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

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Abstract

Job advertisements are a key tool for companies to attract talent. We conduct an RCT in which we randomize the content of job advertisements for STEM positions at one of the largest European technology firms. Specifically, we study how highlighting job flexibility and career advancement in job advertisements causally affects the firm's applicant pool. We find large treatment effects for entry-level positions, but not for senior-level positions: highlighting job flexibility increases the total number of both female and male applicants, while emphasizing career advancement only raises applications from men. Both effects are entirely driven by applicants residing outside the federal state in which the firm is located. In a survey experiment among STEM students, we find that the content of job advertisements shapes young professionals' beliefs about the work environment at the firm. In particular, highlighting career advancement leads to a shift in beliefs towards better career benefits but a lower work-life balance.

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1. Introduction

How do workers decide about which jobs they want to apply to? Earnings are an important factor in this decision, but workers typically consider many other job characteristics as well. This include, for example, the job's location, job flexibility, career, personal development opportunities, as well as a firm's culture. The decision to apply then depends on (i) a worker's preferences for these job characteristics as well as on (ii) her beliefs about them being provided at a particular job or firm. Preferences for job characteristics may vary greatly across individuals (Ashraf et al. 2020), in particular between women and men (Flory et al. 2015, Wiswall and Zafar 2018). For example, some individuals may prefer to work in a particularly dynamic or challenging environment while others value flexibility. Beliefs about job characteristics on the other hand depend on the type of information companies provide. One way for companies to shape such beliefs about job characteristics is job advertisements.[1]

In job advertisements, firms not only inform 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, Card et al. 2024). This may lead to potential applicants perceiving jobs as more attractive and thus may help firms to attract more talented workers, a key strategic and scarce resource in today's knowledge-driven economy (Coff 1997, Bapna et al. 2013, Del Carpio and Guadalupe 2022) where many firms report skilled labor shortages.[2] Beyond increasing the number of applications, if highlighting certain job characteristics leads to a better fit between worker's preferences and job characteristics, this can also improve the matching process. The type of information that is highlighted in job advertisements can thus be of key importance for firms, workers, and the worker-firm match alike.

In this paper, we study how job characteristics highlighted in job ads affect the size and composition (i.e., gender, quality, fit, region of residence) of the pool of applicants, and young professionals' beliefs. We run an RCT within one German unit of one of Europe's largest technology firms, which employs around 3,000 workers. In our RCT, we randomized job characteristics highlighted for all STEM vacancies posted by the firm for a period of 12 months. Specifically, we posted the same job ad three times, with a sequence of treatments randomized at 10-day intervals: In one instance, we emphasized the firm's high level of job flexibility (*flexibility* treatment); in another instance, we highlighted career advancement, in form of career advancement, skill development, and wage growth opportunities (*career* treatment), and in one instance without highlighting either characteristic (*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) and (ii) in-depth pre-RCT interviews carried out among the firm's managers, workers, and workers' representatives revealed that both flexibility and career advancement are two distinctive features of the jobs in the

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

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

unit of the study firm.

Our empirical investigation is grounded in a conceptual framework that guides the empirical analysis. In the conceptual framework potential applicants receive utility from job-specific ability and job characteristics, such as job flexibility and career opportunities. Highlighting specific job characteristics (the treatment) is then interpreted as a signal that leads to belief-updating about the attractiveness of the job (the mechanism) inducing a change in the likelihood to apply (the outcome). Based on this, we derive a number of empirical predictions, which we test in our study. First, both treatments should increase the total number of applications, but the effect is expected to be larger for entry-level jobs than for senior-level jobs. The reason is that the signal increases perceived attractiveness, but the informational value of the signal is larger for entry-level workers. 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 correlate with worker productivity or background characteristics (Nekoei 2022), we also expect changes to the composition of the applicant pool, which we study in an exploratory manner. Last, both treatments should cause a positive belief shift about the expected level of job flexibility and career opportunities.

In our RCT, we find large treatment effects of entry-, but not for senior-level positions: for entry-level positions, we observe an increase in applications of 44 percent for the *flexibility* and of 35 percent for the *career* treatment, respectively. The effects are driven by men in the *career*, and women and men in the *flexibility* treatment. New applicants mainly come from Germany, but not from an area close to the firms units' location, suggesting that the treatments allow the firm to source talent from a wider regional labor market.

Our results show that highlighting certain characteristics increases job attractiveness among young professionals. However, what employers ultimately care about is not just the size of the applicant pool, but the number of top candidates applying for a position and their prospective productivity on the job ((Del Carpio and Guadalupe 2022). On the upside, we find that young professionals applying in the *career* treatment are significantly more often rated as applicants with a *good fit* and are more often invited for a job interviews. In the *flexibility* treatment, we find no significant effects. On the downside, we cannot rule out that applicants exposed to the treatment demand slightly higher wages and more job flexibility.

To assess whether the increase in applications for entry-level positions is indeed driven by belief-updating, we complement our RCT data with data from several survey experiments among a total of 2000 STEM students. Each survey experiment was run in parallel to a job posting and with participants whose educational background matched the requirements of the particular job advertisement. We find that both treatments significantly shift beliefs by $12 - 14$ percent of a standard deviation among a respective target group of potential applicants. Moreover, while the *career* treatment increased beliefs about career advancement, it simultaneously *lowered* expectations about workplace flexibility.

The contribution of this paper is threefold. First, our findings demonstrate that experimentally-

induced highlighting of content in job advertisements can affect the size and composition of the applicant pool. This evidence complements a literature exploiting large-scale regulatory changes to show that a removal of gender preferences in job ads increased applications from the previously non-preferred gender in China (Kuhn and Shen 2023) and to more gender-neutral hiring outcomes in Austria (Card et al. 2024). It also relates to several interventions aiming to reduce gender imbalances especially in training programs or public-sector jobs, by avoiding stereotypical language, signaling interest in employee diversity, or by highlighting past employee performance (Dal Bó et al. 2013, Ashraf et al. 2020, Flory et al. 2021, Del Carpio and Guadalupe 2022, Del Carpio and Fujiwara 2023, Delfino 2024). In terms of evidence, our paper differs from these studies in that we focus on highlighting flexibility and career advancement, i.e., on job amenities that are commonly part of job advertisements. In that respect, our second contribution becomes important, namely that we can show how subtle differences in the highlighting of job amenities can serve as a *tool* to shape the sorting into companies with belief-updating as important *mechanism*. Besides, our RCT provides evidence of which types of individuals respond to a certain type of job amenity offered, thus revealing information about underlying preferences. This relates to the evidence provided in Del Carpio and Guadalupe (2022), who has shown that a treatment reducing gender stereotypes adversely affects selection. Third, we provide first evidence of how information about highlighting job amenities in advertisements affects the beliefs of potential applicants regarding both expected job characteristics and the working environment. Such changes in beliefs, albeit not explicitly, are the focus in the employer-branding literature (Lievens and Slaughter 2016).

As regards all three contributions, our paper also relates to 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 men and women (Wiswall and Zafar 2018, Ashraf et al. 2020, Coffman et al. 2024, Vattuone 2024). Firm 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 Schumacher 2017, Hoffman et al. 2018). 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 - 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 the resulting data. Section 4 presents the results of the field experiment in terms of its effects on the number of applications, both overall and by type of position and gender. Section 5 discusses the underlying belief-related mechanisms on hands of data from a complementary survey experiment. Section 6 discusses additional robustness analyses. Section 7 concludes.

2. Conceptual framework

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 through a change in expected utility from job flexibility and career advancement, respectively. The framework is inspired by Delfino (2024) and is formalized in Section 8.1 of the Appendix.

In our framework, an individual considers applying to a job advertised by one firm. That individual applies to the job if the expected utility derived from the job is larger than the (fixed) utility from an outside/alternative offer. Potential applicants derive utility from the immediate wage payment, the individual returns to ability, the expected level of flexibility, and career-advancement opportunities provided by the firm. Ex-ante, individuals are uncertain about job flexibility and career advancement offered by the job, but hold a belief about both. Additionally, we allow for beliefs about these two job characteristics to be correlated. This implies that some applicants may believe that these two characteristics are not related (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 is not possible without flexibility (a positive trade-off).[3] 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 that 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 two types of individuals, either with or without previous work experience (i.e., senior-level workers and entry-level workers). We assume that the distributions of prior beliefs differ between these workers. Longer activity in the labor market comes arguably with better networks, and thus likely with more knowledge of the industry and firms.[4] 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 provided flexibility and career-advancement opportunities provided at the firm.[5] 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 positively update their beliefs about that job characteristic. More positive beliefs in turn lead to a higher expected job utility and to an increase in the likelihood to apply for the job. As senior-level applicants hold more precise and positive beliefs about the provided level of flexibility and career-advancement opportunities at the firms, their expected utility gain should be smaller than for entry-level applicants.

