(Mis)Perceptions of the Labor Market*

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Abstract

Workers and firms make costly decisions based on what they think is valued in the labor market. We study whether employers and workers hold accurate perceptions about the preferences of others through a series of incentivized field experiments on one of Europe's largest freelance platform. First, we elicit employer and worker preferences over a rich set of worker, employer, and job characteristics using randomized worker profile and job offer evaluations. Second, we elicit beliefs about these preferences, from the other side of the market as well as from competitors, and we test their accuracy. We document substantial *perception gaps* about labor market preferences on both sides of the market, including about the value of posted wages, human capital, market reputation, job amenities like remote work, and demographic characteristics. Third, we implement a personalized information treatment to correct these gaps and show that it changes participants' market behavior. To help interpret our results, we develop a theoretical framework showing how the *perception gaps* we document can distort both pricing and investment decisions. Consistent with the model, we find that workers and firms with larger *perception gaps* have worse market outcomes. Our findings highlight an important source of information frictions in labor markets and their economic consequences.

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1 Introduction

Workers and firms make costly decisions based on what they think is valued in the labor market. Workers choose which skills to invest in, which jobs to apply to, how to present themselves, and what wages to ask. Firms choose what to pay and which job amenities to offer. When these beliefs are inaccurate, workers may invest in characteristics firms do not value or misjudge how to position themselves relative to other workers, while firms may spend on compensation or amenities that do little to attract workers or compete effectively with other firms.

Such misperceptions can distort investment, pricing, and matching even when information about available workers and jobs is readily accessible. Yet we know relatively little about whether workers and employers accurately perceive each other's preferences. Observed labor market outcomes are not sufficient to answer this question: wages, credentials, and amenities are chosen endogenously, and the resulting matches reflect the beliefs and decisions of both sides of the market. It is therefore difficult to distinguish what market participants value from what others believe they value.

In this paper, we conduct a series of incentivized field experiments on one of Europe's largest freelance work platform to identify *perception gaps* – discrepancies between the preferences of market participants and beliefs of other participants about these preferences – for a rich set of worker, firm, and job characteristics. We first conduct *Evaluation* experiments to elicit recruiters' (workers') preferences over worker (recruiter and job) characteristics. We then conduct *Prediction* experiments to elicit recruiters' and workers' beliefs about these preferences.

We study *perception gaps* regarding both demand and competition. In particular, we study four sets of beliefs: (i) workers' beliefs about recruiters' preferences for worker characteristics; (ii) recruiters' beliefs about workers' preferences for recruiter and job characteristics; (iii) recruiters' beliefs about competing recruiters' preferences for worker characteristics; and (iv) workers' beliefs about competing workers' preferences for recruiter and job characteristics. Together, our findings provide a comprehensive assessment of perceptions on both sides of the labor market.

In the *Evaluation* experiments, we present recruiters with hypothetical worker profiles that closely resemble those shown to recruiters on the platform when contacting a worker and present workers with hypothetical job offers that closely resemble those shown to workers when they are contacted. Recruiters (workers) first select one of nine job categories that characterizes the type of job they hire for (perform) on the platform. They then evaluate 25 profiles (job offers) within their job category and report i) their interest in hiring the worker (accepting the job) and ii) the likelihood that the worker would accept an offer from them (that a recruiter would have offered them the job). Profiles and offers are tailored to each job category and specifically to participating recruiters' stated hiring needs and participating workers' expertise, based on information from real profiles and offers on the platform.

Within each profile and offer, we independently randomize key characteristics drawn from real platform data. Worker profiles vary human capital, market reputation, work conditions (e.g., in-person availability), demographics (gender and ethnicity), and asked wage. Job offers vary the offered wage, firm characteristics and reputation, non-wage amenities (e.g., remote work), job duration, and recruiter demographics. This design delivers causal estimates of the return to each characteristic while preserving realism and relevance. Evaluations are incentivized following the Incentivized Resume Rating (IRR) approach of Kessler et al. (2019): although profiles and offers are hypothetical, participants' evaluations are used to recommend them real workers and for real jobs.

Results for recruiters indicate negative responses to higher asked wages, although these also act as signals of competence, attenuating the negative price effect. Recruiters also value market reputation and work experience, but, consistent with these already adequately signaling competence, they do not value more general ability signals like having worked at prestigious firms or having a higher-education degree. We find no evidence of gender discrimination and only limited evidence of discrimination against workers of Middle Eastern and North African (MENA) origin. Recruiter evaluations indicate similar interest in hiring ethnic minority profiles, but they are evaluated slightly more negatively (5% of a standard deviation) on the likelihood that they would accept a job offer.

Results for freelancers indicate strong wage sensitivity, with higher offered wages generating large increases in acceptance interest. Freelancers attach little value to characteristics of the recruiter or their organization (e.g., market reputation, recruiter demographics) but attach substantial value to working conditions. For example, remote work is highly valued and longer jobs are marginally preferred, while jobs requiring tight or stressful deadlines are penalized.

Next, in the *Prediction* experiments, we recruit recruiters and workers to predict the average evaluations of participants from the *Evaluation* experiments, within their own job category. Using the same profiles and offers, we randomly assign participants to one of four groups. Half of recruiters predict how workers evaluated job offers, while the other half predict how recruiters evaluated worker profiles. Similarly, half of workers predict recruiters' profile evaluations, and the other half predict workers' offer evaluations. Each participant makes 25 predictions. Predictions are incentivized based on their accuracy using a binarized scoring rule (Healy and Leo, 2025). Comparing estimates between the *Evaluation* and *Prediction* experiments tests the accuracy of beliefs about the valuation of each characteristic, identifying misperceptions across and within each side of the market.

The results reveal several economically meaningful *perception gaps* on both sides of the market and regarding both demand and competition. On average, participants make prediction errors of approximately 1.68 points on a 10-point scale — roughly two thirds of a standard deviation in evaluation ratings — and more than half of these errors are explained by misperceptions about the value of specific characteristics we randomize.

Beliefs about worker preferences are the most accurate, although both recruiters and competing workers misperceive preferences consequentially, namely on wages and working conditions: they overestimate how reactive workers are to offered wages relative to other characteristics and underestimate how much workers value remote work. These gaps can be quite substantial in terms of valuation and tend to be slightly larger for predictions of recruiters than those of competing workers. For example, the gap on remote work corresponds to an underestimation of workers' willingness to forego wages for remote work by €300-400 per month.

Predictions of recruiter preferences are the least accurate. Workers strikingly underestimate the negative effect of higher asked wages on recruiter interest and both workers and competing recruiters substantially overestimate the returns to market reputation, work experience, and prestigious credentials. We also find evidence that predictors expect recruiters to discriminate against workers of MENA origin, especially when these predictors are themselves of MENA origin. These gaps are larger for predictions of workers than those of competing recruiters and they are substantial, with some amounting to misperceptions of recruiter willingness to pay for certain characteristics by over €1,000 per month.

These gaps are robust to a number of measurement and interpretation considerations. They vary meaningfully across different job categories, namely tech and non-tech jobs, and they do not appear smaller for more experienced market participants. We also estimate that average gaps conceal substantial heterogeneity among individual predictors; since misperceptions distort behavior and outcomes at the individual level, even the absence of an average gap can be associated with important aggregate distortions.

After participants make their predictions, we implement a personalized information treatment about the marginal impact of each characteristic on evaluations to correct perceptions. Most participants report finding the feedback useful, especially regarding wages, and intend to change their market behavior in response (profiles for workers and job offers for recruiters). We test how worker intentions translate to real changes using data on profile updating around the time of the experiment within a Differences-in-Differences design using non-contacted workers as a comparison group. We find a three to five percentage point or 300-500% increase in the rate of workers updating their profile on the day of the treatment, showing that market participants recognize the importance of these information frictions and indicating substantial scope for policy interventions.

We then study the consequences of *perception gaps*. First, we present a theoretical framework focusing on beliefs of workers and recruiters about the preferences of the other side of the market. The model highlights two channels through which gaps distort market outcomes. First, holding characteristics fixed, gaps distort pricing decisions. Second, allowing for investment in characteristics (e.g., organizing production for remote work), the same gaps distort investments. In both cases, gaps can reduce expected surplus by preventing some matches and lowering surplus from realized matches. The framework yields insights on important economic phenomena through the lens of these information frictions. For firms, it relates intuitively to pay premia, (lack of) compensating differentials, and labor shortages. For workers, it relates to skill mismatch and over-credentialing, unemployment, and wage inequality.

In line with the model, we document that individual-level perception gaps elicited through the experiment correlate with behavior and outcomes in the market. In particular, both workers and recruiters are more likely to overestimate preferences for characteristics they posses or offer, consistent with investment distortions. Workers (recruiters) who overestimate preferences for characteristics they posses (offer) also ask higher (offer lower) wages, consistent with pricing distortions. These distortions are associated with real market consequences: workers (recruiters) with larger perception gaps regarding the value of characteristics they possess (offer) have fewer successful matches and have lower earnings (pay higher wages).

This paper contributes to six strands of literature, with our main contribution consisting of identifying *perception gaps* about market preferences over a rich set of worker and job characteristics, on both sides of a real labor market. First, estimating returns to workers' search and investment decisions as well as the impact of their demographic characteristics has often proven challenging (Topel, 1991; Card, 2001; Charles and Guryan, 2011). We provide causal estimates of the returns to a rich set of worker characteristics relating to human capital, market reputation, discrimination, working conditions, and asked wage, using incentivized experiments set within an economically meaningful labor market environment.

More importantly, we compare expected returns to their realized counterparts. Because worker decisions depend on subjective beliefs which may or may not correspond to objective returns, measuring both is essential but empirically challenging (Fuster and Zafar, 2023; Caldwell et al., 2025; Lepage et al., 2025). Even for fixed characteristics, beliefs matter because they influence related behavior like pricing. Existing evidence is rare and limited in scope, typically focusing on a narrow set of characteristics or on college students' beliefs about employer preferences for characteristics like grades and internships (Exley et al., 2024; Caron and Erda, 2026).[1] Our results show that even workers already active

[1]Exley et al. (2024) and Caron and Erda (2026) use results from IRRs with college recruiters to incentivize college students' predictions about the impact of omitting GPA on CVs and about other elements typically contained on student CVs, respectively. Relating to beliefs of anticipated discrimination, Angeli

in the labor market missperceive the value of several characteristics that they possess or could possess.

Second, a growing literature studies how firms set wages and non-wage amenities to attract and retain workers, who attach substantial value to working conditions (Mas, 2025). We provide causal estimates of the returns to a rich set of employer and job characteristics including wages, market reputation, non-wage amenities, and recruiter demographics.[2] Again, more importantly, comparing employers' subjective expectations of these returns to realized returns in an incentivized way has rarely been feasible, even though such comparisons are central to understanding how compensation policies translate into hiring outcomes. The only related evidence of which we are aware is from a contemporaneous paper using an unincentivized survey with vignettes to show evidence consistent with German firms underestimating workers' valuation for non-wage amenities (Cordes and Müller, 2026). Our results show that employers have more accurate beliefs about the other side of the market than workers do, but that they still hold important misperceptions about worker preferences for both wages and non-wage amenities.

Third, labor market returns depend not only on demand, but also on supply from competing workers and firms. Strategic positioning is central to succeeding in economic markets and depends on beliefs about competitors' preferences and choices, which may also be inaccurate (He et al., 2023; Bertheau and Hoeck, 2025; Cullen et al., 2025).[3] To our knowledge, we are the first to experimentally estimate *perception gaps* about competitors' preferences in the labor market, finding that they are similar but quantitatively smaller than gaps about the preferences of the other side of the market.

Taking our results on both sides of the market together makes clear how coordination failures from these information frictions can arise. Since each side potentially misperceives their own side, the other side, and others' misperceptions, it appears exceedingly complex for agents to learn about the market, even from a large set of observed outcomes. The set of market participants, equilibrium prices and investments, and matching can all be

et al. (2023) find that residents of Brazilian favelas overestimate the extent of discrimination they may face, which distorts their job application behavior.

[2]Russell and Shah (2025) uses an IRR experiment to elicit worker preferences over amenities in India to show that firms frequently omit to mention that they provide amenities valued by workers in their job ads.

[3]A large literature in industrial organization studies the role of firms' biased beliefs about their competitors. See Aguirregabiria and Jeon (2020) for a review.

distorted by the *perception gaps* we document.

Fourth, we contribute to the literature on information frictions and their implications for market efficiency and welfare. Agents routinely hold misperceptions about others (Bursztyn and Yang, 2022; Bursztyn et al., 2023; Exley et al., 2025) and workers (Conlon et al., 2018; Mueller et al., 2021; Bryan et al., 2022; Sockin and Sojourner, 2023; Jäger et al., 2024; Miano, 2025) as well as firms (Friedrich and Zator, 2024; Abebe et al., 2025) have inaccurate beliefs about certain aspects of the labor market like wage distributions. We instead focus on inaccurate beliefs about other market participants' preferences, which shape labor market returns. As our theoretical framework and information treatment make clear, inefficient pricing and investment decisions can arise from these misperceptions even absent commonly studied frictions such as search or bargaining. The *perception gaps* we document provide an information microfoundation for labor market frictions and could constitute a source of monopsony power for better-informed agents.

Fifth, we implement incentivized field experiments combining strengths from prior approaches. Our collaboration with the platform provides rich administrative data on profiles, offers, and job outcomes, near-universal access to users, and the ability to recommend real workers and jobs to participants.[4] We extend the IRR literature by estimating preferences on both sides of the market, with larger samples of participants and tailored profiles and offers within narrow job categories. We are also able to assess the representativeness of our participant pool and validate our experimental results using data on platform behavior, a key advantage of our setting. In particular, we show that the preferences and *perception gaps* we estimate relate intuitively to recruiters' hiring needs, to workers' profile characteristics, and to realized market outcomes. For example, reported interest in hiring a profile or accepting a job in the *Evaluations* experiment depends sharply on whether the experimental profile is above or below a recruiter's budget for their next hire and whether the experimental offer is above or below a worker's asked waged indicated on their platform profile. Similarly, workers who indicate only being available for remote work on their profile are more likely to overestimate how much recruiters value this characteristic on a worker's profile.

[4]See Deschamps et al. (2025) for an example of combining administrative data with experiments on both sides of a market to estimate the role of safety concerns in carpooling.

Our collaboration allows us to conduct experiments without deception, under the truthful guise of the platform conducting studies to improve its matching, without mentioning to participants that they are part of an academic study. This mitigates concerns with experimenter demand bias (Agan et al., 2023). Doing so within the IRR methodology has some advantages over other approaches like correspondence studies (Bertrand and Mullainathan, 2004; Kline et al., 2022) because participants make several evaluations on a detailed scale and across more than one dimension, going beyond binary callbacks.[5] Our *Evaluation* experiments share similarities with vignette experiments (e.g., Maestas et al. (2023)), but are conducted in a market setting with high stakes – the average job on the platform carries a wage budget of several thousands of euros. Furthermore, by showing realistic profiles and offers which vary several characteristics, we avoid concerns with vignette studies yielding biased preference estimates when considering one or a few characteristics in isolation (Jäger et al., 2026). Crucially, the incentivized evaluations allow for a straightforward and transparent incentivization of the *Prediction* experiments. Our approach could be applied to study information frictions in other settings, including housing, consumer, and capital markets.

Sixth, we contribute to the literature on online labor markets and freelancing, sectors of rapidly growing importance, especially following the COVID-19 pandemic. For example, 38% of the U.S. workforce performed some freelance work in 2023, for a total of 1.27 trillion in annual earnings (Upwork Research Institute, 2023). Moreover, most workers in our experiments report that freelance work accounts for a majority of their total earnings. The ability of platforms to match their users is key for success, whether for freelancing, traditional job boards, or rental and marketplaces (Cullen and Farronato, 2021; Echenique et al., 2023). Our results indicate that platforms lose out on beneficial matches because users misperceive preferences of other users, leading them to behave inefficiently.[6] Our results also indicate scope for changes in the design and recommendation algorithms of platforms, with the notion of providing information to users, whether

[5]Correspondence studies are also less well-suited to study both sides of the market at once. In our setting, firms contact workers, precluding a traditional correspondence study sending profiles to firms. In other settings often considered in correspondence studies, workers are typically not contacted by firms without first applying, precluding a correspondence study sending job offers to workers.

[6]Entry in these markets may also be distorted by the *perception gaps* we document, providing a channel through which workers misperceive returns to freelancing or gig work relative to traditional salaried work (Pires, 2022; Freeland et al., 2026).

through pricing guidance, algorithmic nudges, or the provision of information on job-level outcomes.[7] Relative to traditional labor markets, the environment we study arguably provides richer information to users, features frequent interactions over shorter-term contracts, and involves narrowly defined tasks, suggesting that the information frictions we document could be even more important in other settings.

The rest of the paper is organized as follows. In section 2, we introduce the platform and administrative data. In section 3, we describe the experimental design of the *Evaluation* and *Prediction* experiments, as well as our empirical strategy. In section 4, we present the results of the *Evaluation* experiments. In section 5, we present the results of the *Prediction* experiments and evidence on *perception gaps*. In section 6, we present the results of the information treatment to correct perceptions. In section 7, we investigate the consequences of the information frictions we document, presenting a theoretical framework followed by quantification exercises of the impact of gaps on platform outcomes. Section 8 concludes.

2 The platform

We study one of the largest platforms for freelance work in Europe. Founded over 10 years ago, it operates online in over 15 countries and had a total revenue of around 1 billion € in 2025. We focus on its largest market, France. The platform covers a wide range of mostly high-skilled occupations, including technology (e.g., developers) and other jobs like marketing and communication. Jobs vary substantially in duration (from one day to six months), daily wage rates (€125 to €1200), weekly hours (part-time to full-time), and working conditions (e.g., fully remote to fully in person). The average completed job has a budget of several thousands of euros and lasts around one month, indicating that jobs are economically meaningful. For 75% of workers in our experiments, freelancing is their main source of income.

We refer to freelancers as "workers," though they are independent contractors under French law, rather than employees. Jobs do not constitute employment contracts, and

[7] Roussille (2024) shows how an information-based design change on an online platform can play an important role in mitigating inequality in the context of the gender ask gap.

standard regulations regarding salaries, benefits, dismissals, etc. typically do not apply, resulting in flexible arrangements. Recruiters seeking to hire workers are typically representatives of a firm or organization, but may also represent individuals. Organizations represented on the platform range from single-person businesses to the largest French firms with tens of thousands of workers. Each account is tied to a specific individual recruiter, with an organization having multiple accounts if they have multiple recruiters on the platform, for example for different units or job types.

To join the platform, workers and recruiters create a free account and profile. Once completed and approved, worker profiles become visible to recruiters.[8] As is common in online labor markets, recruiters initiate contact after viewing profiles, including their asked wage (Roussille, 2024).[9]

Recruiters search for workers using keywords and filters that generate customized lists of profiles. They then contact workers by sending a "job offer," specifying the job description and its conditions. Alternatively, recruiters may purchase a paid matching service in which the platform directly contacts a shortlist of recommended workers on behalf of the recruiter. Our experimental design mirrors the process of using the search engine, which accounts for the vast majority of matches, though we leverage the matching service to incentivize worker evaluations as detailed below. The existence of this paid service highlights recruiters' willingness to pay for targeted recommendations, which we use to incentivize recruiter evaluations.

When contacted—either by a recruiter or via the platform's matching service—workers decide whether to apply by submitting a quote, which the recruiter may then accept, refuse, or propose changes to. Negotiation can follow by iterating over the quote, but our experiments abstract from this process by eliciting evaluations at the specific conditions stated on profiles and offers. We therefore focus on these two margins of the process: (i) how recruiters evaluate worker profiles when deciding whom to hire, and (ii) how workers evaluate job offers when deciding whether to accept a job.

[8] For a profile to be complete and valid, the worker must have connected recently, be available to accept jobs, have filled out key sections of their profile, and have received a minimum rating for completed projects.

[9] A large share of workers in the U.S. are asked for a desired salary during recruitment, even if it is not included in their application (Agan et al., 2020).

2.1 Administrative data

We have access to administrative data covering platform activity between 2021 and May 2026, including the content of profiles, job offers, and realized job outcomes. We use these data for several important purposes. First, they allow us to construct realistic and relevant profiles and job offers based on actual platform content. Second, linking experimental participants to their administrative records enables us to assess representativeness, validate experimental findings against platform information, and relate preferences and *perception gaps* to market behavior and outcomes. Third, this linkage allows us to examine whether our information treatment affects behavior, in particular workers changing their profile.

We present an overview of the platform's French activity for 2025 in Table 1, restricted to the subset of job types considered in our experiment: development, integration, translation, growth marketing, copywriting, as well as social media and community management. For confidentiality reasons, some of the summary statistics are reported as 10th-90th percentile ranges rather than means and some observation counts are reported as broad indicative ranges rather than exact counts. Panel (a) summarizes the universe of workers in those categories, restricted to profiles active and visible to recruiters for at least three months during the year. Workers are in their mid thirties on average, have been on the platform for just over two and a half years, and have slightly more than 11 years of work experience. The 10th percentile has completed 0 jobs and the 90th percentile has completed 7, while workers in the top 10% have often completed dozens of jobs. The average daily asked wage is €460. Most workers report being available full time and for in-person work. Just over 70% have completed at least a Master's degree, slightly over 40% of them are female, and slightly over 15% are classified as being of MENA origin.[10]

We then consider offers made by recruiters during the year in Panel (b). Recruiters who made at least one job offer have been on the platform for just over two years on

[10]Gender and ethnicity are not included in the platform data, but the researchers impute it from users' first names. For ethnic origin, we use the INSEE national first-name database, *Fichier des prénoms* (available at `https://www.data.gouv.fr/datasets/fichier-des-prenoms-depuis-1900`), augmented with data from Jouniaux (2001) and Hawramani (2015). This methodology has been used in previous work (e.g., Algan et al. (2022); Laouénan and Rathelot (2022)). Individuals of MENA origin represent the largest ethnic minority in France and have been the main focus of the French literature on discrimination. Regarding gender, we use the tool Genderize (available at `https://genderize.io/`), which infers the gender statistically most likely to be associated with a first name based on large-scale online data.

average, with most of them having offered between 1 and 5 jobs. The typical budget for a job varies largely, between €200 and €1,3870, for an average duration of one month. Just under 40 percent of offers require full-time work and around 17% require on-site work. Although we do not provide a breakdown of firm size in the table for confidentially reasons, most recruiter accounts are associated with smaller firms, consistent with over 90% of firms in the French labor market having less than 10 employees (Institut national de la statistique et des études économiques, Insee), although larger firms are slightly overrepresented on the platform.

3 Experimental design

This section describes the design of our field experiments and our empirical strategy for estimating *perception gaps* about labor market preferences. We describe the job categories included in the experiments, the construction of worker profiles and job offers, the experimental procedure, and the empirical strategy.

3.1 Job categories

The experiments focus on some of the most popular jobs on the platform: development, growth marketing, communication, and translation. These span tasks that differ substantially in skill requirements, wages, and work conditions (e.g., duration).

We partition these job types into narrower job categories. Development is divided into five categories: front-end, back-end, full-stack, mobile, and integration/content management system (CMS)/webmaster; communication is divided into two categories: content redaction as well as social media and community management. Along with growth marketing and translation, there are nine categories in total. These categories were defined in collaboration with the platform to ensure that workers within a category perform similar tasks using comparable skills and that the segmentation reflects how recruiters search on the platform. See Appendix D for a short description of each job category as provided to participants in the experiment and Table B.1 for some summary statistics by job category.

Profiles and job offers are constructed at the job category-level and, as detailed below, incorporate category-specific expertise (e.g., Java versus Python for developers). As a result, profiles and job offers shown to participants closely mirror their market segment, strengthening both incentive compatibility and the salience of the information treatment. It also ensures that the *perception gaps* we document capture participants' beliefs about their own specific market segment, rather than an aggregation of beliefs across more or less relevant segments. In contrast, prior work typically considers much broader categories like groupings of college majors and occupational groups (Kessler et al., 2019), or simplifies descriptions to more generic lists of attributes (Maestas et al., 2023).

We focus on these categories for two other reasons. First, they account for substantial supply and demand, allowing us to recruit sufficiently large participant samples within each category for both the *Evaluation* and *Prediction* experiments. Second, assessments for these jobs rely largely on characteristics included on profiles and offers. In contrast, some creative jobs (e.g., graphic design) depend heavily on individual artistic portfolios, which would be more difficult to randomize while preserving realism.

3.2 Constructing profiles and offers

Profiles and offers are designed to closely follow the format, layout, and content observed on the platform, but they are streamlined and standardized.

The content and distribution of each randomized characteristic are informed by administrative platform data, separately by job category. For example, the range of asked wages on profiles is based on the true range of the empirical distribution of asked wages within the relevant job category; the content of listed work experiences is based on real descriptions of work experiences in that job category; and the share of offers indicating part-time work requirements is based on the corresponding platform frequency in that job category. All attributes are independently randomized within each profile and offer, with the exception of a few characteristics only defined for those with at least one completed job on the platform, as discussed below.

3.2.1 Freelancer profiles

Appendix A presents an example of an experimental profile translated into English and the original French version. We briefly summarize the characteristics included and randomized below; more details are provided in Appendix A.

All profiles are constructed to be located in France, specifically in the participating recruiter's region, fluent in French, and proficient in English.[11] Profiles are also indicated as currently available, signaled on the platform through an "availability badge." These design choices ensure that recruiters evaluate profiles based on their underlying attributes, rather than concerns about geographic accessibility or platform activity.[12]

Asked wage. We fix the daily asked wage on a profile as the wage that a recruiter would have to pay to recruit the worker. In practice, asked wages are a strong predictor of realized wages (correlation of 0.93), consistent with prior evidence (Roussille, 2024).

Work experience. Experience is captured through total years of experience (on and off the platform) and a description of some specific past experiences. Years of experience are displayed using the platform's ranges (less than 3 years, 3–7 years, 8–15 years, more than 15 years) along with the exact number shown above the description of specific past experiences.

Each specific experience listed on a profile includes the name of the firm worked for, as well as a summary of tasks and achievements. Because only a limited number of experiences are visible by default on a profile (with the rest accessible by clicking additional buttons), we display one or two experiences per profile.[13] We construct a job category-specific bank of experiences from a random sample of real profiles, including firm names and free-text descriptions. Dates are removed and descriptions are standardized into two bullet points. All entries were manually reviewed by the research team and the platform to ensure relevance for the job category and remove references to gender, ethnicity, or senior managerial roles.

We identify a subset of experiences as "prestigious" based on the name of the associated firm, corresponding to French firms among the top 40 by market capitalization, known as the CAC40 (e.g., L'Oréal) and foreign firms of comparable or greater size (e.g., Amazon).[14]

[11] Most workers in the job categories we study report at least working proficiency in English on their profile, and virtually all report being fluent in French, including ethnic minority profiles.

[12] While existing work shows that commuting distance matters for job decisions (Le Barbanchon et al., 2021), the decision to commute or relocate across regions is less relevant for temporary freelance jobs.

[13] Since displaying only one or two experiences may appear unusual for workers with many years of experience, we explicitly indicate that only a representative subset is shown.

[14] The classification was reviewed by the platform to ensure that "non-prestigious" firms did not include widely recognized start-ups that might also be perceived as prestigious.

Prestige is randomized at the profile level: profiles display either no prestigious experience or exclusively prestigious experiences (one or two).

We test the impact of the following experience characteristics on evaluations: i) years of experience, ii) a second displayed work experience, and iii) listed work experiences are "prestigious" based on the included firm names.

Education. Profiles report the worker's highest completed degree and its institution. We include the following degrees, which are most common on the platform: higher technician certificate (BTS in France), university vocational diploma (DUT in France), bachelor's degree (license in France), and Master's (PhDs are rare). Education credentials are drawn from a random sample of real profiles within each job category. We remove degree dates and fields of study; fields vary little within job categories and dates could create inconsistencies with other profile characteristics.

We test the impact of having a Master's degree on evaluations, by far the most common highest completed degree, relative to one of the three others.

Market reputation. Profiles include the number of completed jobs on the platform, reviews for those jobs, and sometimes a reputation badge. A substantial share of active workers have never completed a job. To reflect this, we randomize a point mass at zero completed jobs and draw positive counts from the empirical distribution of completed jobs for remaining profiles.

For completed jobs, recruiters may leave a rating and optional text review. As is not uncommon in online markets, ratings are almost universally 5 out of 5, limiting their informational content. In contrast, there is meaningful variation in the share of completed jobs that receive a review, suggesting that leaving a review or not could be the relevant margin through which (lack of) satisfaction is signaled. We therefore randomize this share while assigning a constant average rating of 5 to reviewed profiles.[15]

Finally, we randomize the presence of a reputation badge, which is awarded to workers who complete jobs exceeding a certain value threshold over a given period. Recruiters can infer that the badge signals platform success, but do not observe the precise criteria for its assignment.

[15] We abstract from text reviews, which are less frequent, require additional clicks to view, and are overwhelmingly generically positive.

We test the impact on evaluations of the number of completed jobs, separating the impact of a first versus the impact of additional ones beyond the first, of the share of completed jobs for which a review was left, and of a reputation badge.

Work conditions. Profiles indicate whether the worker is available only for remote work or also for in-person jobs, and whether they are available full-time or part-time only. Part-time availability is indicated as 2–3 days per week, corresponding to the modal part-time arrangement on the platform.

Demographics. Demographic characteristics are signaled through first names and profile pictures. Pictures on the platform must correspond to the individual and typically consist of a professional headshot. For each job category, we compile lists of the 20 most common distinctively male and female French names of European origin and of MENA origin among workers. Names are randomly assigned to profiles from these lists.

Each name is paired with a picture matching its gender and ethnic origin. Pictures are AI-generated and blurred to preserve the salience of gender and ethnicity while limiting the transmission of additional signals.[16]

Results below indicate that gender and ethnicity are salient since participants anticipated discrimination against certain groups, but that they do not indicate to participants that the study's purpose relates to discrimination. Indeed, only one participant out of 69 in our piloting included discrimination among a list of potential purposes of the study when prompted using an open-ended question, consistent with our communication of the experiment as a platform initiative to improve matching.

We test the impact of signaled gender and ethnicity (independently) on evaluations.

Expertise keywords. Profiles include expertise keywords. Even within a job category, such keywords can be critical for determining suitability—for example, programming languages for developers (e.g., Java). Since jobs are often specific and relatively short, there is limited scope for general training or formation. Accordingly, as detailed further below, in the *Evaluation* experiments, recruiters are shown only profiles that possess the expertise keywords they themselves report as necessary prior to the evaluation stage.[17] Other

[16] Pictures were generated by randomly varying personal attributes (e.g, glasses, skin tone, clothes color, age) with the same distribution across ethnic origin and gender (with the exception of gendered attributes like facial hair or veils for a subset of individuals). The propensity of veils for female profiles of MENA origin was selected to match that of real profiles on the platform.

[17] Because profiles often list multiple expertise keywords beyond those required for a given job, we

profile elements are constructed to remain internally consistent with the listed expertise. For example, work experiences do not reference skills absent from the profile's expertise list.

3.2.2 Job offers

Appendix A presents an example of an experimental job offer translated into English and the original French version. We summarize the included and randomized characteristics below; Appendix A details their construction.

Job offers contain more free text entered by recruiters, similar to a standard job advertisement. We use text analysis of real offers to inform the content and structure of experimental offers. Each constructed offer corresponds to a job located in France, specifically in the participating workers's region, with a start date listed as "as soon as possible," the most common option on the platform.[18]

Offers include a task description that we draw from a category-specific pool of descriptions based on real offers. We do not test hypotheses related to task content, but their inclusion enhances realism. Descriptions were reviewed by both the platform and the research team to ensure relevance and consistency within each job category.

Offered wage. We fix the offered daily wage as the wage that a worker would receive if they accept.

Market reputation. Offers signal recruiter reputation through (i) the number of completed jobs on the platform (i.e. the number of times they hired a worker) and (ii) reviews from workers. We follow the same approach as for profiles: a point mass of recruiters has zero completed jobs, while positive counts are drawn from the empirical distribution. For recruiters with at least one completed job, we randomize the share that receive a review, while assigning a constant average rating of 5.

We test the impact on evaluations of the number of completed jobs, separating the impact of a first versus the impact of additional ones beyond the first, and of the share

randomly include 0–3 additional keywords on experimental profiles. These are selected to be similar to the required expertise to ensure natural combinations. We find that the presence of superfluous keywords does not affect evaluations.

[18]Since recruiters contact workers with offers, there is typically no mention of hard requirements that are easy to assess from a profile, like experience or education, since workers would not receive an offer for which they do not qualify along those margins.

of completed jobs for which a review was left.

Recruiter prestige. Each offer begins with a brief introduction of the recruiter and/or firm and lists organization size and industry in the right margin. We introduce a prestige signal analogous to that used for profiles, relying on the same classification of "prestigious" firms described above.[19] Because prestige is highly correlated with organization size, we do not attempt to separately identify their effect.

Work conditions. Each offer randomizes job duration, remote versus in-person requirements, and full versus part-time (2–3 days per week) requirement. Job duration varies from less than one week to six months.

Other job characteristics are occasionally mentioned in free text. We standardize and randomize two of the most common: whether the work is performed as part of a team, and whether the job involves tight or pressing deadlines.

We test the impact of the following five arrangements on evaluations: duration (in months), remote (yes versus no), full-time versus part time, teamwork requirement versus no mention of a requirement, and tight deadline requirement versus no mention of timelines.

Demographics. Offers include the first name of the recruiter but no picture.[20] This name corresponds to the individual responsible for hiring. We randomize names using job-category-specific lists of the most common names and again distinguish four groups: men and women of European origin, and men and women of MENA origin.

Expertise keywords. Offers include required expertise keywords. Because it would be implausible for workers to receive offers for tasks they cannot perform, we tailor offers to match each participating worker's self-reported expertise. For example, if a worker reports being able to code in Java but not Python, offers shown to them may require the former, but not the latter. Task descriptions are tailored to each job category and expertise keyword to ensure internal consistency. This helps address one key warning from Kessler et al. (2019) regarding the design of IRR studies: to carefully tailor content

[19] To avoid associating real firms with experimentally generated offers, we do not mention firm names and instead signal prestige through size and descriptions. For example, a prestigious firm may be described as "a large firm part of the CAC40," whereas a non-prestigious firm may be described as "a small regional business."

[20] Since offers have no pictures, similarity in results on the impact of demographic characteristics across profiles and offers suggests that the results below are unlikely to be driven by experimental choices regarding the inclusion of pictures in profiles.

to the needs of the participants.

3.3 Evaluation experiments

These experiments elicit preferences of recruiters about worker characteristics and of workers about recruiter and job characteristics. See Appendix D for the recruitment messages and experimental instructions.

3.3.1 Recruitment

In line with the platform's usual communication, participants were contacted through their email address, late in fall 2025, restricting to users recently active on the platform in the job categories included in our experiment, meaning recruiters who contacted at least one worker about a job and workers available to be recruited.[21] The look and content of the email sent to prospective participants mirrored official communication.[22]

The stated purpose was to participate in a study by the platform to improve its matching by better understanding how workers select jobs and how recruiters select workers. There was no mention of academic research or of the researchers, although it was mentioned that the platform reserves the right to share study data with associated researchers and that findings could be released publicly. This mitigates potential concerns regarding experimenter demand effects from being aware of being in an academic study, while mitigating concerns from deception.

Recruiters (workers) received €50 (20) for completing the experiment – which lasted an average of 17 minutes, not counting a few outliers taking over an hour – along with a chance to win one randomly-drawn prize of €1,000.

[21] This strengthens incentivization by ensuring that receiving recommendations is valuable to the participants and strikes a balance between ensuring that participants are active in the market without selecting on success (e.g. completed jobs), which would have distorted results with respect to the average user. Still, as we discuss below, our sample of respondents is indeed positively selected in terms of completed jobs with respect to platform averages.

[22] We were unable to include the very largest firms in our set of recruiters because their accounts are handled directly by platform representatives. Since these firms would have made up a very small fraction of potential respondents, it is unlikely that this restriction meaningful affects our results or that we could have analyzed heterogeneity along this dimension.

3.3.2 Evaluations and incentivization

Participants first choose a job category. For recruiters, this is the category in which they expect to hire their next worker. For workers, this is the primary category in which they offer their services. A description of each category is provided to ensure that recruiters, who may not be experts in the job for which they hire, select the right category for their needs. If a recruiter or worker indicates that none of the listed categories are relevant for them, they are screened out of the experiment.

Second, recruiters (workers) select the expertise keyword(s) necessary for their next job (that they possess). Recruiters can report that they are unsure about the expertise they need, or indicate other required expertise not included in the provided list.[23] The selected category and keyword(s) together determine the pool from which profiles or offers are drawn for each participant, approximating how the platform's search engine returns a list of profiles based on job category and selected keywords. Tailoring profiles and offers to each participant increases relevance and strengthens incentives for truthful reporting.

Next, participants are given instructions for their evaluations. They are told that profiles and offers are based on information from real profiles and offers, but do not represent available workers or jobs on the platform. Since the platform routinely conducts tests and rolls out changes to how profiles and offers are displayed as well as to their matching algorithm, such a premise is likely to appear quite natural to participants.

Each participant makes 25 evaluations, fewer than the 40 in the original IRR (Kessler et al., 2019). We made this decision taking into account the larger pools of workers and recruiters on the platform, allowing us to preserve statistical power while reducing scope for experimental fatigue and making results less sensitive to a few potential outliers. Having fewer evaluations per participant does reduce precision when making recommendations based on individual-level preferences, but as discussed below, the recommendations we made based on these individual preferences were seen as highly relevant by recruiters.

To incentivize truthful evaluations, as in the IRR methodology, recruiters were told that their evaluations would be used to recommend them five workers for their next job

[23] The small fraction of recruiters who indicated being unsure or who only entered custom keywords (3%) were shown profiles at random within their job category, across any combination of expertise keywords. Results are similar when omitting them.

and workers were told that a random 25% subset of them would be recommended to the platform's matching team for one job based on their evaluations. Accordingly, the more careful and honest their evaluations are, the more valuable their recommendations are.[24] See Appendix A for details on the mapping from evaluations to recommendations.

These recommendations should be of high value to participants, since recruiters sometimes pay the platform to avoid searching and receive personalized recommendations, and we provide a similar service by basing recommendations on their evaluations. It is also often believed (and we show below) that workers improve their profile by completing jobs, and the average value of a job is several thousands of euros.

To investigate the quality of recommendations, we surveyed recruiters after sending them their recommendations. Although the sample is limited to 60 recruiters who answered this follow-up survey, 96% of them indicated that at least one recommendation was relevant or very relevant for their next job. We believe this is the first evidence on the IRR methodology's incentivization procedure and it's consistent with our procedure yielding high-quality recommendations.

Evaluations are made along two dimensions: i) interest in hiring the worker or accepting the job and 2) likelihood that a job offer would be accepted or received. Specifically, recruiters evaluate each profile from 1 to 10 based on the following questions:

To what extent would you be interested in hiring this person under the conditions indicated on their profile? Suppose that they would accept an offer if you contacted them.

and

What is the likelihood that this person would accept to work for you if you contacted them for a job?

Workers evaluate each job offer from 1 to 10 based on the following questions:

If you were contacted for this job, to what extent would you be willing to accept it under the stated conditions?

and

If this recruiter viewed your profile, what is the likelihood that they would contact you for this job?

[24] Workers are told that they will only be recommended for one job regardless of their evaluations to avoid incentives to maximize their expected number of recommendations, for example by evaluating positively jobs that are more common, regardless of their preferences.

