shows the gender difference in preferences for job characterists. The two outcome variables are standardized composite scores measuring the preference for flexible working conditions and career advancement. Both regression include control variables for high school, GPA, migration background, university degree, and family status. Robust standard errors are presented in parantheses.
*< 0.1, **< 0.05, ***< 0.01

Beliefs

Table G.20: Belief-updating about working environment

	Beliefs about working environment				
	Female	Family	Income	Ambitious	Career
	(1)	(2)	(3)	(4)	(5)
Flexibility	1.031*	0.896	-0.737	-0.323	-1.199
	(0.574)	(0.909)	(1.159)	(1.337)	(1.231)
Career	0.817	-0.285	1.260	1.933*	0.505
	(0.885)	(1.088)	(1.374)	(0.980)	(1.413)
Control mean	33.10	47.25	35.62	56.67	39.19
Bootstrap p: $\beta_{ca} = 0$	0.39	0.80	0.42	0.09	0.75
Bootstrap p: $\beta_{f} = 0$	0.08	0.35	0.55	0.79	0.29
Observations	2014	2014	2014	2014	2014
No. Clusters	20	20	20	20	20

Notes: This table shows the impact of the treatments on the beliefs about the working environment. *Friendly* working environment adds up beliefs about the share of colleagues being female and having a family. *Competitive* working environment adds up survey questions about beliefs about the share of colleagues prioritizing career over family, being eager to have a career, having an STEM degree, and earning a high income. The outcome variables are standardized; thus, the marginal effects need to be interpreted in terms of standard deviations. All estimations include job-ad and lab fixed effects. Control variables include gender, high-school GPA, migration background, university degree, and family status. Standard errors are clustered on the job-ad level are reported in parentheses. The first row of additional statistics shows the p-value from a test of the linear hypothesis that the treatment effects are equal in magnitude (using wild bootstrapped standard errors). The first row of additional statistics shows the p-value from a test of the linear hypothesis that the treatment effects are equal in magnitude (using wild bootstrapped clustered standard errors). The second and third rows of additional statistics show the p-values from wild bootstrapped clustered standard errors (Cameron et al. 2008).
*< 0.1, **< 0.05, ***< 0.01

Table G.21: Distractor items

	Beliefs about distractor items						
	Part-time (1)	Travel (2)	Location (3)	Security (4)	Reputation (5)	Old (6)	STEM (7)
Flexibility	-0.086	-0.236	0.005	-0.150	-0.081	-0.118	-1.029
	(0.142)	(0.161)	(0.101)	(0.127)	(0.130)	(1.074)	(0.972)
Career	-0.250	-0.137	-0.117	-0.148	0.018	-1.648	1.133
	(0.196)	(0.255)	(0.153)	(0.102)	(0.137)	(1.152)	(1.113)
Bootstrap p-val $H_0: \beta_f = \beta_{ca}$	0.327	0.642	0.334	0.984	0.422	0.118	0.051
Bootstrap p-val $H_0: \beta_f = 0$	0.58	0.21	0.94	0.29	0.50	0.89	0.30
Bootstrap p-val $H_0: \beta_{ca} = 0$	0.22	0.62	0.49	0.18	0.90	0.18	0.31
Observations	2014	2014	2014	2014	2014	2014	2014
No. Clusters	20	20	20	20	20	20	20
Controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes

Notes: This table illustrates the impact of the treatments on the individual items excluded from our indicators: opportunity to work part-time, travel requirements for the job, attractive work location, secure workplace, reputation of the employer, and share of old employees as well as with a STEM background. Controls include gender, high-school GPA, migration background, university degree, and family status. Standard errors clustered on job-ad level are reported in parentheses. The first row of additional statistics shows the p-value from a test of the linear hypothesis that the treatment effects are equal in magnitude (using wild bootstrapped clustered standard errors). The first row of additional statistics shows the p-value from a test of the linear hypothesis that the treatment effects are equal in magnitude (using wild bootstrapped standard errors). The second and third row of additional statistics show the p-values from wild bootstrapped clustered standard errors (Cameron et al. 2008).
$^{*}< 0.1$, $^{**}< 0.05$, $^{***}< 0.01$

Detailed questionnaire

Job Advertisement - Questions - without location

Now suppose you are currently looking for a job and the position is advertised at a study firm's location within reasonable commuting distance of your current home and you are interested in the job.

Note: Please click HERE if you would like to read the job advertisement again.

1. What do you think: What would your day-to-day work at the study firm look like if your application were successful?

   Please answer on a scale from 0 (does not apply at all) to 10 (fully applies).

   (a) Good work-life balance, i.e., sufficient time for private matters.

   0 1 2 3 4 5 6 7 8 9 10

   (b) Almost completely avoiding overtime

   0 1 2 3 4 5 6 7 8 9 10

   (c) Possibility to work part-time and flexible working arrangements.