[3] 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)).

[4] The economic literature notes, for instance, that more experienced workers receive information through better co-worker networks (Glitz 2017).

[5] All results derived from the model still hold even if the prior belief of experienced workers is slightly more negative than that of inexperienced workers, as long as it is not too far away and the prior of the experienced workers is sufficiently more precise. See the discussion around Proposition 1 in Section 8.1 of the Appendix for details.

As regards differential preferences, it is conceivable that the preferences for flexibility and career advancement differ in particular between female and male applicants. Wiswall and Zafar (2018), for example, find that females have a relatively higher willingness to pay for jobs with more flexibility than males and that males have a relatively higher willingness to pay for jobs with a higher potential for career-advancement opportunities than females. 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.[6] 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 highlighting career-advancement opportunities. Subsequently, the increase in the number of applications should be larger for female (male) applicants if flexibility (career-advancement) is highlighted in a job ad.

The above framework yields several empirical predictions for what might happen when a job ad highlights 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 senior-level positions as applicants for entry-level positions know less about the industry and firm and thus hold less precise priors about flexibility and career advancement opportunities and 3) highlighting flexibility (career) should lead to a stronger increase in applications for women (men) than men (women) due to differential preferences.

The framework does not yield predictions about the expected change in applicant quality or background characteristics. This depends ultimately on the correlation of worker productivity and background characteristics with workplace preferences. We will investigate this in an exploratory manner. In the next Section, we discuss the experimental design in more detail.

3. RCT Implementation & Data

The study firm. We conducted an RCT in collaboration with one of Europe's largest technology firms. The multi-national semiconductor company generated a total revenue of roughly 11 billion euro in the business year 2021 with a total workforce of roughly 60,000 workers. The semiconductor industry experienced strong growth in demand in the past and is expected to grow further according to industry experts (see, e.g., Burkacki et al. 2022).

For our project, we collaborate with one of the firm's unit. The unit produces semiconductors particularly for electric cars, trains, windmills, solar panels, and heat pumps and grew substantially in the last years. In 2021, the unit employed 3,000 workers, who have a mean tenure of 12 years. Recently the unit won a prestigious award for being an attractive employer.

All employees of the unit are located in one plant. The plant is situated in a rural area in Germany, around 100 km away from the next urban center and big university. 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, and physics. The share of female

[6] 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 Table C.18 in Section 8.4.2 of the Appendix.

STEM workers in the unit is roughly equivalent to the share of female graduates in Germany in STEM subjects OECD.

In the years before 2021, the unit experienced strong growth in demand for its products and the firm's top management expected that the strong growth would continue in the future. Due to the growth, from 2011 to 2021, the workforce at the unit increased by roughly 50%, forcing the unit to constantly hire. Recruiting STEM workers is a major challenge for the unit. Although the unit advertised vacancies internationally on many different job boards, engage in cooperation with local universities, went to regional job fairs and fairs at big universities, and has an active talent-sourcing, the overall number of applications for jobs in the firm is fairly low. On average, for each advertised position, the company receives on average only 12 applications. In preparation for our RCT we discussed with the management of the unit possible ways to increase the number of applications and quickly consented to focus on the content of the unit's job ads. Job ads are (still) among the most important instruments to attract applicants and current research provides evidence about the important role their content plays for application decisions (see, e.g., Del Carpio and Guadalupe 2022, Delfino 2024).

Treatment motivation. To investigate how highlighting flexibility and career advancement in job ads affects application behavior, we needed to ensure that these characteristics were met at the study firm. Hence, to gain a deep understanding of the distinctive job characteristics within the unit, we engaged in in-depth discussions with the unit's management executives, top managers from the HR department and diversity office, the workers' council, and recently hired employees as well as those hired a long time ago. During these interviews, when asked about the distinctive characteristics of jobs of the unit, almost all workers mentioned these two aspects of interest. Importantly, it was explicitly mentioned that those are distinctive characteristics of the jobs in the respective unit of the study firm. First, the plant offers a lot of flexibility in various dimensions. In particular, the plant offers workers the opportunity to work full-time or part-time, and jobs that are shared by two employees are fairly common. The local municipality offers a sufficient number of day-care spots with moderate care fees.[7]. Employees generally state that the culture of the plant is family-friendly; for example, workers state that it is socially accepted in the firm to leave early or work from home when kids are sick or to work only at certain times. The HR department also argued that it is common to design individual solutions for new employees with care-giving responsibilities. Second, because of the growth of the unit in past and the future growth prospects, the unit offers great opportunities for career advancement, skill development and wage growth: there are regularly new leadership positions available in the unit, the firm invests a lot in the skill development of the employees to train future leaders and tech experts, and, as shown by Fox (2009), Brown and Medoff (1989), Groshen (1991), Idson and Oi (1999), firm growth and wage growth within firms are highly correlated.

As highlighted by Wiswall and Zafar (2018) and Mas and Pallais (2020), flexibility and growth

[7]In Germany, the demand for day-care spots for young children is much higher than the supply; the estimated gap for children aged one and younger is 24% (Alt et al. 2017). Thus, daycare is a major challenge for many young parents.

opportunities are two of the job characteristics for which workers have the highest willingness to pay, in particular women for flexibility and men for earnings growth. The fact that i) flexibility and ii) opportunities for career advancement, skill development and wage growth are distinctive job characteristics in our study firm's unit thus provided us with the unique opportunity to test how highlighting these workplace attributes in job ads affect the size and composition of the pool of applicants for jobs in a "real-world" setting.

Treatment design. The recruiting process in our study firm's unit consists of five steps. In a first step, the department that has a vacancy informs the unit's HR department about the title of the position, a job description, and the criteria that the ideal candidate should meet. Then the HR office sets up a hiring committee for the position that is composed of an HR manager and a representative from the department that is looking for the new employee. In a second step, the HR department generates the job ad. In a third step, the firm 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 large majority of candidates apply within this period of time. In a fourth step, the hiring committee screens all applications and classifies the applicants into those ones who meet (*"fit"*) vs. do not meet (*"no fit"*) the outlined criteria of the ideal candidate to a large extent.[8] Fifth, the hiring committee selects and invites candidates for a job interview. Finally, following the interview, the committee decides and makes a job offer, and the HR office negotiates with the candidate. In our RCT, we do not change anything in the recruiting process, with one exception: After the job ad is created by the unit's HR office (step 2) and before the job ad is published (step 3), we implement our treatment.

In our intervention we focus on job ads, which play a central role in the recruiting process. All job ads in the study firm have a similar design. Figure 1 shows a a fictitious sample of a job ad of the study firm's unit. The content is generated via OpenAI (2024) based on job ads that our study firm posted during our RCT.[9] In the *Job title* section at the top of the job ad, the study firm presents the title of the job and provides in a teaser text a superficial description of the advertised job. The *Job description* provides a summary of the job and outlines the specific tasks in bullet points. The *Your profile* section summarizes the requirements the applicant should ideally fulfill. 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 short description of the unit of the study firm, the *Benefits* section provides a long list of employee benefits and workplace attributes (e.g., flexible working hours, sabbatical options, health care programs, employer-funded pension plans) that are provided by the firm. All parts of the job ads are individualized for each specific job, except of the *Benefits* section, which is the same for all vacancies. Thus, before our RCT, all job ads posted by the study firm mentioned flexibility and opportunities for career advancement, but as they were mentioned as part of a long list of other among many other employee benefits and

[8] A small number of applications is screened out immediately by the HR department because key application documents are missing or the candidates are classified as "mass applicants". Those applications are not included in our dataset.

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

workplace attributes, they were not very prominent and in fact easy to miss.

Our treatments consist of two particular statements, one of which (or none) is randomly shown just as the last sentences in the *teaser text*. In our *flexibility* treatment, the statements 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 of flexibility in the jobs in the units in a very general way, without referring to specific dimensions of flexibility (such as flexible working hours, working from home, day care spots). We consciously decided for the general statement as preferences for different dimensions of flexibility likely differ between potential applicants. Moreover, the way flexible working conditions are implemented also differs across jobs. The statement in the *career* treatment reads as follows:

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

As in the *flexibility* treatment, the statement in the *career* treatment is rather general.[10] As the treatments are included in the job ads' teaser text and as the words "flexibility" and "growth" are written in caps, it is very 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.

