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

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

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Abstract

Job advertisements are a key instrument for companies to attract talent. We conduct a field experiment in which we randomize the content of job advertisements for STEM jobs in 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 pool of applicants. We find large treatment effects of entry-, but not for senior-level positions in the firm: highlighting job flexibility increases the total number of female and male applicants, while emphasizing career advancement only raises applications by men. Both effects are entirely driven by applicants residing outside of 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. Most importantly, we find that students expect better career benefits, but lower work-life balance when career advancement are highlighted. Our study highlights how job advertisements affect the total number of applications as well as applicants' quality, diversity, region of residence and beliefs.

***JEL Codes**: M51, M52, D22*
***Keywords**: beliefs, hiring, field experiments, survey experiment, job advertisements, gender*

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1. Introduction

In today's knowledge-driven economy, human capital is of immense strategic importance, especially in the rapidly changing technology sector (Coff 1997, Bapna et al. 2013, Del Carpio and Guadalupe 2022). As digital innovations constantly reshape industries, technology companies face an ever-increasing demand for highly skilled professionals to grow and remain competitive. The rise in demand has in many cases outpaced the available supply of qualified workers, leading to widespread talent shortages across the industry, especially in STEM (Science, Technology, Engineering, and Mathematics) occupations.[1] Thus, optimizing recruitment strategies has become a critical factor for companies to secure top talent and remain competitive.

One of the most important ways for professionals to learn about vacancies in firms is job advertisements.[2] 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, Colella, and Lalive, *forthcoming*). In response to these signals, job candidates update their beliefs about job characteristics and the working environment at the firm, which, depending on their preferences, affect their decision to apply (Mas and Pallais 2017, 2020, Gill et al. 2023, Vattuone 2024). Such preferences for job characteristics vary substantially between applicants, in particular between women and men (Wiswall and Zafar 2018). This paper studies how attributes in job advertisements affect the size and composition (i.e., quality, how candidates fit in, diversity) of the pool of applicants, as well as young professionals' beliefs about job characteristics. It is methodologically challenging to establish a causal effect of highlighting certain workplace attributes in job ads on potential applicant's beliefs, the applicant pool, and resulting hiring success is methodologically challenging. This requires exogenous variation in advertisement texts, ideally for the same position, as well as information about the resulting number and quality of applications. Furthermore, data on applicants' perceptions are necessary to trace out the underlying belief-related mechanisms.

We have collected such data based on a large-scale randomized field experiment in one of Europe's largest technology firms. Our study involved varying the order of specific attributes highlighted in the job advertisements. The ads were posted online for a duration of 30 days. Specifically, we posted the same job vacancy three times, with a sequence of treatments randomized at 10-day intervals: In one instance, we emphasized the firm's flexibility for work-life balance (*flexibility* treatment); in another instance, we highlighted career advancement, in form of good personal and wage growth opportunities (*career* treatment), and in one instance without highlighting either characteristic (*control* treatment). In total, we randomized more than 100 vacancies for "real" STEM jobs over a period of 12 months.

We focus on flexibility and career advancement for three reasons. First, those are two of the most important job characteristics for individuals' sorting decisions (Wiswall and Zafar 2018, Mas

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

[2] In 2018, job boards accounted for half of all job applications and ultimately contributed to 30 percent of successful hires (Jobvite 2019a,b).

and Pallais 2020). Second, preferences with respect to those characteristics differ across genders. Women tend to prefer flexibility more than men, while the opposite is true for career advancement, especially wage growth. Third, in-depth interviews carried out among different groups of managers, workers, and workers' representatives within the firm revealed that both flexibility and career advancement are two features of the firm, that can be highlighted without deception.

Our empirical investigation is guided by a formal model that yields four testable hypothesis. First, both treatments should increase the total number of applications. Second, both treatments should increase the number of applications relatively more for entry-level jobs requiring no previous work experience than for jobs requiring previous work experience. Our setting allows us to study this heterogeneity, as our study firm advertises entry-level jobs as well as senior-level jobs. Third, the *flexibility* (*career*) treatment should increase the number of female (male) applicants relatively more than that of male (female) applicants. Fourth, the mechanism for the above effects is belief-updating of expectations about workplace characteristics by potential applicants. Our model does not provide a sharp hypothesis related to the effects of the treatments on the composition (i.e. quality, background etc.) of the applicant pool, but we study this question in an exploratory manner.[3]

Our main findings can be summarized as follows. By comparing applicant numbers across treatments, we first document that both the *flexibility* and the *career* treatment increase the number of applications for entry-level jobs requiring no previous work experience, while the effect is close to zero for senior-level jobs that require previous work experience. Among inexperienced workers the effect is sizeable, amounting to an increase in applications of 44 percent for the *flexibility* and of 35 for the *career* treatment, respectively. Moreover, the *flexibility* treatment is relatively more attractive to women compared to the *career* treatment, while no significant differences are observed for men between the two treatments. To investigate the effect on the quality of the additional applicants, we mainly rely on ratings of firm recruiters. We find weak evidence that the *career* treatment induces a more positive selection compared to the *flexibility* treatment. Beyond that, we study the regions of residence of the additional applications and find that, for both treatments, new applicants mainly come from Germany, but not from an area close to the firms' location. This provides evidence that the treatments allow the firms to source talent from a wider regional labor market.

To analyze how the ad signal affects underlying belief-related mechanisms, we complement our field experiment with an online survey experiment among more than 2000 STEM students, using the subject pools from 12 German and Austrian economic research laboratories. The online surveys were conducted in parallel to the field experiment and showed students a job advertisement that was posted by the firm (almost) at the same point in time. We randomized the treatments between subjects and invited participants such that their educational background matched the requirements of the particular job advertisement. We find that both treatments shift beliefs in

[3] As highlighted by Nekoei (2023), compositional effects are determined by the correlation of applicants' willingness to pay for particular characteristics, on the one hand, and the particular job characteristic, on the other.

the expected direction. In terms of a composite flexibility score capturing work-life balance, the *flexibility* treatment increases expectations regarding flexible working conditions by 0.132 standard deviations. The *career* treatment increases expectations regarding career benefits (in terms of wage and career progression), again measured by a composite score, by 0.162 standard deviations. Moreover, we find evidence for existing belief trade-offs between workplace characteristics. While the *career* treatment increased beliefs about career advancement, it simultaneously *lowered* expectations about workplace flexibility by 0.094 standard deviations.

The contribution of this paper is threefold. First, our findings demonstrate that experimentally-induced variation in the informational content provided in job advertisements can affect the size and composition of their applicant pool. This evidence complements a literature exploiting large-scale regulatory changes to show that a removal of gender preferences in job ads has led to an increase in applications from the previously non-preferred gender in China (Kuhn and Shen 2023) and to more gender-neutral hiring outcomes in Austria (Card, Colella, and Lalive, *forthcoming*). 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 in the sense that we can investigate how subtle differences in job amenities can affect hiring outcomes and the composition of the applicant pool in terms of region of residence and quality. We do this by utilizing detailed CV data and recruiter ratings. After all, a firm's primary interest may not be in the number of applications overall, but in average or top applicant quality. Besides, this 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. Last, 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 (see, e.g., Wiswall and Zafar 2018, Coffman et al. 2024, Vattuone 2024).

The structure of the paper is as follows. In Section 2, we present the background of our study by providing a description of our study firm and the motivation for our treatments. In Section 3, we present the conceptual framework guiding our empirical analysis. Section 4 presents the experimental design. Section 5 presents the main empirical results of the field experiment. Section 6 discusses potential mechanisms focusing on the results of our complementary survey experiment. Lastly, Section 7 concludes.

2. Background and motivation

2.1. The firm

We conducted a field experiment in collaboration with one of Europe's largest technology firms. This leading company operates in the semiconductor market and generated a total revenue of roughly 16 billion euro in the business year 2023 with a total workforce of roughly 60,000 workers. The semiconductor industry experienced a 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 plant of the company situated in Germany. This particular plant experienced strong growth in the last years as well. From 2012 to 2022, the workforce at the plant increased by roughly 50 percent, from approximately 2,000 employees to 3,000. The majority of employees have a STEM background, specifically in fields such as engineering, manufacturing, construction, computer science, mathematics, and physics.

The share of female STEM workers in the company is roughly equivalent to the share of female graduates in Germany in STEM subjects.[4] In leadership positions, 5-10% of the employees are women. The personnel turnover rate among workers is relatively low.[5] Due to the strong growth, the firm is constantly hiring.

2.2. Motivation of our intervention

An essential step of the corporation with the firm was to gain a comprehensive understanding of the firm's recruiting strategy, its main challenges, and its strategic goals. To do so, we engaged in in-depth discussions with key stakeholders, including top managers from the HR department, the head of diversity, recently hired employees as well as those hired a long time ago (especially women), the head of the workers' council, and management executives. We learned that the firm faces two challenges. First, the overall number of applications is low. On average, for each advertised position, the company receives only 12 applications. Second, the share of female applicants is also low. On average, only 12.8% of applications are from female applicants. This is problematic, as the firm's publicly announced goal is to increase the share of female workers from middle-management onwards to 20%.[6]

The main objective of the cooperation was to find ways to overcome both challenges and, in particular, to increase the total number of applications. As job advertisements are still among the most important instruments to attract applicants, changes to them are nearly costless, 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), we quickly consented that we want to investigate how changes in job advertisements may help to attract more applicants.

[4] As reported by the OECD, in 2021 the share of female graduates in the field of STEM for a bachelor's degree or equivalent level amounts to 16%, and its 22% for a master's degree or equivalent level.

[5] We have no data on personnel turnover, but HR officials told us that it is around 1%.

[6] Before our intervention, the firm already had a number of initiatives in place to increase the total number of applications, in particular from women. They engage in cooperation with local universities, went to regional job fairs and fairs at big universities, and increased active talent-sourcing. However, the recruiting challenges remained.

We conducted a number of in-depth interviews about the recruiting processes and challenges carried out among different groups of workers within the firm. During these interviews, when asking about the distinctive characteristics of jobs within the plant, almost all workers highlighted two aspects. First, the plant offers a lot of flexibility to maintain work-life balance. 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 argue that it is 'socially accepted' in the firm to leave early 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.[8] Second, because of the growth in the sector overall, wages grew substantially in the past. With expected future growth, it is likely that wages and career opportunities (e.g., there are constantly new leadership positions available) will keep growing. Indeed, firm growth and wage growth within firms are highly correlated (Fox 2009, Brown and Medoff 1989, Groshen 1991, Idson and Oi 1999).

From standard economic theory, many individuals take career advancement into account when deciding to apply for a job. Beyond that, the work of Wiswall and Zafar (2018) and Mas and Pallais (2020) has shown that the degree of flexibility of a job is an important job characteristic for job choice and thus application decisions. Further, research shows that flexibility is particularly important for women (Wiswall and Zafar 2018).