Participants are informed that their evaluation of both dimensions are factored in their recommendations.[25] Although the first question explicitly abstracts from likelihood of acceptance or offering ("Suppose that they would accept an offer if you contacted them" and "If you were contacted for this job"), factoring the second question into recommendations incentivizes reporting preferences for a profile or job taking into account the perceived likelihood of success when trying to recruit or obtain such a profile or job. This presumably yields more meaningful preference estimates for understanding behavior, because, while a recruiter with an unattractive job may unconditionally "prefer" hiring the absolute best candidate in the market, they are unlikely to pursue such a candidate in practice. Similarly, while workers we recommend for a job through the platform's matching service may unconditionally prefer the absolute best job available, they likely face higher competition for such a job. In correspondence studies, a lack of callback can indicate either too low or too high perceived quality, but the IRR methodology allows to separate both margins.

Lastly, participants are asked some exit questions to help contextualize their evaluations. For example, recruiters are asked their budget for the next job and whether it has an in-person requirement.

3.4 Prediction experiments

These experiments elicit beliefs of recruiters and workers about the preferences estimated in the *Evaluation* experiments, allowing us to test whether market participants correctly anticipate the preferences of other participants and to conduct an information treatment. See Appendix D for the recruitment messages and experimental instructions.

3.4.1 Recruitment

A new group of participants was recruited early in spring 2026, again through their email address, from a platform email address, and mirroring official communication.[26] The

[25] A third question about perceived competence of a profile by recruiters and self-assessed competence for a job by workers was also included but not incentivized. We use this question below to help interpret some of our results. The specific questions are: "Do you consider this person competent to carry out a project for you?" for recruiters and "Do you feel qualified for this project?" for workers.

[26] Again, we restricted the respondent pool to recently-active accounts, excluding the largest enterprises. Respondents from the *Evaluation* experiments were not eligible to participate in the version of the *Prediction* experiments asking them to predict competitor preferences since they would have been part of the sample they need to predict, but they were eligible to participate in the version that asked

stated purpose was to participate in a platform study to improve its matching by understanding how preferences of recruiters and workers align. Again, there was no mention of an academic study, beyond the right to share results with associated researchers and publish the findings.

Participants were paid based on their predictions as described below, but recruiters (workers) also received €10 (5) for completing the experiment, which lasted an average of 17 minutes not counting outliers taking over one hour, along with a chance to win one randomly-drawn prize of €1,000.

3.4.2 Predictions and incentivization

Participants first choose a job category, though we excluded translation jobs from the list since too few recruiters selected it in the *Evaluation* experiments to estimate *perception gaps*. The construction of profiles and offers is identical to the *Evaluation* experiments, except that we remove expertise keywords since they are no longer needed to make profiles or offers relevant to participants.[27]

Next, participants are given instructions for their predictions. Participants are told about the *Evaluation* experiments, namely that participants knew that profiles and offers did not correspond to real workers and jobs, but that truthful evaluations were incentivized through recommendations. Participants are then split into four groups based on whose evaluations they are tasked with predicting. Half of recruiters predict evaluations of workers for job offers (the other side of the market), while the other half is tasked with predicting evaluations of recruiters for worker profiles (competitors). Similarly, half of workers are tasked with predicting evaluations of recruiters for worker profiles, while the

them to predict preferences of the other side of the market. In practice, these repeat participants account for a minority of the samples and exhibit similar *perception gaps*, so we pool them together with other participants. Participants were not eligible to predict preferences of both the other side of the market and of competitors since the information treatment at the end of each reveals information about how profiles and offers are constructed.

[27] Unlike in the *Evaluation* experiments, participants are not seeking certain workers or jobs. So that this omission does not affect how remaining characteristics are evaluated, we tell participants that those in the *Evaluation* experiments were only shown profiles or offers with the expertise keyword(s) that they had themselves previously selected. Therefore, when for instance making a prediction for a developer profile, participants do not know whether a recruiter who evaluated such a profile needed expertise in Python or Java, but they know that the recruiter would only have been shown that profile if it satisfied their expertise requirement(s), allowing participants to abstract from expertise keyword(s) entirely when making predictions. Furthermore, since we include participant fixed effects when analyzing the *Evaluation* experiments, we purge the effect of expertise keyword(s) from evaluations. The relevant comparison in the *Prediction* experiments is thus to that of a profile or offer without keywords.

other half is tasked with predicting evaluations of workers for offers. Each group is given information on the relevant sample of participants from the *Evaluation* experiments *for their own job category*, namely the number of recruiters or workers (and that they were all active in recent months), completed jobs on the platform, average budget (recruiters) or asked wage (workers), and years of experience (workers) or organizational size (recruiters).

Each participant makes 25 predictions about the average evaluation that a profile or offer received, from 1 to 10, including up to one decimal point. For simplicity, participants are only asked to predict the level of interest in hiring a worker or accepting an offer, the first margin of interest in the *Evaluation* experiments, and are given the exact question that was asked to participants in the *Evaluation* experiments.[28]

To incentivize accurate predictions, payoffs depend prediction accuracy using a binarized scoring rule (Healy and Leo, 2025). Participants are told that their expected payoff is maximized by truthfully reporting their best estimate of the average evaluation that a profile or offer received. See Appendix A for details.

3.4.3 Information treatment

After making their predictions, participants are informed about the characteristics that were randomized on profiles or offers, told that characteristics were randomized independently, and asked to predict the marginal effect of each of them on evaluations from the *Evaluation* experiments. We asked these additional predictions to make the information treatment more salient and precise by basing it on each individual's explicit prediction about the effect of each characteristic. These predictions were incentivized using a similar binarized scoring rule (see Appendix A for details).

Participants are then provided with tables summarizing their predictions next to the "true" estimated values. Whenever a prediction falls within the 90% confidence interval of the value estimated from the *Evaluation* experiments, participants are told that their beliefs are fairly accurate.[29] When outside the confidence interval, they are given advice on potential changes they could make on the platform. For example, freelancers who

[28]It could have seemed somewhat unnatural for recruiters and workers to predict how likely a recruiter or worker in the *Evaluation* experiments would have perceived themselves to have their offer accepted or receive a given offer without information on individual respondents.

[29]When the estimated effect of a characteristic is itself not statistically significantly different from 0 for that job category in the *Evaluation* experiments, this is also indicated to participants.

overestimate recruiters' sensitivity to asked wages are told that they may be able to increase the wage they ask on their profile while remaining more competitive than they thought. See Appendix D for the instructions.

Participants are asked how useful they find the information we provide them and about their intentions to modify their behavior (e.g., profile content). We can test whether respondents actually changed their behavior following the treatment using data on profile modifications by workers.[30]

3.5 Empirical strategy

A key strength of the design is the independent randomization of characteristics, not only across profiles and offers within a participant, but also within each profile and offer. This allows for simple estimation of preferences and beliefs about these preferences, over a rich set of characteristics.

When analyzing either data from the *Evaluation* or *Prediction* experiments, we estimate the following ordinary least squares (OLS) regression model for participant i's rating (R), either from the evaluation or prediction experiment, of profile p

$$\begin{aligned} R_{ip} = \beta_0 &+ \beta_1\, Daily\ wage_{ip} + \beta_2\, At\ least\ one\ job_{ip} + \beta_3\, Number\ of\ jobs_{ip} \\ &+ \beta_4\, Share\ reviews_{ip} + \beta_5\, Reputation\ badge_{ip} + \beta_6\, Years\ of\ experience_{ip} \\ &+ \beta_7\, Second\ experience_{ip} + \beta_8\, Prestigious_{ip} + \beta_9\, Master_{ip} + \beta_{10}\, Remote_{ip} \\ &+ \beta_{11}\, Full\ time_{ip} + \beta_{12}\, Female_{ip} + \beta_{13}\, MENA_{ip} + \alpha_i + \varepsilon_{ip} \end{aligned} \tag{1}$$

where *Daily wage* is the asked wage, *At least one job* is an indicator for having completed at least one job, $Number\ of\ jobs$ is the number of completed jobs, $Share\ reviews$ is the share of jobs with reviews, *Reputation badge* is whether the profile has a reputation badge, $Years\ of\ experience$ is the years of work experience, *Second experience* is whether a second work experience is displayed on the profile, *Prestigious* is whether the one or two

[30]Since we did not know whether data on profile modifications would be available at the time of pre-registration, we did not pre-register this auxiliary analysis, though we did pre-register that we intended to perform additional analyses combining our experimental data with administrative platform data, pending data availability.

displayed work experiences were at a prestigious firm, $Master$ is whether the profile's highest completed education is a Master's degree, *Remote* is whether the profile indicates a preference for working remotely, and $Full\ time$ is whether it indicates availability to work five days a week. $Female$ and $MENA$ are whether the profile picture and name indicate the given gender and ethnic origin, and α_i are participant fixed effects. Standard errors are clustered at the participant level.

We set $Share\ reviews$, *Reputation badge*, and, naturally, $Number\ of\ jobs$ to 0 when $At\ least\ one\ job$ is equal to 0. We also normalize $Share\ reviews$ to 0 for the mean value in our sample, 60%. Hence, β_2 reflects the impact of going from a profile with no completed job, review, or badge, to a profile with some completed jobs, no badge and the average share of reviews for completed jobs. β_3 reflects the impact of an additional job conditional on having completed at least one, holding constant the share of reviews for completed jobs. β_4 represents the effect of going from the average review share to having all completed jobs reviewed, holding constant the number of completed jobs. β_5 reflects the impact of having a reputation badge, holding constant completed jobs and share of reviews for these jobs.

We estimate a similar regression model for the rating or predicted rating of offer o

$$\begin{aligned} R_{io} = \beta_0 &+ \beta_1\, Daily\ wage_{io} + \beta_2\, At\ least\ one\ job_{io} + \beta_3\, Number\ of\ jobs_{io} \\ &+ \beta_4\, Share\ reviews_{io} + \beta_5\, Prestigious_{io} + \beta_6\, Remote_{io} + \beta_7\, Full\ time_{io} \\ &+ \beta_8\, Duration_{io} + \beta_9\, Teamwork_{io} + \beta_{10}\, Tight\ deadlines_{io} \\ &+ \beta_{11}\, Recruiter\ female_{io} + \beta_{12}\, Recruiter\ MENA_{io} + \alpha_i + \varepsilon_{io} \qquad (2) \end{aligned}$$

where $Daily\ wage$ is the offered wage, $Prestigious$ is whether the firm is signaled as prestigious, *Remote* is whether the job is to be done remotely, $Fulltime$ is whether availability five days a week is required, *Duration* is the indicated length of the job, $Teamwork$ is whether the offer mentions that teamwork will be necessary, and $Tight\ deadlines$ is whether it mentions tight or urgent deadlines. $Recruiter\ Female$, and $Recruiter\ MENA$ are whether the recruiter's name indicates the given gender and ethnic origin. We again include participant fixed effects, and standard errors are clustered at the participant level.

Our primary contribution is to identify *perception gaps* between i) the preferences of recruiters and beliefs of workers and other recruiters about these preferences, and ii) the preferences of workers and beliefs of recruiters and other workers about these preferences. To estimate these gaps, we jointly consider evaluations and predictions by augmenting Equations 1 and 2 with interaction terms between each randomized characteristic and an indicator variable P_i for whether the rating is from the *Prediction* experiments. We also reweigh observations from the *Prediction* experiments to match the distribution of job categories from the *Evaluation* experiments to avoid perception gaps potentially arising from imbalance in job categories across the two experiments.

In particular, we estimate the following regression models:

$$R_{ip} = \beta_0 + \mathbf{X}'_{ip}\boldsymbol{\beta} + (P_i\mathbf{X}_{ip})'\,\boldsymbol{\gamma} + \alpha_i + \varepsilon_{ip}, \tag{3}$$

and

$$R_{io} = \beta_0 + \mathbf{X}'_{io}\boldsymbol{\beta} + (P_i\mathbf{X}_{io})'\,\boldsymbol{\gamma} + \alpha_i + \varepsilon_{io}, \tag{4}$$

where $\mathbf{X}_{ip}$ denotes the vector of randomized characteristics of profile p listed in Equation (1), and $\mathbf{X}_{io}$ denotes the vector of randomized characteristics of offer o listed in Equation (2). The coefficient vector $\boldsymbol{\beta}$ captures the effects of the randomized characteristics in the *Evaluation* experiments, while $\boldsymbol{\gamma}$ captures the corresponding perception gaps, that is, the differences between predicted effects and effects on actual evaluations.

These specifications correspond to the ones we pre-registered, along with most heterogeneity and robustness analyses presented below. A few heterogeneity analyses presented below were not pre-registered, which we mention when discussing them.

4 Results of the *Evaluation* experiments

Our pre-registered recruitment target is 350 recruiters and 800 workers, after excluding participants not hiring in or working within the job categories included in the experiment as well as participants who spend on average fewer than 10 seconds per profile or offer.[31] After applying our exclusion criteria, we are left with 348 recruiters and 824 workers. We additionally exclude eight recruiter evaluations for which profile names and pictures were incorrectly displayed.

Table 2 reports estimates from equations (1) and (2). Columns 1 and 2 present the estimated effects of profile characteristics on recruiters' hiring interest and on their assessment of the likelihood that the worker would accept an offer from them, respectively. Columns 3 and 4 report the estimated effects of job offer characteristics on workers' interest in accepting the job and on their assessment of the likelihood of receiving such an offer, respectively. All specifications include respondent fixed effects, so we compare how the same respondent evaluates different profiles or offers controlling for potential differences in how respondents use the rating scale (i.e. being more or less severe). Estimates are quite precise: for characteristics with no statistically significant effect, we can generally rule out economically large impacts.

4.1 Recruiter preferences

Recruiters' hiring interest is affected by several profile characteristics, namely the asked wage, market reputation, and work experience.

Since we ask recruiters their interest in hiring a worker under the specific conditions listed on the profile, the asked wage can be interpreted as a price. As expected, higher asked wages reduce hiring interest. Moving from the 25th to the 75th percentile of the randomized wage distribution, corresponding to €300, decreases recruiters' hiring interest by 24% of a standard deviation in profile evaluations.

As shown in Figure B.1, the relationship is non-linear. Asked wage increases have little effect over the lower half of the distribution but generate a pronounced decline in hiring interest at higher levels. This pattern aligns with recruiters' stated hiring budgets, which we elicit at the end of the experiment. In fact, recruiters evaluate profiles with higher asked wages more positively when they fall within their budget and strongly penalize

[31] Recruiters spent 31 seconds evaluating each profile on average (median of 17), while workers spent an average of 35 seconds per offer (median of 21). These figures are similar to those of Kessler et al. (2019) and in line with prior estimates, ranging from 7 to 45 seconds (Culwell-Block and Sellers, 1994; Dishman, 2018).

profiles with asked wages that exceed it, with a €300 increase in that region reducing hiring interest by 65% of a standard deviation (Table B.2). This correspondence between experimental preferences and real budget constraints supports the validity of the design.

Asked wages also function as a signal of competence, partially offsetting their direct price effect (Wolinsky, 1983). As shown in Table B.3, higher-wage profiles are rated as more competent. Controlling for perceived competence when estimating the effect of wages on hiring interest increases the magnitude of the negative wage coefficient by roughly 30%. Also consistent with the asked wage acting as a signal of quality, profiles with higher asked wages are expected to be less likely to accept a job offer, as shown in column 2. Lastly, we find a negative price effect across the quality distribution of profiles. In Figure B.2, we split profiles in quartiles of predicted quality based on recruiter evaluations, omitting the price, and show a negative effect of a higher ask on evaluations within each quartile.

Market experience also plays an important role in recruiters' evaluations. Profiles with at least one completed job on the platform receive a clear advantage of 12% of a standard deviation, consistent with the well-documented "cold start" problem in online markets (Yuan and Hernandez, 2023), where new entrants often struggle to get a first job.[32] Profiles with a completed job are also marginally expected to be more likely to accept a job offer, indicating that it may act as a signal of commitment and dependability.

Additional completed jobs beyond the first are also valued: moving from the 25th to the 75th percentile of the randomized distribution of completed jobs increases hiring interest by 12% of a standard deviation and also increases the perceived likelihood of the worker accepting a job offer. The reputation badge—introduced by the platform as a signal of success—generates a similar increase in interest as obtaining a first completed job. Since such signals are valued by recruiters, they presumably amplify disparities by benefiting already-successful profiles. In contrast, the share of completed jobs that received reviews has little detectable effect on evaluations, consistent with recruiters either not paying attention to it or believing that variation in whether a review is left or not is largely random.

[32] Table B.4 further provides some evidence that in the absence of completed jobs, recruiters place greater weight on general experience and additional work experiences shown on the profile.

More general experience is also valued. Moving from the 25th to the 75th percentile of the randomized distribution of years of experience increases hiring interest by 14% of a standard deviation. In addition, profiles displaying two detailed work experiences rather than one receive a 24% of a standard deviation increase in interest and are also expected to be more likely to accept a job offer. This effect should not necessarily be interpreted as simply reflecting a higher total number of past experiences, since recruiters are informed that only a representative subset is shown on profiles. A second experience likely also provides additional information about the worker's capabilities and fit.

In contrast, whether past experiences occurred at prestigious firms or not has little effect on hiring interest. This is despite evidence that the signal was salient, since profiles with prestigious experiences are rated as less likely to accept an offer. This muted effect may reflect the composition of recruiters in our sample—few represent large firms —or the fact that platform jobs are defined around specific skills, limiting the value of a broad prestige signal, but we show below that prestigious experiences did impact the probability that a profile be rated particularly highly, even if it has little impact on average ratings.

A Master's degree has little effect on evaluations, consistent with recruiters prioritizing job-specific experience and market reputation over broader ability signals. Given that many jobs are specialized and require skills that can be acquired through targeted programs or certifications, a Master's degree may carry limited added value.[33]

Stated preferences over work conditions—whether the worker indicates mostly being available remotely or only part-time—have little effect on average recruiter evaluations. This likely reflects that most recruiters seek remote or flexible arrangements and hire for jobs requiring less than full-time work. Consistent with this, for the subset of recruiters who do indicate at the end of the experiment that they require in-person work for their next job, we find suggestive evidence of a strong penalty for profiles indicating only being available remotely (Table B.5). Moreover, profiles with full-time availability are expected to be more likely to accept a job offer, indicating that it can still constitute an advantage in the hiring process for these workers.

Finally, we find no evidence of gender discrimination and limited evidence of ethnic

[33] In exploratory analyses that are not pre-registered, we tested whether a Master's degree obtained from a prestigious French institution affects evaluations and found little evidence that it does. Results are available upon request.

discrimination. While profiles of MENA origin do not receive lower hiring interest or assessed competence, they are rated as less (5% of a standard deviation) likely to accept a job offer, with the effect becoming more precise when restricting to recruiters of non-MENA origin, as discussed below. These results suggest that, to the extent that ethnic minorities face a disadvantage, it could relate to their perceived responsiveness or reliability, rather than competence-related concerns. In Table B.6, we split the sample of evaluators by whether they report above or below-median to a question at the very end of the experiment asking them how important diversity is in their hiring decisions, showing that the negative rating on likelihood of accepting a job offer for MENA profiles appears driven exclusively by the latter group. We find little evidence that other characteristics on a profile are evaluated differently depending on the gender or ethnicity signaled on it (Table B.7).[34]

Our results align with previous IRR evidence and the correspondence study literature on gender, but differ from correspondence studies documenting substantial discrimination against workers of MENA origin in France.[35] Since callback rates in correspondence studies conflate the hiring interest and acceptance margins, our results are qualitatively consistent with those studies, but our estimated magnitudes appear smaller. This is consistent with the view that freelancing reduces exposure to discriminatory barriers. Jobs are defined around specific self-contained tasks and interactions are typically short-term, remote, and transactional, plausibly limiting concerns leading to discrimination in other settings. Although budgets are economically meaningful, the contractual stakes are also lower than for traditional employment—there are no long-term commitments, dismissal costs, or broader legal liabilities—which may further reduce discriminatory screening (Benson and Lepage, 2024).

It seems unlikely that the null results on hiring interest are driven by demographics not being salient or participants expecting that demographics would not be used for recommendations, because we do find an effect on the probability that MENA profiles

[34]Exploratory analyses that are not pre-registered comparing profiles and offers from the greater Paris area versus the rest of France also suggest similar conclusions across both regions. Results are available upon request.

[35]In a recent large-scale correspondence study conducted with the French Ministry of Labor, evidence of substantial hiring discrimination was found based on MENA origin (approximately 30% lower callback rate), but not based on gender (Dares et al., 2021a,b).

would accept an offer, which is also incentivized through recommendations.[36] Moreover, as we show below, discrimination against MENA profiles in hiring interest was anticipated by participants in the *Prediction* experiments.

To help interpret magnitudes, we express preference estimates in monetary terms by rescaling each coefficient relative to that of the wage, purged of its signaling value (Figure 1). Recruiters are willing to pay over €2,000 more per month in full-time equivalent wages for workers with an established platform reputation—measured by completed projects or a badge—and more for workers with greater experience and a second detailed work experience.

4.2 Worker preferences

Workers' interest in accepting a job is also shaped by several characteristics of the job offer, though the relevant dimensions are different from those driving recruiter evaluations of profiles. Unsurprisingly, workers place substantial weight on the offered wage. In contrast, they attach little value to recruiter or firm characteristics, including market reputation. Instead, they respond strongly to amenities of the job itself, particularly work conditions.

The offered wage is the most important determinant of workers' interest. Moving from the 25th to the 75th percentile of the randomized wage distribution increases acceptance interest by 1.1 standard deviation in worker evaluations. Unlike for the recruiter side, the relationship appears approximately linear across the wage distribution (Figure B.1). Workers also report a higher perceived likelihood of receiving higher-paying offers. This may reflect selection: participants have above-average market experience, making it reasonable for them to expect to be matched with higher-paying jobs.[37] We find a strong shift around the point where the wage on an experimental offer crosses the participating worker's asked wage indicated on their real profile on the platform (Table B.2). Workers are much more sensitive to wage increases when it is below their asked wage and less so for wages that exceed it, consistent with an interpretation of the asked wage as a reference or

[36]Null findings on demographics in (Kessler et al., 2019) have also been ascribed to participants being aware that they were part of an academic study on recruitment, but recall that this is not the case in our experiments.

[37]Given the incentive structure, workers are not rewarded for mechanically rating high-paying jobs favorably unless they believe they are competitive for them, as recruiters choose among multiple recommended candidates.

reservation point. The fact that preferences estimated in our experiments strongly relate in an intuitive way to real behavior from outside the experiments again corroborates the design's validity.

In contrast, recruiter market experience (completed projects and review shares) and recruiter demographics have no discernible effect on workers' evaluations. Several features of the market may explain this asymmetry. First, there is excess supply of workers in the market. Recruiters can readily find many candidates for their jobs, whereas workers face strong competition for jobs and receive offers more irregularly (they only indirectly affect the offers they receive through optimizing their profile). Second, reputation signals are less salient on offers than on profiles, the former primarily emphasizing tasks, wages, and work modalities. Third, once job contracts are signed, worker payment for completed work is guaranteed through the platform, mitigating concerns such as recruiters withholding payment (Benson et al., 2020).

One exception is the organizational prestige signal, which reduces workers' interest in accepting a job by 8% of a standard deviation. Evidence from Table B.3 indicates that this effect is largely driven by workers feeling less qualified for these jobs. Moreover, some advantages associated with large employers—such as non-wage amenities and career progression—are less relevant in a freelance setting. Workers also report being less likely to receive offers from these organizations, reinforcing the interpretation that such jobs are perceived as less attainable. Further corroborating this is the fact that this penalty is not present among workers with substantial platform reputation, as shown below.

Workers place substantial weight on work conditions, most notably remote work. Offers allowing remote work receive evaluations that are 27% of a standard deviation higher on average and workers report a higher perceived likelihood of receiving such offers. Workers who indicate a preference for remote work on their profile are also estimated to have a higher preference for remote jobs in the experiment, although those who indicate also being available in person still prefer remote jobs (Table B.5). Again, experimentally-estimated preferences and platform outcomes appear aligned.

Workers attach little weight to whether work is indicated as being performed in teams, but they report 10% of a standard deviation lower interest in jobs that mention tight or urgent deadlines. This is consistent with willingness to pay to avoid stressful environments and with tight deadlines potentially complicating scheduling across concurrent jobs. We also find a small, suggestive positive effect of job duration on both acceptance interest and perceived likelihood of receiving an offer, while full-time requirements have no substantive impact. Figure B.1 indicates that jobs of less than one week are rated substantially lower, with a more muted impact of increasing duration beyond a few weeks.

Again, to help interpret magnitudes, we express preference estimates in monetary terms in Figure 1. Workers are willing to forego roughly €1,500 per month to work remotely. Conversely, they require compensation of about €500 per month to accept jobs from prestigious organizations or those involving tight deadlines. Our estimates suggest that workers are willing to accept around 15% lower wages for the option to work from home, higher than Mas and Pallais (2017) and similar to Cordes et al. (2026) who estimate a WTP of 8% and 15%, respectively.

4.3 Robustness and heterogeneity

The results are robust to including fixed effects for the order in which profiles or offers are shown (Table B.8), replacing respondent fixed effects with job category fixed effects (Table B.9), and retaining the small subset of respondents who spent on average fewer than 10 seconds per evaluation (Table B.10). Adjustments for multiple hypothesis testing also yield similar results (Table B.11). Reweighting evaluations so that the participant sample is representative of the platform population also has limited impact on the estimates, especially for interest in hiring a profile or accepting a job (Table B.12). Estimates are similar when comparing the first (1-12) to the second half (13-25) of evaluations (Table B.13).[38] They also vary relatively little across participant gender and ethnicity (Tables B.14 and B.15).

Our results are robust to relaxing the linearity assumption along the 10-point evaluation scale. Our main specification assumes that recruiters and workers treat a one-unit change along the scale equivalently (e.g., going from 3 to 4 is equivalent to going from

[38] We do find some evidence that recruiters place increasing weight on detailed work experiences in later evaluations. This could indicate that recruiters eventually determine that more of the relevant information they need is contained in those experiences rather than other aspects of the profile, and therefore focus more heavily on their content. This analysis was not-pregistered and is thus exploratory.

7 to 8). Analyses using ordered probit regressions, which only require that participants value higher ratings more favorably on average, yield similar conclusions (Table B.16).

Table B.17 reports results separately for tech and non-tech jobs. The patterns are largely similar across the two groups, with a few differences. Non-tech recruiters evaluate profiles indicating a preference for remote work more favorably, whereas tech recruiters place value on full-time availability. Tech workers value remote work relatively more and also value longer project duration, likely reflecting higher set-up costs, such as familiarizing themselves with existing technical infrastructure. Non-tech workers respond more negatively to offers signaling substantial teamwork.

Table B.18 analyses the impact of characteristics on whether profiles and offers are rated particularly highly, rather than the impact on average evaluations, investigating whether certain characteristics are more or less important specifically for higher quality candidates.[39] Qualitative conclusions remain, with two exceptions: the benefit of a first completed job is close to 0, indicating that the "cold start" problem may primarily affect profiles that are otherwise unable to stand out, and prestigious work experiences increase the likelihood of a profile being rated particularly highly.

Table B.19 presents results separately by participants' platform experience as indicated by their user account. Substantive conclusions are broadly similar across less and more experienced participants. Results restricted to workers with more substantial experience (at least five completed jobs) are also similar, but with some evidence that these workers do not penalize offers from prestigious firms and do not expect to be less likely to receive such offers (Table B.20).[40] Results are also similar when splitting the sample of worker respondents by whether they have below or above-average years of freelancing experience (Table B.22).

[39]We consider two outcomes: 1) whether the profile or offer receives a participant's highest evaluation and 2) whether it receives a rating of 9 or 10. The first measure can be seen as approximating the notion of "hiring", to the extent that a recruiter may pursue only their top rated candidate.

[40]We do not present the corresponding analysis for recruiters due to lower sample size, but we present exploratory heterogeneity analyses of recruiter preferences by firm size, which were not pre-registered but show similar results for small and larger firms, beyond some evidence that small firms put more weight on a profile having complete at least one job (Table B.21).

5 Results of the *Prediction* experiments and *perception gaps*

Our pre-registered recruitment target is 700 recruiters and 1,600 workers, after excluding participants not hiring in or working within the job categories included in the experiment and those spending fewer than six seconds per profile or offer on average.[41] After applying our exclusion criteria, we are left with a sample of 709 recruiters and 1,601 workers.

On average, participants make large prediction errors of around 1.75 per profile or offer, in absolute value on the scale from 1 to 10, even including individual fixed effects to capture the fact that evaluators and predictors may differ in their use of the 10-point scale. These errors correspond to about two-thirds of a standard deviation in evaluations from the *Evaluation* experiments.

Our primary interest is in understanding to what extent these errors are systematically driven by misperceptions about the impact of characteristics randomized on profiles and offers. Before looking at each characteristic individually, we quantify the contribution of *perception gaps* to average prediction errors, considering all characteristics jointly. To do so, we calculate, at the individual participant level, the impact they expect each characteristic to have on evaluations in the *Evaluation* experiments as implied by their 25 predictions, minus the true estimated impact of the characteristic from the *Evaluation* experiments.

In particular, we estimate respondent-specific coefficients using a hierarchical linear model and recovering Empirical Bayes estimates under a Gaussian prior. This procedure shrinks noisy unit-level estimates towards the population mean, avoiding overfitting and ensuring the coefficients do not become too large. We use these individual coefficients to recover individual-level predictions for each profile or offer that depend only on the characteristics randomized on profiles and offers.[42] We estimate that slightly *more than*

[41]Respondents spend a median time of 13.4 seconds per profile (25.6 seconds on average) and 18.2 seconds per offer (30 secs on average) We select a lower time cutoff for predictions than evaluations, six versus ten seconds, because we ask participants one question per profile or offer, rather than three.

[42]Formally, for profile or offer i, we recover $P_i^{eb} = \Sigma_j \beta_{kj}^{eb} X_j$, where β_{kj}^{eb} are the Empirical Bayes coefficients and X_j is a randomized characteristic. We then recover two prediction errors, 1) the difference between the Empirical Bayes prediction and the actual evaluation, the "systematic perception gap" ($e_i^{eb} = P^{eb} - \Sigma_j \beta^{ev} X_j$), and 2) the difference between the individual's predicted evaluation of the profile or offer and the actual evaluation ($e_i = P_i - \Sigma_j \beta^{ev} X_j$), which is the sum of both idiosyncratic and systematic errors. We then regress the indirect error on the empirical Bayes error and study the R-squared, which

half of the total errors individuals make can be explained by misperceptions they hold specifically about the impact of characteristics randomized on profiles and offers.[43]

We next estimate prediction errors across these characteristics. Since average *perception gaps* may hide heterogeneity that cancels itself out (i.e. overestimation by some and underestimation by others), we also look at gaps across job categories and individuals after presenting our main results.

5.1 Predicting recruiter preferences

We first study beliefs about recruiters' preferences over worker profile characteristics, presenting results of both workers' and other recruiters' predictions of these preferences.

Column 1 of Table 3 shows estimates of equation 1 where the dependent variable is the prediction of the value given to a profile by recruiters, combining predictions of both workers and other recruiters. Columns 2-3 separate predictions of recruiters and workers. Predictions imply that every randomized characteristic on a profile except the worker's gender and the asked wage (full time availability) for worker (recruiter) predictions are expected to affect recruiter evaluations. While this contrasts from the results of the *Evaluation* experiments presented above in which we only found a subset of characteristics to statistically significantly affect recruiter evaluations, predicted impacts of characteristics largely go in the correct direction.

Next, we estimate equation 3, testing for the presence of perception gaps by comparing estimates from the *Evaluation* and the *Prediction* experiments. We present the interaction terms, which identify differences between recruiters' preferences for characteristics and beliefs about these preferences, isolating perception gaps. A positive value means that predictors overestimate the importance of a characteristic for recruiters, while a negative one means that they underestimate it. Lastly, since perception gaps may not only differ

tells us how much variation in the indirect error can be explained by systematic misperceptions measured by the empirical Bayes procedure.

[43] The remaining variation in errors could arise from several sources. Some content on profiles and offers is not captured by the characteristics we test, including a worker's interest in a particular task or industry and a recruiter's assessed fit of a worker given their industry-specific experience and tasks described in their experiences. It could also arise from our analyses assuming independent linear relationships between each characteristic and a profile or offer's (predicted) evaluation. Key for our purpose is the observation that, beyond these other potential factors, *perception gaps* about randomized characteristics play a major role in driving prediction errors.

meaningfully by type of job, but cancel out altogether, we also present results separately for tech and non-tech jobs.

Results are presented in Table 4, with column 1 pooling predictions of workers and other recruiters, and columns 2-3 presenting both separately. In Table B.23, perception gaps are further separated by tech and non-tech jobs. We find evidence of several statistically significant perception gaps, arising both from misperception regarding the quantitative importance of characteristics which do statistically significantly affect recruiter evaluations of profiles and regarding characteristics for which we do not identify important recruiter preferences. Conceptually, perception gaps distort behavior and are therefore important regardless of whether they concern a characteristic that does or does not in fact affect recruiter evaluations of profiles.

We interpret perception gaps in terms of their size relative to estimated coefficients from the *Evaluation* experiments, but since some of these coefficients can be quite small, resulting gaps can be very large. Accordingly, we also express gaps in terms of their size relative to one standard deviation in evaluations from the *Evaluation* experiments, capturing whether a gap is expected to be large enough to meaningfully affect a profile's assessment, even when it relates to only one out of the several characteristics we randomize.

The estimated perception gap of workers regarding the asked wage is of a similar size to the estimated coefficient of the asked wage on recruiter evaluations, implying a gap of approximately 100%. While we do document that the effect of the asked wage on recruiter interest is nonlinear and somewhat muted by the asked wage acting as a competence signal, recruiters still clearly penalize higher asked wages, all else equal, and workers underestimate this penalty, leading them to overestimate recruiters' evaluation of a profile by 7% of a standard deviation for each additional €100 in asked wages. In contrast, competing recruiters have more accurate beliefs regarding how the asked wage would affect recruiter evaluations of a profile, with their perception gap being less than half the size and marginally statistically significant.

Workers and especially competing recruiters overestimate the returns to market reputation, with some evidence of perception gaps regarding the value of having completed a job, having completed more jobs conditional on having completed at least one, a higher share of completed jobs with reviews, and of the reputation badge. The magnitudes amount to relative gaps ranging from 50% to several times the size of the estimated preference from evaluators and to prediction errors of 4% to 17% of a standard deviation in profile evaluations. These gaps seem to largely arise from tech jobs, in which perception gaps are substantially larger.

Workers overestimate the return to experience by 8% of a standard deviation for each additional 10 projects completed, with a larger gap in tech jobs. They also vastly overestimate the return to prestigious work experiences by around 200% overall, overestimating the marginal benefit of prestigious work experiences on a recruiter's evaluations by 8% of a standard deviation, largely driven by non-tech. Directionally, competing recruiters also estimate these returns, but the estimated gaps are smaller and statistically non-significant.

Profiles indicating a preference for remote-only work are expected to be penalized by both workers and competing recruiters, namely in non-tech jobs. Those indicating availability for full-time work are expected to be favored, again especially in non-tech jobs. In contrast, we estimated that neither meaningfully affects evaluations, leading to gaps of around 8% of a standard deviation in evaluations.

Lastly, MENA profiles are not expected to be discriminated against overall, but discrimination is expected in tech, where the bulk of MENA workers are, by both workers and other recruiters. The perception gap corresponds to around 8% of a standard deviation in recruiter evaluations and, for workers, appears driven specifically by participants who themselves are of MENA origin. Otherwise, perception gaps vary relatively little by respondent gender and ethnicity (Table B.25).

Overall, we can marginally reject that perception gaps regarding recruiter preferences are the same for workers and competing recruiters (p-value 0.051). Gaps also do not seem to close with experience in terms of projects completed on the platform or years of freelancing experience (Tables B.26, B.27, B.28), and they are robust to retaining the small subset of respondents who spent on average fewer than 6 seconds per prediction (Table B.29) and adjustments for multiple hypothesis testing (Table B.30).

Perception gaps relate intuitively to predictor characteristics. Namely, workers with higher asked wages on their profile and recruiters who offer higher wages underestimate recruiters' price sensitivity by substantively more (Table B.31). Directionally, workers who report being available to work in person overestimate the penalty recruiters attach to profiles indicating only being available to work remotely by more, though the difference is small as all workers overestimate this penalty. In addition, recruiters who hire workers remotely overestimate the penalty that other recruiters attach to profiles indicating remote-only availability (Table B.32).

To help interpret magnitudes, Figure 2 shows perception gaps expressed in terms of the monetary value attached to each characteristic from the *Evaluation* experiments. Values are substantial, with workers overestimating the increased willingness to pay of recruiters for workers with better market reputation, more experience, prestigious work experiences, full-time availability or with a Master's degree and overestimating their decreased willingness to pay for remote workers, on average by slightly more than €1,000 per month. Competing recruiters also estimate the increased willingness to pay of other recruiters for workers with better market reputation and overestimate their decreased willingness to pay for remote or MENA workers, by over €1,000 per month. On average, perception gaps in absolute value amount to misperceptions of €1,274 and €1,028 per month per characteristic for workers and competing recruiters.

So far, we have restricted attention to average gaps across broad job types, but these averages are likely to hide heterogeneity across narrower job categories and, even more so, across individual predictors. Indeed, perception gaps vary importantly across broad job categories, namely between tech and non-tech jobs. To further investigate how perception gaps may be attenuated by pooling individual job categories into tech and non-tech, we calculate gaps at the individual job level and take their average, in absolute value. On average, across individual job categories, gaps correspond to a difference of 0.2 on the 10-point scale, corresponding to 10% of a standard deviation in recruiter ratings of profiles, for each characteristic (Figure B.3). This indicates substantial heterogeneity across job categories, as most gaps are substantially smaller than 0.2 when averaged across categories.

Since *perception gaps* estimated at the job category level and averaged across categories do not require us to reweigh predictions across job categories to preserve an equal share of participants in each category across evaluations and predictions, it also allows to investigate how reweighting affect the misperceptions we document. One reweighting scheme is to weigh each participant to make our predictors representative of the average user on the platform within the categories included in our experiment. This investigates whether potential selection into predictors participating in the experiment affects our estimates. A second reweighting scheme instead reweighs evaluators to be representative of the average user on the platform within the same job categories, as we did in Table B.12, while leaving predictions untouched. This investigates whether potential selection into evaluators participating in the experiment affects our estimates. That is, it tests whether misperceptions arise from predictors predicting the average preferences on the platform correctly, but gaps arising from sample selection into the evaluation sample. This may be unlikely to arise because we explicitly gave information to predictors about the sample of evaluators so that they would predict preferences of our sample of evaluators, but in any case, both reweighting exercises have negligible impacts on the gaps we document (Figures B.4 and B.5).

Perception gaps also likely vary systematically among individuals within a job category such that some over and others underestimate the impact of each characteristic. Individual-level *perception gaps* are also important to study because implications for welfare and efficiency can differ importantly by whether a near-zero aggregate market prediction gap reflects everyone having approximately accurate beliefs, or half the market largely underestimating the importance of a characteristic and the other half largely overestimating it.

To investigate this, we turn to the direct predictions of each characteristic's marginal impact on recruiter evaluations that we asked respondents after they made their profile predictions and before the information treatment. We use these predictions because they provide us with a direct estimate of each characteristic's predicted impact for each participant. In contrast, individual-level coefficients recovered from profile predictions are noisier because several characteristics vary within each profile. Still, it is worth noting that there is a very strong relationship between the two prediction measures as shown in

Figure B.6, with a correlation of 0.93.

Individual-level *perception gaps* are shown in Figure 3, showing large heterogeneity across individual predictors and a substantial share of predictors with large misperceptions. Averaging across characteristics, around one quarter of participants have prediction errors above 0.5 in absolute value on the 10-point likert scale, corresponding to a misperception of around one quarter of a standard deviation in recruiter evaluations of profiles *for a single given characteristic* and often several times larger than the characteristic's true estimated impact on recruiter evaluations.