Randomization. To study the effects of highlighting job characteristics in job ads, it is possible to randomize the treatments within or across job ads. As the jobs advertised during our RCT were rather heterogenous, we randomize the treatment within job ads, each over a period of 10 days. We chose 10 days for each of our three treatments as the firm posts all job ads for at least 30 days and as the large majority of candidates apply within this period of time.[11]

Thus, our randomization procedure is as follows: After the job ad is created by the unit's HR office after 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 10 days. After 10 days, a random draw decides which of the two remaining treatments is posted. Then, from day 11 to 20 the same job ad is posted with a teaser text corresponding to one of the two remaining treatments. Finally, from day 21 to 30, the same job ad is posted with a teaser

[10] A sample ad showing the *career* and the *flexibility* treatment is presented in Section 8.2.1 of the Appendix.

[11] The total number of applications is slightly larger in the first 10 days compared to the days 21 to 30, which is mainly driven by a peak of incoming applications on the first three days when a job ad is posted. As outlined in the pre-registration, we only include applications arriving in the first 30 days after the job ad is posted in our dataset. For some job ads, the firm does not find suitable candidates within 30 days and the firm posts the job ad longer. In a small number of cases, the study firm's unit posted job ads for less than 30 days and hired – in most cases – internal employees on those positions; we did not include those job ads in our dataset.

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; option for home office; 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.

text corresponding to the remaining treatment condition. Each job ad is thus posted sequentially under each treatment condition.[12] As we cannot exactly measure the time of the treatment switch – some job boards implemented the treatment switch immediately, while others need a few hours –, we exclude the day of the treatment switch and the day immediately after (days 10, 11, 20, 21).[13]

The randomization and posting of the job ads was conducted by a freelancer, who was employed as an external employee by the study firm and payed by the research team. We provided the randomization schedule to the freelancer, which he/she strictly had to follow. The freelancer was not involved in any other tasks of the HR department, and employees in the HR department were not informed about the chosen treatments for the different time periods of the job ads.[14]

The RCT took place between October 2022 and October 2023 and includes all vacancy requiring a STEM background for which a job ad was posted in the respective period.[15]

Research ethics. Our research project was approved by the firm's workers' council and by an Ethics Committee of the Faculty of [NAME BLINDED FOR PEER REVIEW] of the University [NAME BLINDED FOR PEER REVIEW]. We pre-registered our RCT with the American Economic Association and set up a privacy protection process to ensure that we as researchers did not gain access to any personal data from applicants.

Data The resulting data comprise information on 105 job ads, for which the firm received a total of $1,583$ applications. The applicant data include the date of application, the applicants' gender, their place of residence (if available), as well as their performance in the hiring process, i.e., recruiter ratings, interview invitation, hiring outcome, as well as anonymized data from the applicants' CVs.

Table 1 summarizes the data. It provides information on the *daily* number of applications by gender, by quality (in terms of recruiter ratings and interview invitation), and by region of residence. To assess whether the treatment led to applications from a wider regional pool, we categorize applicants as either living in Germany, but not in the federal state of the firm (Germany w/o state), living in the federal state of the location of the firm (State), and applicants from abroad (International).

[12] In Section 8.2, we present in Table C.8 the distribution job ads by period and treatment.

[13] Including days 11 and 21 yields qualitatively similar results, see Section 8.3.

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

[15] We excluded one job ad, as it was an extreme outlier, receiving approximately 15 times the usual number of applications.

Table 1: Summary statistics: Daily application data

	Control		Flexibility		Growth	
Variables (daily)	Mean	SD	Mean	SD	Mean	SD
A. Applications by gender						
Total	0.374	0.910	0.451	1.867	0.368	0.835
Male	0.302	0.756	0.360	1.438	0.305	0.676
Female	0.072	0.297	0.091	0.516	0.063	0.314
B. Applications by recruiter ratings						
A rating	0.039	0.210	0.028	0.164	0.047	0.237
B rating	0.075	0.298	0.059	0.249	0.074	0.297
C rating	0.093	0.333	0.089	0.331	0.082	0.312
Screened out	0.166	0.685	0.276	1.809	0.164	0.574
Invited for interview	0.076	0.292	0.062	0.250	0.083	0.299
C. Applications by region of residence						
Germany w/o state	0.138	0.504	0.198	1.015	0.158	0.456
State	0.113	0.340	0.113	0.457	0.106	0.373
Abroad	0.111	0.385	0.118	0.503	0.089	0.332
Observations	921		903		906	

Notes: This table shows the mean and standard deviations of daily applications received by gender, recruiter rating, and region of residence. Control refers to the control treatment, Flexibility refers to the *flexibility* treatment, and Career refers to the *career* treatment. The difference in the number of observations is due to a slight imbalance in treatment/period assignment. In Section 8.2, we present in Table C.8 the distribution job ads by by period and treatment.

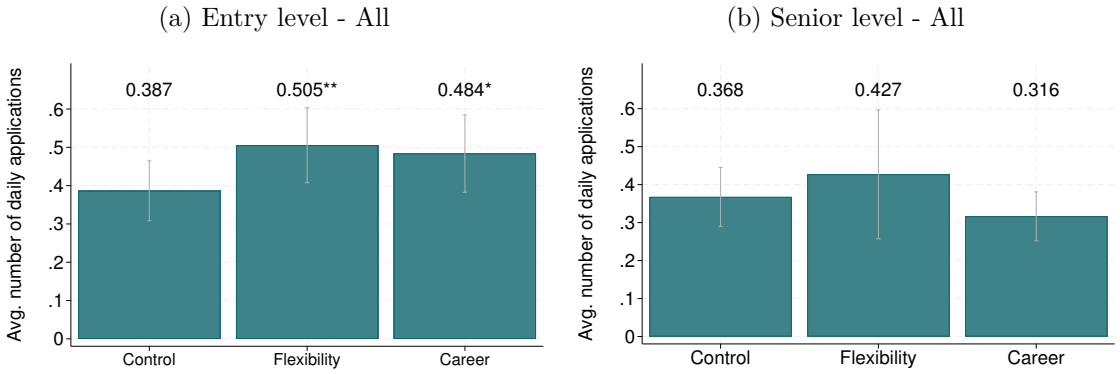
4. Results

In this section, we first provide descriptive evidence on the how our treatments relate to the daily number of applications, and how these differ by entry and senior level positions as well as gender. We then present our estimation strategy and causal treatment effects. Furthermore, we analyze how the treatments affect the quality and composition of the applicant pool. To do so, we rely mainly on recruiter ratings to assess applicant quality, and on CV data to investigate changes in the applicants' region of residence.

4.1. Descriptive evidence

We start out by visualizing how the number of daily applications varies by treatment status. Figure 2 shows the average number of daily applications for entry-level positions (2a) and senior-level positions (2b). Figure 2a illustrates that both treatments boost the number of applications for entry-level positions. The effects are sizable, amounting to 0.118 additional applications per day for the *flexibility* treatment and to 0.097 additional applications per day for the *career* treatment. The data displayed in Figure 2b unveils no significant changes for senior-level positions.

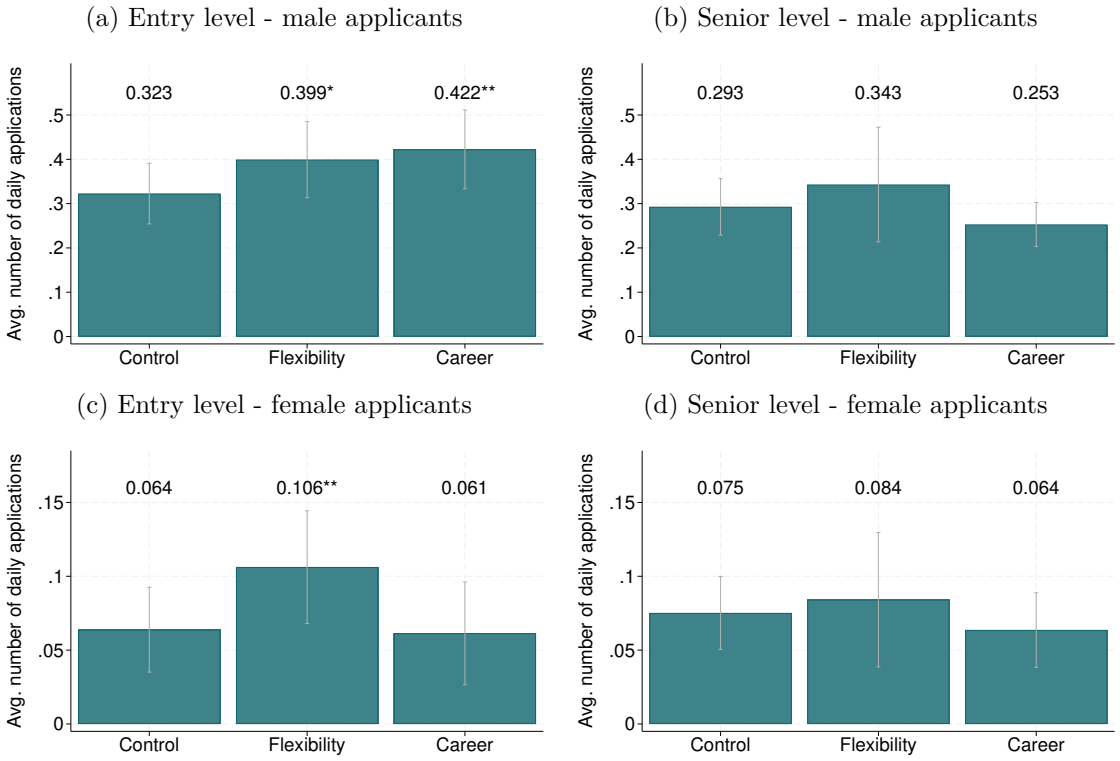
Figure 2: Average number of daily applications