Given the importance of career advancement and flexibility for application decisions in general and their overwhelming presence at the firm, we agreed to test the effect of highlighting these job characteristics in the companys job advertisements.[9] Before we started with the research project, we presented the project outline to the work council of the firm, who provided their agreement and support.

2.3. Details of the hiring process

The hiring process consists of three steps and is managed by one person from the HR department, the 'Talent attraction manager', who mainly takes care of the administrative process, as well as a 'Hiring manager', who is usually the head of the department for which the position is advertised. The final hiring decision as well as steps in between are made by the 'Hiring manager' supported by the 'Talent attraction manager'. Step one is an initial screening and evaluation by the Hiring manager and the Talent attraction manager. This evaluation is either an A, B, C, or 'No rating'.

[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 professionals.

[8]The job security in the plant is also fairly high. However, this is not a unique selling point of the plant, as legal barriers to terminate employment contracts are high, especially in large companies, and in Germany in general.

[9]Before our intervention, the firm did not highlight (e.g., in job ads or on the homepage) the large opportunities for flexibility and career advancement, but only mentioned it in very small text at the bottom of the page. When we asked the HR department in our study firm why flexibility and career advancement were not highlighted in the job ads, they told us that the reason for this are HR policy and the multinational firm's standare centralized HR policies and standardized IT-systems of the multinational firm.

An *A* rating is given to candidates who are highly promising and meet the outlined criteria of the ideal candidate by 70-100 percent. A *B* rating is assigned to candidates who meet the criteria by 50-70 percent. A *C* rating is for applicants who lack most of the required qualifications or possess characteristics that make them unsuitable for the position, with a fit of less than 50 percent. The 'No rating' category is usually for people who are screened out at the very beginning of the hiring process though is sometimes assigned to superior or disabled candidates who are definitely invited but do not meet the necessary requirements to fit the position. Stage two of the process consists of an interview, usually conducted with the Hiring manager and the Talent attraction manager. After the interview, both decide whether they want to make a job offer; if so, the negotiation between the designated applicant and the firm starts. If this is successful, the candidate is eventually hired.

3. Conceptual framework

In this section, we discuss a conceptual framework that illustrates how highlighting job flexibility or career advancement in job ads affects belief-updating and the expected job utility of potential applicants.[10] The idea is to provide an intuition for how a change in job ads might affect workers' application behavior through a change in expected utility from job flexibility (*flexibility* treatment) and career advancement (*career* treatment), respectively. The goal is to derive testable hypotheses about the size and characteristics of the applicant pool, treatment effect heterogeneities, and changes in worker beliefs, which guide our empirical analysis. The framework is formalized in Section 8.1 of the Appendix. In the following, we verbally describe its main implications and related hypotheses.

Consider the following framework, which reflects upon relevant characteristics for an application decision. There are two types of individuals, either with or without previous work experience. Each individual considers applying to a job advertised by one firm (i.e., our study firm). An applicant applies to the job if the expected utility derived from the job is larger than the (fixed) utility from an outside/alternative offer. The utility derived from a job for an applicant is composed of the (fixed) wage payment, the individual returns to ability, the expected level of flexibility, and career-advancement opportunities provided by the firm. Individuals are uncertain about job flexibility and career advancement, 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 (i.e., no trade-off), while some others might think that career growth comes at the cost of flexibility (i.e., a negative trade-off) or that career growth is not possible without flexibility (i.e., a positive trade-off).[11]

Moreover, we assume that the distributions of prior beliefs differ between experienced and inexperienced applicants. Longer activity in the labor market comes arguably with better networks,

[10] For a related framework based on a similar idea, see Delfino (2024).

[11] Arguably, there are other job characteristics that might matter and enter the utility function. As these are not part of our study, we abstract from those.

and thus likely with more knowledge of the industry and firms.[12] 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-growth opportunities.[13] Indeed, we assume that the true level of flexibility and career opportunities provided by the firm is assumed to be higher than experienced and inexperienced applicants expect.

We interpret the different treatments, namely the highlighting of *flexibility* and *career* in the job ads, as a way for the company to signal flexibility and career-advancement opportunities. These informational treatments induce applicants to update their beliefs.

As the firm signals its true levels of flexibility and of the career-growth opportunities it provides, both of which surpass the applicants' initial beliefs, both treatments should lead applicants to hold more positive expectations about the provided level of flexibility and career-growth opportunities after updating. As both characteristics lead to a higher expected utility of applicants, both should lead to an increase in applications. For this to hold, it is merely necessary that applicants' beliefs about the trade-off between flexibility and career-advancement opportunities are not too negative. We summarize this discussion in Hypothesis 1.

Hypothesis 1. *On average, both treatments lead to an increase in applications.*

Next, we discuss possible effect heterogeneities. As we assume that experienced applicants hold more precise and positive beliefs about the provided level of flexibility and career-advancement opportunities, and both groups receive the same signal, this implies that the expected utility gain of experienced applicants is smaller than for inexperienced applicants. As utility gains lead to more applications, we expect that both treatments lead to a relatively larger increase in applications among inexperienced candidates compared to experienced candidates. We summarize this discussion in Hypothesis 2.

Hypothesis 2. *The increase in applications should be larger for entry-level job ads targeting applicants with no previous work experience than for senior-level job ads targeting applicants with previous work experience.*

Additionally, it is conceivable that the preferences for flexibility differ between female and male applicants. In fact, Wiswall and Zafar (2018) 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 wage-growth 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. 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

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

[13] 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.

job ad highlighting career-advancement opportunities. We summarize this discussion in Hypothesis 3.

Hypothesis 3. *Job ads highlighting flexibility should lead to a relatively stronger increase of female applicants than job ads highlighting career advancement. Job ads highlighting career advancement should lead to a relatively stronger increase of male applicants than job ads highlighting flexibility.*

The above hypotheses rely on the belief-updating of potential applicants upon observing the treatments. Thus, a necessary requirement is that the *flexibility* treatment leads to a positive shift in beliefs about the provided workplace flexibility, while the *career* treatment induces a positive shift in beliefs about career advancement. We summarize this discussion in Hypothesis 4.

Hypothesis 4. *Job ads highlighting flexibility should lead to a positive shift in beliefs about the provided workplace flexibility, while job ads highlighting career advancement should induce a positive shift in beliefs about career advancement.*

The framework does not allow us to develop a hypothesis regarding the expected change in terms of applicant quality. Ultimately, this depends on the correlation between preferences for workplace flexibility, career-growth opportunities and job-specific ability. We will investigate this in an exploratory manner.

In the next Section, we discuss the experimental design in more detail.

4. Experimental design

4.1. Job ads and treatments

The job advertisements have a uniform structure and are presented on the homepage of the company as well as on different job boards. This includes mainly three job boards: Indeed, LinkedIn, and one local job board.[14] Most of the applications, however, are received by the company via their own homepage. The purpose of the job advertisements is to inform potential applicants about the vacancy and to convince potential and ideally suitable applicants to apply.

Figure 1 shows an example of a generic job ad of the company mirroring their structure and presenting the main blocks providing information about the job and the company. At the very top, the company presents varying pictures of employees at work. These pictures usually show female and male applicants as well as a culturally diverse workforce. The job titles are usually very short and consist of three terms. Right below the job title, the ads provide a so-called 'teaser text'. This text provides a superficial description of the advertised job and the company. It is rather short and concise. The short overview provides a list of the hard facts concerning the job in form of bullet points. This includes the desired start date and whether it is an entry-level position or a senior-level position. The job description is a more detailed description of the job and its tasks. The requirements block contains a list of bullet point naming the desired qualifications of

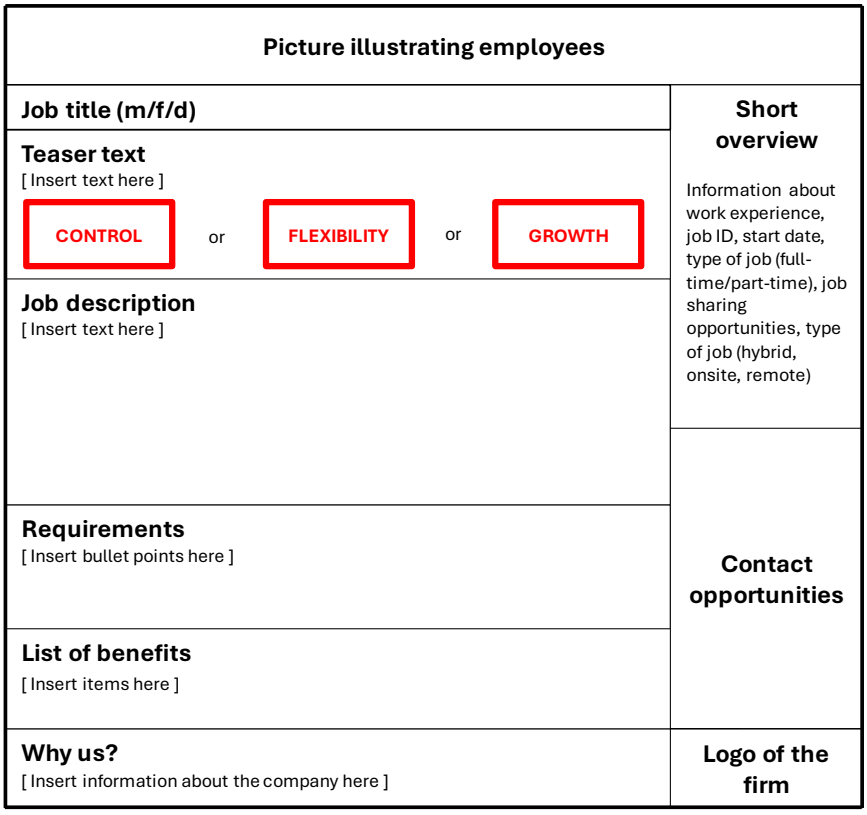
[14] Mentioning the name of this job board would threaten the anonymity of the study firm.

applicants. The benefits block contains a list of job benefits provided by the company.[15] The contact opportunities block shows the name and e-mail address of the responsible Talent attraction manager who can be contacted in case of further questions.

Our treatments consist of two particular statements, one of which (or none) is randomly shown just below the 'teaser text', as highlighted by the red boxes in Figure 1. The exact treatment texts are presented in Figure 2. The *flexibility* treatment reads: "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". It thus highlights the opportunity of flexibility in a very general way. This is necessary, as the potential and detailed conditions for flexibility vary with the particular job. The aim of the treatment is to signal that the firm guarantees to provide an above-average level of flexibility conditional on the requirements of the job. The *career* treatment reads:"GROWTH is very important to us! With us, you do not only grow personally, but also your salary". It signals that the firm provides a job that allows for wage and career opportunities, as well as opportunities for personal growth. Similarly to the *flexibility* treatment, the specific conditions for career advancement depend on the exact job, as career-advancement opportunities and pay rises depend on the respective task and department. Again, the idea behind the treatment is to provide a general signal that the firm is committed to offering above-average career-advancement opportunities.