   0 1 2 3 4 5 6 7 8 9 10

   (d) Flexible working hours.

   0 1 2 3 4 5 6 7 8 9 10

   (e) Work location in an attractive region.

   0 1 2 3 4 5 6 7 8 9 10

   (f) Opportunity to work abroad for a period of time.

   0 1 2 3 4 5 6 7 8 9 10

   (g) Taking business trips from time to time.

   0 1 2 3 4 5 6 7 8 9 10

(h) Secure workplace.

0 1 2 3 4 5 6 7 8 9 10

(i) High income.

0 1 2 3 4 5 6 7 8 9 10

(j) Good salary growth.

0 1 2 3 4 5 6 7 8 9 10

(k) Opportunity to negotiate salary increases regularly..

0 1 2 3 4 5 6 7 8 9 10

(l) Family-friendly working environment and corporate culture.

0 1 2 3 4 5 6 7 8 9 10

(m) Good career/promotion opportunities.

0 1 2 3 4 5 6 7 8 9 10

(n) High reputation of the work and the employer.

0 1 2 3 4 5 6 7 8 9 10

(o) Challenging tasks on the job.

0 1 2 3 4 5 6 7 8 9 10

(p) Support from the employer in organizing childcare.

0 1 2 3 4 5 6 7 8 9 10

(q) Opportunities to regularly work from home.

0 1 2 3 4 5 6 7 8 9 10

2. When you think about the working environment of the advertised position: What do you estimate - what proportion of the workforce...

Please use the sliders to give an estimate in %.

- is female?

  0 to 100

- has children?

  0 to 100

- is older than 45 years?

  0 to 100

- earns more than €90,000 gross per year?

  0 to 100

- has a degree in a STEM field (mathematics, engineering, natural sciences, or another technology-oriented course of study)?

  0 to 100

- is their job more important than their private life?

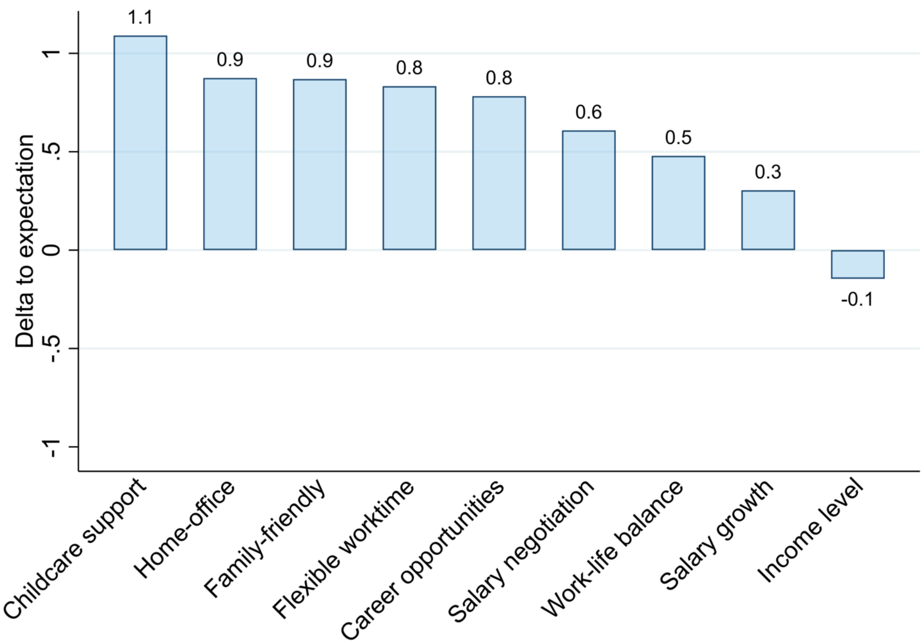
  0 to 100

- has strong ambitions to make a career?

  0 to 100

Summary statistics and results

Figure H.7: Post interviews - Delta to expectation for job characteristics



Notes: This figure shows the average perceived difference of several job characteristics with respect to their initital expectations and the actual perception when working there. Corresponding summary statistics can be found in Table H.22. The exact formulation of the survey questions can be found in Appendix H. In total, 24 hired candidates participated in the interviews.