Lastly, although our focus is on *perception gaps*, a related, weaker condition to investigate whether beliefs are accurate is to test whether participants hold an accurate ranking of characteristics in terms of their relative importance. Again using direct predictions, which give an explicit and transparent participant-level ranking, we estimate that 68% of participants correctly predict at least one of the top three important characteristics, but this drops to 20% when considering those who predict at least two of the top three, showing important inaccuracies even in correctly identifying which characteristics matter most to recruiters.

5.2 Predicting worker preferences

Column 4 of Table 3 shows estimates of equation 2 where the dependent variable is the prediction of workers' evaluations of job offers. Columns 5-6 separate predictors into recruiters and other workers. Workers are predicted to prefer offers characterized by higher wage, posted by a recruiter with at least one completed job on the platform, that allow for remote work, and that are longer. Workers are predicted to penalize offers with tight or urgent deadlines and those from prestigious employers. Qualitatively, these predictions are consistent with worker preferences estimated above, apart from our null finding on the impact of completed projects and recruiters also expecting offers by female recruiters to be favored. Predictors thus appear to have a fairly good understanding of which characteristics workers value, but as we show next, not so much of the extent to which they value them.

In Table 4, we document several substantial, statistically significant perception gaps.

Column 1 presents results combining predictions of recruiters and other workers, while columns 2-3 separate the two. In Table B.24, perception gaps are further separated by tech and non-tech jobs. First, both recruiters and workers overestimate how reactive workers are to the offered wage on an offer, especially in non-tech, meaning that each €100 increase increases worker interest by 8-14% of a standard deviation in evaluations less than they think.

The negative impact of a job offer coming from a prestigious organization is largely unanticipated, specifically by recruiters and workers in non-tech, yielding positive perception gaps of around 8-10% of a standard deviation on average.

Workers underestimate how much their peers value remote work, by about 25% or 7% of a standard deviation, and while recruiters in tech and non-tech both predict that workers value remote work, they expect similar valuation, tech recruiters thus failing to predict the substantially higher valuation of tech workers for remote jobs, underestimating the predicted effect by nearly 40% or 13% of a standard deviation.

Perception gaps of recruiters regarding full-time requirements cancel out across tech and non-tech, but are both at least marginally statistically significant and correspond to about 6% of a standard deviation. Both recruiters and other workers overestimate the value workers attach to longer jobs, by more than double, corresponding to an anticipated return that is 1-1.5% of a standard deviation higher than the true return for each additional month.

Workers expect other workers to attach a higher penalty to offers with mentions of tight or urgent deadlines, by about two thirds or 6.4% of a standard deviation more than they do. In contrast, there is some suggestive evidence that recruiters expect workers to penalize offers from recruiters of MENA origin in tech. Prediction gaps overall vary relatively little by respondent gender and ethnicity (Table B.33).

Overall, we can reject that perception gaps regarding worker preferences are the same for recruiters and competing workers (p-value 0.028). Gaps again do not seem to be smaller for participants with more experience in terms of projects completed on the platform or years of freelancing experience (Tables B.27, B.28, B.34), and they are robust to retaining the small subset of respondents who spent on average fewer than 6 seconds per prediction

(Table B.35) and adjustments for multiple hypothesis testing (Table B.36).

Perception gaps again relate intuitively to predictor characteristics: workers with higher asked wages on their profile and recruiters with larger budgets overestimate workers' price sensitivity by substantively more (Table B.37). Directionally, recruiters who hire for in-person work underestimate workers' preferences for remote work by more, though the gap is not statistically significant. In addition, workers indicating in-person availability largely underestimate their competitors' preference for remote work (Table B.32).

Some of these gaps, when expressed in terms of the monetary value attached to each characteristic from the *Evaluation* experiments, are very substantial, as shown in Figure 2. For example, the underestimation of workers' valuation for longer jobs corresponds to underestimating the value of job duration by €150-200 per month per additional month of duration and the underestimation of workers' valuation for remote work to underestimating the value of that amenity by around €300-400 euro per month. The value of offers from prestigious organizations is overestimated by €200-600, that of offers indicating urgent deadlines is underestimated by around €400 per month by workers, and that of offers from recruiters with at least one previous completed job is overestimated by around €300 per month by recruiters. On average, perception gaps in absolute value amount to misperceptions of €150-170 *per characteristic*, which amount to substantial distortions, but much smaller than those identified regarding recruiter preferences.

In Figure B.3 we estimate gaps for each characteristic separately for each job category, take their absolute value, and average across categories. On average, gaps correspond to a difference of 0.15 to 0.2 on the 10-point scale, corresponding 6-8% of a standard deviation in worker ratings of offers for each characteristic and often larger than the actual estimated impact of the characteristic on evaluations. Reweighting either evaluators or predictors to be representative of users on the platform for the job categories included in our experiments when estimating gaps does not substantially alter the results (Figures B.4 and B.5).

Again, these average gaps dissimulate substantial heterogeneity across individual predictors as shown in Figure 3. Around 15% of participants have prediction errors above

0.6 in absolute value on the 10-point likert scale, corresponding to around one quarter of a standard deviation in worker evaluations of offers *for a single given characteristic* and often several times larger than the characteristic's own impact on worker evaluations.

Regarding how participants predict the ranking of characteristics in terms of importance, we estimate that 86% correctly predict at least one of the top three, while 50% predict at least two. Taking the evidence together makes clear that users on the platform are better able to predict worker than recruiter preferences, though some important *perception gaps* remain, both about ranking and marginal impacts.

6 Results of the information treatment

After making their predictions, participants in the *Prediction* experiments are provided with information on the estimated impact of each characteristic from the *Evaluation* experiments.

Overall, over three quarters of participants reported that the information we provided them with was useful for at least one group of characteristics out of wage, market reputation, experience, work conditions, and demographics. Information about asked and offered wages was deemed most useful, while that on demographics was deemed least useful, in particular by male and non-MENA participants. Workers and recruiters found their respective information similarly useful on average (both 76%). Information about the preferences of the other side of the market was deemed more useful (86% of respondents) than that about competitors (67% of respondents).

In line with participants generally finding the information useful, a majority of them report intending to change their market behavior in response to the treatment. Recruiters are more likely to report intending to change something (74%) than workers (65%). Conditional on intending to change their behavior, recruiters are most likely to intend changing their job offer descriptions, rather than how they select workers or the conditions at which they offer their jobs. Workers are most likely to report intending to change their profile description rather than the terms of the jobs they accept or their criteria for selection jobs.

Testing realized impacts on market behavior is challenging for recruiters since job offers are not proposed with high frequency and our number of participants is more limited. In contrast, workers profiles are continuously active and visible on the platform, so a worker intending to change their behavior could readily do so by modifying their profile after the information treatment.

We test this using daily data on profile modifications of workers. We have access to data recording profile activity for all users on the platform. For every day in the ten days surrounding the day in which they take the experiment (these correspond to different days for different participants), we create indicator variables for whether a worker's profile was modified that day. As a control group, we use workers who were included in the pool of potential participants but were not contacted since we hit our pre-registered number of participants before contacting them (the order of potential participants in our contact lists is random). We then estimate the following equation:

$$\text{Change}_{it} = \sum_{d=-10}^{10} \beta_d \left(\text{Treat}_i \times 1\{t - \tau_i = d\}\right) + \alpha_i + \delta_t + \varepsilon_{it}, \tag{5}$$

where Change_{it} is an indicator equal to one if worker i changes their profile on calendar day t. Treat_i is an indicator for workers who participated in the experiment and received the information treatment, while τ_i denotes worker i's treatment date. The indicator $1\{t - \tau_i = d\}$ is equal to one when day t is d days relative to the treatment date. The coefficients β_d therefore capture the difference in the probability of changing one's profile between treated workers and the comparison group at each event time d. We estimate coefficients for the ten days before and after treatment, including the treatment date. The terms α_i and δ_t denote worker and calendar-day fixed effects, respectively.[44] Standard errors are clustered at the worker level.

The results are shown in Figure 4. The daily frequency of profile modifications is fairly flat for the treatment group relative to the control group in the days before participants complete the experiment and increases markedly for the treatment group in the day of the experiment and also slightly for the day that follows it, before returning around the pre-treatment baseline after. The estimated increase of around 0.05 percentage points in panel

[44] To accurately measure worker and calendar fixed effects, we include profile activity data from January 1st until ten days after the final treatment date. To avoid post-treatment bias, we additionally drop observations for the treatment group taking place after the ten-day post-survey window.

(a) in the day following the experiment for those who receive information about recruiter preferences corresponds to an increase of around 500% from the baseline probability. The estimated treatment effect of receiving information about competitors is smaller, but still large at over 200%. Panel (b) presents results separating participants by whether they mentioned being likely or not to update their profile following the information treatment, indicating particularly large increases for those who reported intending to change their profile. Figure B.7 shows a similar analysis restricting to changes in asked wages, which are easier to adjust on a profile than some other characteristics (e.g. education). It shows a large impact of the treatment on the specific propensity of workers to update their asked wages.

Overall, there is clear evidence of behavioral changes by treated workers consistent with them attempting to optimize based on their updated market perceptions.

7 Consequences of *perception gaps*

In this section, we present a theoretical framework to help interpret our evidence, discuss broader labor market implications of the information frictions we document, and perform quantification exercises relating *perception gaps* to market outcomes.

7.1 Theoretical framework

Workers and recruiters interact in a decentralized labor market where jobs are formed when a recruiter contacts a worker and the worker accepts the offer. Recruiters value characteristics of workers (e.g., experience), while workers value characteristics of jobs and recruiters (e.g., remote work). Agents do not observe these preferences, but make decisions based on their subjective expectations. Two sources of distortion arise when expectations are inaccurate. First, even when worker and job characteristics are fixed, misperceptions distort pricing. Second, when agents can invest in characteristics, misperceptions distort investments. These distortions reduce efficiency: some matches fail to occur and matches that do occur generate less surplus.

7.1.1 Baseline model

There is a continuum of workers indexed by $i \in [0, 1]$ and a continuum of recruiters indexed by $j \in [0, 1]$. Each worker i has observable characteristics x_i. Worker characteristics map into a value to recruiters

$$v_i \equiv v(x_i),$$

interpreted as expected productivity or fit. Each recruiter j has observable job characteristics y_j. Job characteristics map into a value to workers

$$u_j \equiv u(y_j),$$

interpreted as non-wage utility from job j. For now, consider v_i and u_j as fixed.

Timing

1. Worker i publicly posts an asked wage $w_i \geq 0$.

2. Each worker is randomly matched to a single recruiter j. The recruiter observes (x_i, w_i) and chooses whether to make an offer and, if so, offers wage $p \geq 0$.

3. The worker accepts or rejects the offer (if any). If an offer is accepted, a match occurs and the wage equals p (there is no bargaining).

Worker acceptance Given an offer p, a worker's utility from accepting is

$$U(p; w) = u + p - w + \varepsilon,$$

where ε is an i.i.d. logit shock (scale normalized to 1) capturing idiosyncratic, match-specific utility components like personal fit that are observed by the worker at the time of acceptance but unobserved by recruiters.[45] We interpret w as a publicly-posted baseline reservation wage or reference point which workers cannot adjust in response to an offer, with job-specific non-wage utility shifting the effective acceptance threshold such that a worker may still accept an offer with wage below w.

[45]The logit structure ensures that acceptance decisions are smooth rather than deterministic, guaranteeing interior wage-setting decisions for recruiters.

The probability of acceptance is

$$A(p; u, w) = \sigma(u + p - w), \qquad \sigma(z) = \frac{1}{1 + e^{-z}}.$$

If the worker does not accept an offer, either because no offer arrives or because the offer is rejected, their utility is normalized to zero.

Recruiter problem If the recruiter hires the worker at wage p, their payoff is $v - p - c$ with $c > 0$ representing a fixed cost of making an offer, incurred regardless of whether the offer is accepted. If they do not make an offer, their payoff is 0. The recruiter solves

$$\max\left\{0,\ \max_{p\geq 0} A(p; u, w)(v - p) - c\right\}.$$

Let

$$p^*(w; v, u) \in \arg\max_{p\geq 0} A(p; u, w)(v - p), \qquad \Pi^*(w; v, u) = \max_{p\geq 0} A(p; u, w)(v - p),$$

so that the maximized value of making an offer is $\Pi^*(w; v, u) - c$. An offer is made if and only if $\Pi^*(w; v, u) \geq c$. Let

$$q^*(w; v) = \Pr(\Pi^*(w; v, u) \geq c)\,.$$

Conditional on making an offer, increasing p intuitively trades off a higher probability of acceptance with a lower surplus conditional on acceptance. Recruiters are willing to pay more and are more likely to make an offer to workers with higher v. Recruiters who believe they have a higher u expect to have more attractive non-wage amenities and to be able to offer less while preserving the probability of acceptance, so they are also more likely to make an offer to workers.

Worker problem The worker chooses w to maximize expected payoff:

$$\max_{w\geq 0}\ q^*(w; v) \cdot \mathbb{E}\big[A\big(p^*(w; v, u); u, w\big)\ \big(u + p^*(w; v, u) - w\big)\ \big|\ \Pi^*(w; v, u) \geq c\big]$$

where the first term denotes the probability of getting an offer, and the second term in brackets denotes the expected payoff, conditional on receiving one.

The worker's posted ask w lowers the probability of acceptance conditional on getting an offer, since acceptance depends on the difference between the offered wage and the ask. This is partially offset by recruiters anticipating this lower acceptance probability and optimally adjusting their offered wage. These forces reduce the recruiter's expected surplus from making an offer and therefore the probability that they make an offer.

Workers are willing to accept less for jobs with higher u, though workers who believe they have a higher v also expect they can ask for more while preserving the probability of getting an offer and securing a higher payoff conditional on accepting an offer.

7.1.2 Pricing distortions

We focus on how beliefs about preferences of the other side of the market shape behavior in the market. See Appendix C for an extension to beliefs about the preferences of competitors.

Workers may overestimate or underestimate how recruiters value their characteristics x_i. We model this as

$$\hat{v} = v + \Delta,$$

where $\Delta \in \mathbb{R}$ is the worker's *perception gap*, which can be positive or negative. Similarly, recruiters may misperceive how workers value their job characteristics y_i:

$$\hat{u} = u + \Gamma,$$

where $\Gamma \in \mathbb{R}$ is the recruiter's gap. We abstract from modeling uncertainty and learning about v and u to focus on the simplest setting showing how perception gaps distort behavior.

Recruiters solve the same problem, now forecasting acceptance using $\hat{u}$:

$$\widehat{A}(p; \hat{u}, w).$$

Let $p^{\Gamma}(w; v, \hat{u})$ and $\Pi^{\Gamma}(w; v, \hat{u})$ be the equivalent of $p^{*}(w; v, \hat{u})$ and $\Pi^{*}(w; v, \hat{u})$ with $\widehat{A}$

and let $q^\Gamma(w;v) = \Pr\big(\Pi^\Gamma(w;v,\hat{u}) \geq c\big)$. Recruiters misperceive how their job characteristics affect workers' valuation, and therefore the worker's acceptance, which affects their decision to make an offer or not, and the wage offered when making an offer.

Worker problem A worker forecasts the probability of receiving an offer using $\hat{q}^\Gamma(w;\hat{v}) = \Pr\big(\Pi^\Gamma(w;\hat{v},\hat{u}) \geq c\big)$ and solves

$$\max_{w\geq 0}\ \hat{q}^\Gamma(w;\hat{v}) \cdot \mathbb{E}\big[A\big(p^\Gamma(w;v,\hat{u});u,w\big)\ \big(u + p^\Gamma(w;v,\hat{u}) - w\big)\ \big|\ \Pi^\Gamma(w;v,\hat{u}) \geq c\big]\,.$$

Workers misperceive how their characteristics affect recruiter valuation, and therefore both the likelihood of receiving an offer, and the wage that they would be offered conditional on receiving an offer.

Proposition 1 (Perception gaps and pricing)**.** *Fix a worker and a recruiter, and compare outcomes under distorted beliefs to the correct-beliefs benchmark.*

1. ***Pricing distortions.*** *Recruiters who overestimate the attractiveness of their jobs post offered wages that are too low relative to the correct-beliefs benchmark, while those who underestimate this attractiveness post wages that are too high. Symmetrically, workers who overestimate their market value post asked wages that are too high, while workers who underestimate it post asks that are too low.*

2. ***Matching.*** *Pricing distortions affect the probability of a match. Recruiters who overestimate the attractiveness of their jobs are more likely to make an offer, but the probability of match conditional on an offer is lower. Those who underestimate the attractiveness of their jobs are less likely to make an offer, but the probability of a match conditional on an offer is higher. Similarly, worker distortions weakly increase match probability for those who underestimate their value, but decrease it for those who overestimate it.*

3. ***Expected payoff loss.*** *Whenever perception gaps alter pricing or offer decisions, they strictly reduce the agent's own expected payoff relative to the correct-beliefs optimum.*

Proof. See Appendix C. □

Intuitively, agents are pricing based on a wrongly-perceived demand curve, which naturally affects the likelihood of matching and lowers expected total surplus both by preventing some mutually beneficial matches and reducing surplus in matches that do occur.

7.1.3 Investment distortions

We extend the model by allowing workers and recruiters to endogenously choose a binary characteristic prior to entering the market.[46] The timing of the model is otherwise unchanged.

Each worker chooses $x \in \{0, 1\}$ at cost κ_x, where κ_x is independently drawn from a continuous distribution G_x with support on $\mathbb{R}_+$. The characteristic affects the worker's true value to recruiters:

$$v(x) = v_0 + v_1 x, \qquad v_1 > 0.$$

Each recruiter chooses $y \in \{0, 1\}$ at cost κ_y, where κ_y is independently drawn from a continuous distribution G_y with support on $\mathbb{R}_+$. The characteristic affects the worker's true utility from the job:

$$u(y) = u_0 + u_1 y, \qquad u_1 > 0.$$

Agents face uncertainty about how the market values characteristics. Workers misperceive the marginal return of x:

$$\hat{v}(x) = v_0 + (v_1 + \Delta)x,$$

where $\Delta \in \mathbb{R}$ is a worker-side investment perception gap which can be positive or negative.

Recruiters misperceive the marginal return of y:

$$\hat{u}(y) = u_0 + (u_1 + \Gamma)y,$$

[46] One could alternatively assume that investments are made in period t, once in the market, for period $t + 1$. This has no impact on qualitative predictions of the model, but is expositionally less relevant for characteristics like education.

where $\Gamma \in \mathbb{R}$ is a recruiter-side investment perception gap which can be positive or negative.

To isolate the role of investment distortions, we assume that, conditional on (x, y), wage posting, offer decisions, and acceptance follow the baseline model. In particular, recruiters correctly anticipate acceptance behavior given $u(y)$, and workers correctly anticipate offer behavior given $v(x)$. Thus, subjective beliefs affect outcomes only through the ex ante choice of x and y, not through pricing or acceptance conditional on those choices. In practice, perception gaps likely affect both pricing and investment, but we keep the two channels separate for expositional simplicity.

Let $J(x)$ denote the worker's true expected payoff in the baseline model conditional on characteristic x, and let $\Pi(y)$ denote the recruiter's true expected payoff conditional on characteristic y.

Workers choose $x = 1$ if and only if

$$\hat{J}(1) - \hat{J}(0) \geq \kappa_x,$$

where $\hat{J}(x)$ is computed using perceived value $\hat{v}(x)$.

Recruiters choose $y = 1$ if and only if

$$\hat{\Pi}(1) - \hat{\Pi}(0) \geq \kappa_y,$$

where $\hat{\Pi}(y)$ is computed using perceived utility $\hat{u}(y)$.

Proposition 2 (Perception gaps and investment)**.** *Consider the investment extension and suppose that pricing and acceptance decisions are efficient conditional on investment choices.*

1. ***Investment distortions.*** *Workers (recruiters) who overestimate the return to investing in the characteristic over-invest, while those who underestimate it under-invest.*

2. ***Matching.*** *Under-investment reduces the prevalence of high-productivity workers and high-utility jobs, causing some matches that would occur under correct beliefs*

to fail to occur. In contrast, over-investment increases the market value of workers and jobs, weakly increasing the probability of match.

3. ***Expected payoff loss.*** *Whenever perception gaps alter choices, they strictly reduce the agent's own expected payoff net of investment costs.*

Proposition 2 implies systematic over- or under-provision of skills and amenities, depending on the distribution of belief wedges. Under-investment leads to lower matching, while over-investment can increase matching, but at a surplus that does not compensate workers and recruiters for their costly investment, reducing expected payoffs.

7.1.4 Broader labor market implications

The framework and evidence help connect *perception gaps* to several well-known interconnected labor market phenomena.

Unemployment The model generates unmatched workers —interpretable as unemployment — even in the absence of bargaining or search frictions. Workers who acquire skills that are more in demand and price their bundle of skills more accurately given labor demand are more likely to be hired, perception gaps thus creating unemployment.

Labor shortages The model generates unfilled jobs interpretable as vacancies. Employers who invest too little in offering desirable non-amenities and fail to price their job accurately given those amenities are more likely to struggle to fill their vacancies, perception gaps thus creating labor shortages.

(Lack of) Compensating differential Firms who under-invest in non-wage amenities may need to increase their wages to compensate, but those who over-invest may not be able to recoup their costs through lower wages, creating an apparent lack of compensating differential. Moreover, firms may not know how to accurately price their non-wage amenities after having acquired them, also muting the presence of compensating differentials.

Pay differences and wage inequality Mispricing from perception gaps generates excess dispersion in asked and offered wages. Over- and underpricing coexist in the market even among agents with identical characteristics, contributing to observed pay differences among similar firms and wage differences among similar workers.

Monopsony power Firms who better understand the preferences of their workforce are able to set pay and amenities to better attract and retain workers, contributing to individual-level variation in monopsony power across firms.

Credentialing and skills mismatch In practice, workers do not only decide how much to invest, but also which type of skills and credentials to acquire. Workers may both under and over-invest in credentials like education, particularly across certain types of jobs or fields, potentially generating both over-credentialing and skill shortages. These may contribute to the unemployment and labor shortages in certain occupations as discussed above, but also affect realized matches. For example, workers who acquire "too much" of a certain type of education may find themselves employed in jobs that don't use these skills, and employers who offer conditions that are imperfectly catered to the preferences of the workers whose skills they seek may find themselves attracting workers with other skills, creating mismatches.

7.2 *Perception gaps* and market outcomes

In this section, we study how perception gaps relate to participant characteristics, pricing, and job outcomes on the platform.

We first study the correlation between perception gaps and the characteristics of participants. Proposition 2 of the framework states that workers and recruiters who overestimate the return to a particular characteristic should be more likely to invest in that characteristic. While we do not observe specific investment decisions, if workers invest in part based on their perception gaps, then this would result in workers and recruiters systematically overestimating the importance of characteristics they possess, relative to those they do not.

We test this prediction by estimating whether individual perception gaps for a given characteristic predict the presence of that characteristic on a worker's profile or recruiter's offers.[47] We use perception gaps estimated using the Empirical Bayes procedure described in Section 5.0. The results are presented in columns 1 and 3 of Panel (a) of Table 5. For both workers and recruiters, overestimating the value of a characteristic is positively

[47] Characteristics less likely to reflect a choice or investment are excluded, namely gender, MENA origin, years of experience, and share of reviews.

correlated with the likelihood of their profile or offer containing that characteristic.

Next, we study the correlation between perception gaps and wages asked or offered on the platform. Using estimated preferences from the *Evaluation* experiment combined with information on characteristics from profiles and offers, we estimate a measure of market value for each participant profile or offer on the platform, excluding the wage, approximating ν and u in the framework. These measures are simply the sum of estimated preferences for all randomized characteristics on a profile or offer, each multiplied by the quantity of the characteristic on the given profile or offer.

We combine these estimates of market value for each profile and offer to the participant's predicted market value for their own profile or offer by the other side of the market. Using Empirical Bayes estimates from the *Prediction* experiments, again with information on the characteristics of each participant, we compute predicted ratings $\hat{\nu}$ and $\hat{u}$ by taking the sum of the predicted impact of each characteristic multiplied by the quantity of that characteristic on the profile or offer. We then standardize ν, u, $\hat{\nu}$ and $\hat{u}$ across job categories for comparability.

By taking the difference between the estimated market value of a participant's profile or offer and the participant's own estimated perceived value of their profile or offer, we obtain an estimate of Δ and Γ from the framework, representing how much participants under or over-value their non-wage characteristics, on average. The framework predicts that overoptimistic workers should ask wages that are "too high" and overoptimistic recruiters should offer wages that are "too low" relative to the market value of their profile or offer. Similarly, although not included in the framework, we would expect that perception gaps regarding the effect of wages themselves on evaluations would also correlate with wages on profiles and offers, with workers (recruiters) who underestimate recruiters' (workers') price sensitivity asking (offering) higher (lower) wages.

We test these predictions in columns 2 and 4 of Panel (a) of Table 5, where the outcomes are asked and offered wages standardized across job categories. Column 2 shows that workers with profiles estimated to be of higher value to recruiters ask for higher wages, but that conditional on this estimated value, workers who are more (over)optimistic about their value also set higher asked wages. This effect is sizable - a one standard deviation increase in the overestimation measure is associated with a 13% of a standard deviation increase in asked wages. Similarly, perception gaps regarding the effect of wages also have an effect, showing that workers who believe that recruiters are less price sensitive than they are ask for higher wages.

Column 4 shows analogous results for recruiters. There is a negative relationship between offered wages and the estimated market value of a job's non-wage characteristics to workers, consistent with a compensating differential. Controlling for this value, recruiters who are one standard deviation more (over)optimistic about the value of their job's non-wage characteristics set wages that are 5% of a standard deviation lower. Lastly, recruiters who believe that workers are more sensitive to wages than they are set higher wages. Overall, perception gaps regarding wage and non-wage preferences thus predict both asked and offered wages in the market.

Lastly, we test whether perception gaps correlate with market outcomes in Panel (b) of Table 5. We focus on perception gaps in absolute value, which represent how wrong freelancers and recruiters are about the value of their profile or job offers as well as how wrong they are about wage sensitivity in the market. Workers with larger perception gaps about the value of their non-wage characteristics have fewer successful matches and earn lower average monthly revenue, with decreases of 12% and 17% of a standard deviation for a one standard deviation increase in perception gaps. Similarly, recruiters with larger perception gaps have fewer accepted job offers and, conditional on hiring a worker, pay higher wages. A one standard deviation increase in perception gaps is associated with effects of 14% and 22% of a standard deviation in the outcomes. Effects of perception gaps on wage sensitivity generally go in the expected direction but are not statistically significant except for column 4, indicating that recruiters who have less accurate beliefs about workers' wage sensitivity pay higher wages.

Overall, perception gaps elicited in the experiment are thus correlated with real market outcomes, namely in terms of characteristics of participants, their pricing decisions, and their success in terms of matching and revenue.

8 Conclusion

This paper provides rare evidence on the presence and consequences of *perception gaps* in labor markets. Using incentivized field experiments on a large European freelance platform, we jointly measure actual preferences of workers and recruiters alongside beliefs about these preferences. Our results reveal systematic and economically meaningful misperceptions on both sides of the market, spanning wages, human capital, reputation, work arrangements, and demographic characteristics.

These gaps matter. We show that they imply meaningful distortions in perceived value attached to several characteristics and that correcting them through a personalized information intervention leads to changes in behavior, indicating that agents operate under biased beliefs but are responsive to better information. To interpret our findings, we develop a theoretical framework highlighting how misperceptions distort both pricing and investment decisions. By affecting wage setting, job search, and human capital choices, these distortions can reduce match rates, match quality, and overall surplus. Consistent with this, we present evidence that *perception gaps* estimated in the experiment correlate with market behavior and outcomes.

Our findings contribute to a broader understanding of information frictions in labor markets. While much of the literature has focused on search costs or bargaining frictions, we show that inaccurate beliefs about others' preferences constitute an independent and important source of inefficiency. Moreover, because both workers and firms misperceive not only the other side of the market but also their competitors, these frictions can generate complex coordination failures and potentially persistent inefficiencies.

From a policy and platform-design perspective, our results highlight the potential value of improving information flows. Providing targeted feedback, better signals about market returns, or algorithmic guidance could help align beliefs with reality and improve matching outcomes. Given that online labor markets already offer relatively rich information environments, the importance of perception gaps in our setting suggests that such frictions may be even more pronounced in traditional labor markets and are also likely to be present in other markets, suggesting opportunities for future research.

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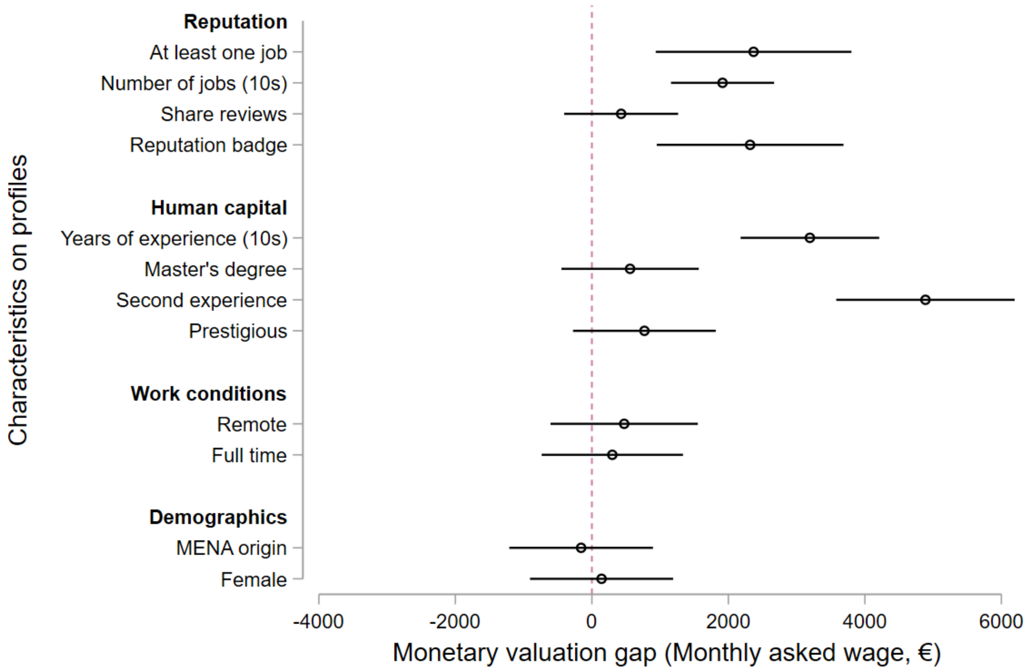
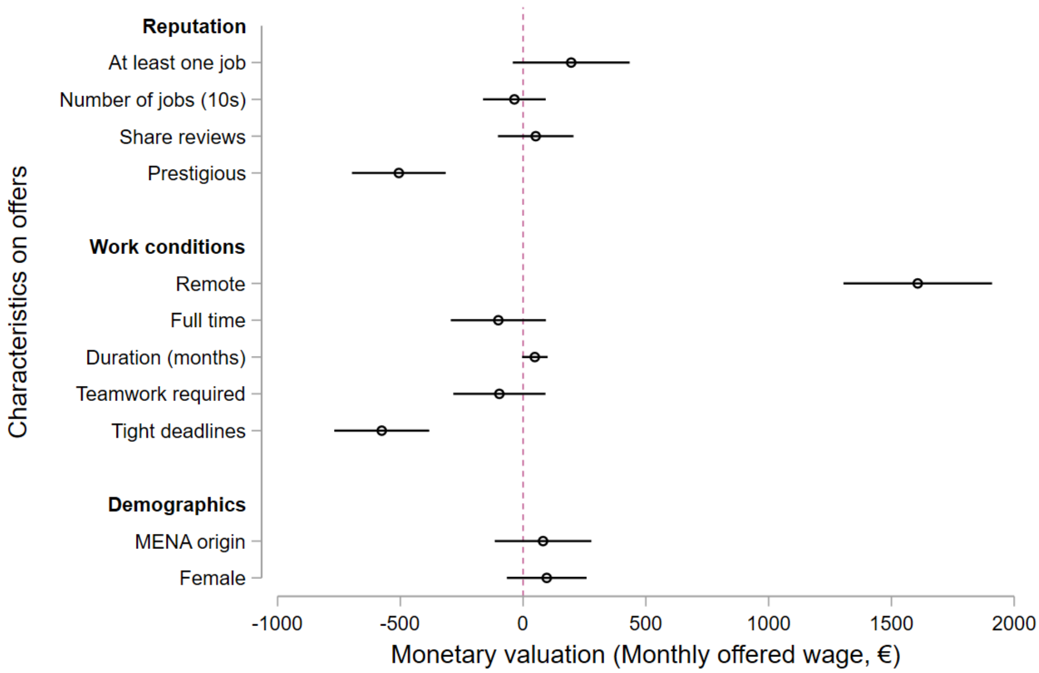
Figures

Figure 1: Estimated preferences from the *Evaluation* experiments expressed in monetary valuation

(a) Recruiter preferences



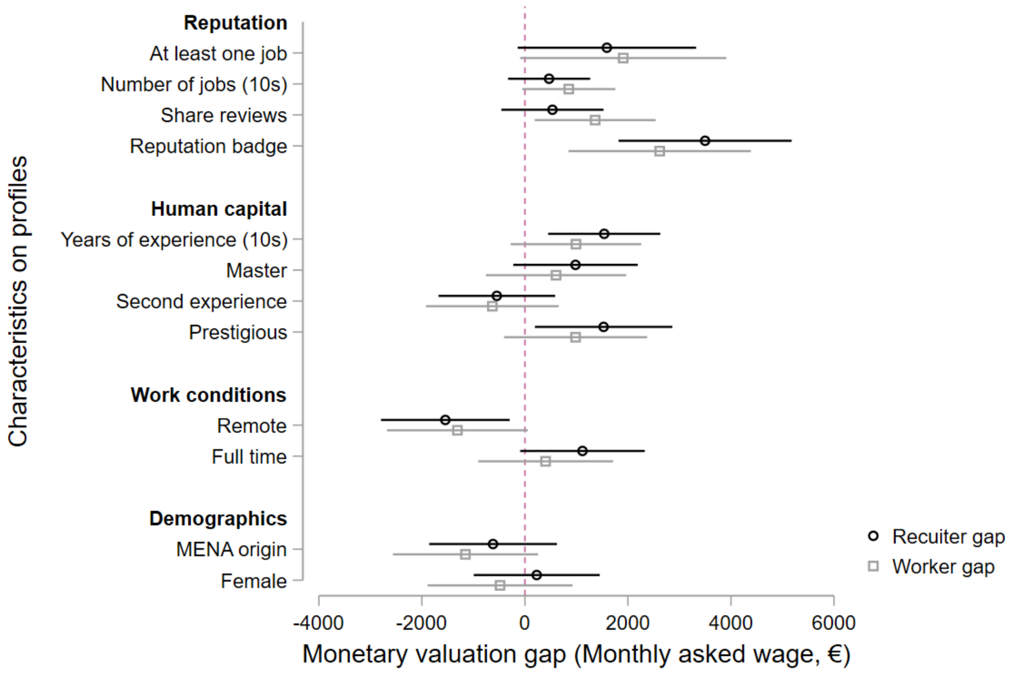
(b) Worker preferences



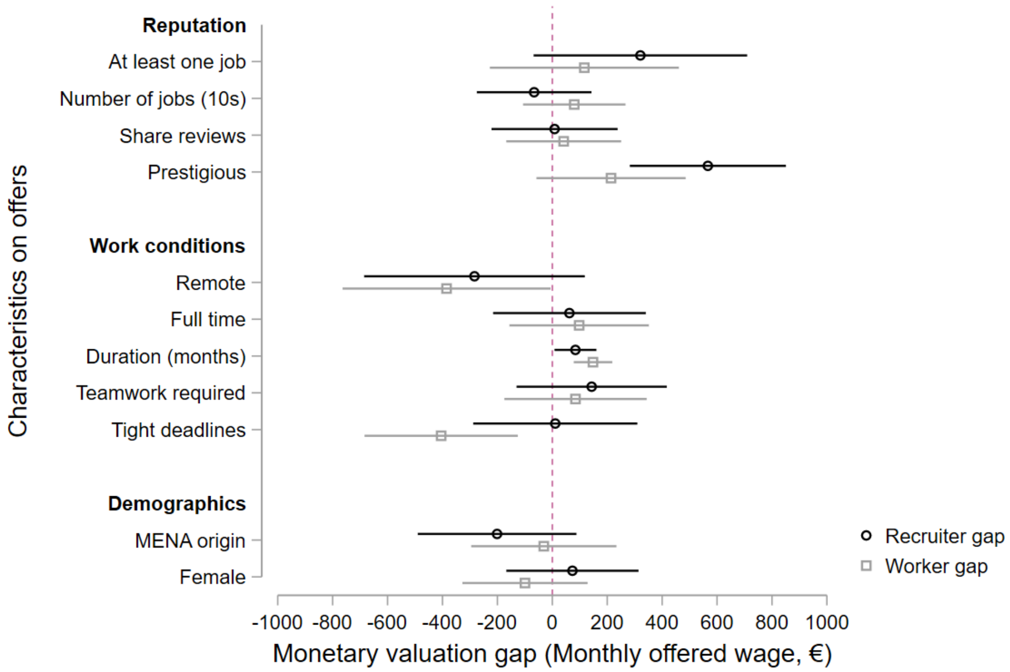
Notes: This figure presents estimates of monetary valuations for each characteristic x randomized on profiles and offers, computed as β_x/β_z, where βs refer to regression coefficients from equations 1 and 2. In Panel (a), β_z refers to the negative of the estimated asked wage coefficient from equation 1, controlling for the reported competence of a profile to purge the signaling component of the asked wage (Table B.3). In Panel (b), β_z refers to the estimated offered wage coefficient from equation 2 (Table 2). Bars represent 95 % confidence intervals, with standard errors computed through the delta method.