[15]This includes opportunities for coaching, different career paths, and health programs, among others.

Figure 1: Structure of the job ads

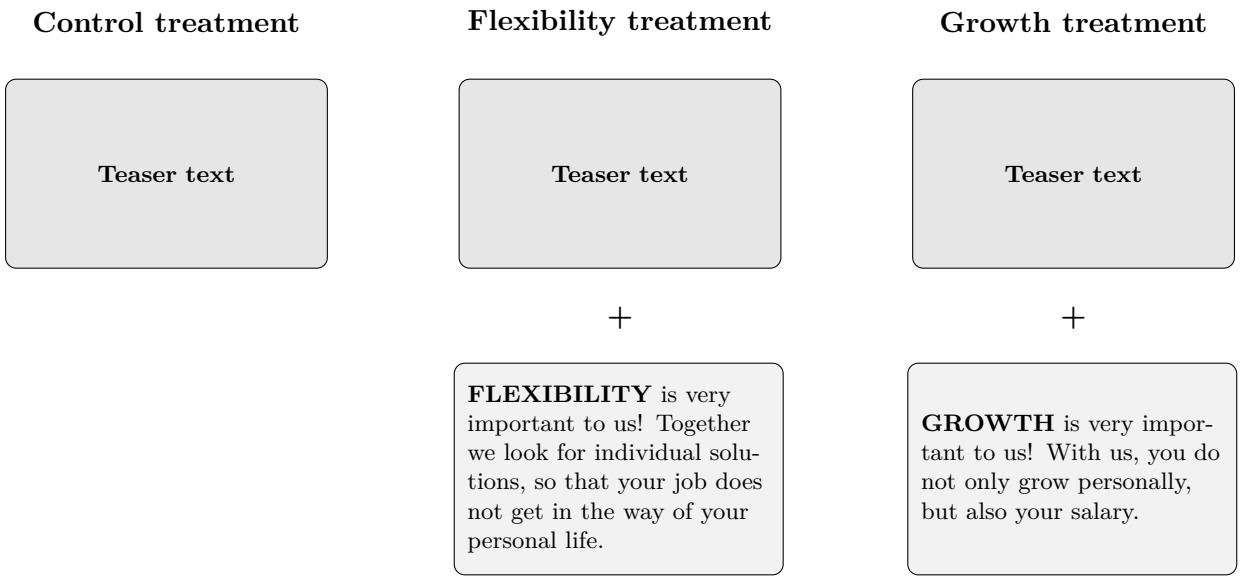


Notes: This figure presents a generic job ad of the study firm mirroring the structure and presenting the main blocks providing information about the job and the company. At the very top, the company presents varying pictures of employees at work. The job titles are usually very short and consist of three terms. Right below the job title, the ads provide a so-called 'teaser text'. This text provides a superficial description of the advertised job and the company. The short overview provides a list of the hard facts concerning the job in form of bullet points. This includes the desired start date and whether it is an entry-level position or a senior-level position. The job description is a more detailed description of the job and its tasks. The requirements block contains a list of bullet points naming the desired qualifications of applicants. The benefits block contains a list of job benefits provided by the company.

4.2. Randomization

In the past, the majority of job applications are received within the first 30 days of the job being online. Due to the limited number and considerable heterogeneity of jobs advertised by the firm within one year, we randomize the treatment within job ads, each over a period of 10 days. Thus, our randomization procedure is as follows: Once a department reports a vacant position to the HR department and the job posting is approved, a random draw determines the treatment – 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. This means that from day 11 to 20 the same job ad is posted with a teaser text corresponding to one of the two remaining treatments. Finally, after 20 days, so from day 21 to 30, the same job ad is posted with

Figure 2: Treatment design



Notes: This figure presents the implemented variations (treatments) of the 'teaser text' of the job ads of the study firm. The *control* treatment shows only the 'teaser text', while the *flexibility* treatment shows the 'teaser text' plus the flexibility statement. The *career* treatment shows the 'teaser text' plus the career-advancement statement.

a teaser text corresponding to the remaining treatment.[16] Each job ad is thus posted sequentially under each treatment condition.

The randomization was conducted by an external intermediary person, who was hired as an external employee by the company. We provided the randomization schedule to this person. As a "firewall" measure, this person was not involved in any other tasks of the HR department, nor in any of the research. Recruiters were not informed about the chosen treatments for the different time periods of the jobs.[17] The field experiment took place between October 2022 and October 2023. It only included job ads requiring a STEM background. Throughout our treatment period, we randomized a total of 105 job ads as part of our experiment.[18]

4.3. Data

Our main analysis draws on firm data about a total number of 1,084 applications, applicant characteristics, and applicant ratings. The sample comprises all applicants who applied to job ads in

[16]Some job ads are posted longer than 30 days until the position is filled. As outlined in our pre-registration, we do not include applicant data collected after the 30-day period.

[17]As a safeguard for the field experiment, one of our research assistants checked every day that the 'right' job ad was posted online on each platform. The research assistant documented the treatments every day, without being informed about the scheduled treatment. The research assistant detected three inconsistencies in terms of a missing treatment switch when scheduled. This explains the slight imbalance of three daily observations in Table 1 presenting the summary statistics.

[18]Initially, we randomized 136 job ads. However, 31 job ads were either not posted for the full 30 days, were posted by recruiters without obeying the randomization protocol, or were designed ex-ante for a designated desired candidate. Thus, we exclude the corresponding data from our analysis.

Table 1: Summary statistics: Daily application data

	Control		Flexibility		Career	
Variables (daily)	Mean	SD	Mean	SD	Mean	SD
A. Applications by gender						
Total	0.374	0.906	0.422	1.750	0.374	0.824
Male	0.301	0.745	0.336	1.349	0.302	0.666
Female	0.074	0.305	0.087	0.491	0.071	0.323
B. Applications by recruiter ratings						
A rating	0.038	0.206	0.027	0.161	0.045	0.229
B rating	0.074	0.297	0.057	0.248	0.075	0.294
C rating	0.087	0.320	0.088	0.328	0.084	0.322
Screened out	0.175	0.692	0.250	1.683	0.170	0.571
Invited for interview	0.075	0.288	0.059	0.244	0.082	0.294
C. Applications by region of residence						
Germany w/o state	0.134	0.496	0.185	0.951	0.154	0.446
State	0.117	0.348	0.106	0.433	0.104	0.365
Abroad	0.109	0.381	0.114	0.486	0.100	0.344
Observations	1,047		1,051		1,052	

Notes: This table shows the mean and standard deviations of daily applications received by gender, quality, and region of residence. Control refers to the control treatment, Flexibility refers to the *flexibility* treatment, and Career refers to the *career* treatment.

our experiment between October 2022 and October 2023, with a maximum of two applications each.[19] The data comprise 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, and hiring outcome). Besides, we draw on anonymized data from the applicants' CVs.[20]

Table 1 displays a summary of 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 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 (Abroad).

Our main outcome variable is the total number of daily applications per job advertisement, overall and by gender. A focus of our analysis is the investigation of heterogeneous effects across entry-level and senior-level jobs.

[19]We drop 4.8% of the applicants, who applied more than two times, as these are classified as mass applicants by our study firm. It is plausible to assume that these application decisions are not driven by our treatments. Some applicants even sent up to 20 applications during our experimental time period.

[20]As part of the field experiment, we collect sensitive and personal data from applicants. To align with data-protection standards, we implemented several processes aimed at GDPR compliance. Central to our approach is the establishment of an anonymous intermediary person, who is hired as an external employee of the firm and prepares the data in a sufficiently anonymized way so that we can use it for our analyses. The most important guideline overall was to ensure that we never handle personal data that could lead to individual identification.

5. Main empirical analysis - Field experiment

In this section, we present our estimation strategy and the main results. Our aim is to investigate how both treatments affect the total number of applications. We split the analysis between job ads for entry-level and senior-level positions. Furthermore, we analyze how the treatments affect the composition of the applicant pool. To do so, we rely primarily on recruiter ratings to assess applicant quality, and on CV data to investigate changes in the applicants' region of residence.

5.1. Empirical strategy

Our goal is to uncover the causal effect of highlighting flexibility or career advancement on the number of daily applications. Each job ad is observed for both treatments, *flexibility* and *career*, and the control period. Our data thus 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 the treatment effects of interest, we rely on the following linear specification:

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

Here, 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 belongs to the *Flexibility* or *Career* group 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. In total, our estimations include 26 observations per job advertisement: on average one per day. As we cannot exactly measure the time of the treatment switch, we exclude the day t of the treatment switch and the day $t+1$ after the treatment switch.[21] 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 8.2 of the Appendix).[22]

5.2. Main result

We first provide descriptive evidence on the relationship between the presented job ad and the number of applications received per day. Figure 3 shows the average number of daily applications for entry-level positions in total (3a), by gender (3c, 3e) as well as the average number of daily applications for senior-level positions in total (3b) and by gender (3d, 3f). Starting off with the

[21] This choice is made to mitigate concerns with respect to potential spillovers. In Section 8.2.1 of the Appendix, we present the results of our main analysis including day $t+1$. The results are qualitatively similar. Additionally, we present a discussion in Section 8.2.2 of the Appendix including further analyses providing evidence that spillovers do not pose an identification threat.

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

comparison of 3a and 3b, we observe that both treatments boost the number of applications for entry-level positions. The effects are sizeable, amounting to 0.119 additional applications per day for the *flexibility* treatment and to 0.0973 additional applications per day for the *career* treatment. Figures 3d and 3f present treatment effects separately by gender. We find that both treatments increase the number of male applicants to entry-level positions by roughly equal amounts, namely by 0.0765 applications per day in response to the *flexibility* treatment, and by 0.0997 applications per day in response to *career* treatment. Among female applicants, only the *flexibility* treatment leads to an increase in applications (by 0.0424 applications per day). The *career* treatment leads to a slight, but insignificant, decrease of -0.0025 applications per day. Considering Figures 3b, 3c and 3e, we observe almost no changes for the *career* treatment and slight, but insignificant, increases for the *flexibility* treatment (0.0592 overall, 0.0503 for males, and 0.009 for females).

We proceed by discussing the estimation results from an OLS fixed-effects regression of Equation (1), as presented in Table 2. Columns 1 to 3 show the estimated treatment effects on the total number of applications to entry-level jobs, while Columns 4 to 6 show the estimated effects for senior-level jobs. All estimations include job ad and time fixed effects and standard errors clustered on job-ad level.[23]

We begin to discuss the results for the entry-level job ads. We observe that the *flexibility* and the *career* treatment increase the number of applications on average. 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%.[24]

Column 3 shows the results for female applicants only. We observe that the *flexibility* treatment is estimated to increase the daily number of female applicants by 0.052, corresponding to an increase of 82%, but no significant increase for the *career* treatment. The null $\beta_f = \beta_{ca}$ is rejected for standard significance levels with a corresponding p-value of 0.012.[25]

Extrapolating these point estimates to a full 30-day period, the *flexibility* treatment is estimated to increase the total number of applications approximately by 5.13. Out of these 5.13 additional applications, 3.57 are estimated to be from male and 1.56 from female applicants. The *career* treatment is estimated to generate 4.11 additional applications, of which roughly all are from male applicants.