Notes: This figure shows the average number of daily applications for each treatment by required experience level of the job ad. The bar represents the mean, while the gray lines show 95% confidence bands. The stars denote the the respective p value for the one-sided test that $\mu_f < \mu_c$ and $\mu_{ca} < \mu_c$, where μ denotes the mean of the number of daily applications of the respective treatment group.
$^{*}< 0.1$, $^{**}< 0.05$, $^{***}< 0.01$

Figure 3 presents the number of daily applications separately by gender. It suggests that both treatments increase the number of male applicants to entry-level positions by roughly equal amounts, namely by 0.076 applications per day in response to the *flexibility* treatment, and by 0.099 applications per day in response to *career* treatment. Among female applicants, only the *flexibility* treatment leads to an increase in applications (by 0.042 applications per day). For the *career* treatment, we observe almost no difference. For senior-level positions, we again observe differences in the number of daily applications. While these plots give a first indication of possible treatment effects, they leave out important factors such as the strong heterogeneity in posted job ads, and the number of days since a respective job ad went online.

Figure 3: Average number of daily applications by gender



Notes: This figure shows the average number of daily applications for each treatment by gender and required experience level of the job ad. The bar represents the mean, while the gray lines show 95% confidence bands. The stars denote the the respective p value for the one-sided test that $\mu_f < \mu_c$ and $\mu_{ca} < \mu_c$, where μ denotes the mean of the number of daily applications of the respective treatment group.
*< 0.1, **< 0.05, ***< 0.01

4.2. Empirical strategy

Our goal is to uncover the causal effect of highlighting flexibility or 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 per ad. To uncover causal treatment effects, we rely on the following linear specification:

$$y_{it} = \beta_f \mathit{Flexibility}_{it} + \beta_{ca} \mathit{Career}_{it} + \alpha_i + \lambda_t + \epsilon_{it}, \tag{1}$$

where y_{it} denotes the number of applications received for job ad i on day t. The variables $\mathit{Flexibility}_{it}$ 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 $t \in \{1, 2, 3, ...8, 9, 12, 13, 14..., 18, 19, 22, 23, ..., 30\}$ denotes the number of days since the job ad first went online, excluding day t and day $t+1$ of the treatment switch. In total, our estimations include 26 observations per job advertisement: on average one per day. 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.

We rely on OLS fixed-effects regressions to derive our main results, but also provide robustness evidence based on Poisson fixed-effects regressions to account for the count-level nature of the dependent variable (see Section 8.3 of the Appendix).[16]

4.3. The causal effect on number of daily applications

The descriptive evidence presented above suggests that both highlighting flexibility and career advancement increases the number of daily applications, mainly among entry level-positions and that females (male) entry-level candidates respond more to the flexibility (career) treatment. Table 2 now presents causal estimates that account for time and job ad fixed effects. Column 1 shows the estimated treatment effect on the total number of applications. Column 2 displays the impact on the total number of applications to entry-level jobs, while Column 3 shows the estimated effects for senior-level jobs. All standard errors clustered on job-ad level.[17]

Table 2: Effect on the number of applications

	No. of applications - OLS		
	All	Entry-level	Senior-level
	(1)	(2)	(3)
Flexibility	0.091	0.171**	0.060
	(0.087)	(0.067)	(0.119)
Growth	0.018	0.137*	-0.028
	(0.034)	(0.079)	(0.033)
Bootstrap p-val $H_0: \beta_f = 0$	0.426	0.010	0.864
Bootstrap p-val $H_0: \beta_{ca} = 0$	0.594	0.076	0.358
Mean dep. variable	0.374	0.387	0.368
Observations	2727	829	1896
No. of Clusters	105	32	73

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, Column 2 (3) for entry-level (senior-level) positions. 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).
*< 0.1, **< 0.05, ***< 0.01

By examining Columns 1 and 2, we observe no significant average treatment effect. Although point estimate of the *flexibility* treatment is positive, it is very noisy. However, for entry-level job ads, we find that both the *flexibility* and the *career* treatment increase the number of appli-

[16] To account for 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).

[17] 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 of Table 2.

cations. The *flexibility* treatment is estimated to increase the total number of daily applications by approximately 0.171, which, given a mean of the *control* treatment of 0.39, corresponds to a relative increase of 44%. The *career* treatment is estimated to increase the total number of daily applications by approximately 0.137, which corresponds to a relative increase of 35%.[18]

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 5.13. The *career* treatment generates 4.11 additional applications.

How do these findings relate to the predictions from our theoretical framework presented in Section 2? With respect to our first hypothesis, namely that highlighting flexibility or career advancement should increase the overall number of applications, We find mix evidence. While, overall, both treatments positively — but not significantly — affect the overall, these effects are close to zero for senior-level positions. For entry-level positions, however, we consistently find large positive effects. This provides support for our second prediction, namely that the increase in applications should be larger for entry-level positions than for senior-level positions. To assess this hypothesis formally, we can test for significant differences in effect sizes between both types of positions. For the *flexibility* treatment, we find significantly larger effects on entry-level positions compared to senior-level positions when using a Poisson model ($p = 0.036$), but only suggestive evidence in the OLS estimation ($p = 0.207$). For the *career* treatment, we can reject the null hypothesis of equal treatment effect sizes in both models ($p = 0.025$ for OLS, $p = 0.065$ for Poisson.)

4.3.1. Treatment effects by gender

Since previous evidence reports that women and men differ in their preferences for job flexibility and career advancement, expect heterogeneities in treatment effects across genders. Table 3 thus presents the results the estimation of equation 1 by gender and type of position.

[18] Performing the same estimations by means of a Poisson fixed-effects regression - which is presented in Table C.9 in Section 8.3.1 of the Appendix - yields similar results, even with slightly larger relative magnitudes. It is estimated that the *flexibility* treatment increases the total number of applications by 57%, and the *career* treatment is estimated to increase the total number of applications by 40%.

Table 3: Effect on the number of applications by gender

	No. of applications - OLS					
	Male applicants			*Female applicants*		
	All	Entry-level	Senior-level	All	Entry-level	Senior-level
	(1)	(2)	(3)	(4)	(5)	(6)
Flexibility	0.071	0.119*	0.054	0.020	0.052***	0.006
	(0.070)	(0.061)	(0.096)	(0.020)	(0.018)	(0.026)
Growth	0.021	0.133*	-0.021	-0.003	0.004	-0.007
	(0.030)	(0.072)	(0.028)	(0.014)	(0.023)	(0.017)
p-val $H_0: \beta_f = \beta_{ca}$	0.492	0.828	0.442	0.049	0.014	0.396
Bootstrap p-val $H_0: \beta_f = 0$	0.446	0.050	0.866	0.322	0.006	0.948
Bootstrap p-val $H_0: \beta_{ca} = 0$	0.456	0.072	0.464	0.802	0.842	0.716
Mean dep. variable	0.374	0.387	0.368	0.374	0.387	0.368
Observations	2727	829	1896	2727	829	1896
No. of Clusters	105	32	73	105	32	73

Notes: This table shows the impact of the treatments on the number of applications received per day by gender. Columns 1 to 3 (4 to 6) show the effect on the number of male (female) applicants. Columns 1 and 4 show the effect for all job ads, Columns 2 and 5 (3 and 6) for entry-level (senior-level) positions. 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 first row of additional statistics shows the p-value from a test of the 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).
*< 0.1, **< 0.05, ***< 0.01

Columns 1 to 3 show the results for applications from male candidates. The *flexibility* treatment increases the daily number of male applicants by 0.119, corresponding to an increase of 37%. For the *career* treatment, we find an increase of 0.133 (41%) applications from male candidates per day.