Figure 2: Monetary value of perception gaps

(a) Profile characteristics



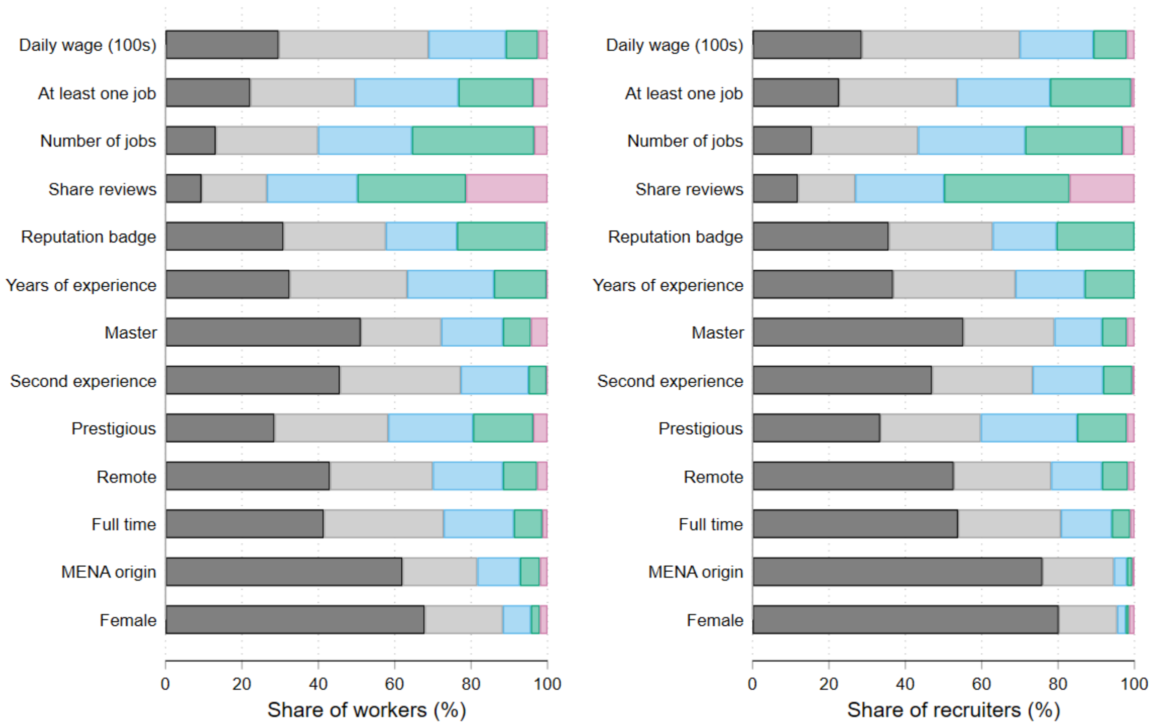
(b) Offer characteristics



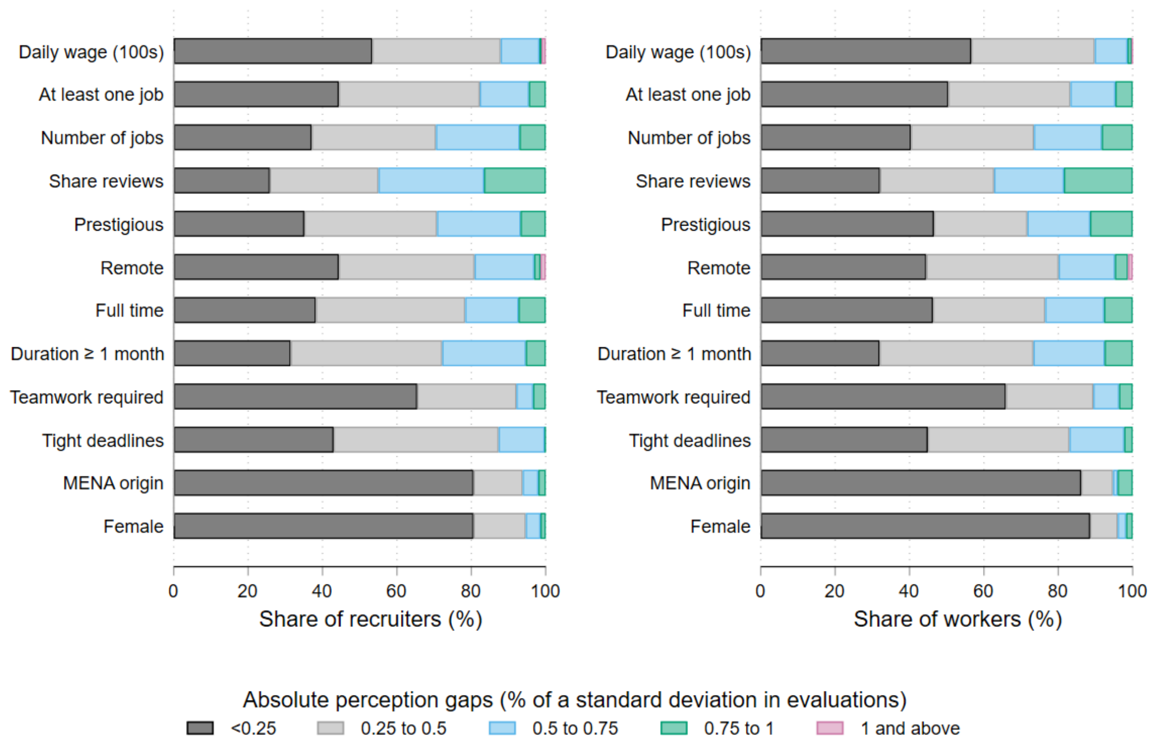
Notes: Each point represents the perception gap for a particular characteristic x, normalized by the daily wage regression coefficient estimated in the *Evaluation* experiments. This valuation is computed as $\frac{\beta_x^p - \beta_x}{\beta_z}$ for offers and as $\frac{\beta_x^p - \beta_x}{-\beta_z}$ for profiles, where β_X is the regression coefficient for a particular characteristic in the *Evaluation* experiment and β_x^p is the regression coefficient for characteristic x in the *Prediction* experiment. In Panel (a), β_z refers to the estimated asked wage coefficient from equation 1, controlling for the reported competence of a profile to purge the signaling component of the asked wage (Table B.3). In Panel (b), β_z refers to the estimated offered wage coefficient from equation 2 (Table 2). Bars represent 95 % confidence intervals, with standard errors computed through the delta method.

Figure 3: Individual-level perception gaps

(a) Profile characteristics - perception gaps about recruiter preferences



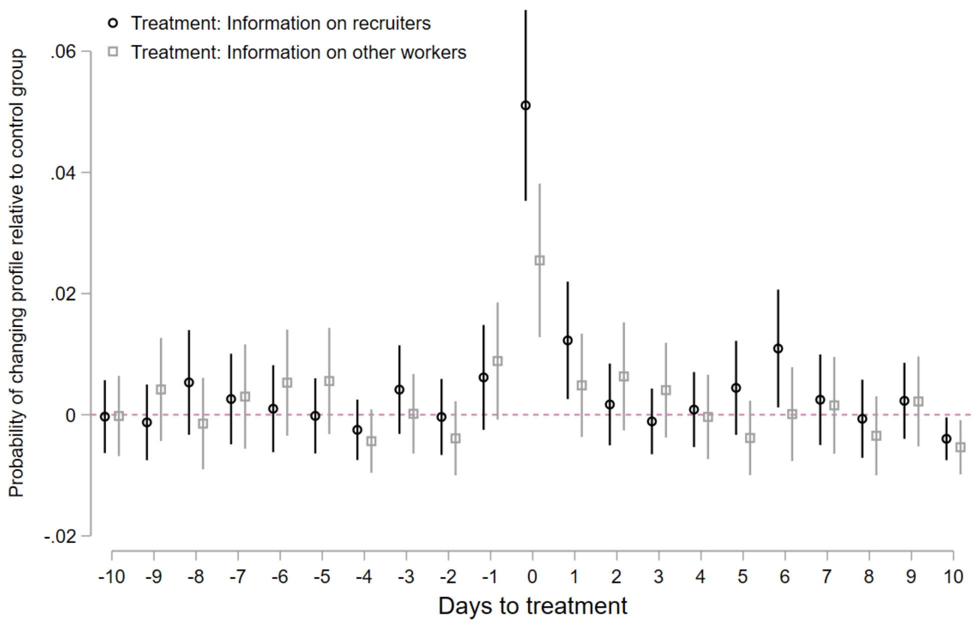
(b) Offer characteristics - perception gaps about worker preferences



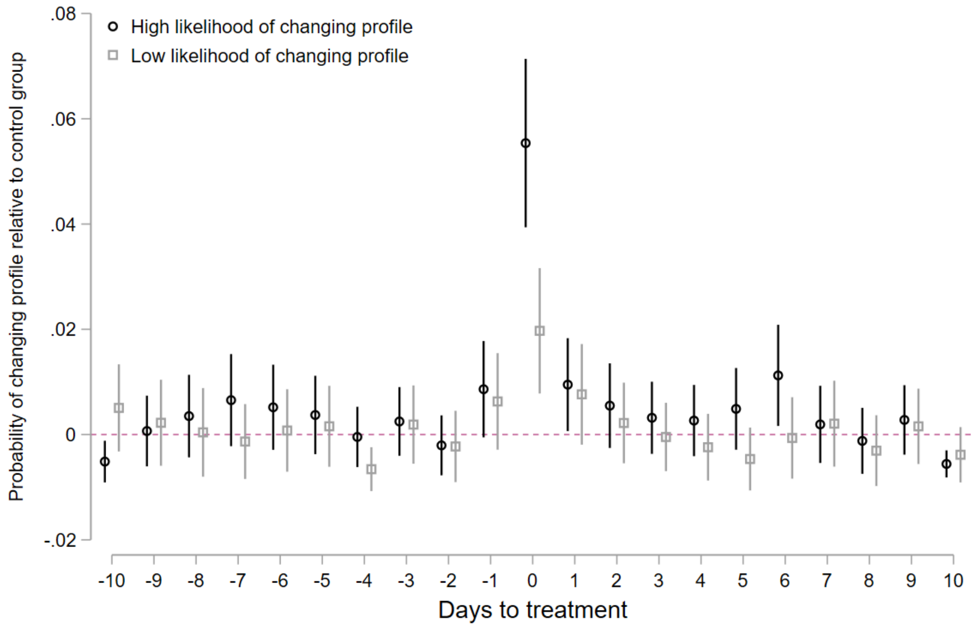
Notes: The figure plots the distribution of individual level errors for each characteristic. These errors are computed by subtracting estimated preferences of participants in the *Evaluation* experiment at the job category level from the prediction of each participant about that characteristic's marginal impact on evaluations from the *Prediction* experiment. Errors are normalized by the standard deviation of the demeaned outcome variable in the *Evaluation* experiment.

Figure 4: Differences-in-Differences estimates of changes in worker profiles following the information treatment

(a) By whether information related to recruiters or other workers



(b) By self-reported likelihood of changing their profile in the experiment



Notes: This figure shows the daily differential probability of workers changing their profile in the treatment versus comparison group. Timing is centered around the day in which respondents receive the information treatment (0), controlling for worker and calendar day fixed effects. We consider the following elements when determining whether a profile was changed: asked wage, availability for on site or remote work, number of educational degrees on profile, number of work experiences, and availability for part-time or full-time work. The sample consists of respondents to the experiment (treated group) and of 2,392 workers who were scheduled to be recruited for the experiment but were not contacted since we reached our targeted sample (comparison group). Workers were ordered randomly within the contact list. Each worker's profile is observed every day between the first of January and the 23rd of March 2026. The baseline rate of profile updating before the experiment is 0.9%. Bars represent 95 % confidence intervals.

Tables

Table 1: Summary statistics of the market

Panel (a) Workers	
Age	34.89
	(8.46)
Number of jobs	[0.00–7.00]
Asked wage	434.22
	(187.31)
Years on platform	4.16
	(2.45)
Years of experience	10.58
	(6.10)
Full-time availability (%)	72.5
Remote-only availability (%)	44.3
Master's degree (%)	70.6
Female (%)	34.4
MENA origin (%)	13.8
Number of workers	25,000–75,000

Panel (b) Offers by recruiters	
Years on platform	2.27
	(2.34)
Number of offers per recruiter	[1.00–5.00]
Budget per recruiter (1,000s)	[0.20–13.87]
Job duration (months)	1.14
	(2.38)
Full-time requirement (%)	38.4
On-site requirement (%)	9.4
Female recruiter (%)	29.2
MENA recruiter (%)	7.5
Number of offers	15,000–50,000

Notes: Panel (a) reports summary statistics for workers in the nine job categories in the *Evaluation* experiments. Workers are included if their profile was created before 2025 and they were visible to recruiters for at least 90 days in 2025. Panel (b) reports summary statistics for offers made by recruiters in the same job categories and job-level characteristics are averaged at the recruiter level. Continuous variables are reported as means, with standard deviations in parentheses, unless otherwise indicated. Indicator variables are reported as percentages. In Panel (a), Years of experience corresponds to workers' total years of experience in the labor market. In Panel (b), offers with budget or duration above the 99th percentile are excluded prior to aggregation. Gender and ethnicity of workers and recruiters are imputed from first names. For confidentiality reasons, some quantities are reported as 10th–90th percentile ranges rather than exact values. The number of workers and recruiters is also reported as a broad range rather than an exact count.

Table 2: Estimated preferences from the *Evaluation* experiments

Evaluator:	Recruiters		Workers	
Object:	Profiles		Offers	
Dependent variable:	Hire	Accept likelihood	Accept	Offer likelihood
	(1)	(2)	(3)	(4)
Daily wage (100s)	-0.154***	-0.134***	0.912***	0.173***
	(0.025)	(0.018)	(0.029)	(0.018)
At least one job	0.232***	0.097*	0.081	0.035
	(0.070)	(0.055)	(0.050)	(0.041)
Number of jobs (10s)	0.187***	0.052**	-0.015	-0.011
	(0.033)	(0.024)	(0.027)	(0.022)
Share reviews	0.042	0.008	0.021	0.003
	(0.042)	(0.034)	(0.033)	(0.025)
Reputation badge	0.227***	0.042		
	(0.065)	(0.049)		
Years of experience (10s)	0.313***	0.006		
	(0.043)	(0.033)		
Master	0.055	-0.049		
	(0.050)	(0.039)		
Second experience	0.478***	0.176***		
	(0.047)	(0.040)		
Prestigious	0.075	-0.126***	-0.210***	-0.160***
	(0.052)	(0.044)	(0.040)	(0.031)
Remote	0.046	0.042	0.667***	0.139***
	(0.053)	(0.038)	(0.061)	(0.033)
Full time	0.029	0.101**	-0.042	0.011
	(0.052)	(0.042)	(0.041)	(0.028)
Duration (months)			0.020*	0.021**
			(0.011)	(0.008)
Teamwork required			-0.040	-0.023
			(0.040)	(0.030)
Tight deadlines			-0.239***	-0.051*
			(0.041)	(0.030)
MENA origin	-0.015	-0.075*	0.034	0.038
	(0.053)	(0.042)	(0.042)	(0.033)
Female	0.014	0.047	0.040	-0.017
	(0.052)	(0.041)	(0.034)	(0.028)
Number of observations	8,692	8,692	20,600	20,600
Number of respondents	348	348	824	824
Outcome mean	6.014	6.856	6.164	6.496
Outcome standard deviation	1.971	1.525	2.557	1.794

Notes: This table reports results from estimating Equations 1 and 2 by OLS and using evaluations from participants in the *Evaluation* experiments. All regressions control for respondent fixed effects. Outcomes are measured on a 10-point Likert-scale. "Hire" corresponds to a recruiters' stated interest in hiring a given worker profile. "Accept likelihood" corresponds to a recruiter's expected likelihood that a worker with the given profile would accept a job offer from them. "Accept" corresponds to a workers' stated interest in accepting a given job offer. "Offer likelihood" corresponds to a worker's expected likelihood that a recruiter with the given job would offer it to them. Estimates correspond to one-unit increases in the corresponding variables, except for the following cases: *Daily wage* is measured in hundreds of euros; *Number of jobs* and *Years of experience* are measured in tens; *Share reviews* corresponds to an increase from the average share of ratings shown on a profile (60%) to having all jobs completed with a review (100%). *At least one job* corresponds to the change from having no completed job to having at least one job with an average number of reviews left per completed job, while *Number of jobs* captures the intensive margin of additional completed jobs. Each participating recruiter evaluates 25 randomized worker profiles (columns 1–2) and each participating worker evaluates 25 job offers (columns 3–4). Further details on the distribution of randomized characteristics can be found in Appendix A. Further details on experimental instructions and questions asked to participants can be found in Appendix D. Standard errors are clustered at the respondent level. $^{*}p < 0.10$, $^{**}p < 0.05$, $^{***}p < 0.01$.

Table 3: Estimates from the *Prediction* experiments

Predictor:	Combined	Workers	Recruiters	Combined	Recruiters	Workers
Object:	Profiles			Offers		
Dependent variable:	Hire (predicted)			Accept (predicted)		
	(1)	(2)	(3)	(4)	(5)	(6)
Daily wage (100s)	-0.044***	-0.020	-0.101***	1.078***	1.060***	1.086***
	(0.012)	(0.015)	(0.021)	(0.020)	(0.034)	(0.024)
At least one job	0.379***	0.370***	0.401***	0.152***	0.195***	0.132***
	(0.039)	(0.048)	(0.069)	(0.039)	(0.062)	(0.048)
Number of jobs (10s)	0.257***	0.246***	0.284***	0.017	-0.011	0.030
	(0.018)	(0.023)	(0.031)	(0.020)	(0.034)	(0.025)
Share reviews	0.117***	0.093***	0.174***	0.022	0.012	0.026
	(0.022)	(0.026)	(0.039)	(0.022)	(0.035)	(0.028)
Reputation badge	0.546***	0.572***	0.486***			
	(0.034)	(0.043)	(0.055)			
Years of experience (10s)	0.456***	0.474***	0.420***			
	(0.025)	(0.030)	(0.045)			
Master	0.147***	0.158***	0.120***			
	(0.026)	(0.031)	(0.045)			
Second experience	0.419***	0.421***	0.413***			
	(0.025)	(0.030)	(0.043)			
Prestigious	0.210***	0.228***	0.175***	-0.068**	0.040	-0.115***
	(0.030)	(0.038)	(0.044)	(0.030)	(0.042)	(0.039)
Remote	-0.109***	-0.116***	-0.093**	0.552***	0.581***	0.538***
	(0.023)	(0.028)	(0.040)	(0.037)	(0.056)	(0.047)
Full time job	0.116***	0.137***	0.066	-0.017	-0.025	-0.012
	(0.025)	(0.031)	(0.041)	(0.025)	(0.040)	(0.032)
Duration (months)				0.068***	0.051***	0.075***
				(0.007)	(0.012)	(0.009)
Teamwork required				-0.012	0.000	-0.018
				(0.027)	(0.041)	(0.035)
Tight deadlines				-0.345***	-0.224***	-0.399***
				(0.031)	(0.047)	(0.039)
MENA origin	-0.093***	-0.075**	-0.128***	0.003	-0.047	0.025
	(0.026)	(0.032)	(0.046)	(0.027)	(0.043)	(0.034)
Female	0.022	0.043	-0.027	0.034	0.084**	0.012
	(0.026)	(0.031)	(0.046)	(0.024)	(0.035)	(0.031)
Observations	28,975	20,150	8,825	28,775	8,900	19,875
Number of predictors	1159	806	353	1151	356	795
Outcome mean	6.340	6.405	6.193	5.996	5.943	6.019
Outcome standard deviation	1.778	1.782	1.768	2.186	2.050	2.245

Notes: This table reports results from estimating Equations 1 and 2 by OLS and using predictions from participants in the *Prediction* experiments. All regressions control for respondent fixed effects. Outcomes are measured on a 10-point Likert-scale. "Hire" corresponds to the prediction of recruiters' stated interest in hiring a given worker profile. "Accept" corresponds to the prediction of workers' stated interest in accepting a given job offer. Each participant made 25 predictions. Columns 1 and 4 combine predictions of both workers and recruiters regarding the same object, while columns 2-3 and 5-6 separate predictions by whether they were made by recruiters or workers. See Table 2 for additional details. Standard errors are clustered at the respondent level. $^{*}p < 0.10$, $^{**}p < 0.05$, $^{***}p < 0.01$.

Table 4: Estimated *perception gaps*

Predictor:	Combined	Workers	Recruiters	Combined	Recruiters	Workers
Object:	Profiles			Offers		
Dependent variable:	Hire (estimated and predicted)			Accept (estimated and predicted)		
	(1)	(2)	(3)	(4)	(5)	(6)
Daily wage (100s) × P_i	0.112***	0.137***	0.055*	0.189***	0.171***	0.197***
	(0.028)	(0.029)	(0.033)	(0.035)	(0.045)	(0.038)
At least one job × P_i	0.166**	0.156*	0.188*	0.067	0.110	0.047
	(0.081)	(0.085)	(0.098)	(0.065)	(0.081)	(0.071)
Number of jobs (10s) × P_i	0.057	0.046	0.084*	0.020	-0.008	0.032
	(0.038)	(0.040)	(0.045)	(0.035)	(0.044)	(0.038)
Share reviews × P_i	0.077	0.053	0.134**	0.012	0.002	0.017
	(0.047)	(0.049)	(0.057)	(0.040)	(0.048)	(0.043)
Reputation badge × P_i	0.318***	0.344***	0.257***			
	(0.075)	(0.079)	(0.086)			
Years of experience (10s) × P_i	0.134***	0.151***	0.097			
	(0.050)	(0.053)	(0.063)			
Master × P_i	0.086	0.097	0.059			
	(0.057)	(0.060)	(0.068)			
Second experience × P_i	-0.056	-0.054	-0.062			
	(0.054)	(0.056)	(0.064)			
Prestigious × P_i	0.132**	0.150**	0.097	0.133***	0.241***	0.086
	(0.061)	(0.065)	(0.069)	(0.050)	(0.058)	(0.056)
Remote × P_i	-0.145**	-0.152**	-0.129*	-0.142*	-0.112	-0.156**
	(0.058)	(0.060)	(0.067)	(0.072)	(0.083)	(0.078)
Full time × P_i	0.090	0.110*	0.040	0.035	0.027	0.040
	(0.057)	(0.060)	(0.066)	(0.049)	(0.058)	(0.052)
Duration (months) × P_i				0.053***	0.036**	0.060***
				(0.013)	(0.016)	(0.014)
Teamwork required × P_i				0.040	0.052	0.034
				(0.049)	(0.058)	(0.053)
Tight deadlines × P_i				-0.110**	0.011	-0.164***
				(0.052)	(0.062)	(0.057)
MENA origin × P_i	-0.078	-0.061	-0.113	-0.035	-0.085	-0.013
	(0.059)	(0.062)	(0.070)	(0.050)	(0.061)	(0.055)
Female × P_i	0.001	0.023	-0.047	-0.017	0.032	-0.040
	(0.059)	(0.061)	(0.070)	(0.043)	(0.050)	(0.047)
Observations	37,517	28,692	17,367	48,500	28,625	39,600
Number of predictors	1159	806	353	1151	356	795
Number of evaluators	342	342	342	789	789	789
Evaluator outcome standard deviation	1.970	1.970	1.970	2.549	2.549	2.549

Notes: This table reports results from estimating Equations 1 and 2 by OLS, using evaluations from participants in the *Evaluation* experiments and predictions from participants in the *Prediction* experiments, and augmented by interacting each characteristic with an indicator variable (P_i) for whether the participant was part of the *Prediction* experiments. The estimates shown represent the interaction terms, corresponding to the differences between the predicted impact of each characteristic by participants of the *Prediction* experiments and the estimated impact of each characteristic on evaluations by participants in the *Evaluation* experiments. Columns 1-3 represent differences between the impact of profile characteristics on recruiters' interest in hiring a worker and the predicted impact of these characteristics. Columns 4-6 represent differences between the impact of offer characteristics on workers' interest in accepting a job and the predicted impact of these characteristics. Columns 1 and 4 combine perception gaps of both workers and recruiters regarding the same object, while columns 2-3 and 5-6 separate gaps by whether predictors represent recruiters or workers. Estimates reweighted so that size of job categories are held constant across participants in the *Evaluation* and *Prediction* experiments. See Tables 2 and 3 for further details. Standard errors are clustered at the respondent level. $^{*}p < 0.10$, $^{**}p < 0.05$, $^{***}p < 0.01$.

Table 5: *Perception gaps* and market outcomes

Panel (a): Characteristics and pricing

Predictor:	Workers		Recruiters	
Dependent variable:	Characteristic	Asked wage	Characteristic	Offered wage
	(1)	(2)	(3)	(4)
Perception gap	0.029*		0.037***	
	(0.017)		(0.013)	
Perception gap in market value		0.130***		-0.051**
		(0.033)		(0.022)
Market value		0.379***		-0.082***
		(0.036)		(0.027)
Perception gap in wage sensitivity		0.139***		0.068***
		(0.030)		(0.019)
Observations	7,246	804	8,685	1,069
Outcome mean	0.419	0.099	0.281	-0.050

Panel (b): Job outcomes

Predictor:	Workers		Recruiters	
Dependent variable:	Successful matches	Earnings	Successful matches	Wages
	(1)	(2)	(3)	(4)
Absolute perception gap in market value	-0.121**	-0.177***	-0.146*	0.236***
	(0.057)	(0.065)	(0.083)	(0.089)
Market value	0.163***	0.170***	0.197***	-0.170*
	(0.043)	(0.045)	(0.059)	(0.091)
Absolute perception gap in wage sensitivity	-0.049	-0.016	-0.114	0.038
	(0.050)	(0.052)	(0.074)	(0.102)
Observations	804	804	322	c
Outcome mean	-0.000	-0.000	-0.000	-0.053

Notes: **Panel (a)** reports OLS estimates of the correlation between perception gaps and characteristics of participants and their pricing. For columns 1 and 3 the dependent variable is whether a characteristic is present in a profile/job offer. We only include participants who made predictions about the other side of the market. Continuous variables are rescaled to vary between 0 and 1 for comparability. Characteristics which are less likely to represent a choice: demographics, share of ratings, and years of experience are not included. Perception gaps are calculated as the difference between individual participants' Empirical Bayes estimates for a characteristic and the estimated coefficient for that characteristic from the *Evaluation* experiment. Regressions include job category and characteristic fixed effects. Standard errors are clustered at the profile level for workers and job offer level for recruiters. For columns 2 and 4, the dependent variables are the asked and offered wage standardized by job category and adjusted for time trends. To compute an estimated market value for a profile/job offer, we take the sum of the coefficients from the *Evaluation* experiment multiplied by the quantity of the characteristic on a profile/job offer, excluding wages. This value is then standardized by job category. To compute the perception gap in market value we first take the sum of a participant's Empirical Bayes estimates multiplied by the quantity of the characteristic, and standardize it. This yields an estimate of the participant's perceived value of their profile/offer and we then take the difference between this perceived value and the estimated market value. Number of projects and years of experience are capped at 20 when computing perception gaps and estimating market values to minimize outliers. Robust standard errors in parentheses.
Panel (b) reports OLS estimates of the correlation between perception gaps and job outcomes on the platform. For columns 1 and 2, the dependent variables are the number of successful matches with recruiters and earnings on the platform by workers. For columns 3-4, the dependent variables are the number of successful matches with workers and average wages paid for completed jobs. Dependent variables are standardized by job category and adjusted for time trends. Absolute perception gap in market value corresponds to the absolute value of perception gaps in market value estimated as described in Panel (a). Columns 3-4 also control for whether the recruiter posted their offer through the platform's matching services. Robust standard errors in parentheses.
$*p < 0.10, **p < 0.05, ***p < 0.01$.

A Additional details on the experimental design

A.1 Construction of profiles and offers

A.1.1 Examples

Figure A.1: Worker profile - English

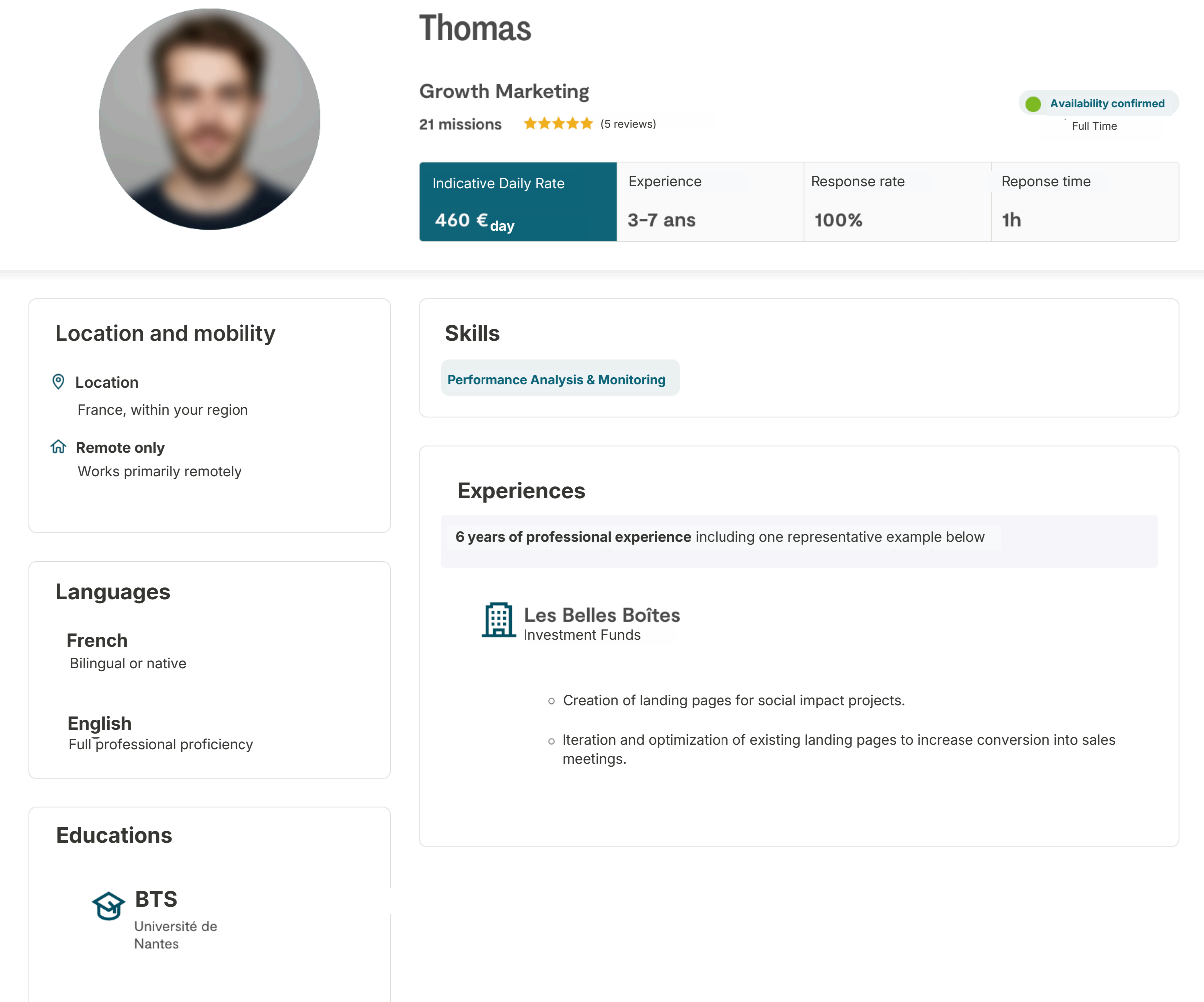


Figure A.2: Worker profile

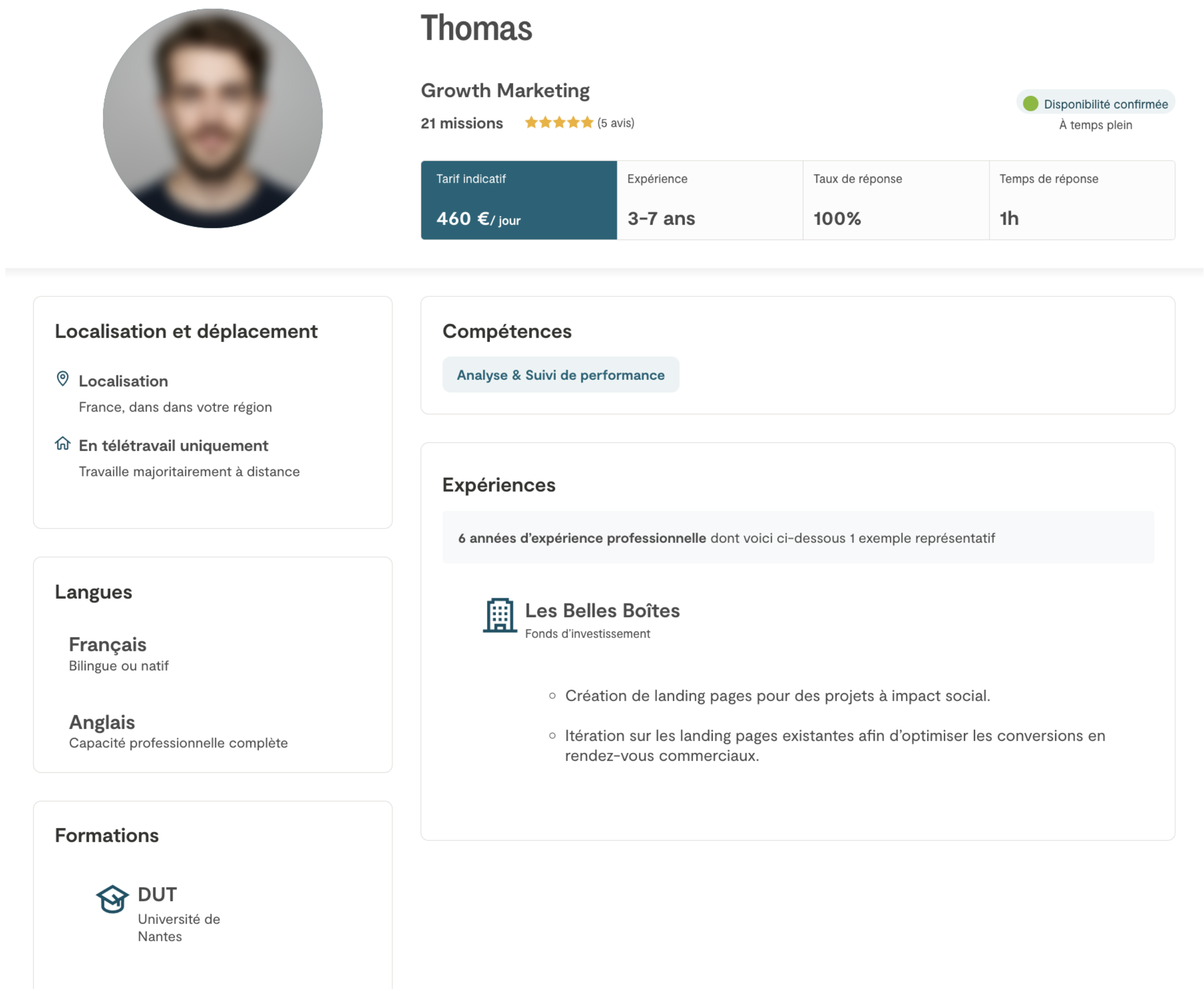


Figure A.3: Job offer - English

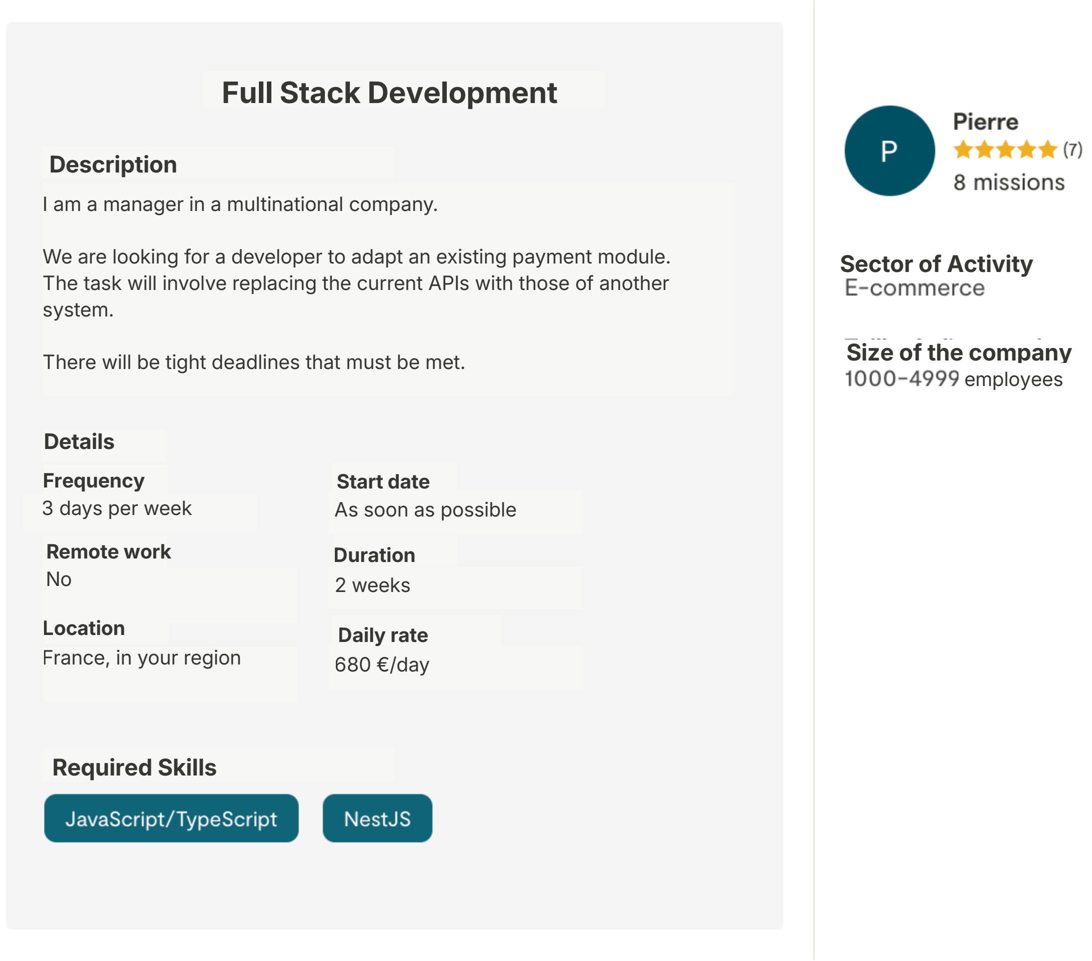
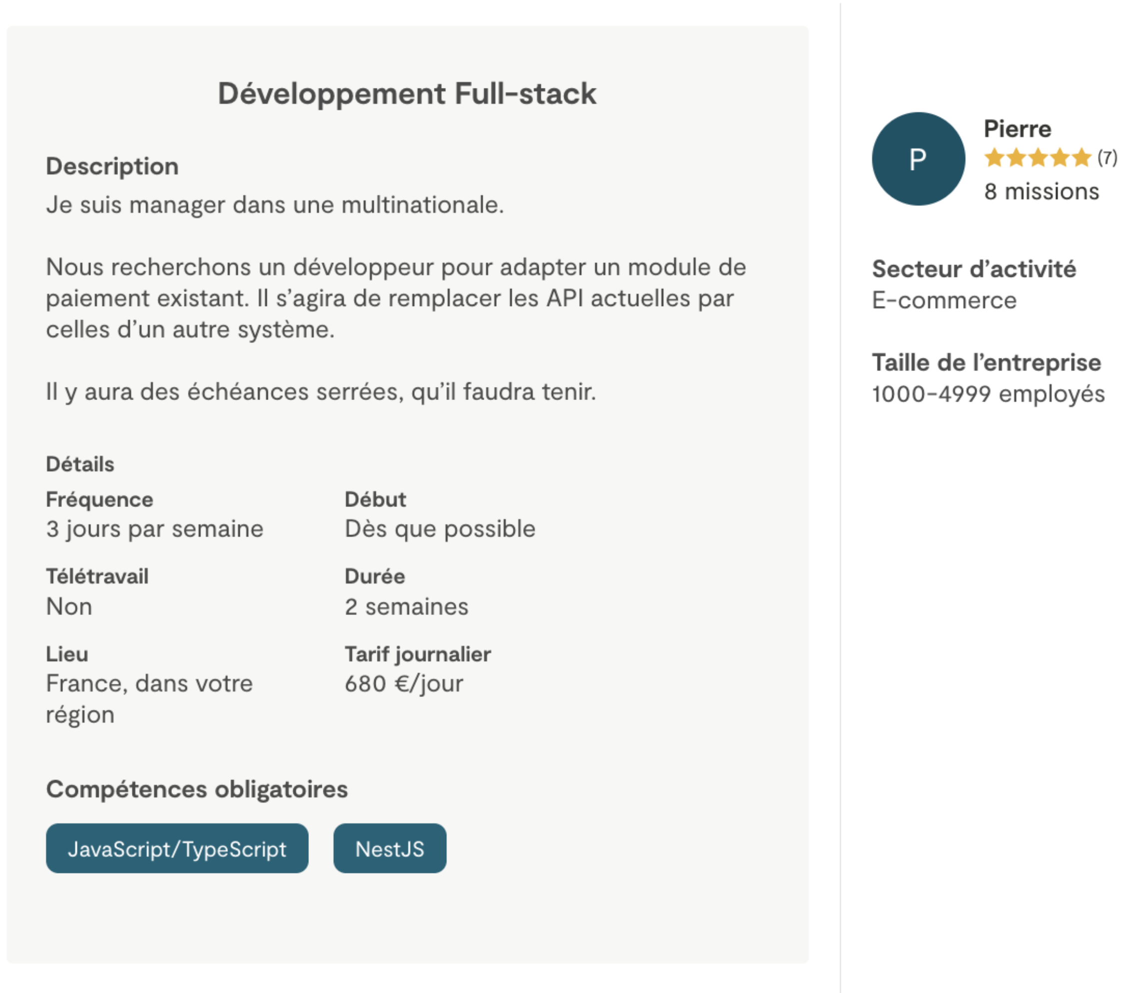


Figure A.4: Job offer



A.1.2 Profiles

When calculating statistics from worker profiles, we restrict to active profiles discoverable to recruiters on the platform. Each characteristic is adapted to each job category, but when differences across categories are minimal on the platform, we harmonize the randomization across job categories. We also round frequencies and distributions to the nearest 0.05 value for fractions and the nearest multiple of 5 for integers. See Table A.1 for an overview of randomized characteristics.