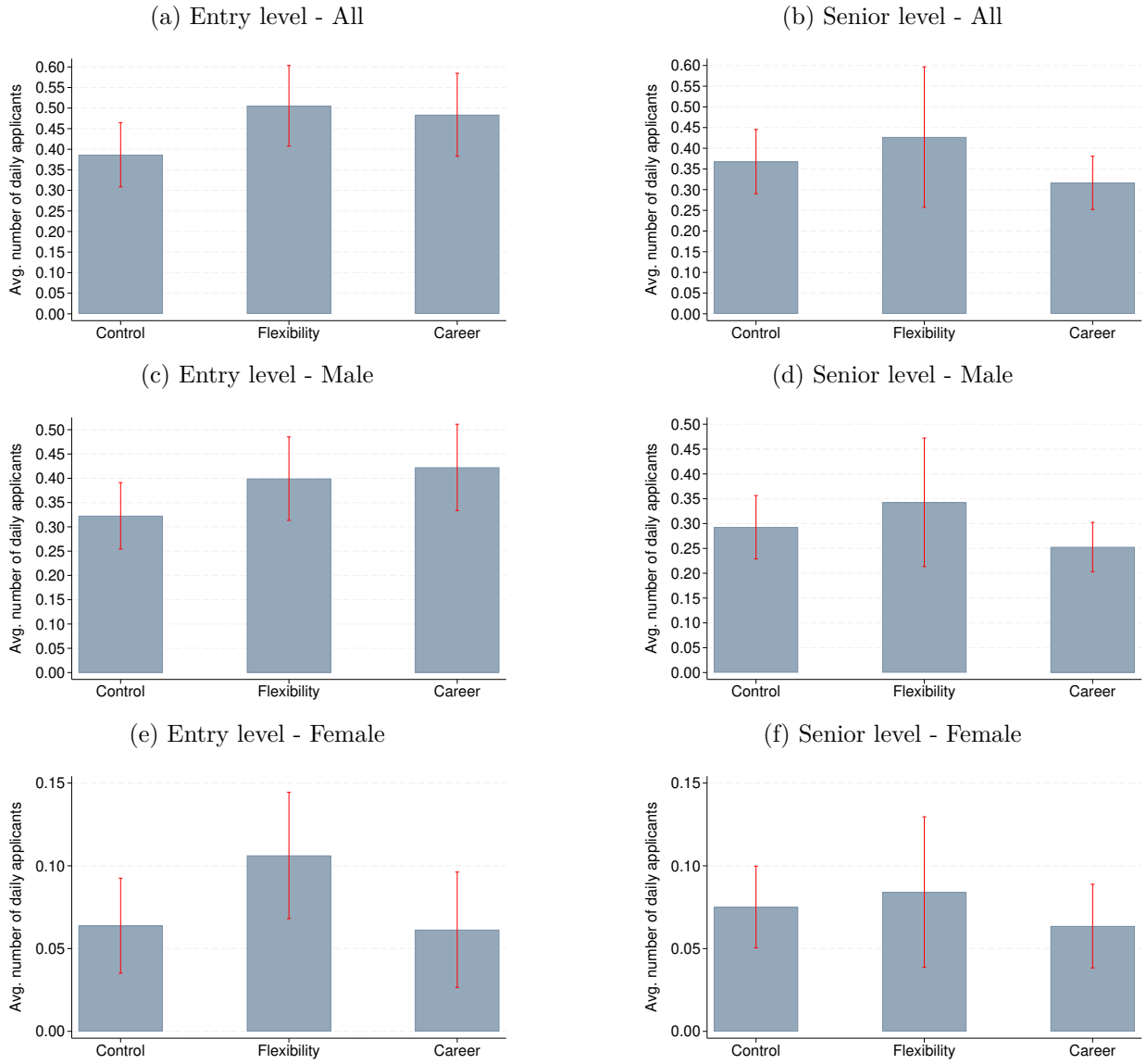
Columns 4 to 6 show the results for senior-level positions, and hence job ads requiring previous

[23] 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.

[24] Performing the same estimations by means of a Poisson fixed-effects regression - which is presented in Table A.1 in Section 8.2.1 of the Appendix - yields similar results, with even smaller standard deviations of the point estimates and 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%.

[25] Again, the Poisson regression 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 40%, and no statistical significant increase for female applicants can be ascertained.

Figure 3: Average number of daily applications



Notes: This figure shows the average number of daily applications for each treatment by gender and experience level of the job ad. The bar represents the mean, while red lines show 95% confidence bands for the mean. We denote by $\bar{y}_c$ the mean estimator for the *control* treatment, and by $\bar{y}_f$ we denote the mean estimator for the *flexibility* treatment, while by $\bar{y}_{ca}$ we denote the mean estimator for the *career* treatment. Figure 3a shows the mean of daily applicants for entry-level positions, with $\bar{y}_c = 0.3865$, $\bar{y}_f = 0.5055$, and $\bar{y}_{ca} = 0.4838$. Figure 3c shows the mean of daily male applicants for entry-level positions, with $\bar{y}_c = 0.3227$, $\bar{y}_f = 0.3992$, and $\bar{y}_{ca} = 0.4224$. Figure 3e shows the mean of daily female applicants to entry-level positions, with $\bar{y}_c = 0.0638$, $\bar{y}_f = 0.1062$, and $\bar{y}_{ca} = 0.0613$. Figure 3b shows the mean of daily applicants to senior-level positions, with $\bar{y}_c = 3678$, $\bar{y}_f = 0.4270$, and $\bar{y}_{ca} = 0.3164$. Figure 3d shows the mean of daily male applicants to senior-level positions, with $\bar{y}_c = 0.2926$, $\bar{y}_f = 0.3429$, and $\bar{y}_{ca} = 0.2528$. Figure 3f shows the mean of daily female applicants to senior-level positions with $\bar{y}_c = 0.07512$, $\bar{y}_f = 0.0841$, and $\bar{y}_{ca} = 0.0636$.

work experience. Across all three specifications, we observe no treatment effects for the total number of applications, neither in total nor separated for female and male applicants.

Next, we relate the results to the hypotheses derived from our conceptual framework. We

find mixed evidence with respect to Hypothesis 1 regarding the increase in applications for both treatments. We find that this increase is only present for entry-level job ads requiring no previous work experience. However, this equally provides strong support for Hypothesis 2, which predicts that the increase in applications should be larger for entry-level positions than for senior-level positions. We cannot reject that the treatment coefficients for male applicants are statistically distinguishable; however, we can indeed reject this hypothesis for female applicants. Thus, we find mixed evidence for Hypothesis 3, as both treatments seem to be equally attractive for male applicants, but the *flexibility* treatment only attracts additional female applicants.

Table 2: Treatment effects on the number of applications

	No. of applications - OLS					
	Inexperienced			*Experienced*		
	All	Male	Female	All	Male	Female
	(1)	(2)	(3)	(4)	(5)	(6)
Flexibility	0.171**	0.119*	0.052***	0.060	0.054	0.006
	(0.067)	(0.061)	(0.018)	(0.119)	(0.096)	(0.026)
Career	0.137*	0.133*	0.004	-0.028	-0.021	-0.007
	(0.079)	(0.072)	(0.023)	(0.033)	(0.028)	(0.017)
Observations	829	829	829	1896	1896	1896
No. of Clusters	32	32	32	73	73	73
Mean dep. variable	0.46	0.38	0.08	0.37	0.30	0.07
Bootstrap p β_f	0.02	0.06	0.01	0.89	0.83	0.93
Bootstrap p β_{gr}	0.11	0.07	0.92	0.39	0.43	0.77

Notes: This table shows the impact of the treatments on the number of applications received 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. Columns 1 to 3 present the effects for job ads requiring no previous work experience, while Columns 4 to 6 present the effects for job ads requiring previous work experience. Column 1 and 4 show the effect for the total number of applications, while Columns 2 and 5 only show the effect for the number of male applicants, and Columns 3 and 6 only show the effect for the number of female applicants.Standard errors clustered on job-ad level are reported in parentheses. The last two rows show the p values from wild bootstrapped clustered standard errors (Cameron et al. 2008).
*< 0.1, **< 0.05, ***< 0.01

5.3. Further results

In this Section, we analyze how the composition of the applicant pool is affected. We present two sets of analyses. First, we analyze changes to the distribution of the applicants' region of residence. As highlighted by Moretti (2011), an increase in amenities can cause an exogenous labor-supply shock that may increase worker mobility. Second, as discussed by Nekoei (2023), in case job-specific abilities correlate with preferences for certain amenities, it may affect the quality composition of the applicant pool.

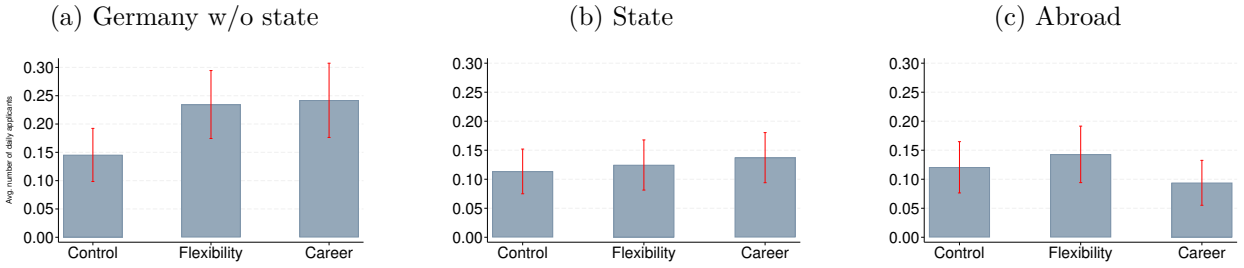
5.3.1. Region of residence

We categorize the applications by applicants living in the federal state of the location of the firm (State), applicants living in Germany, but not in the federal state of the firm (Germany w/o state), and applicants from abroad (Abroad).

We start with a descriptive analysis by considering Figure 4, which presents the mean of the respective daily number of applications by each region of residence category for each treatment. Figure 4a shows the mean of daily applicants living in Germany w/o state, while Figure 4b shows the mean of daily applicants living in the federal state, and Figure 4c that of the number of daily applicants living abroad. Considering the bar charts, we observe strong increases of applicants from Germany w/o state (increases by 0.089 for the *flexibility* treatment and by 0.0965 for the *career* treatment), while we observe no remarkable increases for applicants from the two other categories. Already simple T-tests for mean comparison confirm this, as the difference of means for applicants from Germany w/o is significant for both treatments, while we find no significant differences for the other two regional categories.[26] As an alternative, we present in Section 8.2.3 in Table A.3 the re-estimation of Equation (1) with the applicants from a particular region category as outcome variable. The results are similar to the mean comparisons presented above.