Columns 4 to 6 show the results for applications from females. We observe that the *flexibility* treatment increases the daily number of applicantions from females by 0.052, corresponding to an increase of 81%, but no significant increase for the *career* treatment.[19]

Next we assess whether the flexibility and career treatment effects differ significantly among male and female applications, i.e., to answer the question whether males have a significantly higher preference for career advancement than for flexibility and vice versa for females. Here, we cannot reject that the null of equal treatment coefficients among male applicants ($p = 0.828$ for OLS, $p = 0.859$ for Poisson), but we can indeed reject this hypothesis for female applicants ($p = 0.012$ for OLS, $p = 0.032$ for Poisson.). This provides evidence for our empirical prediction that the application increase upon the *flexibility* treatment is larger for female than for male applicants. However, we find no support for the prediction that the *career* treatment is relatively more attractive for males.

[19] Again, performing the same estimations by means of a Poisson fixed-effects regression - which is presented in Table C.10 in Section 8.3.1 of the Appendix - yields similar results, with estimated increases for the *flexibility* treatment by 47% for males and by 102% for females. The *career* treatment is estimated to increase the number of male applicants by 44%, and no statistical significant increase for female applicants can be observed.

Extrapolating the estimates to a full 30-day period, we estimate that out of the 5.13 additional applications generated from the *flexibility* treatment, 3.57 are estimated to be from male and 1.56 from female applicants.

4.4. Effects on applicant quality

We next turn to the important question, whether highlighting career advancement or flexibility might not only affect the number and gender composition of applications, but also their quality. Such quality effects are conceivable if job-specific abilities or social preferences may correlate with preferences for job characteristics (Deserranno 2019, Nekoei 2022, Del Carpio and Guadalupe 2022). We use two measures as a proxy for quality. First, we take recruiter ratings to assess the fit of an application to the advertised position. We define a good fit if the applicant is evaluated suitable to advance in the recruiting process (i.e., an A or B rating meaning a match of at least 50% with the outlined criteria in the job ad). Second, we investigate how many applicants are invited for an interview.

Table 4 presents the results of the treatments on applicant quality.[20] Column 1 shows the effects on the number of applicants with a good fit and Column 2 on the number of applicants invited for an interview. The *flexibility* treatment neither affects fits nor invitation rates. However, the point estimate of 0.053 is weakly statistically significant when relying on wild bootstrap standard errors (Cameron et al. 2008). For the *career* treatment, we observe significant increases of 0.062 applicants with a good fit and of 0.071 applicants invited for an interview per day. There are no significant differences between treatments. However, given that the point estimates for the *career* treatment are slightly larger and statistically more precise, we interpret this as tentative evidence that the selection of applicants is slightly better under the career treatment.

4.5. Effects on the geographic dispersion of the applicant pool

We proceed by investigating whether our treatments increased the geographic area from which the firm receives its applications. The right part of Table 4 shows the corresponding results. We use three different outcome variables, Column 3 shows the treatment effects for applicants living in the (federal) state in which the unit of the firm is located. Column 4 shows the treatment effects for applicants living in Germany but not in the state in which the unit of the firm is located. Column 5 shows the treatment effects for applicants living abroad.

We observe that the treatment effects for applicants living in the state of the firms' unit and abroad is small and very noisy, while the estimated treatment effect for applicants living in Germany but not in the state of the unit is large and statistically significant. Hence, the increase in applications seems largely driven by these 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.

[20] The corresponding results of a Poisson fixed-effects regression are presented in Table C.12 in Section 8.3.2 of the Appendix. It yields similar results.

Table 4: Effect on the number of applications by quality and region of residence

	No. of applications - OLS				
	Quality		*Region of residence*		
	Good fit	Interview	State	Germany w/o State	International
	(1)	(2)	(3)	(4)	(5)
Flexibility	0.053	0.039	0.020	0.121**	0.033
	(0.033)	(0.027)	(0.031)	(0.047)	(0.042)
Growth	0.062**	0.071*	0.034	0.125**	-0.025
	(0.030)	(0.038)	(0.039)	(0.050)	(0.026)
p-val $H_0: \beta_f = \beta_{ca}$	0.799	0.294	0.658	0.942	0.102
Bootstrap p-val $H_0: \beta_f = 0$	0.090	0.170	0.564	0.008	0.490
Bootstrap p-val $H_0: \beta_{ca} = 0$	0.040	0.080	0.394	0.014	0.358
Mean dep. variable	0.110	0.085	0.113	0.145	0.121
Observations	829	829	829	829	829
No. of Clusters	32	32	32	32	32

Notes: This table shows the impact of the treatments on the number of applications for entry-level positions received per day. Columns 1 and 2 (3 to 5) show the effect on the quality of applicants (treatment effects by region of residence of applicants). Column 1 shows the treatment effects on the number of applicants with a good fit (i.e., 50% match of an applicant with the outlined criteria or more) and Column 2 on the number of applicants invited for an interview. Column 3 shows the treatment effects on the number of applicants living in the state where the firms' unit is located and Column 4 on the number of applicants living in Germany but not in the state of the firms' unit. Column 5 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 row of additional statistics shows the p-value from a test of the 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).
*< 0.1, **< 0.05, ***< 0.01

While the previous discussion sheds light on the composition of the treatment effects, it do not show if the treatments lead to a change of the overall distribution of applicants. To do so, we repeat the exact same analysis as before but use as outcomes the share of applicants as a fraction of the total number of applicants. The results are presented in Table 5.

Considering Columns 1 and 2, we observe no significant treatment effect on the respective shares. This provides evidence that the increase in applications does not come at the cost of lower quality applicants.

Considering Columns 3 to 5, we observe equally that the share of applicants living in the state of the firm as well as abroad does not change significantly. However, both treatments significantly increase the share of applicants who reside in Germany but at a greater distance from the firm, specifically outside the state where the firm is located.

Table 5: Effect on the number of applications by quality and region of residence

	Share of applications - OLS				
	Quality		*Region of residence*		
	Good fit	Interview	State	Germany w/o State	International
	(1)	(2)	(3)	(4)	(5)
Flexibility	0.034	0.020	-0.005	0.062*	0.003
	(0.028)	(0.023)	(0.025)	(0.033)	(0.024)
Growth	0.035	0.050	0.016	0.072**	-0.035
	(0.026)	(0.033)	(0.029)	(0.031)	(0.021)
p-val $H_0: \beta_f = \beta_{ca}$	0.958	0.254	0.393	0.776	0.059
Bootstrap p-val $H_0: \beta_f = 0$	0.266	0.354	0.830	0.064	0.882
Bootstrap p-val $H_0: \beta_{ca} = 0$	0.194	0.134	0.560	0.026	0.092
Mean dep. variable	0.085	0.065	0.100	0.112	0.093
Observations	829	829	829	829	829
No. of Clusters	32	32	32	32	32

Notes: This table shows the impact of the treatments on the share of applications of a particular type of applicants for entry-level positions received per day. Columns 1 and 2 (3 to 5) show the effect on the quality of applicants (treatment effects by region of residence of applicants). number of male (female) applicants. Column 1 shows the treatment effects on the share of applicants with a good fit (i.e., 50% match of an applicant with the outlined criteria or more) and Column 2 on the share of applicants invited for an interview. Column 3 shows the treatment effects on the share of applicants living in the state where the firms' unit is located and Column 4 on the share of applicants living in Germany but not in the state of the firms' unit. Column 5 shows the treatment effects on the share 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 row of additional statistics shows the p-value from a test of the 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).
*< 0.1, **< 0.05, ***< 0.01

5. Mechanisms

Since, highlighting career advancement or flexibility acts as an information signal to potential applicants, the most likely mechanism through which the treatment operates is applicants' belief updating about job characteristics, as formalized in Section 2. While our main data allows us to observe treatment effects in a real-world setting, it does not provide information about the underlying beliefs of potential applicants. Hence, to assess if belief updating is indeed the underlying mechanism behind our significant treatment effects among applications for entry-level positions, we conducted a survey experiment among STEM students. We chose specifically STEM-students as these are individuals who will soon enter the labor market and then apply for the types of positions for which our treatments have a large impact on application numbers. The survey experiment allows us to investigate whether, and to which extent the treatments change beliefs about the job characteristics and the working environment among entry-level workers.