Asked wages are drawn from category-specific uniform distributions, with the minimum and maximum values based on the 10th and 90th percentiles of asked wages for each job category. We chose the uniform distribution because it allows us to have more power over the entire range of the distribution.

Years of work experience are drawn from category-specific uniform distributions from 1 to an upper limit equal to the 90th percentile of the distribution for each job category. Since the upper limit is similar across categories, we choose the same value for each category. The number of work experiences shown on a profile was also randomized to be 1 or 2 with equal probability, while the share of workers with prestigious experiences was set at 0.25. To populate work experiences, we draw a random sample of real experiences in free text format and process each drawn experience to standardize the text and remove mentions of gender, ethnicity, very senior positions, and overly-specific jargon or technical references that would not be relevant to the broader job category. Every entry was reviewed and edited for quality and consistency.

Both the number of experiences and the prestigious classification are uniform across job categories. The share of workers with prestigious experiences is overrepresented in the experiment, both because we restrict to only one or two work experiences while real profiles may have several more, with only one or two being "prestigious", and because we set prestigious experiences to either apply to none or all (1 or 2) experiences within a profile. These decisions were made to increase power and salience.

Education credentials are populated by drawing and processing a random sample of education information included in profiles, available in free text format. We extract the institution and education credentials from each text using regex-based rules. If more than one credential is present, we order them to identify the highest one. Approximately 70% of highest credentials correspond to Master's degrees. The remaining 30% is composed of license, DUT, and BTS degrees, which account for the most common degrees after Master's.

We randomize 30% of profiles to have no completed job on the platform. This balances our ability to detect a penalty from having no completed job with our ability to test hypotheses regarding characteristics only defined for profiles with some completed jobs. In our analyses, we consider one minus this indicator, which we label "At least one job".

The number of jobs is drawn from sub-category-specific uniform distributions from 1 to an upper limit equal to the approximate 90th percentile of the distribution for each job category. In practice, this number is set to 0 when the binary indicator for not having completed a job is 1.

The badge is assigned to profiles with probability 0.25. In practice, the badge indicator is set to 0 when the binary indicator for not having completed a job is 1.

The share of jobs for which a review was given is drawn from a uniform distribution between 0.2 and 1. The average share on the platform is around the middle point of this range at 0.6, and the average share of reviews is roughly constant across the distribution of jobs completed, beyond the first five jobs or so, motivating the independence between this randomization and that of the number of jobs completed. In practice, the share of reviews is set to 0.6, the mean value, when the binary indicator for not having completed a job is 1.

The share of profiles indicating a preference for remote work and full time availability are similar across job categories and around 0.5 and 0.7, respectively, which correspond to their randomized shares.

Lastly, the share of profiles with names and pictures indicating gender and ethnicity was assigned based on name analysis of workers' first names, separately by job category. The share of minority profiles in the experiment (MENA as well as women in some tech categories) is sometimes increased slightly with respect to their platform counterparts to ensure that each of the four groups account for at least 5% of profiles and that women as well as MENA profiles each account for at least 20% of profiles within a category. This was done to ensure sufficient power to detect meaningful effects while representing only a minor distortion.[48]

Profiles have a few additional fields that we abstract from in the experiment to keep the number of characteristics tractable and because they tend to be more job-specific. In particular, workers can indicate special certifications received (which are rare for the jobs included in the experiment), upload portfolios of their work (for example, logos created), and links to code repositories (e.g. GitHub).

A.1.3 Offers

We calculate statistics from existing job offers. Each offer characteristic is adapted to each job category, but again, when differences are small, we harmonize the randomization across categories for simplicity. Again, we also round integers to the nearest multiple of 5 and fractions to the nearest 0.05. See Table A.2 for an overview of randomized characteristics.

Offered wages are drawn from category-specific uniform distributions, with the minimum and maximum values corresponding to the approximate 10th and 90th percentiles of offered wages for each job category.

The randomization for the number of completed jobs and share of jobs reviewed are analogous to that of profiles.

Recruiter prestige on the platform would typically be signaled through firm names, but we omit names from offers for concern of associating real firms with experimental offers. We introduce the signal in the description of the firm usually included at the beginning

[48]For example, even a ten percentage point boost would only involve a participant seeing a total of two or three more profiles of that group during the experiment.

of the free text included on offers. In particular, we use the following sentences:[49]

- We are a CAC 40 company.
- I am a manager in a CAC 40 company.
- We are a large publicly listed company.
- I am a manager in a large publicly listed company.
- We are a multinational company.
- I am a manager in a multinational company.
- We are a global leader in our sector.
- I am a manager in a company that is a global leader in its sector.

It is difficult to assess the share of offers from prestigious firms since they disproportionately arise through the platform's matching service rather than from recruiters using the search engine, but they are overrepresented in the experiment at a share of 0.25 to ensure enough power.

The share of offers indicating a requirement for in-person work is similar across categories at around 0.25, both on the platform and in the experiment. For our analysis, we compute one minus this indicator to harmonize specifications across profiles and offers. Full time requirements vary substantially in tech vs non-tech jobs and are randomized with probability 0.65 and 0.3. Job duration also varies substantially across categories, discretized into numbers of weeks to cover the range on the platform, specifically from the 10th to the 90th percentile.

[49]For offers that do not have the prestige signal, we still include a similar sentence to keep the length and content similar. Namely, we use the following sentences (translated)

- We are a small and medium-sized enterprise (SME).
- I am a manager in an SME.
- We are a regional company.
- I am a manager in a regional company.
- We are a locally established company.
- I am a manager in a locally established company.
- Rooted in our region, our company is a well-recognized local player.

The share of offers indicating teamwork and tight or urgent deadlines is based on a set of sentences included under the task description in the offer. These sentences are inspired by information extracted from the content of offers using regex-based rules. We use the following sentences (translated) for teamwork:

- You will collaborate closely with members of our team.
- This assignment will require close coordination with our team.
- The assignment involves strong interaction with the rest of the team.
- You will interact regularly with our team throughout the assignment.
- The assignment will require close collaboration with our team.

and for tight deadlines:

- Meeting tight deadlines is essential.
- Tight deadlines will need to be respected.
- There will be tight deadlines that must be met.
- You will need to work quickly and efficiently to meet deadlines.
- The timeline is tight and the project will require a sustained pace.

It is challenging to accurately assess the share of offers with those mentions, but they are somewhat overrepresented in the experiment, with a share of 0.25 to ensure enough power.

The share of profiles with names indicating gender and ethnicity were assigned based on name analysis of recruiters' first names, separately by job category, analogously to the process for profiles.

Each offer also includes a more specific task description to increase realism. To populate these, we draw a random sample of real descriptions in free text format and process each drawn description using *Gemini* to standardize the text into two sentences and remove mentions of gender, ethnicity, very senior positions, personal information, and other content that would not be relevant to the broader job category. Every entry was reviewed and edited for quality and consistency, namely to ensure consistency with the selected expertise keyword(s). Participants in the *Evaluation* experiments were thus only presented job offers in which the task content was consistent with their selected expertise keyword(s).

Table A.1: Randomization of profile characteristics

Characteristic	Developers	Integration	Translator	Marketing	Copywriting	Content
Daily wage	U[200,800]	U[150,600]	U[150,550]	U[200,800]	U[150,650]	U[150,650]
Remote (0/1)	0.5	0.5	0.5	0.5	0.5	0.5
Full time (0/1)	0.7	0.7	0.7	0.7	0.7	0.7
Master (0/1)	0.7	0.7	0.7	0.7	0.7	0.7
Female European (0/1)	0.15	0.20	0.55	0.25	0.50	0.55
Male European (0/1)	0.60	0.60	0.25	0.55	0.30	0.25
Female MENA (0/1)	0.05	0.05	0.125	0.05	0.15	0.15
Male MENA (0/1)	0.20	0.15	0.075	0.15	0.05	0.05
Share reviews	U[0.2,1]	U[0.2,1]	U[0.2,1]	U[0.2,1]	U[0.2,1]	U[0.2,1]
Profile has no job (0/1)	0.3	0.3	0.3	0.3	0.3	0.3
Number of jobs	U[1,20]	U[1,50]	U[1,60]	U[1,40]	U[1,40]	U[1,20]
Years of experience	U[1,20]	U[1,20]	U[1,20]	U[1,20]	U[1,20]	U[1,20]
Second experience (0/1)	0.5	0.5	0.5	0.5	0.5	0.5
Prestigious (0/1)	0.25	0.25	0.25	0.25	0.25	0.25
Badge (0/1)	0.25	0.25	0.25	0.25	0.25	0.25

Notes: Values are based on corresponding values from the platform but should not be interpreted as exact platform values. Values are rounded, harmonized across categories whenever similar, and certain rarer characteristics are boosted for power. Developers regroup 4 job categories in the experiment: back-end developers, front-end developers, full-stack developers, and mobile developers.

Table A.2: Randomization of job offer characteristics

Characteristic	Developers	Integration	Translator	Marketing	Copywriting	Content
Daily wage	U[200,700]	U[200,500]	U[125,350]	U[200,650]	U[150,500]	U[125,430]
Full time (0/1)	0.65	0.65	0.3	0.3	0.3	0.3
Duration (weeks)	{1,2,3,4,8,12,24}	{<1,1,2,3,4,8}	{<1,1,2,3,4,8}	{<1,1,2,3,4,8,12,24}	{<1,1,2,3,4,8,12,24}	{1,2,3,4,8,12,24}
In person (0/1)	0.25	0.25	0.25	0.25	0.25	0.25
Female European (0/1)	0.25	0.30	0.40	0.30	0.40	0.40
Male European (0/1)	0.55	0.50	0.40	0.50	0.40	0.40
Female MENA (0/1)	0.05	0.075	0.10	0.075	0.075	0.125
Male MENA (0/1)	0.15	0.125	0.10	0.125	0.125	0.075
Share reviews	U[0.2,1]	U[0.2,1]	U[0.2,1]	U[0.2,1]	U[0.2,1]	U[0.2,1]
Recruiter has no job (0/1)	0.3	0.3	0.3	0.3	0.3	0.3
Number of jobs	U[1,25]	U[1,25]	U[1,35]	U[1,25]	U[1,25]	U[1,25]
Teamwork (0/1)	0.25	0.25	0.25	0.25	0.25	0.25
Tight deadlines (0/1)	0.25	0.25	0.25	0.25	0.25	0.25
Prestigious (0/1)	0.25	0.25	0.25	0.25	0.25	0.25

Notes: Values are based on corresponding values from the platform but should not be interpreted as exact platform values. Values are rounded, harmonized across categories whenever similar, and certain rarer characteristics are boosted for power. Developers regroup 4 job categories in the experiment: back-end developers, front-end developers, full-stack developers, and mobile developers.

A.2 Recommendations in the *Evaluation* experiments

Recommendations are implemented following the procedure established in Kessler et al. (2019). We use ridge regressions, allowing us to estimate preferences for attributes at the individual level while disciplining coefficients by shrinking them towards 0. We select optimal penalization parameters for recruiters and workers through cross validation by splitting our samples into estimation and hold-out samples with probability 0.5. We run pooled regressions in the estimation samples with different values of the penalization parameter, and select the one which minimizes prediction error in the hold-out samples. We repeat this process 100 times for recruiters and for workers with different estimation and hold-out samples, and use the average of the best-performing penalization parameters as the optimal penalization parameters, one for recruiters and one for workers. We then run ridge regressions at the individual level to recover preferences of each recruiter and worker.

For each recruiter, we use the resulting estimates combined with information on the pool of workers available on the platform to assess how suitable each of them would be to the recruiter, excluding gender and ethnicity. To further guarantee relevant recommendations, we incorporate additional filters based on specific expertise keywords chosen by the recruiter (we sort workers base on share of matched expertise keywords, and keep workers with the same or higher level of expertise keywords as the hundredth worker) and questions that we ask recruiters at the end of the experiment: minimum years of experience, whether they require either remote or in person work, their maximum budget, and the city in which the job would be done if they request on site work. Finally, we use the ridge regression estimates to predict the five best matched workers for that recruiter from this subsample of workers, weighing parameters estimated from the question about interest to hire 2/3 and worker's probability to apply 1/3. Each recruiter was then emailed their recommendations, within 10 days of completing the experiment.

For each worker, we standardize the distribution of the weighted parameters corresponding to each attribute in order to identify relative preferences of workers. Again, we weight parameters estimated from the question about interest in the job 2/3 and recruiters' probability of offering it to them 1/3. We set 0.75 and -0.75 standard deviation as thresholds determining whether a worker has a relative preference or aversion for a particular attribute, compared to other workers. We then informed the platform's matching team, who are in charge of recommending workers for jobs through their paid matching service, of these preferences and that they should be used to recommend the worker for one project.

A.3 Prediction bonuses in the *Prediction* experiments

For 5 randomly selected predictions out of 25, recruiters (workers) receive a bonus of €5 (2) with probability decreasing in their quadratic prediction error compared to the predicted evaluation of a randomly-chosen participant from the *Evaluation* experiments for a profile (offer) with the same characteristics. In particular, the probability of receiving a bonus is $1 - [\frac{p-x}{3}]^2$ where p is the predicted evaluation of the participant and x is the predicted evaluation of the randomly-chosen participant, both on a scale from 1 to 10.

Moreover, for 3 randomly selected characteristics about which we ask participants for direct predictions as part of the information treatment, recruiters (workers) also receive a bonus of €5 (1.5) with probability decreasing in their quadratic prediction error compared to the estimated effect of that characteristic on the evaluations of a randomly-chosen participant from the *Evaluation* experiments. In particular, the probability of receiving a bonus is $1-[\frac{p-x}{1}]^2$ where p is the participant's predicted impact of the characteristic on the average evaluations of participants from the *Evaluation* experiments and x is the estimated impact of the characteristic on the evaluations of the randomly-chosen participant.

B Additional figures and tables

Table B.1: Summary statistics by job category, 2025

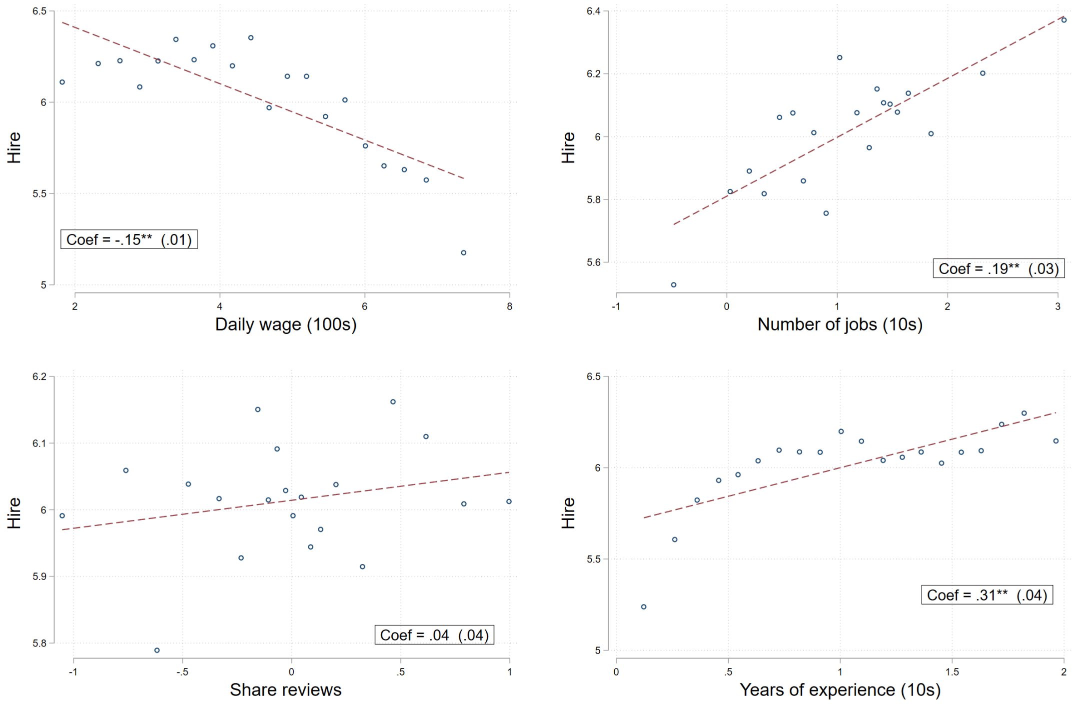
	Developers	Integration	Translation	Marketing	Copywriting	Content
Budget (1,000s)	[0.30–34.78]	[0.20–3.00]	[0.13–2.00]	[0.25–9.60]	[0.20–6.90]	[0.17–13.20]
Duration (months)	1.40	0.38	0.39	0.98	1.00	1.59
	(3.04)	(1.32)	(1.56)	(3.25)	(4.21)	(3.05)
Full-time requirement (%)	49.2	28.8	34.5	29.0	25.8	24.9
On-site requirement (%)	5.0	4.0	4.9	5.2	3.1	11.8
Share of total jobs (%)	29.0	11.8	11.8	27.0	15.3	5.1

Notes: This table reports summary statistics by job categories. Developers regroup 4 job categories in the experiment: back-end developers, front-end developers, full-stack developers, and mobile developers. Continuous variables are reported as means, with standard deviations in parentheses, unless otherwise indicated. Indicator variables are reported as percentages. For confidentiality reasons, budget amounts are reported as broad ranges using the 10th–90th percentile range rather than exact averages.

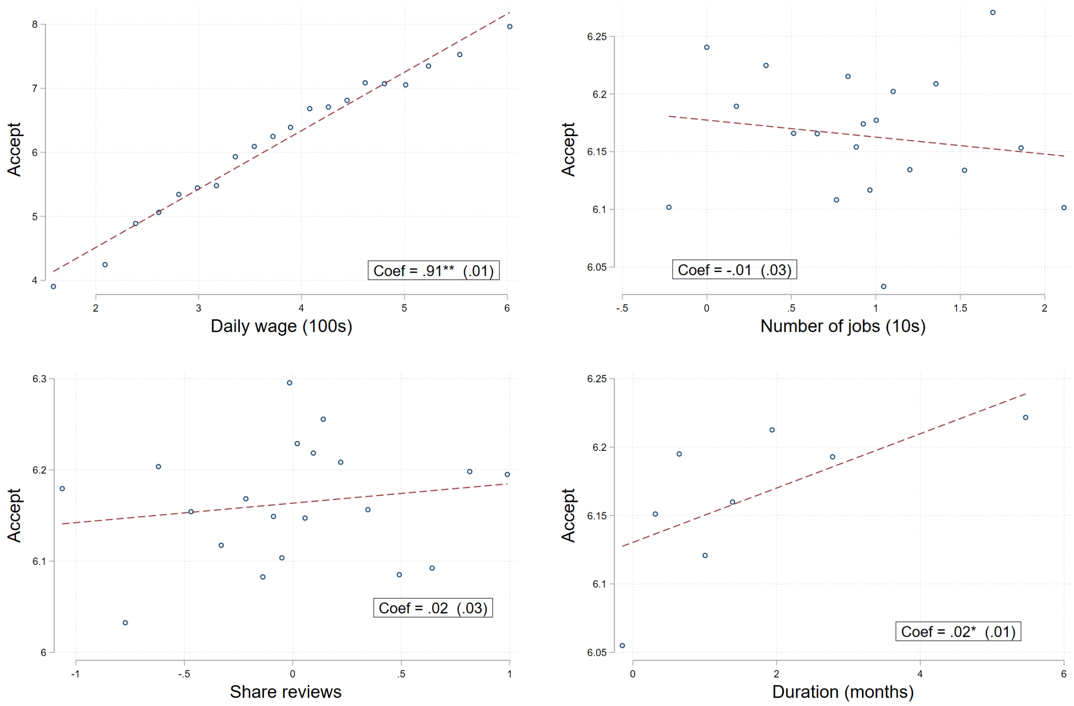
B.1 *Evaluation* experiments

Figure B.1: Estimated impact of continuous characteristics on evaluations

(a) Recruiter evaluations



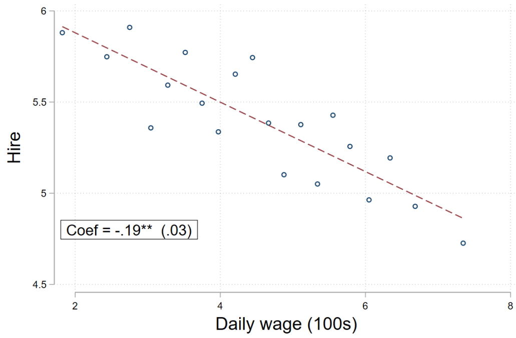
(b) Worker evaluations



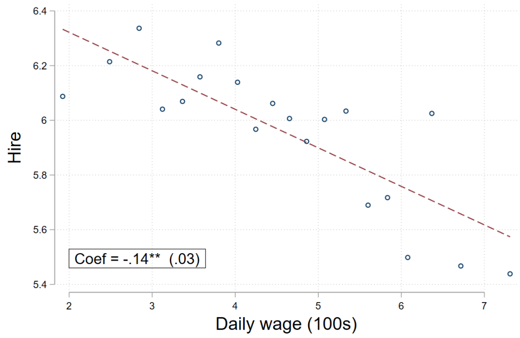
Notes: This figure shows binned scatter plots of the relationship between recruiters' interest in hiring a profile (Panel (a)) or workers' interest in accepting a job (Panel (b)) and the value of continuous randomized characteristics on profiles and briefs, controlling for respondent fixed effects and other randomized variables included on a given profile or offer. Dashed red lines represent fitted slopes, with corresponding regression coefficients and standard errors included in separate text boxes.

Figure B.2: Effect of asked wage on recruiter preferences, split by quartile of profile quality

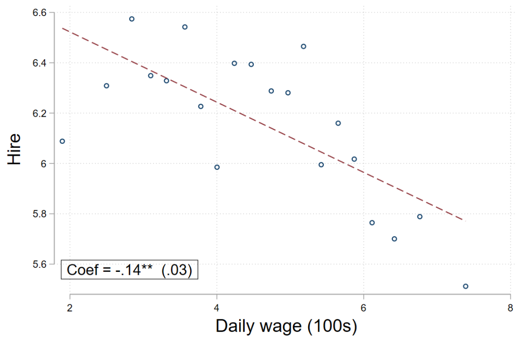
(a) 1st quartile



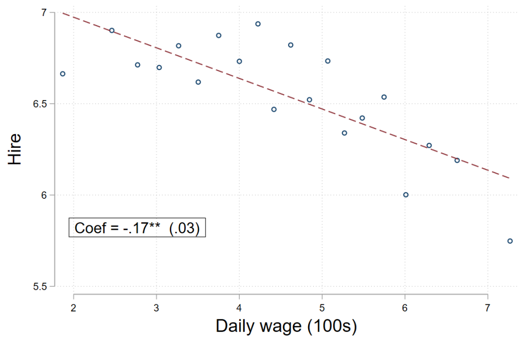
(b) 2nd quartile



(c) 3rd quartile



(d) 4th quartile



Notes: This figure shows binned scatter plots of the relationship between recruiters' interest in hiring a profile and the value of the asked wage on the profile, for different quartiles of profile quality. These quality measures are computed as predicted values of recruiter ratings, omitting the effect of wages. Dashed red lines represent fitted slopes, with corresponding regression coefficients and standard errors included in separate text boxes.

Table B.2: Estimated preferences from the *Evaluation* experiments by wage relative to stated budget and asked wage

Evaluator:	Recruiters				Workers			
Object:	Profiles				Offers			
Dependent variable:	Hire		Accept likelihood		Accept		Offer likelihood	
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Daily wage (100s)	0.211***	-0.427***	-0.010	-0.223***	1.245***	0.232***	0.300***	0.034
	(0.056)	(0.072)	(0.032)	(0.047)	(0.041)	(0.041)	(0.030)	(0.027)
At least one job	0.125	0.292**	0.051	0.160	0.009	0.175**	0.013	0.043
	(0.106)	(0.144)	(0.081)	(0.120)	(0.061)	(0.083)	(0.055)	(0.059)
Number of jobs (10s)	0.205***	0.190***	0.098**	0.014	-0.003	-0.049	-0.022	0.002
	(0.048)	(0.063)	(0.041)	(0.045)	(0.033)	(0.045)	(0.030)	(0.032)
Share reviews	-0.059	0.115	-0.009	0.004	0.035	0.023	0.022	-0.006
	(0.068)	(0.089)	(0.050)	(0.075)	(0.039)	(0.054)	(0.031)	(0.039)
Reputation badge	0.314***	0.267**	-0.009	0.144				
	(0.108)	(0.116)	(0.084)	(0.098)				
Years of experience (10s)	0.331***	0.350***	0.005	0.049				
	(0.072)	(0.090)	(0.046)	(0.069)				
Master	-0.004	0.033	-0.013	-0.172**				
	(0.090)	(0.088)	(0.066)	(0.068)				
Second experience	0.437***	0.497***	0.168**	0.085				
	(0.082)	(0.084)	(0.066)	(0.079)				
Prestigious	0.089	0.045	-0.115	-0.158*	-0.196***	-0.250***	-0.143***	-0.152***
	(0.098)	(0.096)	(0.078)	(0.085)	(0.048)	(0.062)	(0.039)	(0.048)
Remote	-0.013	0.043	-0.053	0.013	0.613***	0.747***	0.170***	0.093*
	(0.077)	(0.105)	(0.063)	(0.087)	(0.067)	(0.096)	(0.041)	(0.051)
Full time	-0.019	0.062	0.022	0.072	-0.010	-0.098	0.003	0.013
	(0.086)	(0.094)	(0.060)	(0.075)	(0.049)	(0.066)	(0.038)	(0.043)
Duration (months)					0.012	0.032*	0.024**	0.020*
					(0.013)	(0.016)	(0.011)	(0.012)
Teamwork required					-0.020	-0.095	-0.041	-0.014
					(0.047)	(0.064)	(0.038)	(0.046)
Tight deadlines					-0.237***	-0.265***	-0.059	-0.074
					(0.048)	(0.065)	(0.037)	(0.050)
MENA origin	-0.051	-0.116	-0.055	-0.136	0.077	-0.015	0.076*	-0.016
	(0.091)	(0.101)	(0.075)	(0.086)	(0.051)	(0.070)	(0.041)	(0.055)
Female	-0.002	-0.044	0.086	-0.044	0.044	-0.072	0.016	-0.107**
	(0.095)	(0.085)	(0.078)	(0.073)	(0.042)	(0.057)	(0.035)	(0.045)
Number of observations	2,745	2,394	2,745	2,394	12,631	7,951	12,631	7,951
Number of respondents	200	186	200	186	778	656	778	656
Outcome mean	6.082	5.665	7.001	6.701	5.418	7.346	6.463	6.548
Outcome standard deviation	1.960	2.020	1.454	1.583	2.526	2.445	1.806	1.752
Sample	Budget≥Wage	Budget<Wage	Budget≥Wage	Budget<Wage	Ask≥Wage	Ask<Wage	Ask≥Wage	Ask<Wage

Notes: This table reports results from estimating Equations 1 and 2 using OLS and participants from the *Evaluation* experiments. They correspond to those from 2, but splitting evaluations by whether the asked wage on a hypothetical worker profile is above the participating recruiter's reported daily wage budget (columns 1-4) and by whether the offered wage on a hypothetical job offer is above or below the participating worker's own asked wage on their platform profile. See Table 2 for more details. All specifications include respondent fixed effects. Standard errors are clustered at the respondent level. $*p < 0.10, **p < 0.05, ***p < 0.01$.

Table B.3: Estimated preferences from the *Evaluation* experiments: competence outcome

Evaluator:	Recruiters			Workers		
Object:	Profiles			Offers		
Dependent variable:	Hire	Competence	Hire	Accept	Competence	Accept
	(1)	(2)	(3)	(4)	(5)	(6)
Daily wage (100s)	-0.154***	0.077***	-0.215***	0.912***	0.039***	0.885***
	(0.025)	(0.018)	(0.019)	(0.029)	(0.013)	(0.028)
At least one job	0.232***	0.189***	0.081**	0.081	0.063	0.037
	(0.070)	(0.072)	(0.041)	(0.050)	(0.044)	(0.041)
Number of jobs (10s)	0.187***	0.182***	0.043**	-0.015	-0.034	0.009
	(0.033)	(0.029)	(0.019)	(0.027)	(0.024)	(0.022)
Share reviews	0.042	0.003	0.039	0.021	0.002	0.020
	(0.042)	(0.040)	(0.028)	(0.033)	(0.026)	(0.027)
Reputation badge	0.227***	0.228***	0.045			
	(0.065)	(0.063)	(0.040)			
Years of experience (10s)	0.313***	0.375***	0.014			
	(0.043)	(0.042)	(0.028)			
Master	0.055	0.042	0.022			
	(0.050)	(0.047)	(0.033)			
Second experience	0.478***	0.503***	0.078***			
	(0.047)	(0.046)	(0.029)			
Prestigious	0.075	0.070	0.020	-0.210***	-0.158***	-0.098***
	(0.052)	(0.048)	(0.032)	(0.040)	(0.032)	(0.032)
Remote	0.046	0.026	0.025	0.667***	0.072**	0.616***
	(0.053)	(0.046)	(0.037)	(0.061)	(0.032)	(0.055)
Full time	0.029	0.027	0.008	-0.042	-0.021	-0.027
	(0.052)	(0.047)	(0.033)	(0.041)	(0.032)	(0.032)
Duration (months)				0.020*	0.017*	0.008
				(0.011)	(0.009)	(0.009)
Teamwork required				-0.040	-0.003	-0.038
				(0.040)	(0.031)	(0.031)
Tight deadlines				-0.239***	-0.070**	-0.189***
				(0.041)	(0.033)	(0.033)
MENA origin	-0.015	-0.021	0.002	0.034	0.038	0.007
	(0.053)	(0.048)	(0.034)	(0.042)	(0.035)	(0.034)
Female	0.014	0.074	-0.045	0.040	0.040	0.011
	(0.052)	(0.047)	(0.034)	(0.034)	(0.029)	(0.029)
Competence - Likert scale (1-10)			0.795***			0.706***
			(0.014)			(0.013)
Number of observations	8,692	8,692	8,692	20,600	20,600	20,600
Number of respondents	348	348	348	824	824	824
Outcome mean	6.014	6.457	6.014	6.164	7.887	6.164
Outcome standard deviation	1.971	1.838	1.971	2.557	1.896	2.557

Notes: This table reports results from estimating Equations 1 and 2 using OLS and participants from the *Evaluation* experiments. Columns 1 and 4 reproduce the results from columns 1 and 3 of 2 for convenience, while columns 2 and 5 show results using an auxiliary outcome that participants had to evaluate, namely how competent recruiters think a given profile would be for their job in column 2 and how competent freelancers would feel to complete the offered job in column 5. Columns 3 and 6 consider the outcome variables from columns 1 and 4 but also include the reported competence rating as a control variable to investigate the role of perceived competence in driving interest in hiring a profile or accepting a job. See Table 2 for more details. All specifications include respondent fixed effects. Standard errors are clustered at the respondent level. $*p < 0.10, **p < 0.05, ***p < 0.01$.

Table B.4: Estimated preferences from the *Evaluation* experiments by number of jobs shown on a profile

Evaluator:	Recruiters			
Object:	Profiles			
Dependent variable:	Hire		Accept likelihood	
	(1)	(2)	(3)	(4)
Daily wage (100s)	-0.151***	-0.168***	-0.171***	-0.129***
	(0.034)	(0.027)	(0.026)	(0.019)
Number of jobs (10s)		0.190***		0.055**
		(0.032)		(0.024)
Share reviews		0.049		0.005
		(0.042)		(0.034)
Reputation badge		0.236***		0.057
		(0.065)		(0.050)
Years of experience (10s)	0.345***	0.299***	-0.069	0.030
	(0.076)	(0.051)	(0.067)	(0.038)
Master's degree	0.111	0.026	-0.108	-0.025
	(0.091)	(0.058)	(0.073)	(0.044)
Second experience	0.555***	0.441***	0.218***	0.157***
	(0.087)	(0.053)	(0.070)	(0.047)
Prestigious	0.101	0.039	-0.145*	-0.111**
	(0.091)	(0.063)	(0.079)	(0.050)
Remote	0.076	0.012	0.010	0.054
	(0.089)	(0.060)	(0.069)	(0.043)
Full time	-0.053	0.080	0.014	0.124**
	(0.087)	(0.060)	(0.072)	(0.050)
MENA origin	-0.062	0.011	-0.088	-0.042
	(0.093)	(0.062)	(0.077)	(0.048)
Female	0.032	0.020	0.188***	-0.028
	(0.090)	(0.060)	(0.071)	(0.049)
Number of observations	2,701	5,991	2,701	5,991
Number of respondents	348	348	348	348
Outcome mean	5.590	6.205	6.701	6.925
Outcome standard deviation	1.990	1.938	1.587	1.493
Number of jobs	None	At least one	None	At least one

Notes: This table reports results from estimating Equation 1 using OLS and participants from the *Evaluation* experiments. They correspond to those from the first 2 columns of Table 2, but splitting evaluations between those of profiles that displayed no completed job on the platform for the hypothetical worker and those of profiles that displayed at least one. See Table 2 for more details. All specifications include respondent fixed effects. Standard errors are clustered at the respondent level. $*p < 0.10, **p < 0.05, ***p < 0.01$.

Table B.5: Estimated preferences from the *Evaluation* experiments by requirements and preferences for remote work

Evaluator:	Recruiters				Workers			
Object:	Profiles				Offers			
Dependent variable:	Hire		Accept likelihood		Accept		Offer likelihood	
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Daily wage (100s)	-0.220***	-0.103	-0.197***	-0.059	0.779***	0.994***	0.158***	0.183***
	(0.046)	(0.070)	(0.035)	(0.037)	(0.047)	(0.037)	(0.029)	(0.022)
At least one job	0.318**	-0.140	0.223**	-0.205	0.126	0.057	0.098	-0.004
	(0.139)	(0.178)	(0.107)	(0.161)	(0.078)	(0.066)	(0.068)	(0.052)
Number of jobs (10s)	0.233***	0.165*	0.009	0.143*	-0.055	0.006	-0.021	-0.005
	(0.057)	(0.098)	(0.038)	(0.076)	(0.041)	(0.036)	(0.035)	(0.028)
Share reviews	0.003	0.105	0.012	0.026	-0.020	0.051	-0.064	0.045
	(0.078)	(0.118)	(0.069)	(0.073)	(0.054)	(0.041)	(0.041)	(0.030)
Reputation badge	0.231*	0.212	-0.008	0.160				
	(0.124)	(0.192)	(0.088)	(0.154)				
Years of experience (10s)	0.197**	0.551***	0.057	0.007				
	(0.079)	(0.118)	(0.054)	(0.083)				
Master	0.027	0.102	-0.158***	-0.061				
	(0.091)	(0.169)	(0.059)	(0.097)				
Second experience	0.381***	0.502***	0.061	0.274***				
	(0.085)	(0.111)	(0.070)	(0.093)				
Prestigious	0.045	0.282*	-0.129	-0.009	-0.277***	-0.163***	-0.185***	-0.145***
	(0.092)	(0.162)	(0.086)	(0.094)	(0.060)	(0.052)	(0.052)	(0.039)
Remote	0.148	-0.345*	0.060	-0.061	0.883***	0.533***	0.184***	0.112***
	(0.100)	(0.194)	(0.077)	(0.082)	(0.103)	(0.074)	(0.053)	(0.042)
Full time	0.033	0.053	0.106	0.093	-0.039	-0.045	-0.052	0.050
	(0.092)	(0.131)	(0.066)	(0.110)	(0.066)	(0.052)	(0.045)	(0.037)
Duration (months)					0.015	0.023*	0.033**	0.013
					(0.019)	(0.013)	(0.014)	(0.010)
Teamwork required					-0.061	-0.026	-0.036	-0.017
					(0.069)	(0.048)	(0.052)	(0.036)
Tight deadlines					-0.195***	-0.261***	0.019	-0.093**
					(0.068)	(0.050)	(0.049)	(0.038)
MENA origin	-0.130	0.029	-0.052	-0.084	0.050	0.021	0.001	0.060
	(0.095)	(0.151)	(0.078)	(0.117)	(0.069)	(0.052)	(0.054)	(0.042)
Female	-0.114	-0.122	0.052	-0.089	-0.002	0.074	-0.049	0.005
	(0.095)	(0.145)	(0.081)	(0.103)	(0.051)	(0.046)	(0.045)	(0.035)
Number of observations	2,597	1,275	2,597	1,275	8,000	12,600	8,000	12,600
Number of respondents	104	51	104	51	320	504	320	504
Outcome mean	5.858	6.076	6.817	6.875	6.190	6.147	6.479	6.507
Outcome standard deviation	2.036	2.041	1.562	1.518	2.516	2.582	1.836	1.766
Preference/requirement	Remote	On site	Remote	On site	Remote	On site	Remote	On site

Notes: This table reports results from estimating Equations 1 and 2 using OLS and participants from the *Evaluation* experiments. They correspond to those from 2, but splitting evaluations by whether the participating recruiter reports requiring in-person work for their next job (columns 1-4) and by whether the participating worker's own platform profile indicates availability for working in-person or primarily remotely (columns 5-8). See Table 2 for more details. All specifications include respondent fixed effects. Standard errors are clustered at the respondent level. $*p < 0.10, **p < 0.05, ***p < 0.01$.

Table B.6: Estimated preferences from the *Evaluation* experiments, by recruiter self-reported preference for diversity

Evaluator:	Recruiters			
Object:	Profiles			
Dependent variable:	Hire		Accept likelihood	
	(1)	(2)	(3)	(4)
Daily wage (100s)	-0.181***	-0.132***	-0.153***	-0.118***
	(0.039)	(0.033)	(0.025)	(0.026)
At least one job	0.074	0.353***	0.071	0.115
	(0.112)	(0.088)	(0.081)	(0.075)
Number of jobs (10s)	0.239***	0.153***	0.060	0.048
	(0.054)	(0.041)	(0.041)	(0.030)
Share reviews	0.084	0.009	-0.000	0.013
	(0.067)	(0.053)	(0.051)	(0.044)
Reputation badge	0.220*	0.241***	-0.022	0.099*
	(0.119)	(0.071)	(0.082)	(0.059)
Years of experience (10s)	0.202***	0.396***	-0.060	0.055
	(0.062)	(0.059)	(0.048)	(0.045)
Master's degree	0.025	0.071	-0.086	-0.024
	(0.078)	(0.065)	(0.056)	(0.053)
Second experience	0.439***	0.511***	0.123**	0.222***
	(0.067)	(0.065)	(0.056)	(0.056)
Prestigious	0.028	0.114*	-0.166**	-0.089
	(0.083)	(0.066)	(0.067)	(0.058)
Remote	-0.105	0.162**	-0.072	0.131***
	(0.089)	(0.063)	(0.057)	(0.049)
Full time	0.016	0.041	0.102	0.102*
	(0.084)	(0.065)	(0.065)	(0.054)
MENA origin	-0.108	0.061	-0.145**	-0.018
	(0.083)	(0.066)	(0.063)	(0.055)
Female	-0.092	0.106	0.050	0.047
	(0.077)	(0.070)	(0.060)	(0.057)
Number of observations	3,875	4,817	3,875	4,817
Number of respondents	155	193	155	193
Outcome mean	5.615	6.335	6.769	6.926
Outcome standard deviation	2.079	1.880	1.566	1.491
Preference for diversity	Low	High	Low	High

Notes: This table reports results from estimating Equation 1 using OLS and participants from the *Evaluation* experiments. They correspond to those from columns 1-4 of Table 2, but splitting the sample by whether the firm reports an above or below median preference for hiring diverse candidates, elicited on a 1-10 scale at the very end of the experiment. See Table 2 for more details. All specifications include respondent fixed effects. Standard errors are clustered at the respondent level. $*p < 0.10, **p < 0.05, ***p < 0.01$.