This provides evidence that highlighting flexible work opportunities and career-progress opportunities allows the firm to source from a larger regional talent pool. However, the informational treatments do not seem to be large enough to be pivotal for an application decision for applicants living abroad, which is in line with the discussions of Moretti (2011) that worker mobility is finite.

Figure 4: Average number of daily applications by region of residence



Notes: This figure shows the average number of daily applicants for each treatment and by region of residence of applicants. Figure 4a shows the numbers for applicants living in Germany, but not in the state of the firm (Germany w/o state), while Figure 4b shows the number of applicants living in the federal state of the firm (State), and Figure 4c shows the average number of applicants living abroad. We denote the mean of the flexibility treatment by $\bar{y}_f$, of the growth treatment by $\bar{y}_{ca}$, and of the control group by $\bar{y}_c$. For Figure 4a, $\bar{y}_c = 0.1454$, $\bar{y}_f = 0.2344$, and $\bar{y}_{ca} = 0.2419$. For Figure 4b, $\bar{y}_c = 0.1135$, $\bar{y}_f = 0.1245$, and $\bar{y}_{ca} = 0.1372$. For Figure 4c, $\bar{y}_c = 0.1206$, $\bar{y}_f = 0.1428$, and $\bar{y}_{ca} = 0.0939$. For applications from Germany w/o state, the null that $\bar{y}_f < \bar{y}_c$ and $\bar{y}_{ca} < \bar{y}_c$ for the daily applicants can both be rejected at the 5% level with a p value of 0.0106 and 0.0092. For all other applicants (from the State and Abroad), we cannot reject the null of smaller means of the treatment groups.

To check how the overall distribution of applicants is affected, we re-estimate Equation (1) using

[26] The null that $\bar{y}_f < \bar{y}_c$ and $\bar{y}_{ca} < \bar{y}_c$ for applicants from Germany w/o state can be rejected for standard significance levels. For $H_0 : \bar{y}_f < \bar{y}_c$, we reject at the 5% level ($p = 0.0106$), and for $H_0 : \bar{y}_{ca} < \bar{y}_c$, we reject at the 1% level ($p = 0.0092$).

Table 3: Treatment effects on the number of applications

	Region of residence of applicants - OLS		
	Germany w/o state	State	Abroad
	(1)	(2)	(3)
Flexibility	0.133*	-0.067	-0.050
	(0.076)	(0.070)	(0.077)
Career	0.149***	0.004	-0.148**
	(0.050)	(0.057)	(0.070)
Observations	380	380	380
No. of Clusters	32	32	32
Mean dep. variable	0.45	0.27	0.26

Notes: This table shows the effect of the treatments on the distribution of region of residence of the applicants. The outcome variables are binary indicators in case applicants live in Germany, but not the federal state of the firm (Germany w/o state), live in the federal state of the firm (State), or live abroad (Abroad). All estimations include job-ad and time fixed effects and are estimated via standard OLS fixed-effects regressions. Thus, the model corresponds to a linear probability model, and the point estimates can be interpreted as marginal probability increases. The interpretation corresponds to the marginal increase in probability of an applicant belonging to one of the categories upon applying to a particular treatment. Standard errors clustered on job-ad level are reported in parentheses.
*< 0.1, **< 0.05, ***< 0.01

standard OLS fixed-effects regressions on the applicant level. Each observation now corresponds to an applicant for job ad i on a particular day t. The result is a linear probability model, which is able to detect whether probability mass is shifted to one category, as the point estimates give the marginal probability increase of belonging to a certain category upon coming from either the *flexibility* or the *career* treatment.

Table 3 presents the results. Column 1 shows the marginal probability change of an applicant living in Germany w/o state, while Column 2 shows the marginal probability change of an applicant living in the state, and Column 3 shows the marginal probability change of an applicant living abroad, conditional on an application coming from the *flexibility* or the *career* treatment in comparison to the *control* group. In line with the previously shown mean comparisons, we observe that, for both treatments, applicants are more likely to live in Germany w/o state (an increase of 0.133 for the *flexibility* and of 0.149 for the *career* treatment), while we observe no statistically significant changes for the *flexibility* treatment for both other regional categories. For the *career* treatment, we observe no change to the share for applicants living in the federal state of the firm, but a negative statistically significant point estimate for applicants living abroad (of -0.148). This negative point estimate does not imply an absolute reduction in the number applicants from abroad. Rather, it points towards a distributional change in favor of applicants from Germany w/o state and from the federal state.

5.3.2. Quality

Similarly to the previous section, we start with a descriptive analysis by considering Figure 5, which presents the average daily number of applications rated either with an A (5a), B (5b), or C (5c), or those applications that are screened out for each treatment (5d).

Comparing simply the means from the graphs, we observe that the increase in applicants in response to both treatments is quite evenly distributed across categories. We only note that the *career* treatment seems to induce an even larger increase of A-rated applicants (by 0.016 for the *flexibility* treatment and by 0.037 for the *career* treatment).[27] As an alternative, in Section 8.2.3 in Table A.4, we present the re-estimation of Equation (1), using the applicants with a particular rating category as outcome variable. The results are similar to the mean comparisons presented above.

Similarly to the investigation of the region of residence of applications, we want to understand whether the treatments cause a change in the overall distribution of ratings. We approach this by re-estimating Equation (1) on the applicant level, i.e., conditional on having applied. This means that each observation corresponds to one applicant for job ad i on day t and that the point estimates identify marginal probability increases with respect to one rating category.

Table 4 presents the results. Column 1 shows the results for A ratings, Column 2 for B ratings, Column 3 for applicants with C ratings, and Column 4 for applicants who have been screened out. We observe overall no strong distributional changes for both treatments. Considering the point estimates for the *flexibility* treatment from Columns 1 to 4, we observe point estimates close to zero, which are insignificant. This shows that the *flexibility* treatment managed to attract additional applicants without compromising the quality distribution in terms of recruiter ratings. Considering the point estimates for the *career* treatment, we also observe no statistically significant, and point estimates are close to zero for applicants rated B and C. However, we observe a positive point estimate with a t-statistic of 1.55, for A-rated applicants and a negative point estimate of similar size for screened-out applicants with a t statistic of -1.05, mirroring the descriptive finding of an even larger increase in A-rated applicants with a comparably lower increase of screened out applicants attracted by the *career* treatment.[28]

To complement the analysis, Column 5 of Table 4 presents the results of a linear probability model, for which the outcome variable is another quality indicator, namely whether an applicant is invited to an interview. We estimate the marginal probability increase of an applicant being invited to an interview upon having applied to the *flexibility* or the *career* treatment. Corresponding to the indication of the weak positive distributional change, we observe a positive weakly significant point estimate of 0.103 for the *career* treatment, indicating a higher likelihood of being invited for an interview when applying to a *career*-treatment job ad.

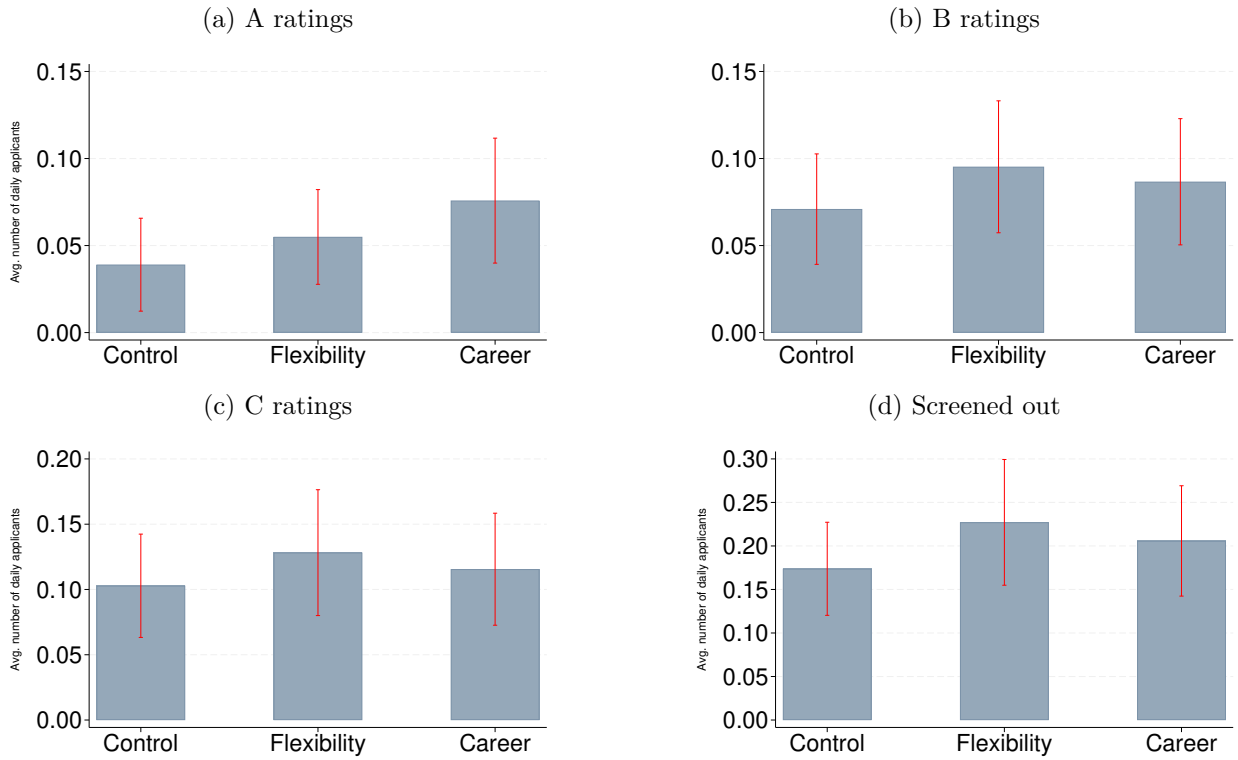
Overall, we conclude that the analysis provides evidence that the additional applicants were

[27] This is confirmed by the fact that already a simple T-Tests rejects the null of equal means for the daily applicants with an A rating.

[28] Furthermore, for the estimation in Column 1, the null that $\beta_f > \beta_{ca}$ can be rejected at the 10% level ($p = 0.065$).

attracted without significant changes to the quality distribution of applicants. More precisely, we find no indications of changes for the *flexibility* treatment and even weak indications of a positive shift for the *career* treatment.