5.1. Experimental design

The job ads for entry-level positions are targeted at candidates who recently graduated from university in a STEM field. In line with this target group, we collected survey responses from a total of 2,136 STEM-graduates across 12 different labs in Germany and Austria.[21] For our analysis, we drop the 5% of survey participants with shortest response times, leaving us with a total of 2,014 observations.[22] As most of these participants recently graduated, or were about to graduate, they are an ideal subject pool to elicit beliefs about the job characteristics and work-environment in entry-level STEM positions. As the presented job ads are for high-skilled and complex jobs in the technology industry, it is important to align the required educational background of the job ad with the actual educational background of survey participants. Thus, we for each experiment, we invited only those individuals who possessed the educational background required by the job ad.

The experimental procedure was as follows: Whenever an entry-level job ad was posted and was part of our field experiment, we initiated a corresponding lab session. We thus conducted the survey experiment in "real time", i.e., by aligning it with the company's actual recruitment period for the position. This is something we communicated as part of the survey to create a more realistic atmosphere without being deceptive.[23] As the number of students with a STEM background in economic research labs at universities was limited, we needed to contact many different labs at different universities to gather a sufficient number of responses. Due to administrative procedures and guidelines, not all the labs were available at the same time, but rather on a rolling basis over the course of our field experiment. Due to the restrictions of the size of the participant pool, only 20 out of 32 entry-level positions in our main data were part of the survey experiment. We thus randomized treatments, but not job ads. Whether a job ad was part of the survey experiment depended solely on the availability of an economics research lab, a sufficiently large participant pool, and the job ad being online during the availability of the pool. Our target for each survey wave was to recruit at least 45 participants. In total, we conducted 47 different survey experiments on a total of 20 job ads. All job ads were part of more than one survey wave to be able to account for lab fixed effects in the empirical analysis.

The structure of the survey experiment was as follows: The survey started with questions about the educational background, demographics, and preferences for workplace characteristics of the participants. The second and main block of the survey showed participants a job ad from our field experiment and informed them that this was a real job currently posted by the company. The name of the firm was revealed, and we presented the job randomly ad either with the *control*, the *flexibility*,

[21] Detailed information about the labs and participant numbers can be found in Table C.13 in Section 8.4.1 of the Appendix.

[22] All results are qualitatively similar when those observations are not dropped.

[23] We selected job ads for real positions that were actively posted at the time, allowing students also to apply for these roles as part of the survey. Towards the end of the process, students had the opportunity to contact the firm directly in order to signal their interest in the job and to receive instructions on how to apply. It is important to note that not even a handful of students (3 out of 2136) actually availed of this opportunity. We tracked them using unique IDs that corresponded to treatment and the specific job advertisement. This method allowed us to identify these individuals in the field-experiment dataset, enabling us to filter out applications that potentially skew our treatment effects.

or the *career* treatment. Thereafter, we elicited the subjects' beliefs about job characteristics as well as the working environment. We removed the information about the workplace location to avoid confounding across lab locations. Instead, we asked participants to assume that the place of work was at a reasonable commuting distance to their current place of living. The last block asked participants about their interest in the presented job.[24] In Section 8.4.1 of the Appendix, we present summary statistics in Table C.15.

5.2. Belief updating about job characteristics

The main focus of the survey experiment is to measure how our treatment shapes beliefs about job characteristics. To do so, we relied on a battery of questions that are based on Ronen (1994) and have also been applied in other studies investigating job characteristics (see, e.g., Gill et al. 2023). In particular, we asked questions about the expected work-life balance, possibility to avoid overtime at work, opportunity for part-time work, for flexible scheduling, the attractiveness of the location of the job, the necessity of work-related travel, job security, provision of a high income, prospects of salary growth, salary negotiation possibilities, a family-friendly workplace, career-advancement opportunities, the firm's reputation, how challenging the tasks of the job are, the childcare support offered by the company, and the possibility to work from home (home-office). Participants were asked to rate statements about these items on a scale from 0 (does not apply at all) to 10 (fully applies) from the perspective of how accurately they expected statements around these items describe the presented job.[25]

Our analysis serves two primary purposes. First, to align our analysis as closely as possible with our theoretical predictions outlined in Section 2, we examine the impact of our treatments on two composite scores for *work-life balance* and *career benefits*, respectively. The *work-life balance* category encompasses expected work-life balance, flexible scheduling, home-office opportunities, childcare support, avoidance of overtime, and family-friendly job characteristics. The *career benefits* category contains the following items: good salary, possibility of salary growth, career-advancement opportunities, the level of challenge of the individual job tasks, and the opportunity of regular salary negotiations. Our outcome variables are composite scores for each category, calculated as the normalized sum of the ratings for each item within the category. Second, we briefly describe which individual items seem to particularly drive potential observed shift in beliefs. This allows us to unveil which exact characteristics individuals associate with workplace flexibilty and career advancement. To do so, we shortly discuss treatment effects of regressions on the single items.

To identify the treatment effects on composite scores, we estimate an equation similar to 1 of the main analysis, with the outcome variables being our two aggregated scores of i) *work-life*

[24]The questionnaire of the survey items used in the following analyses can be found in Section 8.4.3. The remaining part is available from the authors upon request.

[25]For our analysis, we exclude the items on beliefs regarding the location, opportunity for part-time work, work-related travel, job security, and reputation of the firm. These items are not useful for our analysis, as the job security in Germany is extremely high for permanent positions, and strongly regulated; whether the job is full-time or part-time is stated in the ad; and work-related travel is also job-dependent and outlined, if applicable, in the job description. In Section 8.4.2 of the Appendix, Table C.16 presents the regression results for these excluded items in Columns 1 to 5.

balance and ii) *career benefits* items.[26] Additionally, we include further control variables such as gender, high school GPA, migration background, university degree, and family status.[27] As our outcome variables are normalized scores, the estimated marginal effects can be interpreted in terms of standard deviations (*sd*) of the respective composite score.

Table 6: Belief updating about job characteristics

	Beliefs					
	Work-life balance			*Career benefits*		
	(1)	(2)	(3)	(4)	(5)	(6)
Flexibility	0.092**	0.122***	0.123***	-0.032	-0.021	-0.021
	(0.041)	(0.042)	(0.042)	(0.048)	(0.051)	(0.051)
Career	-0.128**	-0.107**	-0.105**	0.136**	0.141**	0.141**
	(0.045)	(0.047)	(0.046)	(0.056)	(0.056)	(0.055)
Bootstrap p-val $H_0: \beta_f = \beta_{ca}$	0.000	0.000	0.000	0.003	0.004	0.004
Bootstrap p $H_0: \beta_f = 0$	0.03	0.01	0.00	0.49	0.68	0.63
Bootstrap p $H_0: \beta_{ca} = 0$	0.02	0.04	0.01	0.03	0.03	0.03
Observations	2014	2014	2014	2014	2014	2014
No. Clusters	20	20	20	20	20	20
Lab FE	No	No	Yes	No	No	Yes
Controls	No	Yes	Yes	No	Yes	Yes

Notes: The table shows the impact of the treatments on the beliefs about job characteristics. Work-life balance adds up beliefs about flexibility, work-life balance, home-office, childcare support, avoidance of overtime, and a family-friendly workplace culture. Career benefits adds up beliefs about expected salary, salary growth, career opportunities, degree of challenge of the tasks, and the possibility to negotiate salary increases on a regular basis. 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. The control variables include gender, high school GPA, migration background, the university degree, and family status. Standard errors are clustered on job-ad level and 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 second and third row of additional statistics show the p values from wild bootstrapped clustered standard errors (Cameron et al. 2008). $^{*}< 0.1$, $^{**}< 0.05$, $^{***}< 0.01$

The results are presented in Table 6. Columns 1 to 3 show the effect on the composite score of *work-life balance*, while Columns 4 to 6 show the effects on the composite score of *career benefits*. Columns 1 and 4 present the most parsimonious specification and only include job-ad fixed effects, while Columns 2 and 5 further include additional control variables, and Columns 3 and 6 present the most comprehensive specification including, in addition, lab fixed effects. To interpret our results, we focus on our most comprehensive specifications in Columns 3 and 6. We observe that the *flexibility* treatment leads to an increase of about 0.123 *sd* in terms of *work-life balance* provided by the job, while we observe small and noisy point estimates close to zero regarding the provided opportunities for *career benefits*. Considering the effect of the *career* treatment, we observe that it increases beliefs about the provided *career benefits* by 0.141 *sd*, while at the same time decreasing

[26] Our results remain the same when we use principal component analysis and apply endogenous weights to the collection survey items.