Table B.7: Estimated preferences from the *Evaluation* experiments by gender and ethnicity signaled on a profile

Evaluator:	Recruiters							
Object:	Profiles							
Dependent variable:	Hire		Accept likelihood		Hire		Accept likelihood	
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Daily wage (100s)	-0.150***	-0.192***	-0.125***	-0.165***	-0.151***	-0.156***	-0.135***	-0.142***
	(0.030)	(0.030)	(0.021)	(0.027)	(0.027)	(0.037)	(0.020)	(0.028)
At least one job	0.234***	0.188	0.137**	-0.020	0.189**	0.369***	0.081	0.118
	(0.086)	(0.123)	(0.067)	(0.100)	(0.082)	(0.135)	(0.061)	(0.107)
Number of jobs (10s)	0.178***	0.236***	0.047	0.072*	0.209***	0.109*	0.051*	0.043
	(0.036)	(0.064)	(0.030)	(0.040)	(0.037)	(0.061)	(0.027)	(0.047)
Share reviews	0.028	0.112	0.032	-0.042	0.047	0.022	0.022	-0.011
	(0.050)	(0.072)	(0.040)	(0.057)	(0.046)	(0.096)	(0.035)	(0.079)
Reputation badge	0.270***	0.113	0.096	-0.058	0.219***	0.298**	0.054	-0.018
	(0.084)	(0.109)	(0.064)	(0.085)	(0.072)	(0.127)	(0.054)	(0.099)
Years of experience (10s)	0.317***	0.292***	-0.040	0.104*	0.292***	0.364***	-0.009	0.030
	(0.054)	(0.066)	(0.041)	(0.053)	(0.048)	(0.090)	(0.038)	(0.074)
Master's degree	0.084	-0.022	-0.012	-0.134**	0.063	0.058	-0.046	-0.064
	(0.061)	(0.083)	(0.045)	(0.065)	(0.058)	(0.108)	(0.045)	(0.084)
Second experience	0.442***	0.540***	0.162***	0.190***	0.487***	0.515***	0.156***	0.279***
	(0.059)	(0.085)	(0.048)	(0.070)	(0.053)	(0.100)	(0.043)	(0.082)
Prestigious	0.075	0.078	-0.162***	-0.083	0.037	0.171	-0.164***	0.024
	(0.066)	(0.085)	(0.051)	(0.077)	(0.061)	(0.105)	(0.049)	(0.084)
Remote	0.074	0.038	0.096**	-0.034	0.079	-0.019	0.066	-0.064
	(0.062)	(0.092)	(0.045)	(0.062)	(0.061)	(0.098)	(0.043)	(0.074)
Full time	0.085	-0.051	0.105**	0.125*	0.026	0.080	0.128***	0.025
	(0.066)	(0.076)	(0.050)	(0.072)	(0.057)	(0.114)	(0.046)	(0.088)
MENA origin	0.031	-0.133	-0.064	-0.113				
	(0.064)	(0.099)	(0.050)	(0.076)				
Female					0.040	-0.132	0.042	0.072
					(0.061)	(0.113)	(0.046)	(0.094)
Number of observations	5,618	3,072	5,618	3,072	6,737	1,948	6,737	1,948
Number of respondents	348	345	348	345	348	339	348	339
Outcome mean	6.084	5.885	6.906	6.765	6.023	5.985	6.883	6.758
Outcome standard deviation	1.958	1.994	1.512	1.549	1.979	1.943	1.525	1.525
Profile	Male	Female	Male	Female	European	MENA origin	European	MENA origin

Notes: This table reports results from estimating Equations 1 and 2 using OLS and participants from the *Evaluation* experiments. They correspond to those from the first 2 columns of Table 2, but splitting evaluations by the gender and ethnic origin signaled on the hypothetical worker profile. See Table 2 for more details. All specifications include respondent fixed effects. Standard errors are clustered at the respondent level. $*p < 0.10, **p < 0.05, ***p < 0.01$.

Table B.8: Estimated preferences from the *Evaluation* experiments, including order fixed effects

Evaluator:	Recruiter		Worker	
Object:	Profiles		Offers	
Dependent variable:	Hire	Accept likelihood	Accept	Offer likelihood
	(1)	(2)	(3)	(4)
Daily wage (100s)	-0.154***	-0.134***	0.913***	0.174***
	(0.025)	(0.018)	(0.029)	(0.018)
At least one job	0.225***	0.090	0.082	0.037
	(0.070)	(0.055)	(0.050)	(0.041)
Number of jobs (10s)	0.190***	0.054**	-0.015	-0.011
	(0.033)	(0.024)	(0.027)	(0.022)
Share reviews	0.041	0.009	0.021	0.006
	(0.042)	(0.034)	(0.033)	(0.024)
Reputation badge	0.226***	0.049		
	(0.065)	(0.049)		
Years of experience (10s)	0.314***	0.005		
	(0.043)	(0.033)		
Master	0.050	-0.051		
	(0.050)	(0.038)		
Second experience	0.482***	0.179***		
	(0.047)	(0.040)		
Prestigious	0.072	-0.123***	-0.207***	-0.161***
	(0.052)	(0.044)	(0.040)	(0.031)
Remote	0.049	0.041	0.667***	0.139***
	(0.053)	(0.037)	(0.061)	(0.033)
Full time	0.025	0.107**	-0.041	0.014
	(0.052)	(0.041)	(0.041)	(0.028)
Duration (months)			0.020*	0.020**
			(0.011)	(0.008)
Teamwork required			-0.038	-0.024
			(0.040)	(0.030)
Tight deadlines			-0.238***	-0.050*
			(0.040)	(0.030)
MENA origin	-0.015	-0.075*	0.033	0.042
	(0.052)	(0.042)	(0.042)	(0.033)
Female	0.014	0.041	0.038	-0.017
	(0.052)	(0.041)	(0.034)	(0.028)
Number of observations	8,692	8,692	20,600	20,600
Number of respondents	348	348	824	824
Outcome mean	6.014	6.856	6.164	6.496
Outcome standard deviation	1.971	1.525	2.557	1.794

Notes: This table reports results from estimating Equations 1 and 2 using OLS and participants from the *Evaluation* experiments. They correspond to those from Table 2, but with the addition of order fixed effects to account for potential impacts from seeing profiles and offers with certain characteristics earlier versus later in the evaluation phase. See Table 2 for more details. All specifications include respondent fixed effects. Standard errors are clustered at the respondent level.
$*p < 0.10, **p < 0.05, ***p < 0.01$.

Table B.9: Estimated preferences from the *Evaluation* experiments, including job category rather than individual fixed effects

Evaluator:	Recruiters		Workers	
Object:	Profiles		Offers	
Dependent variable:	Hire	Accept likelihood	Accept	Offer likelihood
	(1)	(2)	(3)	(4)
Daily wage (100s)	-0.136***	-0.118***	0.907***	0.179***
	(0.026)	(0.020)	(0.030)	(0.020)
At least one job	0.261***	0.147**	0.040	0.026
	(0.083)	(0.068)	(0.060)	(0.050)
Number of jobs (10s)	0.187***	0.041	0.006	0.012
	(0.035)	(0.027)	(0.032)	(0.027)
Share reviews	0.027	-0.044	-0.002	0.024
	(0.050)	(0.046)	(0.038)	(0.032)
Reputation badge	0.254***	0.036		
	(0.075)	(0.062)		
Years of experience (10s)	0.318***	0.048		
	(0.047)	(0.041)		
Master	0.067	-0.024		
	(0.062)	(0.050)		
Second experience	0.456***	0.142***		
	(0.052)	(0.049)		
Prestigious	0.055	-0.137**	-0.177***	-0.138***
	(0.061)	(0.054)	(0.047)	(0.040)
Remote	0.048	0.042	0.609***	0.085**
	(0.061)	(0.048)	(0.067)	(0.041)
Full time	0.045	0.105**	-0.061	0.009
	(0.061)	(0.053)	(0.048)	(0.037)
Duration (months)			0.017	0.021**
			(0.012)	(0.010)
Teamwork required			-0.071	-0.081**
			(0.047)	(0.039)
Tight deadlines			-0.283***	-0.024
			(0.046)	(0.038)
MENA origin	-0.065	-0.125**	0.045	0.089**
	(0.059)	(0.050)	(0.050)	(0.042)
Female	-0.058	0.017	0.027	-0.009
	(0.060)	(0.052)	(0.041)	(0.035)
Number of observations	8,692	8,692	20,600	20,600
Number of respondents	348	348	824	824
Outcome mean	6.014	6.856	6.164	6.496
Outcome standard deviation	2.444	2.079	3.093	2.461

Notes: This table reports results from estimating Equations 1 and 2 using OLS and participants from the *Evaluation* experiments. They correspond to those from Table 2, but replacing individual fixed effects with job category fixed effects. See Table 2 for more details. All specifications include respondent job category fixed effects. Standard errors are clustered at the respondent level. $*p < 0.10, **p < 0.05, ***p < 0.01$.

Table B.10: Estimated preferences from the *Evaluation* experiments, including fast respondents

Evaluator:	Recruiters		Workers	
Object:	Profiles		Offers	
Dependent variable:	Hire	Accept likelihood	Accept	Offer likelihood
	(1)	(2)	(3)	(4)
Daily wage (100s)	-0.151***	-0.127***	0.892***	0.174***
	(0.024)	(0.017)	(0.029)	(0.017)
At least one job	0.202***	0.068	0.088*	0.035
	(0.068)	(0.054)	(0.050)	(0.041)
Number of jobs (10s)	0.187***	0.059**	-0.017	-0.011
	(0.031)	(0.023)	(0.027)	(0.022)
Share reviews	0.030	0.006	0.022	0.003
	(0.039)	(0.032)	(0.032)	(0.024)
Reputation badge	0.226***	0.063		
	(0.062)	(0.046)		
Years of experience (10s)	0.297***	0.022		
	(0.041)	(0.032)		
Master	0.029	-0.047		
	(0.048)	(0.038)		
Second experience	0.447***	0.171***		
	(0.044)	(0.038)		
Prestigious	0.064	-0.120***	-0.202***	-0.159***
	(0.049)	(0.042)	(0.039)	(0.031)
Remote	0.039	0.026	0.655***	0.135***
	(0.050)	(0.036)	(0.060)	(0.032)
Full time	0.017	0.081**	-0.041	0.011
	(0.048)	(0.039)	(0.040)	(0.028)
Duration (months)			0.018	0.020**
			(0.011)	(0.008)
Teamwork required			-0.051	-0.026
			(0.039)	(0.029)
Tight deadlines			-0.235***	-0.045
			(0.040)	(0.030)
MENA origin	-0.025	-0.069*	0.037	0.040
	(0.050)	(0.040)	(0.041)	(0.033)
Female	0.001	0.026	0.045	-0.015
	(0.049)	(0.040)	(0.034)	(0.028)
Number of observations	9,542	9,542	21,075	21,075
Number of respondents	382	382	843	843
Outcome mean	6.022	6.799	6.177	6.499
Outcome standard deviation	1.954	1.529	2.540	1.787

Notes: This table reports results from estimating Equations 1 and 2 using OLS and participants from the *Evaluation* experiments. They correspond to those from Table 2, but without restricting the participant sample to those who spent at least an average of 10 seconds evaluating each profile or offer. See Table 2 for more details. All specifications include respondent fixed effects. Standard errors are clustered at the respondent level. $*p < 0.10, **p < 0.05, ***p < 0.01$.

Table B.11: Estimated preferences from the *Evaluation* experiments, with p-values corrected for multiple hypothesis testing

Evaluator:	Recruiters		Workers	
Object:	Profiles		Offers	
Dependent variable:	Hire	Accept likelihood	Accept	Offer likelihood
	(1)	(2)	(3)	(4)
Daily wage (100s)	-0.154***	-0.134***	0.912***	0.173***
	[0.00]	[0.00]	[0.00]	[0.00]
At least one project	0.232***	0.097*	0.081	0.035
	[0.00]	[0.07]	[0.14]	[0.77]
Number of projects (10)	0.187***	0.052**	-0.015	-0.011
	[0.00]	[0.02]	[0.61]	[0.88]
Share reviews	0.042	0.008	0.021	0.003
	[0.52]	[0.93]	[0.61]	[0.88]
Superfreelancer badge	0.227***	0.042		
	[0.00]	[0.51]		
Years of experience (10s)	0.313***	0.006		
	[0.00]	[0.93]		
Master	0.055	-0.049		
	[0.48]	[0.34]		
Second experience	0.478***	0.176***		
	[0.00]	[0.00]		
Prestigious	0.075	-0.126***	-0.210***	-0.160***
	[0.20]	[0.00]	[0.00]	[0.00]
Remote	0.046	0.042	0.667***	0.139***
	[0.58]	[0.40]	[0.00]	[0.00]
Full time	0.029	0.101***	-0.042	0.011
	[0.79]	[0.00]	[0.54]	[0.88]
Duration (months)			0.020*	0.021***
			[0.08]	[0.00]
Teamwork required			-0.040	-0.023
			[0.54]	[0.79]
Tight deadlines			-0.239***	-0.051
			[0.00]	[0.12]
Arab origin	-0.015	-0.075*	0.034	0.038
	[0.91]	[0.07]	[0.46]	[0.87]
Female	0.014	0.047	0.040	-0.017
	[0.91]	[0.40]	[0.60]	[0.51]
Outcome mean	6	6.9	6.2	6.5
Number of observations	8,692	8,692	20,600	20,600
Number of respondents	348	348	824	824

Notes: This table reports results from estimating Equations 1 and 2 using OLS and participants from the *Evaluation* experiments. They correspond to those from Table 2, but with p-values corrected for multiple-hypothesis testing using the Romano-Wolf method with 1,000 replications in square brackets. See Table 2 for more details. All specifications include respondent fixed effects. Standard errors are clustered at the respondent level. $*p < 0.10, **p < 0.05, ***p < 0.01$.

Table B.12: Estimated preferences from the *Evaluation* experiments, reweighted to match platform characteristics

Evaluator:	Recruiters		Workers	
Object:	Profiles		Offers	
Dependent variable:	Hire	Accept likelihood	Accept	Offer likelihood
	(1)	(2)	(3)	(4)
Daily wage (100s)	-0.160***	-0.146***	0.808***	0.134***
	(0.034)	(0.032)	(0.045)	(0.028)
At least one job	0.252***	0.077	0.159*	0.023
	(0.093)	(0.082)	(0.085)	(0.071)
Number of jobs (10s)	0.171***	0.042	-0.058	0.026
	(0.041)	(0.033)	(0.042)	(0.032)
Share reviews	0.010	-0.006	-0.057	-0.016
	(0.050)	(0.042)	(0.052)	(0.038)
Reputation badge	0.230***	0.083		
	(0.080)	(0.069)		
Years of experience (10s)	0.390***	0.019		
	(0.052)	(0.047)		
Master	0.075	-0.030		
	(0.068)	(0.053)		
Second experience	0.403***	0.183***		
	(0.062)	(0.049)		
Prestigious	0.023	-0.059	-0.277***	-0.135***
	(0.077)	(0.061)	(0.068)	(0.042)
Remote	0.002	0.041	0.693***	0.098*
	(0.070)	(0.042)	(0.089)	(0.051)
Full time	0.011	0.145***	-0.086	-0.014
	(0.065)	(0.056)	(0.072)	(0.040)
Duration (months)			0.012	0.016
			(0.016)	(0.013)
Teamwork required			-0.034	-0.034
			(0.053)	(0.040)
Tight deadlines			-0.206***	-0.097**
			(0.056)	(0.048)
MENA origin	-0.026	-0.076	-0.084	0.009
	(0.070)	(0.066)	(0.066)	(0.049)
Female	0.002	0.067	0.034	-0.024
	(0.067)	(0.060)	(0.050)	(0.043)
Number of observations	8,692	8,692	20,600	20,600
Number of respondents	348	348	824	824
Outcome mean	5.907	6.748	6.367	6.188
Outcome standard deviation	1.964	1.544	2.414	1.675

Notes: This table reports results from estimating Equations 1 and 2 using OLS and participants from the *Evaluation* experiments. They correspond to those from Table 2, but reweighting observations such that the characteristics of participants match the average characteristics of platform users for the job categories included in the experiment. Reweighting for recruiters is based on: number of jobs they hire for in the past, years on the platform, and firm size. Reweighting for workers is based on: asked wage, number of completed jobs, primary job type, and experience level. See Table 2 for more details. All specifications include respondent fixed effects. Standard errors are clustered at the respondent level. $*p < 0.10, **p < 0.05, ***p < 0.01$.

Table B.13: Effect of attention in the *Evaluation* experiments

Evaluator:	Recruiters				Workers			
Object:	Profiles				Offers			
Dependent variable:	Hire		Accept likelihood		Accept		Offer likelihood	
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Daily wage (100s)	-0.140***	-0.158***	-0.154***	-0.114***	0.903***	0.927***	0.163***	0.186***
	(0.030)	(0.028)	(0.023)	(0.021)	(0.032)	(0.034)	(0.020)	(0.022)
At least one job	0.251**	0.252***	0.077	0.132*	0.067	0.064	0.024	0.033
	(0.099)	(0.097)	(0.075)	(0.079)	(0.077)	(0.070)	(0.061)	(0.051)
Number of jobs (10s)	0.163***	0.171***	0.030	0.051	-0.051	0.020	-0.027	0.007
	(0.039)	(0.047)	(0.030)	(0.035)	(0.040)	(0.038)	(0.032)	(0.028)
Share reviews	-0.014	0.092	0.010	-0.007	0.028	0.030	0.005	0.016
	(0.059)	(0.059)	(0.048)	(0.046)	(0.045)	(0.046)	(0.035)	(0.034)
Reputation badge	0.281***	0.226***	0.023	0.062				
	(0.092)	(0.081)	(0.068)	(0.062)				
Years of experience (10s)	0.465***	0.173***	0.069	-0.045				
	(0.062)	(0.058)	(0.047)	(0.040)				
Master	0.032	0.066	-0.063	-0.027				
	(0.070)	(0.068)	(0.051)	(0.053)				
Second experience	0.357***	0.613***	0.092*	0.271***				
	(0.064)	(0.067)	(0.052)	(0.054)				
Prestigious	0.052	0.088	-0.065	-0.173***	-0.273***	-0.162***	-0.238***	-0.096**
	(0.076)	(0.068)	(0.061)	(0.056)	(0.056)	(0.054)	(0.045)	(0.041)
Remote	0.061	0.048	0.033	0.092**	0.688***	0.675***	0.109**	0.182***
	(0.066)	(0.069)	(0.049)	(0.046)	(0.075)	(0.071)	(0.047)	(0.043)
Full time	0.003	0.061	0.048	0.178***	-0.045	-0.051	0.047	-0.028
	(0.072)	(0.074)	(0.059)	(0.058)	(0.057)	(0.054)	(0.043)	(0.039)
Duration (months)					0.016	0.034**	0.027**	0.020*
					(0.015)	(0.014)	(0.012)	(0.011)
Teamwork required					-0.112*	0.022	-0.092**	0.044
					(0.062)	(0.052)	(0.045)	(0.040)
Tight deadlines					-0.318***	-0.175***	-0.042	-0.042
					(0.059)	(0.054)	(0.045)	(0.041)
MENA origin	-0.044	-0.008	-0.073	-0.092	0.028	0.036	0.022	0.065
	(0.076)	(0.069)	(0.059)	(0.059)	(0.062)	(0.059)	(0.050)	(0.044)
Female	0.004	0.053	0.071	0.010	0.050	0.048	-0.039	0.020
	(0.073)	(0.068)	(0.055)	(0.055)	(0.049)	(0.049)	(0.040)	(0.038)
Number of observations	4,176	4,516	4,176	4,516	9,888	10,712	9,888	10,712
Number of respondents	348	348	348	348	824	824	824	824
Outcome mean	6.062	5.969	6.935	6.782	6.218	6.114	6.519	6.475
Outcome standard deviation	1.991	1.952	1.537	1.510	2.572	2.541	1.817	1.771
Part of experiment	First half	Second half	First half	Second half	First half	Second half	First half	Second half

Notes: This table reports results from estimating Equations 1 and 2 using OLS and participants from the *Evaluation* experiments. They correspond to those from Table 2, but splitting evaluations into the first 12 evaluations versus the last 13. See Table 2 for more details. All specifications include respondent fixed effects. Standard errors are clustered at the respondent level. $*p < 0.10, **p < 0.05, ***p < 0.01$.

Table B.14: Estimated preferences from the *Evaluation* experiments by gender

Evaluator:	Recruiters				Workers			
Object:	Profiles				Offers			
Dependent variable:	Hire		Accept likelihood		Accept		Offer likelihood	
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Daily wage (100s)	-0.155***	-0.154***	-0.125***	-0.159***	0.942***	0.824***	0.193***	0.113***
	(0.030)	(0.049)	(0.021)	(0.036)	(0.035)	(0.049)	(0.021)	(0.027)
At least one job	0.253***	0.178	0.113*	0.061	0.126**	0.001	-0.008	0.117
	(0.087)	(0.118)	(0.067)	(0.096)	(0.060)	(0.093)	(0.048)	(0.077)
Number of jobs (10s)	0.192***	0.189***	0.065**	0.029	-0.010	-0.026	0.008	-0.047
	(0.039)	(0.063)	(0.030)	(0.041)	(0.034)	(0.044)	(0.027)	(0.037)
Share reviews	0.091*	-0.074	0.016	-0.017	0.050	-0.035	0.033	-0.059
	(0.048)	(0.078)	(0.043)	(0.050)	(0.039)	(0.057)	(0.029)	(0.044)
Reputation badge	0.351***	-0.062	0.116**	-0.120				
	(0.082)	(0.096)	(0.058)	(0.087)				
Years of experience (10s)	0.316***	0.306***	-0.022	0.076				
	(0.051)	(0.080)	(0.039)	(0.060)				
Master	0.054	0.051	-0.080*	0.012				
	(0.062)	(0.086)	(0.048)	(0.061)				
Second experience	0.427***	0.601***	0.116**	0.316***				
	(0.056)	(0.088)	(0.046)	(0.075)				
Prestigious	0.042	0.138	-0.098*	-0.194**	-0.139***	-0.339***	-0.143***	-0.190***
	(0.064)	(0.087)	(0.051)	(0.085)	(0.048)	(0.070)	(0.037)	(0.058)
Remote	0.019	0.120	0.044	0.045	0.682***	0.638***	0.137***	0.146**
	(0.062)	(0.106)	(0.043)	(0.075)	(0.076)	(0.100)	(0.040)	(0.057)
Full time	-0.001	0.092	0.051	0.221***	-0.076	0.029	-0.020	0.074
	(0.065)	(0.084)	(0.051)	(0.070)	(0.050)	(0.071)	(0.033)	(0.053)
Duration (months)					0.033**	-0.005	0.022**	0.018
					(0.013)	(0.021)	(0.009)	(0.017)
Teamwork required					0.028	-0.155**	0.018	-0.096*
					(0.050)	(0.066)	(0.036)	(0.053)
Tight deadlines					-0.217***	-0.284***	-0.034	-0.081
					(0.052)	(0.065)	(0.037)	(0.053)
MENA origin	-0.084	0.134	-0.097**	-0.027	0.120**	-0.117	0.062	-0.004
	(0.063)	(0.096)	(0.049)	(0.079)	(0.051)	(0.072)	(0.041)	(0.057)
Female	-0.013	0.063	0.038	0.068	0.032	0.056	-0.050	0.042
	(0.064)	(0.090)	(0.050)	(0.071)	(0.042)	(0.058)	(0.034)	(0.049)
Number of observations	6,021	2,671	6,021	2,671	13,375	7,225	13,375	7,225
Number of respondents	241	107	241	107	535	289	535	289
Outcome mean	6.017	6.007	6.924	6.702	6.084	6.312	6.542	6.411
Outcome standard deviation	1.980	1.952	1.526	1.522	2.594	2.487	1.759	1.857
Gender of respondent	Male	Female	Male	Female	Male	Female	Male	Female

Notes: This table reports results from estimating Equations 1 and 2 using OLS and participants from the *Evaluation* experiments. They correspond to those from Table 2, but splitting the sample by respondent gender. Gender of workers and recruiters is imputed from first names. See Table 2 for more details. All specifications include respondent fixed effects. Standard errors are clustered at the respondent level. $*p < 0.10, **p < 0.05, ***p < 0.01$.

Table B.15: Estimated preferences from the *Evaluation* experiments: MENA origin

Evaluator:	Recruiters				Workers			
Object:	Profiles				Offers			
Dependent variable:	Hire		Accept likelihood		Accept		Offer likelihood	
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Daily wage (100s)	-0.160***	-0.067	-0.136***	-0.102*	0.915***	0.874***	0.170***	0.221**
	(0.026)	(0.074)	(0.019)	(0.055)	(0.030)	(0.129)	(0.018)	(0.089)
At least one job	0.226***	0.389	0.100*	0.052	0.079	0.127	0.025	0.181
	(0.072)	(0.317)	(0.057)	(0.203)	(0.050)	(0.277)	(0.042)	(0.201)
Number of jobs (10s)	0.186***	0.205**	0.049*	0.103	-0.008	-0.103	-0.001	-0.169
	(0.035)	(0.092)	(0.025)	(0.098)	(0.028)	(0.126)	(0.022)	(0.104)
Share reviews	0.039	0.106	0.006	0.040	0.032	-0.144	-0.008	0.158
	(0.042)	(0.241)	(0.035)	(0.116)	(0.033)	(0.136)	(0.024)	(0.141)
Reputation badge	0.212***	0.525	0.040	0.139				
	(0.067)	(0.334)	(0.050)	(0.208)				
Years of experience (10s)	0.296***	0.604***	0.011	-0.097				
	(0.044)	(0.183)	(0.034)	(0.147)				
Master	0.060	-0.022	-0.047	-0.072				
	(0.052)	(0.177)	(0.041)	(0.102)				
Second experience	0.485***	0.328**	0.180***	0.134				
	(0.049)	(0.123)	(0.041)	(0.106)				
Prestigious	0.073	0.159	-0.125***	-0.142	-0.240***	0.278*	-0.177***	0.091
	(0.054)	(0.233)	(0.045)	(0.200)	(0.041)	(0.162)	(0.031)	(0.173)
Remote	0.021	0.526*	0.027	0.311	0.678***	0.478**	0.143***	0.071
	(0.054)	(0.260)	(0.038)	(0.210)	(0.063)	(0.227)	(0.034)	(0.131)
Full time	0.033	0.028	0.129***	-0.381*	-0.053	0.158	-0.002	0.218
	(0.051)	(0.317)	(0.042)	(0.200)	(0.042)	(0.167)	(0.029)	(0.137)
Duration (months)					0.019*	0.024	0.022***	-0.003
					(0.011)	(0.040)	(0.008)	(0.035)
Teamwork required					-0.029	-0.217	-0.017	-0.135
					(0.040)	(0.185)	(0.030)	(0.142)
Tight deadlines					-0.237***	-0.263	-0.037	-0.259*
					(0.042)	(0.161)	(0.031)	(0.142)
MENA origin	-0.021	0.054	-0.085**	0.068	0.029	0.094	0.032	0.129
	(0.055)	(0.175)	(0.043)	(0.188)	(0.042)	(0.225)	(0.034)	(0.157)
Female	0.013	0.028	0.061	-0.222	0.049	-0.108	-0.011	-0.126
	(0.054)	(0.248)	(0.043)	(0.138)	(0.035)	(0.162)	(0.028)	(0.135)
Number of observations	8,192	500	8,192	500	19,325	1,275	19,325	1,275
Number of respondents	328	20	328	20	773	51	773	51
Outcome mean	6.021	5.902	6.845	7.034	6.151	6.351	6.458	7.075
Outcome standard deviation	1.974	1.930	1.523	1.560	2.546	2.719	1.778	2.023
Origin of respondent name	Non-MENA	MENA	Non-MENA	MENA	Non-MENA	MENA	Non-MENA	MENA

Notes: This table reports results from estimating Equations 1 and 2 using OLS and participants from the *Evaluation* experiments. They correspond to those from Table 2, but splitting the sample by respondent MENA origin. Ethnicity of workers and recruiters is imputed from first names. See Table 2 for more details. All specifications include respondent fixed effects. Standard errors are clustered at the respondent level. $*p < 0.10, **p < 0.05, ***p < 0.01$.

Table B.16: Estimated preferences from the *Evaluation* experiments using an ordered probit

Evaluator:	Recruiters		Workers	
Object:	Profiles		Offers	
Dependent variable:	Hire	Accept likelihood	Accept	Offer likelihood
	(1)	(2)	(3)	(4)
Daily wage (100s)	-0.086***	-0.046***	0.415***	0.103***
	(0.013)	(0.013)	(0.015)	(0.010)
At least one job	0.105***	0.083**	0.036	0.023
	(0.038)	(0.038)	(0.024)	(0.024)
Number of jobs (10s)	0.111***	0.108***	-0.008	-0.009
	(0.018)	(0.017)	(0.013)	(0.013)
Share reviews	0.023	0.024	0.007	0.001
	(0.023)	(0.022)	(0.015)	(0.014)
Reputation badge	0.135***	0.140***		
	(0.036)	(0.035)		
Years of experience (10s)	0.164***	0.188***		
	(0.024)	(0.025)		
Master	0.031	0.055**		
	(0.027)	(0.027)		
Second experience	0.252***	0.220***		
	(0.025)	(0.024)		
Prestigious	0.045	0.102***	-0.093***	-0.091***
	(0.028)	(0.028)	(0.018)	(0.018)
Remote	0.023	0.010	0.306***	0.079***
	(0.028)	(0.028)	(0.027)	(0.019)
Full time	0.018	-0.018	-0.021	0.008
	(0.028)	(0.028)	(0.019)	(0.017)
Duration (months)			0.010**	0.013***
			(0.005)	(0.005)
Teamwork required			-0.016	-0.019
			(0.019)	(0.017)
Tight deadlines			-0.115***	-0.038**
			(0.019)	(0.018)
MENA origin	-0.015	0.014	0.016	0.019
	(0.028)	(0.029)	(0.019)	(0.019)
Female	0.005	-0.012	0.019	-0.013
	(0.028)	(0.027)	(0.016)	(0.016)
Number of observations	8,692	8,692	20,600	20,600
Number of respondents	348	348	824	824
Outcome mean	6.014	6.014	6.164	6.496
Outcome standard deviation	1.971	1.525	2.557	1.794

Notes: This table reports results from estimating Equations 1 and 2 using an ordered probit and participants from the *Evaluation* experiments. They correspond to those from Table 2, but replacing OLS estimation with the ordered probit. See Table 2 for more details. All specifications include respondent fixed effects. Standard errors are clustered at the respondent level.
$*p < 0.10, **p < 0.05, ***p < 0.01$.

Table B.17: Estimated preferences from the *Evaluation* experiments by job type

Evaluator:	Recruiters				Workers			
Object:	Profiles				Offers			
Dependent variable:	Hire		Accept likelihood		Accept		Offer likelihood	
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Daily wage (100s)	-0.140***	-0.170***	-0.117***	-0.153***	0.997***	0.768***	0.197***	0.132***
	(0.039)	(0.031)	(0.025)	(0.027)	(0.039)	(0.042)	(0.023)	(0.025)
At least one job	0.282***	0.183*	0.018	0.167**	0.100	0.063	0.045	0.017
	(0.089)	(0.108)	(0.076)	(0.080)	(0.068)	(0.075)	(0.052)	(0.064)
Number of jobs (10s)	0.141***	0.220***	0.095***	0.021	-0.003	-0.028	0.020	-0.037
	(0.042)	(0.048)	(0.034)	(0.033)	(0.040)	(0.037)	(0.028)	(0.033)
Share reviews	0.032	0.055	-0.026	0.041	0.038	0.005	0.017	-0.013
	(0.056)	(0.062)	(0.043)	(0.052)	(0.045)	(0.046)	(0.030)	(0.039)
Reputation badge	0.207**	0.254***	0.116*	-0.033				
	(0.092)	(0.091)	(0.068)	(0.070)				
Years of experience (10s)	0.368***	0.262***	0.050	-0.039				
	(0.060)	(0.061)	(0.045)	(0.049)				
Master	0.063	0.054	-0.049	-0.048				
	(0.074)	(0.068)	(0.056)	(0.054)				
Second experience	0.453***	0.506***	0.134***	0.219***				
	(0.064)	(0.069)	(0.051)	(0.061)				
Prestigious	0.118*	0.027	-0.056	-0.198***	-0.127**	-0.292***	-0.111***	-0.210***
	(0.071)	(0.076)	(0.059)	(0.065)	(0.053)	(0.059)	(0.038)	(0.050)
Remote	-0.055	0.148**	0.033	0.050	0.851***	0.477***	0.185***	0.092*
	(0.077)	(0.075)	(0.048)	(0.059)	(0.092)	(0.078)	(0.044)	(0.049)
Full time	0.153**	-0.093	0.161***	0.040	-0.097*	0.021	-0.004	0.031
	(0.075)	(0.070)	(0.058)	(0.059)	(0.057)	(0.058)	(0.034)	(0.046)
Duration (months)					0.037**	0.003	0.021**	0.021
					(0.015)	(0.016)	(0.009)	(0.014)
Teamwork required					0.047	-0.115**	0.004	-0.048
					(0.054)	(0.058)	(0.036)	(0.047)
Tight deadlines					-0.258***	-0.227***	-0.041	-0.063
					(0.058)	(0.056)	(0.039)	(0.046)
MENA origin	0.026	-0.070	-0.079	-0.067	0.080	-0.006	0.030	0.047
	(0.071)	(0.079)	(0.054)	(0.065)	(0.056)	(0.062)	(0.042)	(0.051)
Female	-0.011	0.035	0.056	0.037	0.073	0.015	-0.035	-0.002
	(0.079)	(0.070)	(0.060)	(0.057)	(0.048)	(0.048)	(0.037)	(0.042)
Number of observations	4,392	4,300	4,392	4,300	10,450	10,150	10,450	10,150
Number of respondents	176	172	176	172	418	406	418	406
Outcome mean	6.163	5.862	6.933	6.777	6.055	6.275	6.693	6.293
Outcome standard deviation	1.961	1.981	1.458	1.590	2.619	2.491	1.618	1.618
Job family	Tech	Non-tech	Tech	Non-tech	Tech	Non-tech	Tech	Non-tech

Notes: This table reports results replicating Table 2 but separating participants in whether they hire or work in tech versus non-tech jobs. Tech includes development and integration jobs. Non-tech includes growth marketing, communication, social media and community managers, and translators. See Table 2 for additional details. Standard errors are clustered at the respondent level. $^{*}p < 0.10$, $^{**}p < 0.05$, $^{***}p < 0.01$.

Table B.18: Estimated preferences from the *Evaluation* experiments for highly-rated profiles and offers

Evaluator:	Recruiters				Workers			
Object:	Profiles				Offers			
Dependent variable:	Hired	Hire>8	Accepted offer	Accept likelihood>8	Accepted	Accept>8	Offered	Offer>8
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Daily wage (100s)	-0.022***	-0.021***	-0.023***	-0.022***	0.082***	0.093***	0.023***	0.023***
	(0.003)	(0.003)	(0.003)	(0.003)	(0.003)	(0.004)	(0.003)	(0.003)
At least one job	-0.006	0.007	-0.008	0.002	0.007	0.002	0.006	0.006
	(0.010)	(0.011)	(0.012)	(0.012)	(0.008)	(0.008)	(0.008)	(0.007)
Number of jobs (10s)	0.028***	0.030***	0.011**	0.011**	-0.004	-0.004	-0.002	-0.005
	(0.005)	(0.005)	(0.005)	(0.006)	(0.004)	(0.005)	(0.004)	(0.004)
Share reviews	0.005	0.005	0.010	0.014**	0.002	-0.002	-0.002	-0.002
	(0.007)	(0.007)	(0.007)	(0.006)	(0.005)	(0.005)	(0.005)	(0.005)
Reputation badge	0.047***	0.033***	0.020*	0.012				
	(0.012)	(0.011)	(0.011)	(0.011)				
Years of experience (10s)	0.025***	0.023***	0.004	-0.000				
	(0.006)	(0.007)	(0.007)	(0.007)				
Master	0.004	0.010	-0.011	-0.015*				
	(0.008)	(0.008)	(0.008)	(0.008)				
Second experience	0.040***	0.037***	0.009	0.007				
	(0.007)	(0.007)	(0.008)	(0.007)				
Prestigious	0.019**	0.014*	-0.013	-0.011	-0.021***	-0.017***	-0.018***	-0.012**
	(0.009)	(0.008)	(0.008)	(0.008)	(0.006)	(0.006)	(0.006)	(0.005)
Remote	-0.000	0.003	-0.002	0.009	0.051***	0.060***	0.017***	0.013**
	(0.007)	(0.007)	(0.008)	(0.007)	(0.007)	(0.008)	(0.006)	(0.006)
Full time	0.009	0.004	0.014*	0.018**	-0.000	-0.003	0.003	0.001
	(0.008)	(0.008)	(0.008)	(0.008)	(0.006)	(0.006)	(0.005)	(0.005)
Duration (months)					0.004**	0.004**	0.003*	0.004***
					(0.002)	(0.002)	(0.001)	(0.001)
Teamwork required					-0.001	-0.001	-0.014**	-0.013**
					(0.006)	(0.006)	(0.006)	(0.005)
Tight deadlines					-0.028***	-0.025***	-0.018***	-0.012**
					(0.006)	(0.007)	(0.006)	(0.006)
MENA origin	-0.008	-0.001	-0.013	-0.005	0.009	0.010	0.005	0.006
	(0.009)	(0.008)	(0.009)	(0.008)	(0.007)	(0.007)	(0.006)	(0.006)
Female	0.006	0.005	0.003	0.006	0.006	0.002	-0.007	-0.002
	(0.008)	(0.008)	(0.010)	(0.009)	(0.005)	(0.006)	(0.005)	(0.005)
Number of observations	8,692	8,692	8,692	8,692	20,600	20,600	20,600	20,600
Number of respondents	348	348	348	348	824	824	824	824
Outcome mean	0.137	0.157	0.207	0.206	0.232	0.284	0.222	0.212

Notes: This table reports results from estimating Equations 1 and 2 using OLS and participants from the *Evaluation* experiments. They correspond to those from Table 2, but using a different set of outcome variables. "Hired", "Accepted offer", "Accepted" and "Offered" are indicator variables equal to 1 for the profile(s) or offer(s) which received a participant's highest evaluations out of their 25 evaluations for a recruiter's interest in hiring the profile, a recruiter's expected likelihood that the profile would accept their offer, a worker's interest in accepting the job, and a worker's expected likelihood that they would be offered such a job, respectively. ">8" is an indicator variable for a given profile or offer receiving an evaluation above 8 out of 10 from a given participant. See Table 2 for more details. All specifications include respondent fixed effects. Standard errors are clustered at the respondent level. $*p < 0.10, **p < 0.05, ***p < 0.01$.