Figure 5: Average number of daily applications by quality



Notes: This figure shows the average number of daily applicants for each treatment and by region of residence. Figure 5a shows the mean number of daily applicants with an A rating, while Figure 5b shows the mean number of applicants with a B rating, Figure 5c shows the mean number of applicants with a C rating, and Figure 5d shows the mean number of applicants who have been screened out. We denote the mean of the flexibility treatment by $\bar{y}_f$, of the growth treatment by $\bar{y}_{ca}$, and of the control group by $\bar{y}_c$. For Figure 5a, $\bar{y}_c = 0.0390$, $\bar{y}_f = 0.0550$, and $\bar{y}_{ca} = 0.0758$. For Figure 5b, $\bar{y}_c = 0.0709$, $\bar{y}_f = 0.0952$, and $\bar{y}_{ca} = 0.0866$. For Figure 5c, $\bar{y}_c = 0.1028$, $\bar{y}_f = 0.1282$, and $\bar{y}_{ca} = 0.1155$. For Figure 5d, $\bar{y}_c = 0.1738$, $\bar{y}_f = 0.2271$, and $\bar{y}_{ca} = 0.2058$. For the mean of daily applications with an A rating the null hypothesis that $\bar{y}_f < \bar{y}_c$ cannot be rejected, while $\bar{y}_{ca} < \bar{y}_c$ can be rejected at the 10% level ($p = 0.0529$). For the other categories, the means are not statistically significant different from each other.

6. Survey experiment and mechanisms

In Section 3, we hypothesized that the effects of highlighting flexibility or career-advancement opportunities in job ads on applicants' behavior is driven by updating beliefs among potential applicants about job characteristics and the working environment (see Hypothesis 4). To assess the plausibility of beliefs as an underlying mechanism of our main treatment effect among inexperienced workers, this section presents the results of a survey-experiment with STEM students.

Table 4: Treatment effects on the number of applications

	Rating and hiring outcomes - OLS				
	A rating	B rating	C rating	Screened out	Interview
	(1)	(2)	(3)	(4)	(5)
Flexibility	-0.002	0.001	-0.001	0.002	-0.004
	(0.035)	(0.057)	(0.049)	(0.053)	(0.056)
Career	0.060	0.003	0.001	-0.064	0.103*
	(0.039)	(0.048)	(0.055)	(0.062)	(0.057)
Observations	380	380	380	380	380
No. of Clusters	32	32	32	32	32
Mean dep. variable	0.11	0.18	0.25	0.25	0.25

Notes: This table shows the effect of the treatments on the distribution of rating categories of applicants. The outcome variables are binary indicators in case applicants are rated with an A (best category), B, C or screened out (least category). All estimations include job-ad and time fixed effects and are estimated via standard OLS fixed-effects regressions. Thus, the model corresponds to a linear probability model and the point estimates can be interpreted as marginal probability increases. The interpretation corresponds to the marginal increase in probability of an applicant belonging to one of the categories upon applying to a particular treatment. Standard errors clustered on job-ad level are reported in parentheses.
*< 0.1, **< 0.05, ***< 0.01

6.1. 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.[29] As most of these participants have graduated shortly or will graduate soon, these subjects are an ideal 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 the lab participant. Thus, we invited only individuals who possess the educational background required by the job ad. This ensures more reliable answers, as those participants are better informed about the tasks outlined in the job ad and the industry overall.

The experimental procedure was as follows: Whenever an entry-level job ad was posted and part of our field experiment, we initiated a corresponding lab session. We thus conducted the survey experiment in 'real-time', 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.[30] As the supply of students with a STEM background in economic research

[29]Detailed information about the labs and participant numbers can be found in the Appendix in Table A.5.

[30]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 directly contact the firm to signal their interest in the job and to receive instructions on how to apply. It's important to note only a few students (3 out of 2136) actually utilized this. 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.

labs at universities is limited, we needed to contact many different labs at different universities to gather sufficiently many 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.[31] Our target for each survey wave was to recruit at least 45 participants. Finally, on average 52 individuals participated per wave. In total we conducted 47 different waves with a total of 20 job ads.[32] All job ads were part of more than one survey wave to ensure that we can include lab fixed effects.

The structure of the survey was as follows: The survey started with some 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 of our field experiment and informed participants that this is a real job currently posted by the company. The name of the firm was revealed and we presented the job ad either with the *control*, the *flexibility* or the *career* treatment. Thereafter, we elicited the probands' beliefs about job characteristics as well as the working environment. We removed the information from the job ad about the workplace location to avoid confounding across lab locations. Instead, we ask participants to assume that the place of work is in a reasonable distance to their current place of living. The last block asked participants about their interest in the presented job.[33] In Section 8.3 of the Appendix, we present summary statistics of the variables measured as part of the survey in Table A.6.

6.2. Beliefs about job characteristics

The main focus of the survey experiment was to measure how our treatment shapes beliefs about job characteristics. To do so, we relied on a battery of questions which 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, overtime at work, the opportunity for part-time work, for flexible scheduling, the attractiveness of the location of the job, the necessity of work-related travel, provided job security, provision of a high income, salary growth prospects, salary negotiation possibilities, a family-friendly workplace, career-advancement opportunities, the firm's reputation, how challenging the tasks of the job are, the offered childcare support from the company, and home-office options. Participants were asked to rate statements about these items on a scale from 1 (does not apply at all) to 10 (fully applies) from the perspective of how accurately they expect these statements to describe the presented job.[34]

[31] We did not randomize the job ads. However, 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.

[32] To increase the quality of respondents' answers, we remove the fastest 5 percent of respondents.

[33] The questionnaire of the survey-experiment is available from the authors upon request.

[34] 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 offered full time or part time is stated on the ad, work-related travel is also job dependent and if applicable outlined in the job task. Table A.9 in the Appendix presents the regression results for these excluded items in Column (1)-(5).

The items which are the focus of our analysis, can be grouped in two categories. The first one is denoted by *work-life balance*, and we allocate the items of expected work-life balance, flexible scheduling, home office and childcare support opportunities, to avoid overtimes, and a family-friendly job. The second one is denoted by *career benefits*, and we allocate the items of good salary, provided salary growth, career-advancement opportunities, how challenging the tasks of the job are, and the opportunity of regular salary negotiations. Our two outcome variables consist of a composite score of each category, which consists of the normalized sum of the ratings of each item.[35]

To identify the treatment effects, we estimate an equation similar to (1) of the main analysis with the outcome variables being our two composite scores of i) *Work-life balance* and ii) *Career benefits* items, but we include lab fixed effects instead of time fixed effects in addition to job ad fixed effects.[36] Additionally, we include further control variables such as gender, high school GPA, migration background, university degree and family status. As our outcome variables are normalized scores, the estimated marginal effects need to be interpreted in terms of standard deviations (sd) of the respective composite score.

Table 5: Belief updating about job characteristics

	Beliefs					
	Work-life balance			*Career benefits*		
	(1)	(2)	(3)	(4)	(5)	(6)
Flexibility	0.106**	0.131***	0.132***	-0.017	-0.008	-0.008
	(0.041)	(0.042)	(0.042)	(0.048)	(0.051)	(0.051)
Career	-0.112**	-0.096**	-0.094**	0.159**	0.163***	0.162***
	(0.044)	(0.044)	(0.044)	(0.057)	(0.056)	(0.056)
Observations	2136	2136	2136	2136	2136	2136
No. of Clusters	20	20	20	20	20	20
Job FE	Yes	Yes	Yes	Yes	Yes	Yes
Lab FE	No	No	Yes	No	No	Yes
Controls	No	Yes	Yes	No	Yes	Yes
Bootstrap p β_f	0.02	0.00	0.01	0.74	0.87	0.86
Bootstrap p β_{gr}	0.01	0.05	0.05	0.01	0.01	0.01

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, projected overtime, and 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 regularly negotiate salary increases. The outcome variables are standardized, thus the marginal effects need to be interpreted in terms of standard deviations. The control variables include gender, high school GPA, migration background, university degree and family status. Standard errors are clustered on job-ad level and are reported in parentheses. The last two rows show the p values from wild bootstrapped clustered standard errors (Cameron et al. 2008).
*< 0.1, **< 0.05, ***< 0.01

[35]Table A.7 in Section 8.3 of the Appendix presents treatment effects for each single item.

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

The results are presented in Table 5. 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 3 present the most parsimonious specification and only include job ad fixed effects, Columns 2 and 4 further include additional control variables, and Columns 3 and 6 present the most comprehensive specification including additionally 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 about 0.132 *sd* of the expected *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 0.162 *sd*, while at the same time decreasing the beliefs about the provided *Work-life balance* by 0.094 *sd*.[37]

Summarizing the results, we find evidence that the treatments indeed lead to belief updating among potential applicants, thereby substantiating our hypothesis that belief-updating is the main driver behind our main treatment effects. Relating this to the hypotheses developed in our conceptual framework, we find strong support for Hypothesis 4. 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 an increase of the former but to a decrease of the latter.[38]

6.3. Beliefs about the working environment

A second purpose of the survey-experiment is to analyze, whether the treatments also affect beliefs about the working environment. 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 making a career, (v) having a STEM degree, and (vi) earning a high income.[39] We allocate these items again into two categories, to calculate composite scores over two aggregated items: the first category is a *friendly* working environment (analogous to work-life balance), and *competitive* working environment (analogous to *career benefits*).

The first outcome, *friendly* working environment, is measured by the normalized sum of the scores of (i) and (ii), while the second outcome variable is *competitive* environment and is measured by the normalized sum of the scores of (iii) to (vi).[40] We identify treatment effects as in the previous Section by re-estimating Equation (1) with lab fixed effects (instead of time fixed effects), job fixed effects and additional controls. As the outcome variables are normalized, we need to interpret the marginal effects terms of standard deviations *sd*.

The results are presented in Table 6. Columns 1 to 3 show the effect on the composite score

[37] Further, to investigate heterogeneities with respect to gender, we re-estimate the equation and include interaction term for being female. We found no evidence that the treatment effect varies by gender.

[38] Relating this to our conceptual framework in the Appendix in Section 8.1, we find evidence that $\tilde{\rho} < 0$.

[39] As a further item, we also elicited the share of colleagues over a particular age as a distraction item, which we exclude in the further analysis. Table A.9 in the Appendix presents the regression result for this item in Column (6).

[40] In Table A.8 in Section 8.3 of the Appendix, we present estimations of the treatment effects for each single item.

of *friendly* working environment, while Columns 4 to 6 show the effects on the composite score of *competitive* working environment. Columns 1 and 3 show the most parsimonious specification and only include job ad fixed effects, Columns 2 and 4 further include additional control variables, and Columns 3 and 6 show the most comprehensive specification including 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 0.086 percentage points of a *sd* in expected friendliness of the working environment, while we observe no effects for the *career* treatment. Considering the effect of the *career* treatment, we observe that it leads applicants to believe that the working environment is by 0.092 *sd* more competitive, while we observe no effects for the *flexibility* treatment. Overall the results are smaller and statistically less precise.