[27] Table C.14 in Section 8.4.1 of the Appendix provides detailed descriptions of the variables.

beliefs about the provided *work-life balance* by 0.105 *sd*.

Summarizing the results, we find evidence that the treatments indeed lead to belief-updating among potential applicants. We find strong support for the prediction, developed in our conceptual framework, that both treatments lead to a positive shift in beliefs about the provided job flexibility and career-advancement opportunities. Interestingly, we find evidence that potential applicants perceive a trade-off between the provided career benefits and work-life balance, as the *career* treatment leads to positive belief updating about career advancement, but to negative belief updating about workplace flexibility.

To provide a deeper understanding of the items mainly driving the observed belief shifts in our two composite scores, we also present treatment effects for each item[28] The *flexibility* treatment significantly increases beliefs that the job offers more flexible scheduling, better work-life balance, and home-office opportunities. While the point estimates for childcare opportunities, family-friendly workplace, and the possibility to avoid overtime are positive as well, they do not appear to be statistically significant.

Conversely, the *career* treatment negatively affects items contributing to the *work-life balance* score, in particular with respect to work-life balance and the support of the employer in organizing childcare. The *career* treatment also positively shifts beliefs on all items contributing to our *career benefits* indicator. This effect seems to be mostly driven by beliefs about the provided career, as we find a highly significant effect on expected salary-growth and positive point estimates (close to being statistically significant) for career-advancement opportunities and salary negotiation-opportunities.

5.3. Beliefs updating about the work environment

In response to the treatments, potential applicants might not only update beliefs about the respective job, but also about the work environment as a whole. As part of the survey, in a second battery of questions we elicited beliefs about the expected share of direct colleagues with a particular personal or character attribute. We focus on six items, the believed share of direct colleagues (i) being female, (ii) having a family, (iii) prioritizing career over family, (iv) eager to have a career, and (v) earning a high income.[29]

In the following, we use each of these items as an outcome variable. We identify treatment effects again by re-estimating equation 1 with lab fixed effects, job-ad fixed effects and additional controls. The estimated coefficients can be interpreted in terms of marginal increases of expected shares in percent. The results are presented in Table 7.

[28] For the corresponding estimates, please see Table C.17 in Section 8.4.2 of the Appendix.

[29] As further distraction items, we also elicited the share of colleagues with a STEM degree and over a particular age as a distraction item, which we exclude in this analysis. Table C.16 in Section 8.4.2 of the Appendix presents the regression result for this item in Column 6 and 7.

Table 7: 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)
Bootstrap p-val $H_0: \beta_f = \beta_{ca}$	0.753	0.302	0.022	0.048	0.202
Bootstrap p $H_0: \beta_f = 0$	0.08	0.35	0.55	0.79	0.29
Bootstrap p $H_0: \beta_{ca} = 0$	0.39	0.80	0.42	0.09	0.75
Control mean	33.10	47.25	35.62	56.67	39.19
Observations	2014	2014	2014	2014	2014
No. Clusters	20	20	20	20	20
Controls	Yes	Yes	Yes	Yes	Yes

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 a 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. 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 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 row of additional statistics show the p values from wild bootstrapped clustered standard errors (Cameron et al. 2008).
*< 0.1, **< 0.05, ***< 0.01

We observe that the *flexibility* treatment increases the expected share of female colleagues. The effect size amounts to 1.03, which corresponds to $1.03/33.10 \approx 3.1\%$ increase compared to the *control* group. For the *career* treatment, we observe a weakly significant increase in the expected share of ambitious colleagues, i.e., in colleagues who are eager to make a career. The effect size amounts to 1.93, which corresponds to $1.93/56.7 \approx 3.4\%$ increase compared to the *control* group.

Although the estimated effect sizes are rather small, these results suggests that the information treatments extend beyond belief-updating about job characteristics onto belief-updating about selecting into a particular type of work environment.

6. Robustness

In this section, we summarize the results of several additional estimations, to assess the robustness of our results.[30]

First, to account for the count-level nature of the dependent variable, we re-estimate equation 1 using a Poisson fixed-effects regression. This analysis yields similar results, with slightly larger relative effect sizes (see Tables C.9 and C.10).

[30]Detailed results are presented in the Appendix Section 8.3.

Second, 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. To further examine spillovers, 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 C.11, show no evidence of strong time trends in the treatment effects. This suggests a lack of spillovers, as such effects should manifest in changing treatment impacts over time. (ii) we re-estimate the main model including lagged treatment variables. Columns 2-4 of Table C.11 show that the point estimates remain stable when accounting for lagged treatments, with only a weakly significant coefficient on the lagged flexibility treatment. Overall, this provides strong evidence that spillovers do not meaningfully impact the size or significance of our main treatment effects.

7. Conclusion

In a rapidly growing technology industry where high-skilled human capital is a key strategic resource, firms face significant challenges in attracting new talent (Coff 1997, Bapna et al. 2013, Del Carpio and Guadalupe 2022). By conducting a field experiment at one of the largest European technology firms, we demonstrate that highlighting flexibility and career-advancement opportunities can increase the number of applications and the regional scope of the applicant pool for entry-level positions. Importantly, this increase in application occurred without significant trade-offs in terms of applicant quality. Highlighting amenities and benefits in job advertisements thus seems to be an effective and rather cost-efficient tool to increase the number of applications, making it an important strategy in the firms' "war for talent". Moreover, our finding that highlighting flexible work opportunities is especially attractive for female applicants is informative to firms and policymakers aiming to increase gender equality in organizations.

We complemented the field experiment with a survey-experiment to examine the belief-related mechanisms behind our main treatment affects, 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 potential applicants to expect higher career benefits and a less good work-life balance. Potential applicants 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 on making a career. This is in line with prior findings by (Belot et al. 2022). Our results thus unveil the importance of job ads in shaping applicants' beliefs about job characteristics and the working environment with potential implications for a firm's overall reputation.

Our findings deliver important insights on how information provision shapes the selection of workers into jobs. First, they show that very minor changes can have substantial effects on applicant behavior. This hints towards important information frictions on the labor market for entry level jobs

(see, e.g., Pissarides 2011, Belenzon and Tsolmon 2016). These effects are astonishing given that the decision over a first job can have long-lasting implications for an individual's career (Kahn 2010). In this respect our results speak to a literature showing that small nudges can have substantial and lasting effects on individuals and organizations (Hong et al. 2015). Second, by highlighting job amenities instead of explicitly searching or not searching for certain types of workers (Flory et al. 2015, Kuhn and Shen 2023), we show that even in regular job ads, the provided information can have important implications for the size and composition of the applicant pool. In this sense, our study provides a link between the (survey) literature on preferences for job attributes (Wiswall and Zafar 2018) and 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- and senior-level workers as well as males and females reacted differently to the provided information provides novel evidence on the heterogeneity of worker preferences in a real-word setting (Del Carpio and Guadalupe 2022, Belot et al. 2022).

While our treatments showed large, significant, and robust effects the number of applications for entry-level jobs, our results do not provide answers on how firms can increase their applicant pool for highly-qualified experienced jobs, i.e., in cases where the overall pool of potential applicants is small and potential employees already hold sufficiently precise beliefs about a respective company. Our results only suggest that in this case an information treatment is much less effective. Future research may also provide better and more large-scale evidence on the impact of highlighting job amenities on the quality of the applicant pool, especially regarding the long-run performance of selected employees.

Technological advances will soon enable firms to target job advertisements not only to specific groups of individuals, but even to individual candidates. Our results suggest that the targeted assignment of job ads could be highly effective in attracting suitable candidates. Combining evidence from this paper with newly developed tools in the optimal treatment assignment literature (see, e.g., Kasy and Sautmann 2021, Opitz et al. 2024) could thus open up new perspectives for hiring strategies with substantial implications for labor market search and matching.

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8. Appendix

8.1. 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.

8.1.1. 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 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:

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

The job-specific ability, α_i, might arbitrarily correlate with workplace preferences for flexibility π_w^f and/or workplace preferences for 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 applicants' 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).

8.1.2. 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 results 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.[31]

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:

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

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

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

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

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,[32]

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

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

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

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

[32] 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).

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 $\theta^f > \bar{\theta}_E^f \geq \bar{\theta}_I^f$ 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 $\theta^f > \bar{\theta}_E^f \geq \bar{\theta}_I^f$ 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_w^f enters (9) positively while π_w^{ca} 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 $\pi_F^f > \pi_M^f$ and $\pi_M^{ca} > \pi_F^{ca}$, 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.*

8.2. Experimental design

Table C.8: 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	315

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.