Table B.19: Estimated preferences from the *Evaluation* experiments by participants' platform experience

Evaluator:	Recruiters				Workers			
Object:	Profiles				Offers			
Dependent variable:	Hire		Accept likelihood		Accept		Offer likelihood	
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Daily wage (100s)	-0.160***	-0.148***	-0.138***	-0.130***	0.844***	0.991***	0.153***	0.199***
	(0.032)	(0.041)	(0.027)	(0.024)	(0.044)	(0.039)	(0.026)	(0.024)
At least one job	0.202**	0.274***	0.112	0.091	0.070	0.091	0.026	0.043
	(0.095)	(0.102)	(0.079)	(0.075)	(0.068)	(0.075)	(0.057)	(0.060)
Number of jobs (10s)	0.193***	0.180***	0.040	0.059*	-0.004	-0.026	0.028	-0.045
	(0.050)	(0.044)	(0.036)	(0.032)	(0.037)	(0.039)	(0.030)	(0.032)
Share reviews	0.009	0.077	-0.008	0.027	0.003	0.062	-0.035	0.047
	(0.060)	(0.057)	(0.047)	(0.047)	(0.046)	(0.045)	(0.036)	(0.034)
Reputation badge	0.302***	0.141	0.034	0.044				
	(0.086)	(0.101)	(0.069)	(0.069)				
Years of experience (10s)	0.323***	0.305***	-0.017	0.038				
	(0.057)	(0.065)	(0.046)	(0.047)				
Master	0.015	0.102	-0.005	-0.095*				
	(0.069)	(0.073)	(0.055)	(0.054)				
Second experience	0.466***	0.493***	0.199***	0.149***				
	(0.067)	(0.066)	(0.058)	(0.053)				
Prestigious	0.131*	0.012	0.004	-0.270***	-0.255***	-0.153***	-0.145***	-0.160***
	(0.071)	(0.077)	(0.059)	(0.064)	(0.060)	(0.052)	(0.044)	(0.045)
Remote	0.051	0.044	0.106**	-0.031	0.655***	0.658***	0.102**	0.164***
	(0.080)	(0.069)	(0.052)	(0.054)	(0.088)	(0.085)	(0.046)	(0.047)
Full time	0.006	0.062	0.118**	0.082	-0.113*	0.017	-0.010	0.028
	(0.070)	(0.076)	(0.059)	(0.058)	(0.062)	(0.055)	(0.039)	(0.041)
Duration (months)					0.030*	0.008	0.033***	0.008
					(0.016)	(0.015)	(0.012)	(0.011)
Teamwork required					-0.025	-0.053	-0.051	0.003
					(0.054)	(0.059)	(0.040)	(0.045)
Tight deadlines					-0.204***	-0.262***	-0.063	-0.034
					(0.057)	(0.058)	(0.042)	(0.044)
MENA origin	-0.089	0.064	-0.119*	-0.037	0.047	0.037	0.079*	0.006
	(0.073)	(0.075)	(0.060)	(0.057)	(0.059)	(0.059)	(0.044)	(0.050)
Female	0.088	-0.073	0.123**	-0.040	0.049	0.035	-0.027	-0.010
	(0.074)	(0.073)	(0.058)	(0.058)	(0.052)	(0.046)	(0.040)	(0.040)
Number of observations	c	c	c	c	c	c	c	c
Outcome mean	5.922	6.121	6.654	7.090	6.251	6.093	6.232	6.746
Outcome standard deviation	1.980	1.962	1.565	1.477	2.499	2.604	1.721	1.845
Number of completed jobs	None	At least one	None	At least one	None	At least one	None	At least one

Notes: This table reports results from estimating Equations 1 and 2 using OLS and participants from the *Evaluation* experiments. They correspond to those from Table 2, but splitting the sample by whether respondents have at least one job completed on the platform, meaning a successful hire for recruiters and a successful job completed for workers. See Table 2 for more details. All specifications include respondent fixed effects. c denotes a suppressed sensitive observation count, please refer to Table 1 for summary statistics on completed jobs. Standard errors are clustered at the respondent level. $*p < 0.10, **p < 0.05, ***p < 0.01$.

Table B.20: Estimated preferences from the *Evaluation* experiments, workers with at least five completed jobs

Evaluator:	Workers	
Object:	Offers	
Dependent variable:	Accept	Offer likelihood
	(1)	(2)
Daily wage (100s)	1.045***	0.222***
	(0.057)	(0.034)
At least one job	-0.028	-0.063
	(0.099)	(0.076)
Number of jobs (10s)	0.022	0.040
	(0.056)	(0.041)
Share reviews	-0.017	-0.002
	(0.064)	(0.046)
Prestigious	-0.067	-0.063
	(0.071)	(0.057)
Remote	0.673***	0.127*
	(0.130)	(0.069)
Full time	-0.008	0.002
	(0.081)	(0.057)
Duration (months)	0.011	0.007
	(0.022)	(0.016)
Teamwork required	-0.076	0.006
	(0.081)	(0.060)
Tight deadlines	-0.272***	-0.008
	(0.081)	(0.058)
Female	0.108*	-0.002
	(0.064)	(0.056)
MENA origin	0.060	0.061
	(0.084)	(0.072)
Number of observations	c	c
Outcome mean	5.999	6.898
Outcome standard deviation	2.625	1.812
Projects	≥ 5	≥ 5

Notes: This table reports results from estimating Equation 2 using OLS and participants from the *Evaluation* experiments. They correspond to those from columns 3-4 of Table 2, but splitting the sample by whether participants have at least five jobs completed on the platform. See Table 2 for more details. All specifications include respondent fixed effects. c denotes a suppressed sensitive observation count, please refer to Table 1 for summary statistics on completed jobs. Standard errors are clustered at the respondent level. $*p < 0.10, **p < 0.05, ***p < 0.01$.

Table B.21: Estimated preferences from the *Evaluation* experiments by firm size

Evaluator:	Recruiters			
Object:	Profiles			
Dependent variable:	Hire		Accept likelihood	
	(1)	(2)	(3)	(4)
Daily wage (100s)	-0.165***	-0.103*	-0.146***	-0.078*
	(0.029)	(0.054)	(0.020)	(0.046)
At least one job	0.274***	0.055	0.131**	-0.043
	(0.078)	(0.173)	(0.063)	(0.124)
Number of jobs (10s)	0.186***	0.195**	0.037	0.105*
	(0.037)	(0.083)	(0.028)	(0.053)
Share reviews	0.047	0.047	0.016	-0.004
	(0.048)	(0.087)	(0.040)	(0.058)
Reputation badge	0.256***	0.175	0.061	-0.028
	(0.077)	(0.114)	(0.057)	(0.101)
Years of experience (10s)	0.286***	0.417***	0.035	-0.062
	(0.048)	(0.102)	(0.037)	(0.077)
Master's degree	0.097*	-0.030	-0.045	-0.013
	(0.056)	(0.106)	(0.044)	(0.072)
Second experience	0.445***	0.579***	0.133***	0.345***
	(0.052)	(0.116)	(0.044)	(0.101)
Prestigious	0.070	0.021	-0.135***	-0.115
	(0.059)	(0.119)	(0.051)	(0.090)
Remote	0.078	-0.102	0.051	-0.028
	(0.057)	(0.146)	(0.044)	(0.062)
Full time	0.046	0.001	0.098**	0.098
	(0.059)	(0.119)	(0.049)	(0.078)
MENA origin	-0.060	0.102	-0.072	-0.103
	(0.057)	(0.134)	(0.047)	(0.094)
Female	0.034	-0.081	0.054	-0.007
	(0.059)	(0.116)	(0.046)	(0.104)
Number of observations	6,842	1,650	6,842	1,650
Number of respondents	274	66	274	66
Outcome mean	6.085	5.758	6.835	6.982
Outcome standard deviation	1.961	2.013	1.529	1.525
Firm size	$\leq$10 employees	$>$10 employees	$\leq$10 employees	$>$10 employees

Notes: This table reports results from estimating Equations 1 and 2 using OLS and participants from the *Evaluation* experiments. They correspond to those from columns 1-2 of Table 2, but splitting the sample by the organization size of participating recruiters. See Table 2 for more details. All specifications include respondent fixed effects. Standard errors are clustered at the respondent level. $*p < 0.10, **p < 0.05, ***p < 0.01$.

Table B.22: Estimated preferences from the *Evaluation* experiments, split by self-reported freelance experience

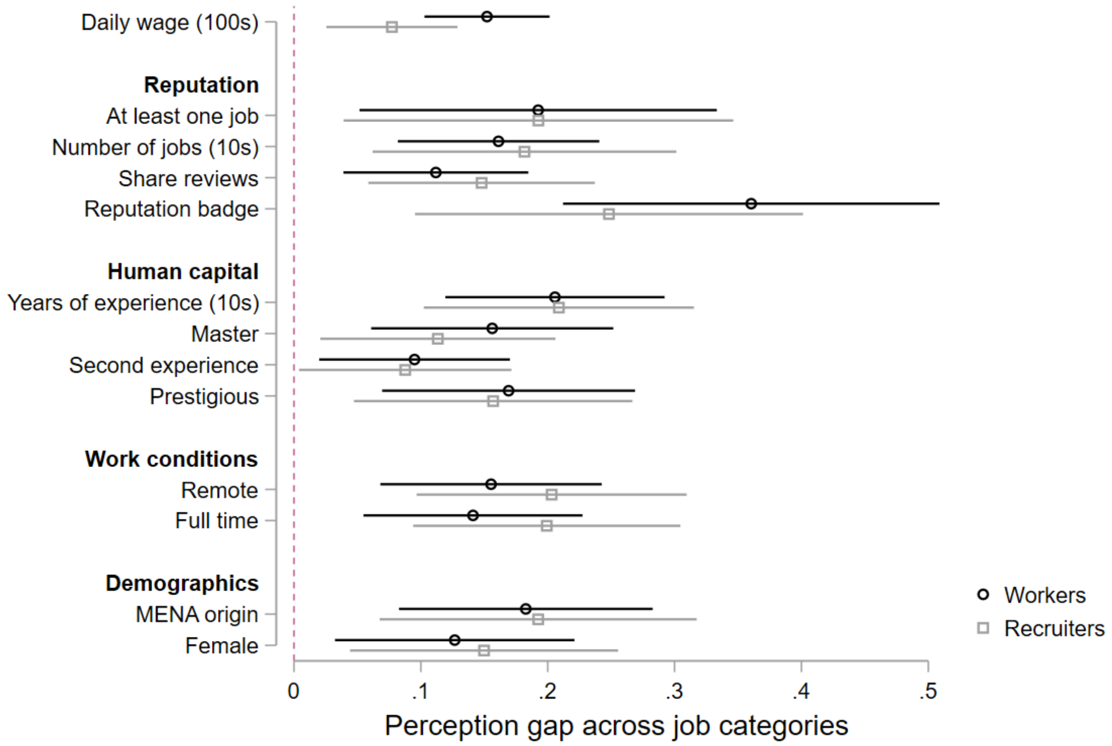
Evaluator:	Workers			
Object:	Offers			
Dependent variable:	Accept		Offer likelihood	
	(1)	(2)	(3)	(4)
Daily wage (100s)	0.804***	1.002***	0.130***	0.209***
	(0.045)	(0.038)	(0.024)	(0.025)
At least one job	0.096	0.075	0.071	0.004
	(0.078)	(0.066)	(0.063)	(0.055)
Number of jobs (10s)	-0.047	0.006	-0.011	-0.010
	(0.044)	(0.034)	(0.035)	(0.028)
Share reviews	-0.050	0.081*	-0.019	0.023
	(0.047)	(0.045)	(0.035)	(0.034)
Prestigious	-0.216***	-0.203***	-0.165***	-0.157***
	(0.057)	(0.055)	(0.044)	(0.044)
Remote	0.571***	0.742***	0.113**	0.159***
	(0.086)	(0.085)	(0.048)	(0.044)
Full time	-0.087	-0.004	0.057	-0.025
	(0.061)	(0.055)	(0.042)	(0.039)
Duration (months)	-0.002	0.039**	-0.000	0.039***
	(0.015)	(0.016)	(0.011)	(0.012)
Teamwork required	0.018	-0.089	0.018	-0.059
	(0.055)	(0.056)	(0.041)	(0.042)
Tight deadlines	-0.179***	-0.284***	-0.081*	-0.025
	(0.059)	(0.056)	(0.046)	(0.040)
Female	0.016	0.058	-0.036	-0.004
	(0.051)	(0.046)	(0.039)	(0.039)
MENA origin	0.018	0.049	-0.015	0.082*
	(0.063)	(0.055)	(0.049)	(0.045)
Number of observations	9,075	11,525	9,075	11,525
Number of respondents	363	461	363	461
Outcome mean	6.319	6.042	6.215	6.718
Outcome standard deviation	2.468	2.625	1.730	1.842
Freelancer experience	$\leq$ 3 years	>3 years	$\leq$ 3 years	>3 years

Notes: This table reports results from estimating Equations 1 and 2 using OLS and participants from the *Evaluation* experiments. They correspond to those from columns 3-4 of Table 2, but splitting the sample by whether the respondent's self-reported freelancing experience is above or below the median. See Table 2 for more details. All specifications include respondent fixed effects. Standard errors are clustered at the respondent level. $*p < 0.10, **p < 0.05, ***p < 0.01$.

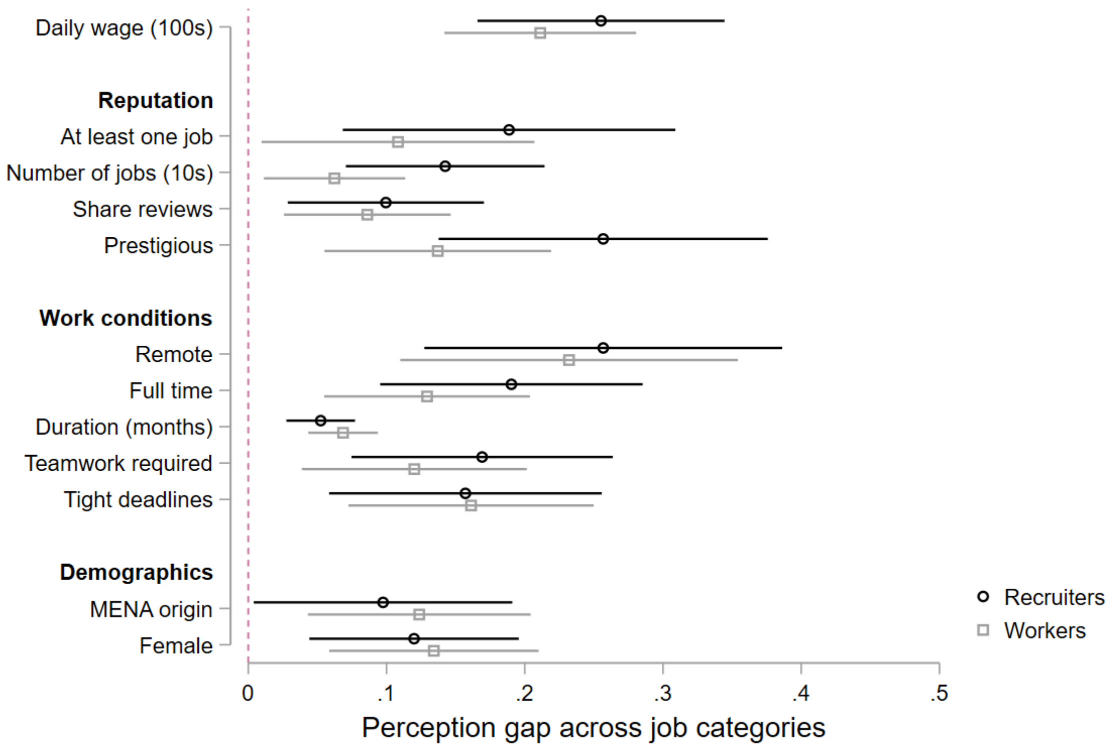
B.2 *Prediction* experiments and perception gaps

Figure B.3: Absolute value of perception gaps averaged across job categories

(a) Profile characteristics



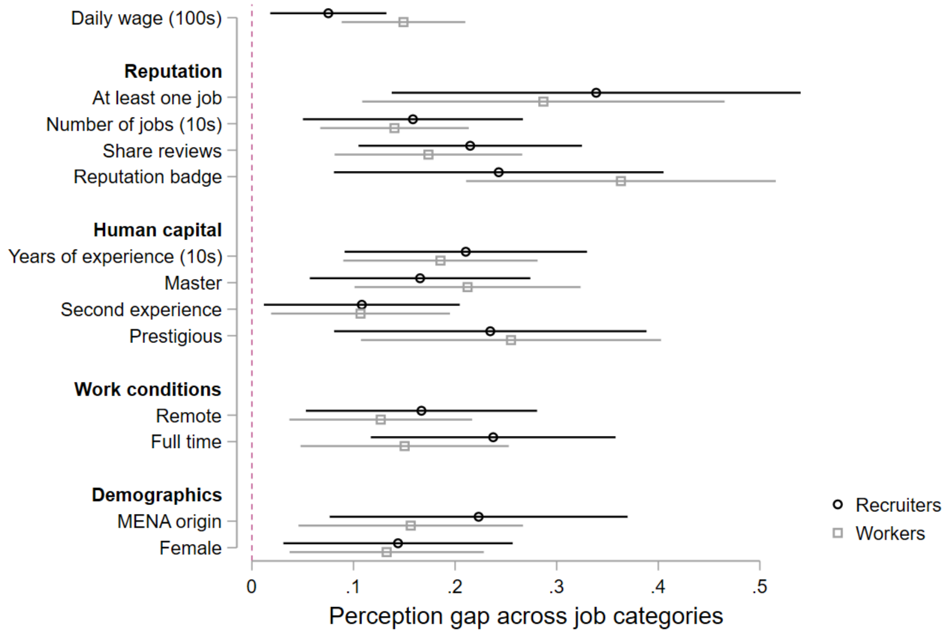
(b) Offer characteristics



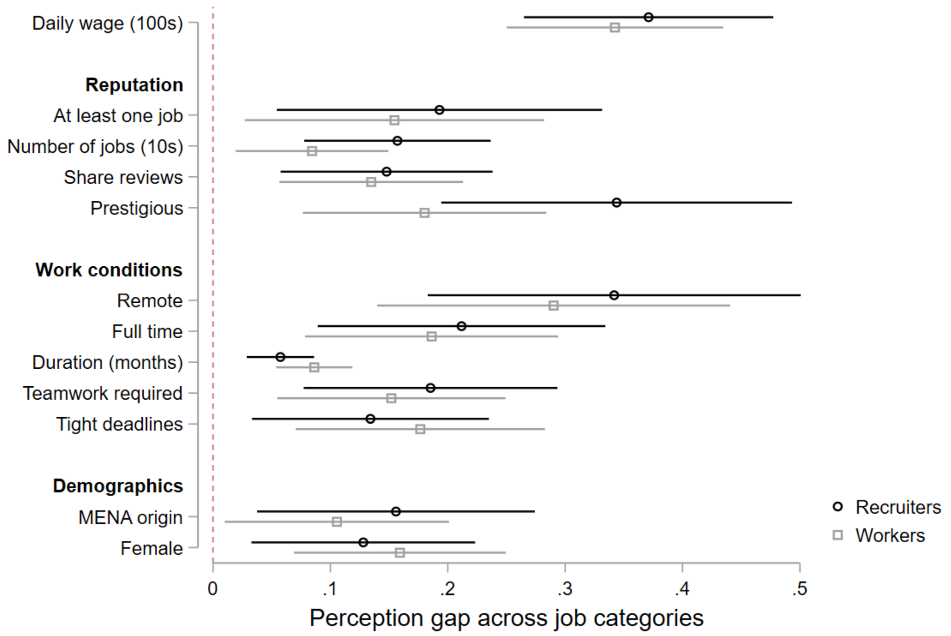
Notes: This figure plots perception gaps estimated at the job category level, transformed to their absolute value, and then averaged across categories. To recover the average perception gap with standard errors, we use a random effects meta-analysis, which weighs coefficients across different job categories using their inverse variance. Standard errors are computed from 500 bootstrapped resamples

Figure B.4: Absolute value of perception gaps averaged across job categories, with participants in the *Evaluation* experiments reweighted to match average platform characteristics

(a) Profile characteristics



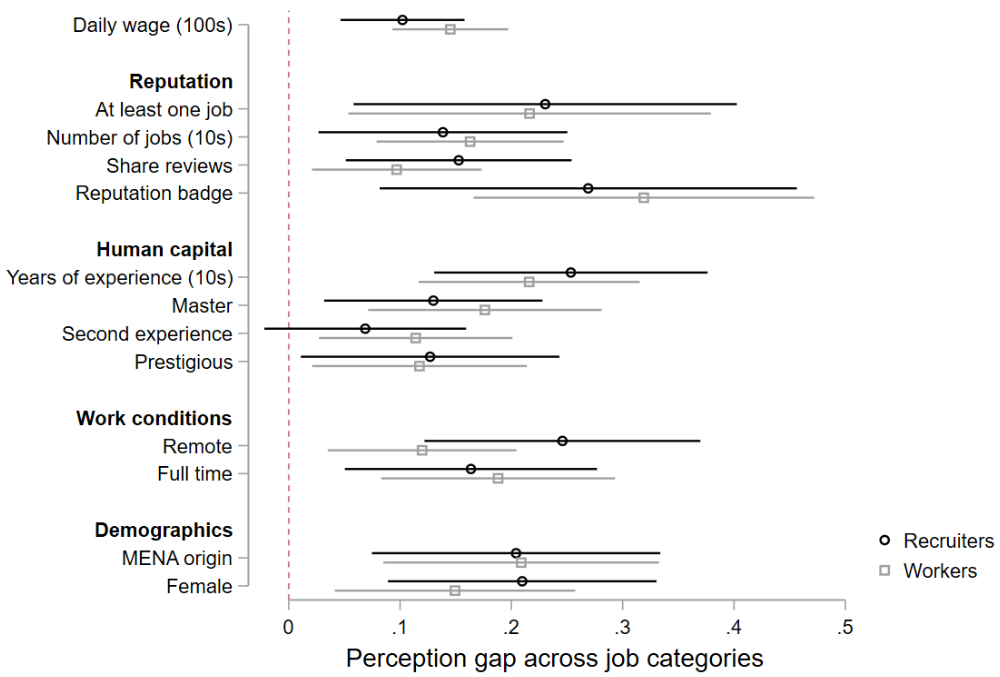
(b) Offer characteristics



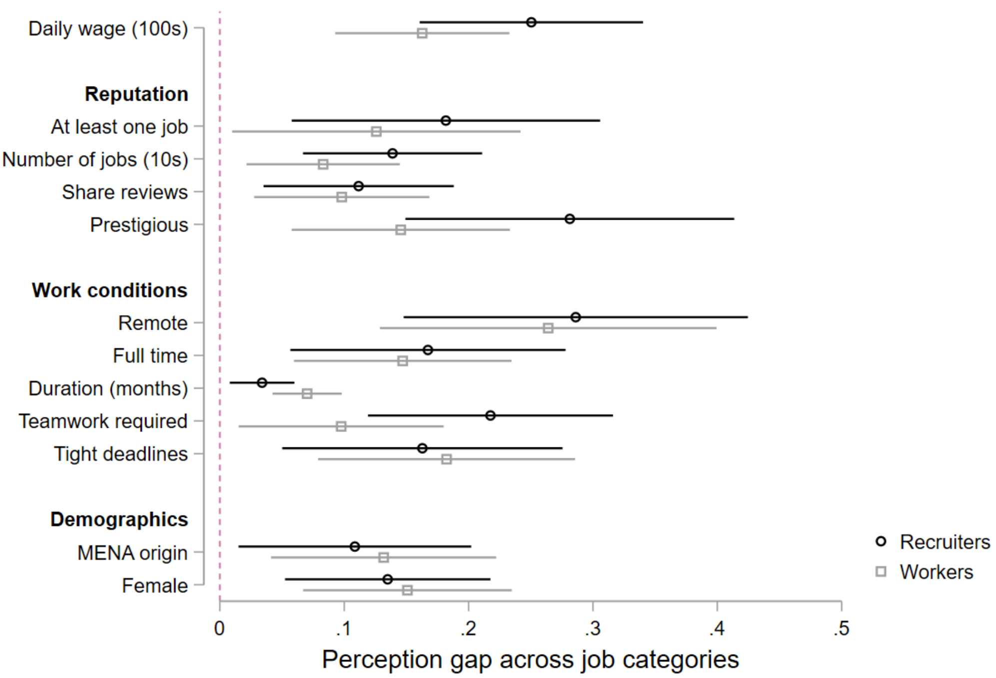
Notes: This figure plots perception gaps estimated at the job category level, where participants from the *Evaluation* experiments are reweighted to match characteristics of average platform users for the job categories in our experiment, transformed to their absolute value, and then averaged across job categories. To recover the average perception gap, we use a random effects meta-analysis, which weighs coefficients across different job categories using their inverse variance. Standard errors computed from 500 bootstrapped replications. Bands represent 95% confidence intervals.

Figure B.5: Absolute value of perception gaps averaged across job categories, with participants in the *Prediction* experiments reweighted to match average platform characteristics

(a) Profile characteristics



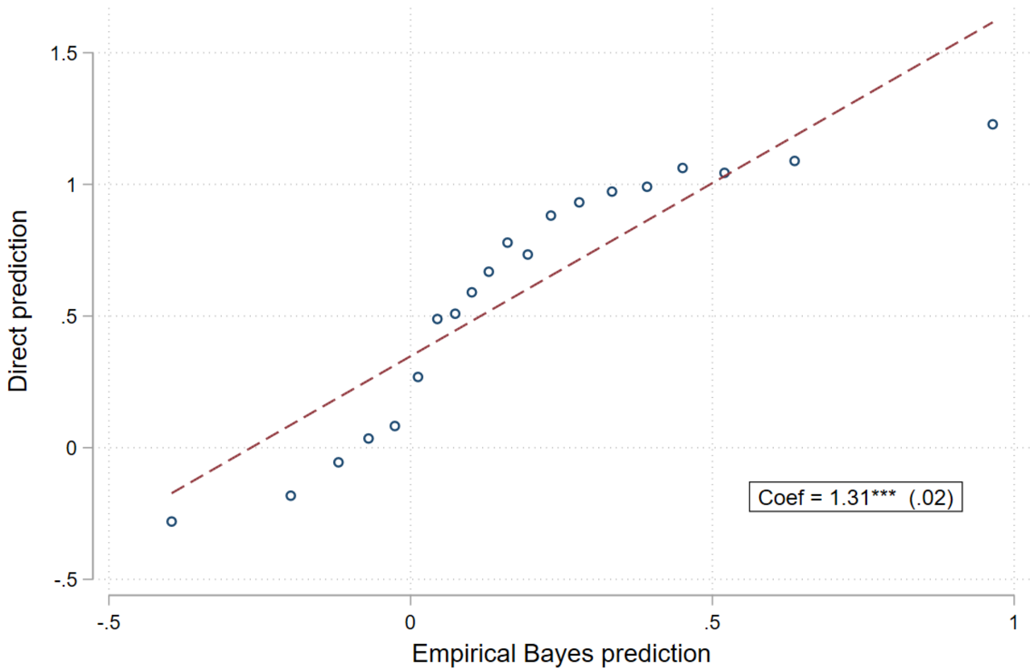
(b) Offer characteristics



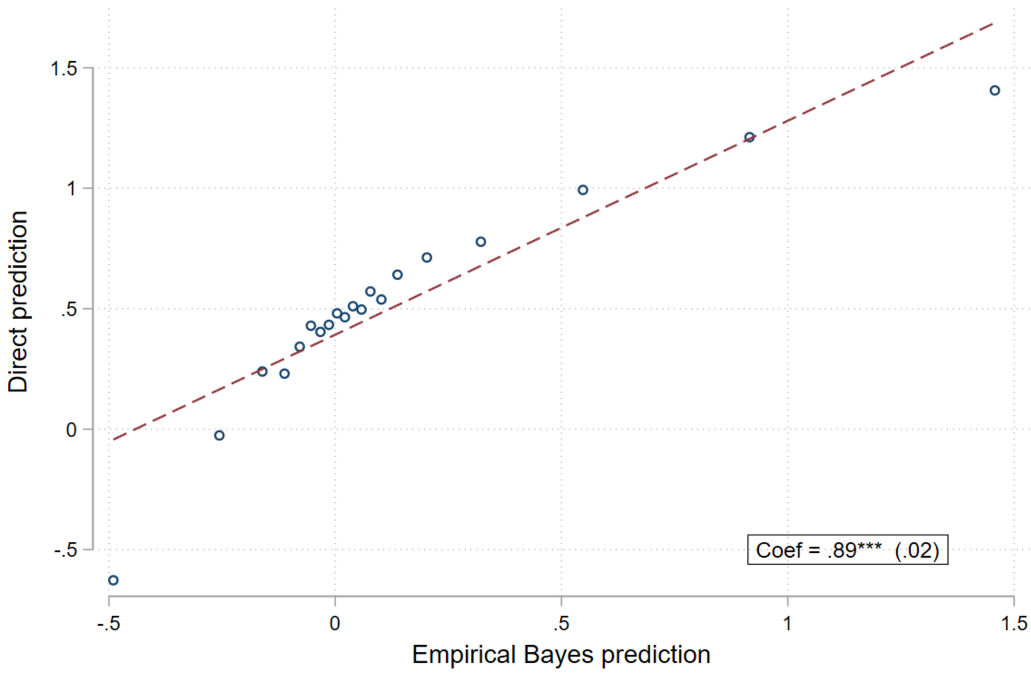
Notes: This figure plots perception gaps estimated at the job category level, where participants from the *Prediction* experiments are reweighted to match averaged platform characteristics, transformed to their absolute value, and then averaged across categories. To recover the average perception gap, we use a random effects meta-analysis, which weighs coefficients across different job categories using their inverse variance. Standard errors computed from 500 bootstrapped replications. Bands represent 95% confidence intervals.

Figure B.6: Correlation between direct and indirect predictions

(a) Profile characteristics



(b) Offer characteristics



Notes: This figure shows binned scatter plots of the indirect predicted value of a characteristic as estimated through an estimation of Equations 1 and 2 at the respondent level with values adjusted using the Empirical Bayes procedure described in Section 5.0 and the direct predicted effect of each characteristic elicited at the end of the *Prediction* experiments. All randomized characteristics are pooled in the figure. Dashed red lines represented fitted slopes, with corresponding regression coefficients and standard errors included in separate text boxes. $^{*}p < 0.10$, $^{**}p < 0.05$, $^{***}p < 0.01$.

Table B.23: Perception gaps of recruiter preferences, by tech and non-tech jobs

Predictor:	Combined		Workers		Recruiters	
Object:	Profiles					
Dependent variable:	Hire (estimated and predicted)					
	(1)	(2)	(3)	(4)	(5)	(6)
Daily wage (100s) × P_i	0.121***	0.103***	0.139***	0.135***	0.080	0.029
	(0.042)	(0.037)	(0.043)	(0.039)	(0.049)	(0.043)
At least one job × P_i	0.150	0.163	0.163	0.119	0.123	0.264*
	(0.104)	(0.124)	(0.109)	(0.133)	(0.134)	(0.143)
Number of jobs (10s) × P_i	0.166***	-0.019	0.174***	-0.038	0.148**	0.032
	(0.050)	(0.055)	(0.054)	(0.058)	(0.064)	(0.063)
Share reviews × P_i	0.089	0.062	0.070	0.029	0.130*	0.140
	(0.063)	(0.072)	(0.065)	(0.075)	(0.077)	(0.086)
Reputation badge × P_i	0.394***	0.225**	0.430***	0.242**	0.311**	0.181
	(0.101)	(0.108)	(0.104)	(0.117)	(0.123)	(0.117)
Years of experience (10s) × P_i	0.158**	0.098	0.196***	0.095	0.074	0.110
	(0.069)	(0.073)	(0.071)	(0.078)	(0.088)	(0.089)
Master's degree × P_i	0.095	0.070	0.094	0.093	0.097	0.010
	(0.081)	(0.080)	(0.083)	(0.085)	(0.097)	(0.095)
Second experience × P_i	-0.074	-0.039	-0.069	-0.046	-0.091	-0.034
	(0.071)	(0.081)	(0.073)	(0.086)	(0.087)	(0.094)
Prestigious × P_i	0.100	0.167*	0.088	0.211**	0.126	0.073
	(0.079)	(0.092)	(0.083)	(0.102)	(0.092)	(0.102)
Remote × P_i	-0.075	-0.213**	-0.098	-0.201**	-0.020	-0.236**
	(0.082)	(0.083)	(0.084)	(0.086)	(0.095)	(0.095)
Full time × P_i	-0.013	0.201***	0.029	0.196**	-0.118	0.206**
	(0.082)	(0.077)	(0.085)	(0.082)	(0.094)	(0.088)
MENA origin × P_i	-0.177**	0.049	-0.167**	0.078	-0.191*	-0.017
	(0.079)	(0.090)	(0.080)	(0.097)	(0.099)	(0.099)
Female × P_i	0.002	-0.004	0.045	-0.006	-0.107	-0.001
	(0.087)	(0.080)	(0.090)	(0.084)	(0.108)	(0.093)
Observations	21,892	15,625	17,467	11,225	8,817	8,550
Number of predictors	700	459	523	283	177	176
Number of evaluators	176	166	176	166	176	166
Evaluator outcome standard deviation	1.970	1.970	1.970	1.970	1.970	1.970
Job family	Tech	Non-tech	Tech	Non-tech	Tech	Non-tech

Notes: This table reports estimates of columns 1-3 from Table 4 split by tech and non-tech jobs. See Tables 4 and B.17 for additional details. Standard errors are clustered at the respondent level. $^{*}p < 0.10$, $^{**}p < 0.05$, $^{***}p < 0.01$.

Table B.24: Perception gaps of worker preferences, by tech and non-tech jobs

Predictor:	Combined		Recruiters		Workers	
Object:	Offers					
Dependent variable:	Accept (estimated and predicted)					
	(1)	(2)	(3)	(4)	(5)	(6)
Daily wage (100s) × P_i	0.111**	0.331***	0.070	0.355***	0.130***	0.319***
	(0.045)	(0.056)	(0.058)	(0.068)	(0.047)	(0.063)
At least one job × P_i	0.016	0.122	0.006	0.223*	0.020	0.071
	(0.083)	(0.102)	(0.104)	(0.127)	(0.091)	(0.113)
Number of jobs (10s) × P_i	0.034	0.008	0.002	-0.013	0.048	0.019
	(0.047)	(0.053)	(0.062)	(0.064)	(0.051)	(0.059)
Share reviews × P_i	-0.025	0.053	-0.052	0.061	-0.014	0.050
	(0.053)	(0.059)	(0.065)	(0.070)	(0.057)	(0.066)
Prestigious × P_i	0.040	0.242***	0.171**	0.325***	-0.015	0.208**
	(0.066)	(0.076)	(0.077)	(0.089)	(0.074)	(0.084)
Remote × P_i	-0.246**	-0.015	-0.321***	0.131	-0.218*	-0.083
	(0.104)	(0.099)	(0.118)	(0.117)	(0.111)	(0.107)
Full time × P_i	0.114*	-0.072	0.157**	-0.142*	0.098	-0.038
	(0.064)	(0.074)	(0.078)	(0.085)	(0.068)	(0.082)
Duration (months) × P_i	0.058***	0.046**	0.041*	0.029	0.065***	0.053**
	(0.018)	(0.019)	(0.024)	(0.022)	(0.019)	(0.021)
Teamwork required × P_i	-0.037	0.117	-0.025	0.136	-0.038	0.108
	(0.065)	(0.073)	(0.080)	(0.083)	(0.070)	(0.081)
Tight deadlines × P_i	-0.109	-0.103	-0.003	0.028	-0.156**	-0.165*
	(0.069)	(0.077)	(0.087)	(0.089)	(0.075)	(0.088)
MENA origin × P_i	-0.119*	0.058	-0.141*	-0.027	-0.110	0.098
	(0.065)	(0.079)	(0.082)	(0.090)	(0.070)	(0.086)
Female × P_i	-0.058	0.017	-0.007	0.068	-0.082	-0.008
	(0.058)	(0.062)	(0.067)	(0.073)	(0.064)	(0.068)
Observations	28,250	20,250	15,150	13,475	23,900	15,700
Number of predictors	698	453	174	182	524	271
Number of evaluators	432	357	432	357	432	357
Evaluator outcome standard deviation	2.549	2.549	2.549	2.549	2.549	2.549
Job family	Tech	Non-tech	Tech	Non-tech	Tech	Non-tech

Notes: This table reports estimates of columns 4-6 from Table 4 split by tech and non-tech jobs. See Tables 4 and B.17 for additional details. Standard errors are clustered at the respondent level. $^{*}p < 0.10$, $^{**}p < 0.05$, $^{***}p < 0.01$.

Table B.25: Perception gaps for recruiter preferences, by predictor gender and ethnicity

Predictor:	Workers				Recruiters			
Object:	Profiles							
Dependent variable:	Hire (estimated and predicted)							
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Daily wage (100s) × P_i	0.143***	0.122***	0.134***	0.167***	0.059*	0.044	0.056*	0.060
	(0.031)	(0.038)	(0.030)	(0.046)	(0.034)	(0.053)	(0.033)	(0.133)
At least one job × P_i	0.145	0.178	0.162*	0.102	0.132	0.369**	0.190*	0.083
	(0.090)	(0.116)	(0.087)	(0.144)	(0.105)	(0.157)	(0.100)	(0.313)
Number of jobs (10s) × P_i	0.065	0.010	0.043	0.067	0.073	0.105	0.091**	-0.007
	(0.044)	(0.049)	(0.041)	(0.069)	(0.048)	(0.070)	(0.046)	(0.142)
Share reviews × P_i	0.076	0.001	0.055	0.028	0.122*	0.174**	0.143**	-0.011
	(0.052)	(0.066)	(0.050)	(0.091)	(0.062)	(0.083)	(0.058)	(0.235)
Reputation badge × P_i	0.315***	0.404***	0.387***	-0.011	0.255***	0.272**	0.252***	0.336
	(0.083)	(0.106)	(0.081)	(0.124)	(0.091)	(0.133)	(0.087)	(0.259)
Years of experience (10s) × P_i	0.197***	0.048	0.135**	0.270***	0.113*	0.042	0.096	0.123
	(0.057)	(0.068)	(0.054)	(0.104)	(0.068)	(0.104)	(0.064)	(0.233)
Master's degree × P_i	0.110*	0.064	0.064	0.366***	0.067	0.034	0.059	0.122
	(0.065)	(0.070)	(0.060)	(0.115)	(0.071)	(0.110)	(0.068)	(0.220)
Second experience × P_i	-0.090	0.024	-0.060	0.009	-0.060	-0.067	-0.032	-0.781***
	(0.058)	(0.078)	(0.057)	(0.105)	(0.068)	(0.102)	(0.064)	(0.280)
Prestigious × P_i	0.123*	0.214**	0.161**	0.064	0.070	0.170	0.102	0.065
	(0.069)	(0.091)	(0.066)	(0.135)	(0.072)	(0.107)	(0.070)	(0.173)
Remote × P_i	-0.159**	-0.142*	-0.139**	-0.264**	-0.112	-0.186*	-0.129*	-0.122
	(0.062)	(0.077)	(0.061)	(0.103)	(0.070)	(0.106)	(0.067)	(0.216)
Full time × P_i	0.121*	0.088	0.102*	0.145	0.082	-0.090	0.043	-0.035
	(0.064)	(0.073)	(0.061)	(0.100)	(0.071)	(0.088)	(0.067)	(0.118)
MENA origin × P_i	-0.116*	0.067	-0.034	-0.265**	-0.161**	0.045	-0.118*	-0.006
	(0.064)	(0.084)	(0.063)	(0.118)	(0.076)	(0.096)	(0.071)	(0.211)
Female × P_i	0.056	-0.043	0.024	0.008	-0.023	-0.118	-0.039	-0.217
	(0.065)	(0.077)	(0.062)	(0.109)	(0.076)	(0.102)	(0.069)	(0.375)
Observations	23,642	13,592	26,267	10,967	15,267	10,642	16,992	8,917
Number of predictors	604	202	709	97	269	84	338	15
Number of evaluators	342	342	342	342	342	342	342	342
Evaluator outcome standard deviation	1.970	1.970	1.970	1.970	1.970	1.970	1.970	1.970
Origin/gender of respondent name	Male	Female	Non MENA	MENA	Male	Female	Non MENA	MENA

Notes: This table reports OLS estimates of Equation 3 using participants from both the *Evaluation* and *Prediction* experiments and augmented by interacting each characteristic with an indicator for whether the participant was part of the *Prediction* experiments. The estimates shown represent the interaction terms, corresponding to the differences between the predicted impact of each characteristic by participants of the *Prediction* experiments and the estimated impact of each characteristic on evaluations by participants in the *Evaluation* experiments. Estimates correspond to those from B.23, but splitting predictors by their gender and ethnic origin. Gender and ethnicity of workers and recruiters are imputed from first names. See Table B.23 for more details. All specifications include respondent fixed effects. Standard errors are clustered at the respondent level.
$*p < 0.10, **p < 0.05, ***p < 0.01$.