Table 6: Belief updating about working environment

	Beliefs					
	Friendly			*Competitive*		
	(1)	(2)	(3)	(4)	(5)	(6)
Flexibility	0.081*	0.084*	0.086*	-0.050	-0.050	-0.041
	(0.045)	(0.044)	(0.044)	(0.051)	(0.054)	(0.054)
Career	0.029	0.033	0.033	0.083	0.088*	0.092*
	(0.041)	(0.040)	(0.040)	(0.050)	(0.050)	(0.051)
Observations	2136	2136	2136	2136	2136	2136
No. Clusters	20	20	20	20	20	20
Job FE	Yes	Yes	Yes	Yes	Yes	Yes
Lab FE	No	No	Yes	No	No	Yes
Controls	No	Yes	Yes	No	Yes	Yes
Bootstrap p β_f	0.10	0.08	0.06	0.31	0.50	0.48
Bootstrap p β_{gr}	0.53	0.47	0.40	0.12	0.10	0.09

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, eager making 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. 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 last two rows show the p-values from wild bootstrapped clustered standard errors (Cameron et al. 2008).
*< 0.1, **< 0.05, ***< 0.01

Our results in Table 6 indicate that our *flexibility* treatment is positively associated with a more *friendly* working environment, whereas the *career* treatment is associated with a more competitive working environment. Overall our results show that the information treatments extend beyond belief updating about job characteristics onto belief updating about selection into the job.

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 heavy trade offs in terms of applicant quality. At most, we find weak evidence for a relatively more positive selection compared to featuring flexible working conditions. Highlighting amenities and benefits in job advertisements is thus 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 how the treatment 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 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 induce the workplace to be more family friendly. Career advancement is associated with a more competitive workplace, which 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 application behavior. This hints towards important information frictions on the labor market for entry level jobs (see, e.g., Pissarides 2011, Belenzon and Tsolmon 2016) and astonishing consequences 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 (Kuhn and Shen 2023, Flory et al. 2015), 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, Gill et al. 2023) and the literature on worker selection into firms (see, e.g., Nekoei 2023, Gill et al. 2023, DeVaro et al. 2024). Third, the fact that inexperienced and experienced workers as well as males and females reacted differently in terms of application behavior and belief updating to the provided information provides novel evidence on the heterogeneity of worker preferences and belief-updating in a real-word setting (Del Carpio and Guadalupe 2022, Belot et al. 2022).

While our results are robust as regards the number of applications for entry-level jobs, they 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 leading to the hypotheses stated in Section 3.

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 agents 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 agent's utility from career advancement and shows a preference for career advancement of $\pi_w^{ca} \in [0, \infty)$.

Potential applicants are ex-ante uncertain about (i) the exact workplace flexibility and (ii) the career-advancement potential at the firm. Their priors for θ_g^f and θ_g^{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 growth. Additionally, applicants have a belief about the correlation between provided flexibility and career advancement. More formally, applicants have a common belief $\tilde{\rho}$ about the correlation coefficient of their priors, $\tilde{\theta}_g^f$ and $\tilde{\theta}_g^{ca}$. Moreover, let $\tilde{\theta}_E^f \perp \tilde{\theta}_I^f$ and $\tilde{\theta}_E^{ca} \perp \tilde{\theta}_I^{ca}$ hold.

For our further analysis, we make two assumptions.

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

Formally, Assumption 1 translates into $\theta^f > \bar{\theta}_E^f \geq \bar{\theta}_I^f$, and $\theta^{ca} > \bar{\theta}_E^{ca} \geq \bar{\theta}_I^{ca}$ as well as $\tau_E^f > \tau_I^f$ and $\tau_E^{ca} > \tau_I^{ca}$ hold. 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. 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 growth 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 $\theta^f > \bar{\theta}_E^f \geq \bar{\theta}_I^f$ and $\theta^{ca} > \bar{\theta}_E^{ca} \geq \bar{\theta}_I^{ca}$.[41] The signal s_c is assumed to be completely uninformative.[42]

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 their priors and signals s_f, s_{ca}. In case applicants observe the signal s_f, their posteriors are given by:

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

$$\hat{\theta}_g^{ca}(\tilde{\theta}_g^f, \tilde{\theta}_g^{ca}, s_f) = \tilde{\theta}_g^{ca} + \tilde{\rho} \cdot \sqrt{\frac{\tau^f}{\tau^{ca}}} \cdot \frac{\tau^{s_f}(s_f - \tilde{\theta}_g^f)}{\tau^{s_f} + \tau^f} \tag{4}$$

[41] We may interpret θ^f and θ^{ca} as the true level of flexibility and career-advancement opportunities provided by the firm.

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

In case applicants observe the signal s_{ca}, their posteriors are given by:

$$\hat{\theta}_g^{ca}(\tilde{\theta}_g^{ca}, s_{ca}) = \frac{\tilde{\theta}_g^{ca}\tau_g^{ca} + \tau^{s_{ca}} s_{ca}}{\tau_g^{ca} + \tau^{s_{ca}}} \tag{5}$$

$$\hat{\theta}_g^{f}(\tilde{\theta}_g^{ca}, \tilde{\theta}_g^{f}, s_{ca}) = \tilde{\theta}_g^{f} + \tilde{\rho} \cdot \sqrt{\frac{\tau^{ca}}{\tau^{f}}} \cdot \frac{\tau^{s_{ca}}(s_{ca} - \tilde{\theta}_g^{ca})}{\tau^{s_{ca}} + \tau^{ca}} \tag{6}$$

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 (4) and (6) collapses to the respective prior beliefs. Since the *control treatment* does not contain information about flexibility or career growth, such job ads do not shift agents' priors.

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

$$\Delta U|s_f(w, g, \tilde{\rho}) = \frac{\tau^{s_f}}{\tau_g^{f} + \tau^{s_f}}(\theta^{f} - \bar{\theta}_g^{f}) \cdot \left(\pi_w^{f} + \pi_w^{ca}\sqrt{\frac{\tau^{f}}{\tau^{ca}}}\tilde{\rho}\right) \tag{7}$$

$$\Delta U|s_{ca}(w, g, \tilde{\rho}) = \frac{\tau^{s_{ca}}}{\tau_g^{ca} + \tau^{s_{ca}}}(\theta^{ca} - \bar{\theta}_g^{ca}) \cdot \left(\pi_w^{ca} + \pi_w^{f}\sqrt{\frac{\tau^{ca}}{\tau^{f}}}\tilde{\rho}\right) \tag{8}$$

Given our previous discussion, we can now analyze the expected utility change in more detail. Considering (7) and (8), 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. Additionally, given our assumptions, $(\theta^f - \bar{\theta}_g^f)$ and $(\theta^{ca} - \bar{\theta}_g^{ca})$ are larger for $g = I$ than for $g = E$. Due to the assumed difference in prior precision, the same is true for $\frac{\tau^{s_f}}{\tau_g^f + \tau^{s_f}}$ and for $\frac{\tau^{s_{ca}}}{\tau_g^{ca} + \tau^{s_{ca}}}$. This leads to Proposition 1, which is the basis for Hypotheses 1 and 2 in our conceptual framework in Section 3.

Proposition 1. *If $\tilde{\rho}$ is not too small, both treatments increase on average the total number of applications, and the increase is on average larger for applicants from group $g = I$.*

Considering (7) and (8) further, we observe that π_w^{ca} and π_w^f enter the expressions positively. Thus, the larger both are, the larger the total expected utility change is. 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 Hypothesis 3.

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. Robustness

In this Section of the Appendix, we present several robustness checks with respect to our main analyses. In Section 8.2.1, we present a re-estimation of Equation (1) to estimate the treatment effects using a Poisson fixed-effects regression. In Section 8.2.2, we provide several analyses providing evidence that spillover effects do not pose an identification threat for our empirical investigation in Section 5.2. In Section 8.2.3, we present regression-based analyses providing alternative estimators for the treatment effects on the composition of the applicant pool in terms of region of residence and quality, which were descriptively analyzed in Section 5.3.

8.2.1. Alternative estimator

Table A.1 presents the results of a re-estimation of Equation (1) using a Poisson fixed-effects estimator. More precisely, we use a Pseudo-Poisson-ML estimator relying on the *ppmlhdfe* package in Stata (Correia et al. 2020). Columns 1 to 3 show the estimated treatment effects on the total number of applications to entry-level jobs, while Columns 4 to 6 show the estimated effects for jobs that require previous work experience. All estimations include job-ad and time fixed-effects, and standard errors clustered on job-ad level.

The results are quite similar compared to the OLS fixed-effects regressions presented in Table 4 in Section 5.2. We begin to analyze the effect on the total number of applications for entry-level job ads. The point estimate of the *flexibility* treatment is 0.449 and highly significant. To interpret these coefficients, we consider the incidence ratio, which is the exponential of the coefficient, and gives the marginal estimated factor change of the mean of the dependent variable. For the *flexibility* treatment, this ratio is 1.57, which means that the estimated increase of applications amounts to 57%. Compared to the estimate in Section 5.2 of an increase of 44%, this estimate is quite similar in magnitude. For the *career* treatment, the point estimate is 0.333, corresponding to an incidence ratio of 1.40 and thus an estimated increase of 40%. Again, this estimate is quite similar in magnitude to the OLS estimate, amounting to an increase of 35%.

Equally, the results in Columns 2 and 3 are comparable to those presented in Table 4. In Column 2, which estimates treatment effects for male applicants only, we estimate an incidence ratio of 1.47 for the *flexibility* treatment, corresponding to an increase of 47% (compared to 37% from the OLS estimation). For the *career* treatment, we estimate an incidence ratio of 1.44, corresponding to an increase of 44% (compared to an estimate of 41% from the OLS regression). In Column 3, which presents the treatment effects for female applicants, we observe an incidence ratio of 2.02, amounting to an estimated increase of 102% (compared to an increase of 82% from the OLS regression). Equally to the results in Section 5.2, we can reject $\beta_f = \beta_{ca}$ for female applicants, but not for male applicants.

Table A.1: Treatment effects on the number of applications

	No. of applications - Poisson					
	Inexperienced			*Experienced*		
	All	Male	Female	All	Male	Female
	(1)	(2)	(3)	(4)	(5)	(6)
Flexibility	0.449***	0.388**	0.704**	-0.005	0.037	-0.205
	(0.147)	(0.162)	(0.315)	(0.161)	(0.182)	(0.203)
Career	0.333**	0.364**	0.095	0.031	0.034	-0.093
	(0.163)	(0.163)	(0.382)	(0.119)	(0.116)	(0.254)
Observations	827	827	569	1662	1610	908
Mean dep. variable	0.46	0.38	0.08	0.37	0.37	0.37
No. of Clusters	32	32	24	64	62	35
IRR Flexibility	1.57	1.47	2.02	0.99	1.04	0.81
IRR Career	1.40	1.44	1.10	1.03	1.04	0.91

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. Columns 1 to 3 present the effects for job ads requiring no previous work experience, while Columns 4 to 6 present the effects for job ads requiring previous work experience. Columns 1 and 4 show the effect for the total number of applications, Columns 2 and 5 only for the number of male applicants, and Columns 3 and 6 only for the number of female applicants. Standard errors clustered on job-ad level are reported in parentheses.
$^{*}< 0.1$, $^{**}< 0.05$, $^{***}< 0.01$

8.2.2. Spillover analysis

In this Section, we investigate potential spillover effects that may arise if interested applicants look at a job ad on several days, with a change in treatment in between. Such spillovers may arise as applicants are exposed to more than one treatment, and may lead to a downward bias in our main estimates. Moreover, it is conceivable that particularly effective or ineffective treatments have lasting effects beyond the ten-day period being shown on the job ad. To alleviate the risk of spillovers in the first place, we have excluded the day of the treatment switch and the day after in our main analysis in Section 5.2.