Table H.22: Post interviews - Summary statistics

Variable	Mean	SD	25%	75%	Min	Max	N
Agreed: Flexibility applies	0.96	0.20	1	1	0	1	24
Agreed: Career applies	0.79	0.41	1	1	0	1	24
Relocated for job	0.50	0.51	0	1	0	1	24
Commute distance (km)	32.67	42.32	6	31	1	200	24
Days until applied	2.33	6.19	0	1.5	0	30	24
Work-life expectation	7.46	1.79	7	8	2	10	24
Work-life currently	7.94	1.16	8	8	5	10	24
Flexible worktime expectation	7.17	1.97	6	8	2	10	24
Flexible worktime currently	8.00	1.62	7	9.5	5	10	24
Income expectation	7.81	1.77	7	9	3	10	24
Income currently	7.67	1.61	7	9	3	10	24
Salary expectations	7.61	1.47	6	9	5	10	23
Salary currently	7.91	1.20	7	9	6	10	23
Salary negotiation expectation	6.74	1.84	6	8	2	9	23
Salary negotiation currently	7.35	1.72	6	9	4	9	23
Family-friendly expectation	7.70	1.49	7	9	5	10	23
Family-friendly currently	8.58	0.88	8	9	6	10	24
Career expectation	7.48	1.50	7	8	5	10	23
Career currently	8.26	1.29	8	9	6	10	23
Childcare opportunities currently	8.23	1.48	8	9	5	10	13
Childcare opportunities expectation	6.91	2.26	7	8	2	9	11
Home-office expectation	7.67	1.40	7	9	5	10	24
Home-office currently	8.54	1.35	8	9	5	10	24

Notes: This table provides summary statistics of the interviews with eventually hired applicants. The exact formulation of the survey questions can be found in Appendix H.

Detailed Questionnaire

Interview with Newly-Hired Employees

At the beginning of the interview, we would like to ask you a few questions about the hiring and application process.

1. Why did you choose the study firm as your employer?

   - [Type an answer]

2. Were you employed by another company before?
    - If yes: Why did you change jobs?
    - [Type an answer]
3. Did you apply for a position at other locations of the study firm?
    - Yes
    - No
4. When you received the job offer from the study firm: Did you have other offers at the same time?
    - If yes, why did you ultimately choose the study firm?
    - [Type an answer]

———————————— *page break* ————————————

1. When exactly did you first see the job posting? (Note: Ideally, please provide a specific date.)
    - [Type an answer]
2. How many days after first seeing the job posting did you apply to the study firm?
    - [Type an answer]
3. How many days after applying did your interview take place?
    - [Type an answer]
4. Did you negotiate anything during the application process (e.g., flexibility, childcare placement, home office, etc.)?

- If yes, what did you negotiate? And do you consider it a success from your perspective?
- Does your salary at the study firm match the salary you requested?
- [Type an answer]

5. Here are a few keywords. After seeing the job posting: What were your immediate thoughts???

   (a) What would your typical workday at the study firm look like in the case of a successful application? Scale from 0 (does not apply at all) to 10 (fully applies)

   (b) What does your actual workday at the study firm look like? Scale from 0 (does not apply at all) to 10 (fully applies)

- Good work-life balance

  0 1 2 3 4 5 6 7 8 9 10

- Option for part-time work / flexible working hours

  0 1 2 3 4 5 6 7 8 9 10

- Flexible work scheduling in everyday life

  0 1 2 3 4 5 6 7 8 9 10

- High income

  0 1 2 3 4 5 6 7 8 9 10

- Good salary growth

  0 1 2 3 4 5 6 7 8 9 10

- Opportunity to regularly negotiate salary increases independently

  0 1 2 3 4 5 6 7 8 9 10

- Family-friendly work environment or corporate culture

  0 1 2 3 4 5 6 7 8 9 10

- Good career and advancement opportunities

  0 1 2 3 4 5 6 7 8 9 10

- Employer support for childcare

  0 1 2 3 4 5 6 7 8 9 10

- Opportunity to work from home regularly

  0 1 2 3 4 5 6 7 8 9 10

6. When you think back over the entire application process: What did you find positive, and what did you perhaps find less good?

7. Did you move your residence or establish a second residence for the job at the study firm?

8. What is your commuting distance (door-to-door to the study firm)?

———————————— *page break* ————————————

1. What is your first thought about it?

   - [Type an answer]

2. What image does this text convey of the study firm as an employer?

   - [Type an answer]

3. Now that you've gotten to know the study firm more closely: Do you think this statement applies to the study firm?

   - [Type an answer]

——————————— *page break* ———————————

To conclude, we would like to ask you a few general questions about yourself.

1. Do you have children? If yes, how old is your youngest child?

    - [Type an answer]

    And now a last question:

2. And finally, one last question that may sound a bit strange, since you've only just started working at the study firm — but it's a standard question from employee surveys in psychology:

    On a scale from 1 (very unlikely) to 7 (very likely): How likely do you think it is that you will still be working at the study firm in...

    - 1 year

        1 2 3 4 5 6 7

    - 3 years

        1 2 3 4 5 6 7

    - 6 years

        1 2 3 4 5 6 7

    - 10 years

        1 2 3 4 5 6 7

Thank you!