8.2.1. Job ads

Figure C.4: 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; option for home office; 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 C.5: 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; option for home office; 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.

8.3. Robustness: Empirical analyses

8.3.1. Main results

Table C.9: Effect on the number of applications - Poisson estimation

	No. of applications - Poisson		
	All	Entry-level	Senior-level
	(1)	(2)	(3)
Flexibility	0.139	0.449***	-0.005
	(0.108)	(0.147)	(0.161)
Growth	0.101	0.333**	0.031
	(0.087)	(0.163)	(0.119)
IRR flexibility	1.15	1.57	0.99
IRR career	1.11	1.40	1.03
Mean dep. variable	0.374	0.387	0.374
Observations	2490	827	1662
No. of Clusters	96	32	64

Notes: This table shows the impact of the treatments on the number of received applications per day. Column 1 shows the effect for all job ads, Column 2 (3) for entry-level (senior-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

Table C.10: Effect on the number of applications by gender - Poisson estimation

	No. of applications - Poisson					
	Male applicants			*Female applicants*		
	All	Entry-level	Senior-level	All	Entry-level	Senior-level
	(1)	(2)	(3)	(4)	(5)	(6)
Flexibility	0.143	0.388**	0.037	0.121	0.704**	-0.205
	(0.122)	(0.162)	(0.182)	(0.148)	(0.315)	(0.203)
Growth	0.124	0.364**	0.034	-0.031	0.095	-0.093
	(0.094)	(0.163)	(0.116)	(0.200)	(0.382)	(0.254)
p-val $H_0: \beta_f = \beta_{ca}$						
IRR flexibility	1.15	1.47	1.04	1.13	2.02	0.81
IRR career	1.13	1.44	1.04	0.97	1.10	0.91
Control mean	0.302	0.323	0.374	0.072	0.064	0.072
Observations	2438	827	1610	1525	569	908
No. of Clusters	94	32	62	59	24	35

Notes: This table shows the impact of the treatments on the number of applications received per day by gender. Columns 1 to 3 (4 to 6) show the effect on the number of male (female) applicants. Columns 1 and 4 show the effect for all job ads, Columns 2 and 5 (3 and 6) for entry-level (senior-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

Table C.11: Robustness - Time heterogeneity and lags for entry-level positions

	No. of applications - OLS			
	(1)	(2)	(3)	(4)
Flexibility	0.227	0.223***	0.173**	0.217**
	(0.161)	(0.075)	(0.067)	(0.080)
Career	0.221	0.137*	0.110	0.123
	(0.169)	(0.077)	(0.089)	(0.088)
Flexibility×Day 11-20	-0.166			
	(0.194)			
Flexibility×Day 21-30	0.003			
	(0.273)			
Career×Day 11-20	-0.069			
	(0.242)			
Career×Day 21-30	-0.169			
	(0.203)			
Lag1 Flexibility		0.141*		0.122
		(0.079)		(0.081)
Lag1 Career			-0.098	-0.049
			(0.080)	(0.081)
Control mean	0.387	0.387	0.387	0.387
Observations	829	829	829	829
No. of Clusters	32	32	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, Column 3 includes it for the *career* treatment and Column 4 includes both. 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

8.3.2. Further heterogeneities

Table C.12: Effect on the number of applications by quality and region of residence

	No. of applications - Poisson				
	Quality		*Region of residence*		
	Good fit	Interview	State	Germany w/o State	International
	(1)	(2)	(3)	(4)	(5)
Flexibility	0.512*	0.326	0.119	0.786***	0.309
	(0.267)	(0.235)	(0.264)	(0.270)	(0.356)
Career	0.511**	0.556*	0.277	0.716***	-0.162
	(0.260)	(0.306)	(0.312)	(0.221)	(0.242)
p-val $H_0: \beta_f = \beta_{ca}$	0.997	0.302	0.545	0.694	0.115
IR flexibility	1.67	1.39	1.13	2.19	1.36
IR career	1.67	1.74	1.32	2.05	0.85
Control mean	0.110	0.085	0.113	0.145	0.121
Observations	545	645	720	723	726
No. of Clusters	22	25	29	28	28

Notes: This table shows the impact of the treatments on the share of applications of a particular type of applicants for entry-level positions received per day. Columns 1 and 2 (3 to 5) show the effect on the quality of applicants (treatment effects by region of residence of applicants). number of male (female) applicants. Column 1 shows the treatment effects on the share of applicants with a good fit (i.e., 50% match of an applicant with the outlined criteria or more) and Column 2 on the share of applicants invited for an interview. Column 3 shows the treatment effects on the share of applicants living in the state where the firms' unit is located and Column 4 on the share of applicants living in Germany but not in the state of the firms' unit. Column 5 shows the treatment effects on the share of applicants living abroad. 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

8.4. Survey experiment

8.4.1. Summary statistics and descriptions

Table C.13: 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
HHU Düsseldorf	8	9	8	25
University of Göttingen	2	3	2	7
University of Hannover	39	38	37	114
University of Heidelberg	14	14	13	41
University of Innsbruck	15	14	15	44
University of Cologne	98	97	95	290
KIT Karlsruhe	49	60	52	161
LMU Munich	79	79	82	240
TUM Munich	79	80	83	242
Total	706	723	707	2,136

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

Table C.14: Variable definitions

Variable	**Description**
Female	Dummy that equals 1 if the individual is female, 0 else
Migration background	Dummy that equals 1 if at least one parent is born outside of Germany, 0 else
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 else

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

Table C.15: Summary statistics by treatment

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

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 5.2). Panel C focuses on the items used to evaluate how the treatments affected expectations regarding the working environment (see Section 5.3). A detailed description of the survey questions related to the items presented in this table can be found in Section 8.4.3 of the Appendix.

8.4.2. Beliefs about job characteristics and working environment

Table C.16: 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).
$^{*} < 0.1$, $^{**} < 0.05$, $^{***} < 0.01$

Table C.17: Belief updating about job characteristics

	Preferred workplace characteristics										
	Work-Life balance						*Career benefits*				
	Flexibility	Work-life balance	Home-office	Child-care	Family	No over-time	Salary	Career	Salary-growth	Challenge	Negotiation
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)
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)
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)
Bootstrap p $H_0: \beta_f = \beta_{ca}$	0.04	0.03	0.08	0.31	0.40	0.23	0.52	0.38	0.90	0.97	0.71
Bootstrap p $H_0: \beta_f = 0$	0.70	0.02	0.76	0.09	0.18	0.13	0.90	0.12	0.00	0.88	0.11
Bootstrap p $H_0: \beta_{ca} = 0$	2014	2014	2014	2014	2014	2014	2014	2014	2014	2014	2014
Observations	20	20	20	20	20	20	20	20	20	20	20
No. Clusters	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes

Notes: The table shows the impact of the treatments on the beliefs about the individual items describing job characteristics. 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. 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 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

Table C.18: Belief updating about job characteristics

	Gender differences in workplace characteristics										
	Work-Life balance						*Career benefits*				
	Flexibility	Work-life balance	Home-office	Child-care	Family	No over-time	Salary	Career	Salary-growth	Challenge	Nego-tiation
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)
Female	0.405***	0.621***	0.544***	1.035***	0.665***	0.214*	-0.129	0.006	-0.170**	-0.012	-0.298***
	(0.094)	(0.078)	(0.114)	(0.134)	(0.114)	(0.112)	(0.080)	(0.094)	(0.086)	(0.096)	(0.113)
Observations	2014	2014	2014	2014	2014	2014	2014	2014	2014	2014	2014
Lab FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes

Notes: The table shows gender differences in workplace preferences, i.e., in preferences for individual job characteristics. The outcome variables are standardized; thus, the marginal effects need to be interpreted in terms of standard deviations. All estimations include lab fixed effects. The control variables are high-school gpa, migration background, university degree and family status. We use robust standard errors and report them in parentheses.
$^{*}< 0.1$, $^{**}< 0.05$, $^{***}< 0.01$ respectively.

8.4.3. Detailed questionnaire

Job Advertisement - Questions - without location

Now suppose you are currently looking for a job and the position is advertised at an 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 regularly negotiate salary increases.

   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 7.5cm3pt6mm 0pt 100

- has children?

  0 7.5cm3pt6mm 0pt 100

- is older than 45 years?

  0 7.5cm3pt6mm 0pt 100

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

  0 7.5cm3pt6mm 0pt 100

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

  0 7.5cm3pt6mm 0pt 100

- is their job more important than their private life?

  0 7.5cm3pt6mm 0pt 100

- has strong ambitions to make a career?

  0 7.5cm3pt6mm 0pt 100