To investigate spillovers, we provide two types of analyses: i) We investigate time heterogeneities in treatment effects; and ii) We investigate the relevance of lagged treatments.

First, we present time heterogeneities in treatment effects with respect to the ten-day periods. More precisely, we re-estimate Equation (1) and include interaction terms for each ten day period. The result is presented in Column 1 of Table A.2. We observe that the baseline point estimates of the treatment effects (measuring the effect for the first ten days) is slightly larger than the ones presented in the main part, while we observe noisy point estimates of the time-interaction effects. Overall, we conclude that there is no evidence for strong time trends in the estimated treatment effect. This evidence speaks against the existence of spillover effects, as spillovers should be more likely to occur over time leading to changes in treatment effects over time.

In Columns 2 to 4, we a re-estimate Equation (1) including the first lag of the treatment. In Column 2, we include only the lag for the *flexibility* treatment, and in Column 3 only the lag for the *career* treatment; in Column 4, we include both. Including lags allows us to investigate whether a particular treatment is predictive of the number of applications beyond the ten-day period. It also allows us to see if including lags changes the magnitude of the estimates of our main treatment effects. From Column 2 to Column 4, we observe that the point estimates are relatively stable and in size all very close to the estimation in the Table 4. We only note a weakly significant point estimate of the *flexibility* lag in Column 2. Overall, this provides strong evidence that spillovers are not relevant for the estimated size or significance of our main treatment effects.

Table A.2: Robustness - Time heterogeneity and lags

	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)
Observations	829	829	829	829
No. of Clusters	0.46	0.46	0.46	0.46
Mean dep. variable	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 *growth* 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

8.2.3. Further results

In this Section, we provide a regression-based analysis of the mean differences analyzed descriptively in Section 5.3. In particular, we re-estimate Equation (1) and use either the total number of applications of each place-of-residence category as an outcome variable (these results are presented in Table A.3), or the total number of each recruiter rating category as an outcome variable (these results are presented in Table A.4).

Table A.3: Treatment effects by category - Region of residence

	Region of residence of applicants - OLS		
	Germany w/o state	State	Abroad
	(1)	(2)	(3)
Flexibility	0.121**	0.020	0.033
	(0.047)	(0.031)	(0.042)
Career	0.125**	0.034	-0.025
	(0.050)	(0.039)	(0.026)
Observations	829	829	829
No. of Clusters	32	32	32
Mean dep. variable	0.21	0.13	0.12

Notes: This table shows the impact of the treatments on the number of received applications per day by region of residence of the applicants. The outcome variable of Column 1 is the number of daily applicants who live in Germany, but not in the federal state of the firm (Germany w/o state). The outcome variable of Column 2 is the daily applicants living in the federal state of the firm (State). The outcome variable of Column 3 is the daily number of applicants living abroad (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.
*< 0.1, **< 0.05, ***< 0.01

Table A.4: Treatment effects by category - Quality

	Quality of applicants - OLS				
	A	B	C	Screened out	Interview
	(1)	(2)	(3)	(4)	(5)
Flexibility	0.018	0.035	0.045	0.073	0.039
	(0.014)	(0.027)	(0.038)	(0.053)	(0.027)
Career	0.035*	0.027	0.030	0.045	0.071*
	(0.018)	(0.018)	(0.026)	(0.060)	(0.038)
Observations	829	829	829	829	829
No. of Clusters	32	32	32	32	32
Mean dep. variable	0.06	0.08	0.12	0.20	0.12

Notes: This table shows the impact of the treatments on the number of received applications per day depending on the quality of the applicant measured by means of recruiter ratings. The outcome variable of Column 1 is the number of daily applicants with an *A* rating. The outcome variable of Column 2 is the number of daily applicants with a *B* rating. The outcome variable of Column 3 is the daily number of applicants with a *C* rating. The outcome variable of Column 4 is the number of daily applicants who were screened out and of Column 5 of applicants being invited to an interview. The estimates are obtained using standard OLS fixed-effect regressions, thus the marginal effects need to be interpreted in terms of change in the number of applications per day. All specifications include job ad and time fixed effects. Standard errors clustered on job-ad level are reported in parentheses.
*< 0.1, **< 0.05, ***< 0.01

8.3. Survey experiment

This section presents additional material of our survey experiment. Table A.5 presents the different labs and the corresponding participant numbers, while Table A.6 presents summary statistics of the data collected. In Section 6, we present all results in terms of composite scores. Table A.7 presents the results for each single item of the composite score for the beliefs about job characteristics (Section 6.2), while Table A.8 presents the results for each single item of the composite scores of the beliefs about the working environment (Section 6.3). Lastly, Table A.9 presents the treatment effects for items not used in our analysis in Section 6.

Table A.5: Survey - Laboratory and treatment

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 A.6: Summary statistics by treatment

	Control		Flexibility		Career	
Variable	Mean	SD	Mean	SD	Mean	SD
A. Background variables						
Female	0.421	0.494	0.375	0.484	0.380	0.486
At least Bachelor degree	0.609	0.488	0.527	0.500	0.556	0.497
At least one child	0.038	0.192	0.043	0.203	0.031	0.174
Migration background	0.458	0.499	0.402	0.491	0.451	0.498
STEM background	0.683	0.466	0.690	0.463	0.696	0.461
B. Beliefs about job characteristics						
Work-life balance	36.297	8.354	37.170	8.732	35.317	8.727
Career benefits	25.565	6.141	25.419	6.305	26.594	5.760
C. Beliefs about working environment						
Friendly	80.414	23.883	82.274	24.445	80.987	22.968
Competitive	130.561	45.175	128.640	43.424	134.330	44.403
Observations	706		723		707	

Notes: This table presents summary statistics categorized by treatment status. Panel A provides an overview of background variables. Panel B focuses on our two indicators characterizing beliefs about job characteristics: work-life balance and career benefits. Work-life balance adds up ratings about expected flexibility, work-life balance, home-office, childcare support, projected overtime, and family-friendly workplace culture (with $\mu = 26.268$, $\sigma = 8.636$). Career benefits adds up ratings about expected salary, provided salary growth, career opportunities, how challenging the tasks of the jobs are, and the possibility of negotiating salary increases (with $\mu = 33.064$, $\sigma = 7.063$). Panel C provides a summary of beliefs about the working environment, including whether it is either friendly (female- and family-oriented) or competitive. Friendly working environment adds up beliefs about the share of colleagues who are female and have a family (with $\mu = 81.233$, $\sigma = 23.78$). Competitive working environment adds up survey questions about beliefs about the share of colleagues who prioritize their career over having a family, who are eager to have a career, who have a STEM degree and earn a high income (with $\mu = 199.722$, $\sigma = 54.264$).

Table A.9: Distractor items

	Part-time	Travel	Location	Security	Reputation	Old
	(1)	(2)	(3)	(4)	(5)	(6)
Flexibility	-0.076	-0.261	0.016	-0.104	-0.053	0.091
	(0.141)	(0.162)	(0.103)	(0.123)	(0.124)	(1.064)
Career	-0.212	-0.198	-0.104	-0.136	0.087	-1.376
	(0.191)	(0.244)	(0.146)	(0.099)	(0.152)	(1.096)
Observations	2136	2136	2136	2136	2136	2136
No. Clusters	20	20	20	20	20	20
Job FE	Yes	Yes	Yes	Yes	Yes	Yes
Lab FE	Yes	Yes	Yes	Yes	Yes	Yes
Controls	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. Controls include gender, high-school GPA, migration background, university degree, and family status. Standard errors clustered on job-ad level are reported in parentheses.
$^{*}< 0.1$, $^{**}< 0.05$, $^{***}< 0.01$

Table A.7: Belief updating about job characteristics

	Preferred workplace characteristics										
	Work-life balance						*Career benefits*				
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)
	Flexibility	Work-life balance	Working from home	Childcare	Family	Overtime	Salary	Career	Salary growth	Challenge	Negotiation
Flexibility	0.305**	0.206***	0.225*	0.133	0.108	0.164	-0.026	-0.038	0.016	0.023	-0.033
	(0.110)	(0.069)	(0.125)	(0.111)	(0.117)	(0.107)	(0.080)	(0.092)	(0.105)	(0.109)	(0.101)
Career	-0.038	-0.229**	-0.021	-0.155	-0.131	-0.232*	0.050	0.233*	0.601***	0.088	0.173**
	(0.107)	(0.099)	(0.131)	(0.111)	(0.105)	(0.130)	(0.083)	(0.123)	(0.088)	(0.137)	(0.080)
Observations	2136	2136	2136	2136	2136	2136	2136	2136	2136	2136	2136
No. Clusters	20	20	20	20	20	20	20	20	20	20	20
Job FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
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

Note: The table shows the impact of the treatments on the beliefs about the individual items describing job characteristics: expected flexibility, work-life balance, working from home, childcare support, family-friendly workplace culture, projected overtime, expected salary, career opportunities, salary growth, and the possibility to negotiate salary increases. Controls include gender, high-school GPA, migration background, university degree and family status. Standard errors are clustered on job ad level and are reported in parentheses. $^{*}< 0.1$, $^{**}< 0.05$, $^{***}< 0.01$ respectively.

Table A.8: Belief-updating about work environment

	Beliefs					
	Friendly		*Competitive*			
	(1) Female	(2) Family	(3) Income	(4) Ambitious	(5) Career	(6) STEM
Flexibility	0.874	1.255	-0.704	-0.148	-1.019	-0.860
	(0.575)	(0.910)	(1.104)	(1.251)	(1.156)	(0.889)
Career	0.881	-0.037	1.330	2.161**	0.555	0.610
	(0.831)	(1.018)	(1.315)	(0.932)	(1.318)	(1.166)
Observations	2136	2136	2136	2136	2136	2136
No. Clusters	20	20	20	20	20	20
Job FE	Yes	Yes	Yes	Yes	Yes	Yes
Lab FE	Yes	Yes	Yes	Yes	Yes	Yes
Controls	Yes	Yes	Yes	Yes	Yes	Yes

Note: This table shows the impact of the treatments on the beliefs about the individual items describing the working environment: the share of colleagues who are female, have a family, the share of colleagues prioritizing career over family, who are eager to have a career, have a STEM degree and earn a high income. Controls include gender, high-school GPA, migration background, university degree, and family status. Standard errors clustered on job-ad level are reported in parentheses. $^{*}< 0.1$, $^{**}< 0.05$, $^{***}< 0.01$ respectively.