Table B.26: Perception gaps for recruiter preferences, by predictor experience on the platform

Predictor:	Workers		Recruiters	
Object:	Profiles			
Dependent variable:	Hire (estimated and predicted)			
	(1)	(2)	(3)	(4)
Daily wage (100s) × P_i	0.129***	0.146***	0.063	0.044
	(0.031)	(0.036)	(0.039)	(0.039)
At least one job × P_i	0.105	0.261**	0.184	0.211
	(0.095)	(0.103)	(0.114)	(0.128)
Number of jobs (10s) × P_i	0.009	0.081*	0.067	0.101*
	(0.045)	(0.047)	(0.052)	(0.058)
Share reviews × P_i	0.058	0.050	0.122*	0.155**
	(0.052)	(0.061)	(0.067)	(0.073)
Reputation badge × P_i	0.321***	0.364***	0.270***	0.247**
	(0.085)	(0.097)	(0.097)	(0.108)
Years of experience (10s) × P_i	0.156***	0.157**	0.117	0.089
	(0.060)	(0.062)	(0.083)	(0.069)
Master's degree × P_i	0.112*	0.081	0.059	0.063
	(0.066)	(0.068)	(0.079)	(0.084)
Second experience × P_i	-0.053	-0.058	-0.030	-0.096
	(0.062)	(0.066)	(0.076)	(0.079)
Prestigious × P_i	0.160**	0.125	0.072	0.130
	(0.072)	(0.081)	(0.080)	(0.084)
Remote × P_i	-0.126*	-0.168**	-0.159**	-0.091
	(0.064)	(0.070)	(0.079)	(0.076)
Full time × P_i	0.058	0.178**	0.024	0.054
	(0.066)	(0.071)	(0.075)	(0.081)
MENA origin × P_i	-0.068	-0.055	-0.138*	-0.090
	(0.068)	(0.073)	(0.081)	(0.087)
Female × P_i	0.037	0.007	0.021	-0.129
	(0.069)	(0.068)	(0.082)	(0.087)
Observations	c	c	c	c
Number of evaluators	342	342	342	342
Evaluator outcome standard deviation	1.970	1.970	1.970	1.970
Experience	No jobs	At least one job	No jobs	At least one job

Notes: This table reports OLS estimates of Equation 3 using participants from both the *Evaluation* and *Prediction* experiments and augmented by interacting each characteristic with an indicator for whether the participant was part of the *Prediction* experiments. The estimates shown represent the interaction terms, corresponding to the differences between the predicted impact of each characteristic by participants of the *Prediction* experiments and the estimated impact of each characteristic on evaluations by participants in the *Evaluation* experiments. Estimates correspond to those from Table B.23, but splitting predictors by whether they completed at least one project on the platform or not. See Table B.23 for more details. All specifications include respondent fixed effects. c denotes a suppressed sensitive observation count, please refer to Table 1 for summary statistics on completed jobs. Standard errors are clustered at the respondent level. $*p < 0.10, **p < 0.05, ***p < 0.01$.

Table B.27: Perception gaps for predictor workers with substantial market experience

Evaluator:	Recruiters	Workers
Predictor :	Workers	
Object:	Profiles	Offers
Dependent variable:	Hire (estimated and predicted)	Accept (estimated and predicted)
	(1)	(2)
Daily wage (100s) × P_i	0.176***	0.326***
	(0.045)	(0.064)
At least one job × P_i	0.290**	0.031
	(0.140)	(0.142)
Number of jobs (10s) × P_i	0.060	0.044
	(0.064)	(0.072)
Share reviews × P_i	-0.026	-0.038
	(0.087)	(0.074)
Reputation badge × P_i	0.446***	
	(0.113)	
Years of experience (10s) × P_i	0.075	
	(0.078)	
Master × P_i	0.032	
	(0.085)	
Second experience × P_i	-0.056	
	(0.083)	
Prestigious × P_i	0.148	0.084
	(0.115)	(0.084)
Remote × P_i	-0.180**	-0.272**
	(0.088)	(0.113)
Full time × P_i	0.224**	0.040
	(0.093)	(0.086)
Duration (months) × P_i		0.043*
		(0.024)
Teamwork required × P_i		0.061
		(0.079)
Tight deadlines × P_i		-0.150
		(0.117)
MENA origin × P_i	-0.051	0.008
	(0.087)	(0.093)
Female × P_i	0.088	-0.146*
	(0.086)	(0.086)
Observations	c	c
Number of evaluators	342	789
Evaluator outcome standard deviation	1.970	2.549
Experience	≥ 5 jobs	≥ 5 jobs

Notes: This table reports OLS estimates of Equations 3 and 4 using participants from both the *Evaluation* and *Prediction* experiments and augmented by interacting each characteristic with an indicator for whether the participant was part of the *Prediction* experiments. The estimates shown represent the interaction terms, corresponding to the differences between the predicted impact of each characteristic by participants of the *Prediction* experiments and the estimated impact of each characteristic on evaluations by participants in the *Evaluation* experiments. Estimates correspond to those from Tables B.23 and B.24, but restricting to predictor workers with at least 5 completed jobs on the platform. See Tables B.23 and B.24 for more details. All specifications include respondent fixed effects. Standard errors are clustered at the respondent level. $*p < 0.10, **p < 0.05, ***p < 0.01$.

Table B.28: Perception gaps of predictor workers, by self-reported freelancing experience

Evaluator:	Recruiters		Workers	
Predictor :	Workers			
Object:	Profiles		Offers	
Dependent variable:	Hire (estimated and predicted)		Accept (estimated and predicted)	
	(1)	(2)	(3)	(4)
Daily wage (100s) × P_i	0.133***	0.142***	0.138***	0.280***
	(0.032)	(0.034)	(0.044)	(0.045)
At least one job × P_i	0.132	0.189*	0.070	0.023
	(0.096)	(0.099)	(0.084)	(0.088)
Number of jobs (10s) × P_i	0.037	0.056	0.050	0.019
	(0.048)	(0.044)	(0.045)	(0.048)
Share reviews × P_i	0.034	0.075	-0.021	0.056
	(0.055)	(0.057)	(0.052)	(0.052)
Reputation badge × P_i	0.366***	0.317***		
	(0.088)	(0.092)		
Years of experience (10s) × P_i	0.184***	0.114*		
	(0.060)	(0.062)		
Master × P_i	0.098	0.096		
	(0.067)	(0.068)		
Second experience × P_i	-0.043	-0.067		
	(0.064)	(0.064)		
Prestigious × P_i	0.139*	0.163**	0.059	0.083
	(0.075)	(0.076)	(0.070)	(0.066)
Remote × P_i	-0.139**	-0.167**	-0.139	-0.172*
	(0.066)	(0.066)	(0.090)	(0.093)
Full time × P_i	0.127*	0.087	-0.011	0.106*
	(0.066)	(0.070)	(0.062)	(0.060)
Duration (months) × P_i			0.074***	0.044***
			(0.017)	(0.017)
Teamwork required × P_i			0.069	-0.008
			(0.066)	(0.063)
Tight deadlines × P_i			-0.171**	-0.160**
			(0.069)	(0.071)
MENA origin × P_i	-0.010	-0.125*	-0.039	0.023
	(0.069)	(0.070)	(0.063)	(0.064)
Female × P_i	0.043	0.000	-0.051	-0.039
	(0.068)	(0.070)	(0.056)	(0.057)
Observations	19,242	17,992	29,875	28,950
Number of predictors	428	378	406	369
Number of evaluators	342	342	789	789
Evaluator outcome standard deviation	1.970	1.970	2.549	2.549
Experience	$\leq$ 3 years exp	$>$ 3 years exp	$\leq$ 3 years exp	$>$ 3 years exp

Notes: This table reports OLS estimates of Equations 3 and 4 using participants from both the *Evaluation* and *Prediction* experiments and augmented by interacting each characteristic with an indicator for whether the participant was part of the *Prediction* experiments. The estimates shown represent the interaction terms, corresponding to the differences between the predicted impact of each characteristic by participants of the *Prediction* experiments and the estimated impact of each characteristic on evaluations by participants in the *Evaluation* experiments. Estimates correspond to those from Tables B.23 and B.24, but restricting to predictor workers with below vesus above median years of freelancing experience. See Tables B.23 and B.24 for more details. All specifications include respondent fixed effects. Standard errors are clustered at the respondent level.
$*p < 0.10, **p < 0.05, ***p < 0.01$.

Table B.29: Perception gaps for recruiter preferences, including fast predictors

Predictor:	Workers			Recruiters		
Object:	Profiles					
Dependent variable:	Hire (estimated and predicted)					
	(1)	(2)	(3)	(4)	(5)	(6)
Daily wage (100s) × P_i	0.137***	0.141***	0.133***	0.060*	0.090*	0.030
	(0.029)	(0.043)	(0.039)	(0.033)	(0.048)	(0.042)
At least one job × P_i	0.170**	0.160	0.154	0.203**	0.133	0.284**
	(0.085)	(0.108)	(0.133)	(0.097)	(0.133)	(0.142)
Number of jobs (10s) × P_i	0.040	0.168***	-0.048	0.067	0.143**	0.007
	(0.040)	(0.053)	(0.058)	(0.045)	(0.063)	(0.064)
Share reviews × P_i	0.049	0.069	0.022	0.142**	0.136*	0.154*
	(0.049)	(0.064)	(0.075)	(0.057)	(0.076)	(0.084)
Reputation badge × P_i	0.341***	0.413***	0.254**	0.296***	0.342***	0.230*
	(0.078)	(0.104)	(0.116)	(0.087)	(0.124)	(0.118)
Years of experience (10s) × P_i	0.138***	0.182**	0.083	0.072	0.051	0.083
	(0.052)	(0.071)	(0.077)	(0.062)	(0.087)	(0.087)
Master's degree × P_i	0.093	0.086	0.093	0.063	0.108	0.008
	(0.059)	(0.083)	(0.084)	(0.067)	(0.096)	(0.093)
Second experience × P_i	-0.063	-0.078	-0.055	-0.069	-0.093	-0.048
	(0.056)	(0.073)	(0.086)	(0.064)	(0.086)	(0.094)
Prestigious × P_i	0.147**	0.092	0.202**	0.098	0.151*	0.048
	(0.064)	(0.083)	(0.100)	(0.068)	(0.091)	(0.100)
Remote × P_i	-0.152**	-0.091	-0.210**	-0.132**	-0.024	-0.239**
	(0.060)	(0.084)	(0.086)	(0.066)	(0.094)	(0.093)
Full time × P_i	0.112*	0.017	0.213***	0.042	-0.105	0.198**
	(0.060)	(0.085)	(0.082)	(0.065)	(0.093)	(0.086)
MENA origin × P_i	-0.060	-0.167**	0.079	-0.124*	-0.209**	-0.025
	(0.062)	(0.080)	(0.096)	(0.070)	(0.100)	(0.097)
Female × P_i	0.024	0.034	0.007	-0.055	-0.096	-0.025
	(0.061)	(0.089)	(0.084)	(0.069)	(0.107)	(0.092)
Observations	29,692	18,167	11,525	17,942	9,067	8,875
Number of predictors	846	551	295	376	187	189
Number of evaluators	342	176	166	342	176	166
Evaluator outcome standard deviation	1.970	1.970	1.970	1.970	1.970	1.970
Job family	All	Tech	Non-tech	All	Tech	Non-tech

Notes: This table reports OLS estimates of Equation 3 using participants from both the *Evaluation* and *Prediction* experiments and augmented by interacting each characteristic with an indicator for whether the participant was part of the *Prediction* experiments. The estimates shown represent the interaction terms, corresponding to the differences between the predicted impact of each characteristic by participants of the *Prediction* experiments and the estimated impact of each characteristic on evaluations by participants in the *Evaluation* experiments. Estimates correspond to those of Table B.23, but including in the participant sample predictors who spent an average of under six seconds per prediction. All regressions include respondent fixed effects. See Table B.23 for additional details. Standard errors are clustered at the respondent level. $^{*}p < 0.10$, $^{**}p < 0.05$, $^{***}p < 0.01$.

Table B.30: Perception gaps for recruiter preferences, corrected for multiple hypothesis testing

Predictor:	Workers			Recruiters		
Object:	Profiles					
Dependent variable:	Hire (estimated and predicted)					
	(1)	(2)	(3)	(4)	(5)	(6)
Daily wage (100s) × P_i	0.137***	0.139***	0.135***	0.055*	0.080	0.029
	[0.00]	[0.00]	[0.00]	[0.10]	[0.13]	[0.89]
At least one job × P_i	0.156**	0.163	0.119	0.188**	0.123	0.264*
	[0.05]	[0.20]	[0.67]	[0.04]	[0.51]	[0.06]
Number of jobs (10s) × P_i	0.046	0.174***	-0.038	0.084**	0.148**	0.032
	[0.38]	[0.00]	[0.77]	[0.05]	[0.01]	[0.95]
Share reviews × P_i	0.053	0.070	0.029	0.134**	0.130	0.140
	[0.41]	[0.48]	[0.83]	[0.01]	[0.13]	[0.15]
Reputation badge × P_i	0.344***	0.430***	0.242**	0.257***	0.311**	0.181
	[0.00]	[0.00]	[0.02]	[0.00]	[0.00]	[0.18]
Years of experience (10s) × P_i	0.151***	0.196***	0.095	0.097	0.074	0.110
	[0.00]	[0.00]	[0.42]	[0.15]	[0.51]	[0.40]
Master's degree × P_i	0.097 *	0.094	0.093	0.059	0.097	0.010
	[0.10]	[0.48]	[0.51]	[0.48]	[0.51]	[0.99]
Second experience × P_i	-0.054	-0.069	-0.046	-0.062	-0.091	-0.034
	[0.41]	[0.48]	[0.82]	[0.47]	[0.51]	[0.97]
Prestigious × P_i	0.150**	0.088	0.211**	0.097	0.126	0.073
	[0.01]	[0.48]	[0.02]	[0.17]	[0.30]	[0.89]
Remote × P_i	-0.152***	-0.098	-0.201***	-0.129**	-0.020	-0.236***
	[0.00]	[0.48]	[0.01]	[0.04]	[0.76]	[0.00]
Full time × P_i	0.110**	0.029	0.196**	0.040	-0.118	0.206**
	[0.05]	[0.71]	[0.01]	[0.55]	[0.36]	[0.01]
MENA origin × P_i	-0.061	-0.167**	0.078	-0.113	-0.191*	-0.017
	[0.41]	[0.02]	[0.73]	[0.14]	[0.07]	[0.99]
Female × P_i	0.023	0.045	-0.006	-0.047	-0.107	-0.001
	[0.59]	[0.71]	[0.92]	[0.55]	[0.51]	[0.88]
Observations	28,692	17,467	11,225	17,367	8,817	8,550
Number of predictors	806	523	283	353	177	176
Number of evaluators	342	176	166	342	176	166
Evaluator outcome standard deviation.	1.970	1.970	1.970	1.970	1.970	1.970
Job family	All	Tech	Non-tech	All	Tech	Non-tech

Notes: This table reports OLS estimates of Equation 1 using participants from both the *Evaluation* and *Prediction* experiments and augmented by interacting each characteristic with an indicator for whether the participant was part of the *Prediction* experiments. The estimates shown represent the interaction terms, corresponding to the differences between the predicted impact of each characteristic by participants of the *Prediction* experiments and the estimated impact of each characteristic on evaluations by participants in the *Evaluation* experiments. Estimates correspond to those from Table B.23, but presenting p-values corrected for multiple-hypothesis testing using the Romano-Wolf method with 1,000 replications in square brackets. See Table B.23 for more details. All specifications include respondent fixed effects. Standard errors are clustered at the respondent level.
$*p < 0.10, **p < 0.05, ***p < 0.01$.

Table B.31: Perception gaps for recruiter preferences, by predictor budgeted wage or asked wage on the platform

Predictor:	Workers		Recruiters	
Object:	Profiles			
Dependent variable:	Hire (estimated and predicted)			
	(1)	(2)	(3)	(4)
Daily wage (100s) × P_i	0.095***	0.175***	-0.002	0.117***
	(0.032)	(0.034)	(0.040)	(0.040)
At least one job × P_i	0.229**	0.104	0.433***	-0.009
	(0.100)	(0.097)	(0.135)	(0.112)
Number of jobs (10s) × P_i	0.060	0.028	0.056	0.091
	(0.047)	(0.045)	(0.053)	(0.061)
Share reviews × P_i	0.039	0.065	0.102	0.127*
	(0.056)	(0.056)	(0.075)	(0.069)
Reputation badge × P_i	0.343***	0.342***	0.280***	0.247**
	(0.091)	(0.089)	(0.106)	(0.103)
Years of experience (10s) × P_i	0.148**	0.163***	0.170**	0.063
	(0.063)	(0.059)	(0.084)	(0.076)
Master's degree × P_i	0.054	0.142**	0.086	0.052
	(0.066)	(0.069)	(0.079)	(0.089)
Second experience × P_i	-0.093	-0.018	-0.068	-0.076
	(0.066)	(0.062)	(0.084)	(0.076)
Prestigious × P_i	0.092	0.199**	0.160*	0.030
	(0.073)	(0.078)	(0.087)	(0.081)
Remote × P_i	-0.153**	-0.141**	-0.141*	-0.144*
	(0.067)	(0.067)	(0.082)	(0.078)
Full time × P_i	0.088	0.127*	-0.012	0.090
	(0.067)	(0.069)	(0.077)	(0.083)
MENA origin × P_i	-0.072	-0.050	-0.107	-0.116
	(0.070)	(0.070)	(0.082)	(0.090)
Female × P_i	0.028	0.024	-0.074	-0.029
	(0.069)	(0.069)	(0.089)	(0.086)
Observations	18,392	18,642	12,567	12,567
Number of predictors	404	394	161	161
Number of evaluators	342	342	342	342
Evaluator outcome standard deviation	1.970	1.970	1.970	1.970
Budgeted or asked wage	Below median	Above median	Below median	Above median

Notes: This table reports OLS estimates of Equation 1 using participants from both the *Evaluation* and *Prediction* experiments and augmented by interacting each characteristic with an indicator for whether the participant was part of the *Prediction* experiments. The estimates shown represent the interaction terms, corresponding to the differences between the predicted impact of each characteristic by participants of the *Prediction* experiments and the estimated impact of each characteristic on evaluations by participants in the *Evaluation* experiments. Estimates correspond to those from Table B.23, but splitting predictors by the value of their average budgeted daily wage on the platform for past job offers, standardized by year and job type for recruiters or their current wage on the platform, standardized by job type for workers. See Table B.23 for more details. All specifications include respondent fixed effects. Standard errors are clustered at the respondent level.
$*p < 0.10, **p < 0.05, ***p < 0.01$.

Table B.32: Perception gaps for recruiter preferences, by predictor propensity to ask for or declare willingness to work on site.

Predictor:	Workers		Recruiters	
Object:	Profiles			
Dependent variable:	Hire (estimated and predicted)			
	(1)	(2)	(3)	(4)
Daily wage (100s) × P_i	0.105***	0.158***	0.061*	0.059
	(0.033)	(0.033)	(0.037)	(0.046)
At least one job × P_i	0.218**	0.121	0.175	0.239*
	(0.105)	(0.093)	(0.117)	(0.127)
Number of jobs (10s) × P_i	0.049	0.040	0.095*	0.036
	(0.046)	(0.046)	(0.053)	(0.059)
Share reviews × P_i	0.056	0.049	0.167**	0.074
	(0.058)	(0.054)	(0.066)	(0.079)
Reputation badge × P_i	0.293***	0.376***	0.214**	0.304***
	(0.089)	(0.089)	(0.097)	(0.115)
Years of experience (10s) × P_i	0.084	0.197***	0.172**	0.028
	(0.061)	(0.060)	(0.071)	(0.093)
Master's degree × P_i	0.031	0.143**	0.088	0.036
	(0.068)	(0.066)	(0.079)	(0.088)
Second experience × P_i	-0.118*	-0.007	-0.058	-0.061
	(0.066)	(0.062)	(0.072)	(0.092)
Prestigious × P_i	0.122	0.170**	0.117	0.099
	(0.076)	(0.074)	(0.079)	(0.090)
Remote × P_i	-0.142**	-0.159**	-0.174**	-0.100
	(0.069)	(0.065)	(0.072)	(0.094)
Full time × P_i	0.119*	0.103	0.024	0.053
	(0.067)	(0.067)	(0.074)	(0.087)
MENA origin × P_i	-0.066	-0.055	-0.186**	0.018
	(0.073)	(0.068)	(0.078)	(0.098)
Female × P_i	-0.013	0.046	-0.072	0.000
	(0.069)	(0.068)	(0.083)	(0.087)
Observations	16,942	20,292	13,992	11,442
Number of predictors	336	470	218	116
Number of evaluators	342	342	342	342
Evaluator outcome standard deviation	1.970	1.970	1.970	1.970
Work on site	No	Yes	No	Some

Notes: This table reports OLS estimates of Equation 3 using participants from both the *Evaluation* and *Prediction* experiments and augmented by interacting each characteristic with an indicator for whether the participant was part of the *Prediction* experiments. The estimates shown represent the interaction terms, corresponding to the differences between the predicted impact of each characteristic by participants of the *Prediction* experiments and the estimated impact of each characteristic on evaluations by participants in the *Evaluation* experiments. Estimates correspond to those from Table B.23, but splitting predictors by whether recruiters ever asked for on site work in their past past job offers, or by their declared willingness to work on site for workers. See Table B.23 for more details. All specifications include respondent fixed effects. Standard errors are clustered at the respondent level. $*p < 0.10, **p < 0.05, ***p < 0.01$.

Table B.33: Perception gaps for worker preferences, by predictor gender and ethnicity

Predictor:	Recruiters				Workers			
Object:	Offers							
Dependent variable:	Accept (estimated and predicted)							
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Daily wage (100s) × P_i	0.168***	0.174**	0.182***	0.016	0.178***	0.207***	0.190***	0.160**
	(0.050)	(0.070)	(0.046)	(0.080)	(0.040)	(0.056)	(0.039)	(0.071)
At least one job × P_i	0.146	-0.011	0.073	0.630***	0.019	0.097	0.028	0.172
	(0.091)	(0.125)	(0.083)	(0.161)	(0.079)	(0.093)	(0.072)	(0.151)
Number of jobs (10s) × P_i	-0.002	-0.014	0.021	-0.427***	0.063	-0.016	0.038	0.006
	(0.050)	(0.064)	(0.045)	(0.110)	(0.043)	(0.051)	(0.039)	(0.085)
Share reviews × P_i	0.020	-0.045	0.010	-0.055	0.002	0.067	0.032	-0.037
	(0.053)	(0.068)	(0.049)	(0.129)	(0.046)	(0.060)	(0.044)	(0.078)
Prestigious × P_i	0.248***	0.224**	0.256***	0.096	0.112*	0.057	0.097*	0.045
	(0.065)	(0.087)	(0.059)	(0.156)	(0.061)	(0.080)	(0.057)	(0.134)
Remote × P_i	-0.126	-0.073	-0.125	0.047	-0.143	-0.237**	-0.193**	-0.066
	(0.091)	(0.122)	(0.085)	(0.189)	(0.087)	(0.093)	(0.079)	(0.147)
Full time × P_i	0.021	0.041	0.017	0.136	0.047	0.027	0.037	0.063
	(0.063)	(0.091)	(0.059)	(0.175)	(0.056)	(0.068)	(0.052)	(0.115)
Duration (months) × P_i	0.037**	0.032	0.029*	0.110**	0.074***	0.029	0.050***	0.110***
	(0.018)	(0.021)	(0.016)	(0.043)	(0.015)	(0.019)	(0.014)	(0.034)
Teamwork required × P_i	0.016	0.139*	0.030	0.325**	0.042	0.040	0.037	0.066
	(0.064)	(0.083)	(0.059)	(0.144)	(0.058)	(0.072)	(0.055)	(0.096)
Tight deadlines × P_i	0.015	0.002	0.020	-0.030	-0.140**	-0.158**	-0.164***	-0.022
	(0.069)	(0.095)	(0.064)	(0.172)	(0.063)	(0.077)	(0.059)	(0.100)
MENA origin × P_i	-0.130*	0.040	-0.082	-0.171	-0.054	0.033	0.005	-0.215**
	(0.067)	(0.087)	(0.061)	(0.205)	(0.059)	(0.073)	(0.055)	(0.104)
Female × P_i	0.076	-0.090	0.052	-0.230*	-0.043	-0.034	-0.031	-0.081
	(0.055)	(0.074)	(0.051)	(0.121)	(0.052)	(0.063)	(0.048)	(0.092)
Observations	26,100	22,250	28,050	20,300	34,200	25,775	37,225	22,750
Number of predictors	255	101	333	23	579	242	700	121
Number of evaluators	789	789	789	789	789	789	789	789
Evaluator outcome standard deviation	2.549	2.549	2.549	2.549	2.549	2.549	2.549	2.549
Origin/gender of respondent name	Male	Female	Non MENA	MENA	Male	Female	Non MENA	MENA

Notes: This table reports OLS estimates of Equation 4 using participants from both the *Evaluation* and *Prediction* experiments and augmented by interacting each characteristic with an indicator for whether the participant was part of the *Prediction* experiments. The estimates shown represent the interaction terms, corresponding to the differences between the predicted impact of each characteristic by participants of the *Prediction* experiments and the estimated impact of each characteristic on evaluations by participants in the *Evaluation* experiments. Estimates correspond to those from B.24, but splitting predictors by their gender and ethnic origin. Gender and ethnic origin are imputed using first names. See Table B.24 for more details. All specifications include respondent fixed effects. Standard errors are clustered at the respondent level. $*p < 0.10, **p < 0.05, ***p < 0.01$.

Table B.34: Perception gaps for worker preferences, by predictor market experience

Predictor:	Recruiters		Workers	
Object:	Offers			
Dependent variable:	Accept (estimated and predicted)			
	(1)	(2)	(3)	(4)
Daily wage (100s) × P_i	0.166***	0.177***	0.149***	0.273***
	(0.057)	(0.055)	(0.042)	(0.049)
At least one job × P_i	0.040	0.177*	0.019	0.073
	(0.105)	(0.097)	(0.079)	(0.098)
Number of jobs (10s) × P_i	0.035	-0.055	0.035	0.043
	(0.054)	(0.056)	(0.044)	(0.050)
Share reviews × P_i	0.029	-0.022	0.008	0.035
	(0.058)	(0.060)	(0.048)	(0.056)
Prestigious × P_i	0.199***	0.282***	0.081	0.097
	(0.068)	(0.076)	(0.062)	(0.079)
Remote × P_i	-0.059	-0.168*	-0.165*	-0.137
	(0.102)	(0.097)	(0.088)	(0.094)
Full time × P_i	-0.019	0.072	0.036	0.040
	(0.070)	(0.071)	(0.058)	(0.066)
Duration (months) × P_i	0.017	0.055***	0.070***	0.042**
	(0.020)	(0.020)	(0.016)	(0.018)
Teamwork required × P_i	0.140**	-0.035	0.024	0.052
	(0.069)	(0.071)	(0.062)	(0.065)
Tight deadlines × P_i	0.054	-0.032	-0.164**	-0.150**
	(0.078)	(0.077)	(0.065)	(0.076)
Female × P_i	0.077	-0.012	-0.021	-0.067
	(0.061)	(0.060)	(0.052)	(0.064)
MENA origin × P_i	-0.043	-0.129*	-0.034	0.021
	(0.077)	(0.072)	(0.061)	(0.070)
Observations	c	c	c	c
Number of evaluators	789	789	789	789
Evaluator outcome standard deviation	2.549	2.549	2.549	2.549
Experience	No jobs	At least one job	No jobs	At least one job

Notes: This table reports OLS estimates of Equation 4 using participants from both the *Evaluation* and *Prediction* experiments and augmented by interacting each characteristic with an indicator for whether the participant was part of the *Prediction* experiments. The estimates shown represent the interaction terms, corresponding to the differences between the predicted impact of each characteristic by participants of the *Prediction* experiments and the estimated impact of each characteristic on evaluations by participants in the *Evaluation* experiments. Estimates correspond to those from Table B.24, but splitting predictors by whether they have completed at least one job on the platform or not. See Table B.24 for more details. All specifications include respondent fixed effects. c denotes a suppressed sensitive observation count, please refer to Table 1 for summary statistics on completed jobs. Standard errors are clustered at the respondent level. $*p < 0.10, **p < 0.05, ***p < 0.01$.

Table B.35: Perception gaps for worker preferences, including fast predictors

Predictor:	Recruiters			Workers		
Object:	Offers					
Dependent variable:	Accept (estimated and predicted)					
	(1)	(2)	(3)	(4)	(5)	(6)
Daily wage (100s) × P_i	0.119***	0.017	0.304***	0.186***	0.116**	0.315***
	(0.045)	(0.059)	(0.068)	(0.038)	(0.047)	(0.063)
At least one job × P_i	0.084	-0.034	0.214*	0.047	0.018	0.073
	(0.079)	(0.100)	(0.125)	(0.070)	(0.090)	(0.111)
Number of jobs (10s) × P_i	0.019	0.035	0.010	0.034	0.050	0.022
	(0.044)	(0.061)	(0.063)	(0.038)	(0.051)	(0.059)
Share reviews × P_i	-0.010	-0.074	0.062	0.024	-0.012	0.066
	(0.047)	(0.064)	(0.070)	(0.043)	(0.057)	(0.065)
Prestigious × P_i	0.253***	0.171**	0.349***	0.091	-0.002	0.202**
	(0.058)	(0.077)	(0.087)	(0.056)	(0.074)	(0.084)
Remote × P_i	-0.156*	-0.351***	0.075	-0.177**	-0.223**	-0.120
	(0.082)	(0.115)	(0.117)	(0.078)	(0.111)	(0.106)
Full time × P_i	0.022	0.137*	-0.129	0.040	0.098	-0.036
	(0.057)	(0.077)	(0.084)	(0.052)	(0.067)	(0.080)
Duration (months) × P_i	0.027*	0.026	0.025	0.057***	0.064***	0.049**
	(0.016)	(0.024)	(0.021)	(0.014)	(0.019)	(0.021)
Teamwork required × P_i	0.055	-0.018	0.132	0.040	-0.048	0.132
	(0.056)	(0.077)	(0.081)	(0.053)	(0.070)	(0.081)
Tight deadlines × P_i	0.036	0.041	0.030	-0.146***	-0.144*	-0.140
	(0.062)	(0.086)	(0.088)	(0.056)	(0.075)	(0.086)
MENA origin × P_i	-0.089	-0.168**	-0.004	-0.023	-0.116*	0.080
	(0.060)	(0.080)	(0.090)	(0.054)	(0.070)	(0.085)
Female × P_i	0.014	-0.033	0.058	-0.038	-0.087	0.001
	(0.049)	(0.067)	(0.072)	(0.047)	(0.064)	(0.068)
Observations	29,275	15,475	13,800	40,250	24,125	16,125
Number of predictors	382	187	195	821	533	288
Number of evaluators	789	432	357	789	432	357
Evaluator outcome standard deviation	2.549	2.549	2.549	2.549	2.549	2.549
Job family	All	Tech	Non-tech	All	Tech	Non-tech

Notes: This table reports OLS estimates of Equation 4 using participants from both the *Evaluation* and *Prediction* experiments and augmented by interacting each characteristic with an indicator for whether the participant was part of the *Prediction* experiments. The estimates shown represent the interaction terms, corresponding to the differences between the predicted impact of each characteristic by participants of the *Prediction* experiments and the estimated impact of each characteristic on evaluations by participants in the *Evaluation* experiments. Estimates correspond to those of Table B.24, but including in the participant sample predictors who spent an average of under six seconds per prediction. All regressions include respondent fixed effects. See Table B.24 for additional details. Standard errors are clustered at the respondent level. $^{*}p < 0.10$, $^{**}p < 0.05$, $^{***}p < 0.01$.

Table B.36: Perception gaps for worker preferences, corrected for multiple hypothesis testing

Predictor:	Recruiters			Workers		
Object:	Offers					
Dependent variable:	Accept (estimated and predicted)					
	(1)	(2)	(3)	(4)	(5)	(6)
Daily wage (100s) × P_i	0.171***	0.070	0.355***	0.197***	0.130***	0.319***
	[0.00]	[0.40]	[0.00]	[0.00]	[0.00]	[0.00]
At least one job × P_i	0.110	0.006	0.223	0.047	0.020	0.071
	[0.31]	[1.00]	[0.10]	[0.82]	[0.98]	[0.81]
Number of jobs (10s) × P_i	-0.008	0.002	-0.013	0.032	0.048	0.019
	[0.99]	[1.00]	[0.95]	[0.80]	[0.63]	[0.88]
Share reviews × P_i	0.002	-0.052	0.061	0.017	-0.014	0.050
	[0.99]	[0.82]	[0.64]	[0.83]	[0.98]	[0.81]
Prestigious × P_i	0.241***	0.171**	0.325***	0.086	-0.015	0.208**
	[0.00]	[0.02]	[0.00]	[0.19]	[0.98]	[0.00]
Remote × P_i	-0.112	-0.321***	0.131	-0.156**	-0.218**	-0.083
	[0.30]	[0.00]	[0.48]	[0.03]	[0.05]	[0.81]
Full time × P_i	0.027	0.157**	-0.142	0.040	0.098	-0.038
	[0.93]	[0.03]	[0.14]	[0.82]	[0.22]	[0.88]
Duration (months) × P_i	0.036**	0.041	0.029	0.060***	0.065***	0.053***
	[0.01]	[0.11]	[0.28]	[0.00]	[0.00]	[0.00]
Teamwork required × P_i	0.052	-0.025	0.136	0.034	-0.038	0.108
	[0.74]	[0.99]	[0.14]	[0.82]	[0.90]	[0.36]
Tight deadlines × P_i	0.011	-0.003	0.028	-0.164***	-0.156**	-0.165*
	[0.99]	[1.00]	[0.95]	[0.00]	[0.03]	[0.06]
MENA origin × P_i	-0.085	-0.141	-0.027	-0.013	-0.110	0.098
	[0.30]	[0.11]	[0.95]	[0.80]	[0.15]	[0.88]
Female × P_i	0.032	-0.007	0.068	-0.040	-0.082	-0.008
	[0.91]	[1.00]	[0.64]	[0.83]	[0.34]	[0.51]
Observations	28,625	15,150	13,475	39,600	23,900	15,700
Number of predictors	356	174	182	795	524	271
Number of evaluators	789	432	357	789	432	357
Evaluator outcome standard deviation	2.549	2.549	2.549	2.549	2.549	2.549
Job family	All	Tech	Non-tech	All	Tech	Non-tech

Notes: This table reports OLS estimates of Equation 4 using participants from both the *Evaluation* and *Prediction* experiments and augmented by interacting each characteristic with an indicator for whether the participant was part of the *Prediction* experiments. The estimates shown represent the interaction terms, corresponding to the differences between the predicted impact of each characteristic by participants of the *Prediction* experiments and the estimated impact of each characteristic on evaluations by participants in the *Evaluation* experiments. Estimates correspond to those from B.24, but presenting p-values corrected for multiple-hypothesis testing using the Romano-Wolf method with 1,000 replications in square brackets. See Table B.24 for more details. All specifications include respondent fixed effects. Standard errors are clustered at the respondent level.
$*p < 0.10, **p < 0.05, ***p < 0.01$.

Table B.37: Perception gaps for worker preferences, by predictor budgeted wage or asked wage on the platform

Predictor:	Recruiters		Workers	
Object:	Offers			
Dependent variable:	Accept (estimated and predicted)			
	(1)	(2)	(3)	(4)
Daily wage (100s) × P_i	0.122**	0.181***	0.025	0.356***
	(0.058)	(0.056)	(0.045)	(0.043)
At least one job × P_i	0.068	0.126	0.050	0.038
	(0.113)	(0.095)	(0.086)	(0.087)
Number of jobs (10s) × P_i	-0.007	-0.007	0.064	0.011
	(0.060)	(0.056)	(0.047)	(0.046)
Share reviews × P_i	-0.023	0.059	-0.004	0.049
	(0.060)	(0.062)	(0.053)	(0.049)
Prestigious × P_i	0.252***	0.255***	0.045	0.125**
	(0.073)	(0.074)	(0.074)	(0.061)
Remote × P_i	-0.116	-0.031	-0.079	-0.240***
	(0.097)	(0.106)	(0.095)	(0.086)
Full time × P_i	0.043	-0.031	0.068	0.003
	(0.069)	(0.074)	(0.062)	(0.060)
Duration (months) × P_i	0.022	0.045**	0.052***	0.066***
	(0.022)	(0.019)	(0.017)	(0.017)
Teamwork required × P_i	0.039	0.044	0.045	0.025
	(0.075)	(0.071)	(0.066)	(0.062)
Tight deadlines × P_i	-0.035	0.079	-0.153**	-0.162**
	(0.085)	(0.076)	(0.072)	(0.066)
MENA origin × P_i	-0.065	-0.096	0.050	-0.081
	(0.071)	(0.082)	(0.067)	(0.062)
Female × P_i	0.016	0.048	-0.037	-0.035
	(0.062)	(0.064)	(0.058)	(0.054)
Observations	23,850	23,850	29,550	29,700
Number of predictors	165	165	393	399
Number of evaluators	789	789	789	789
Evaluator outcome standard deviation	2.549	2.549	2.549	2.549
Budgeted or asked wage	Below median	Above median	Below median	Above median

Notes: This table reports OLS estimates of Equation 4 using participants from both the *Evaluation* and *Prediction* experiments and augmented by interacting each characteristic with an indicator for whether the participant was part of the *Prediction* experiments. The estimates shown represent the interaction terms, corresponding to the differences between the predicted impact of each characteristic by participants of the *Prediction* experiments and the estimated impact of each characteristic on evaluations by participants in the *Evaluation* experiments. Estimates correspond to those from Table B.24, but splitting predictors by the value of their average budgeted daily wage on the platform for past job offers, standardized by year and job type for recruiters or their current wage on the platform, standardized by job type for workers. See Table B.24 for more details. All specifications include respondent fixed effects. Standard errors are clustered at the respondent level.
$*p < 0.10, **p < 0.05, ***p < 0.01$.

Table B.38: Perception gaps for worker preferences, by predictor propensity to ask for or declare willingness to work on site.

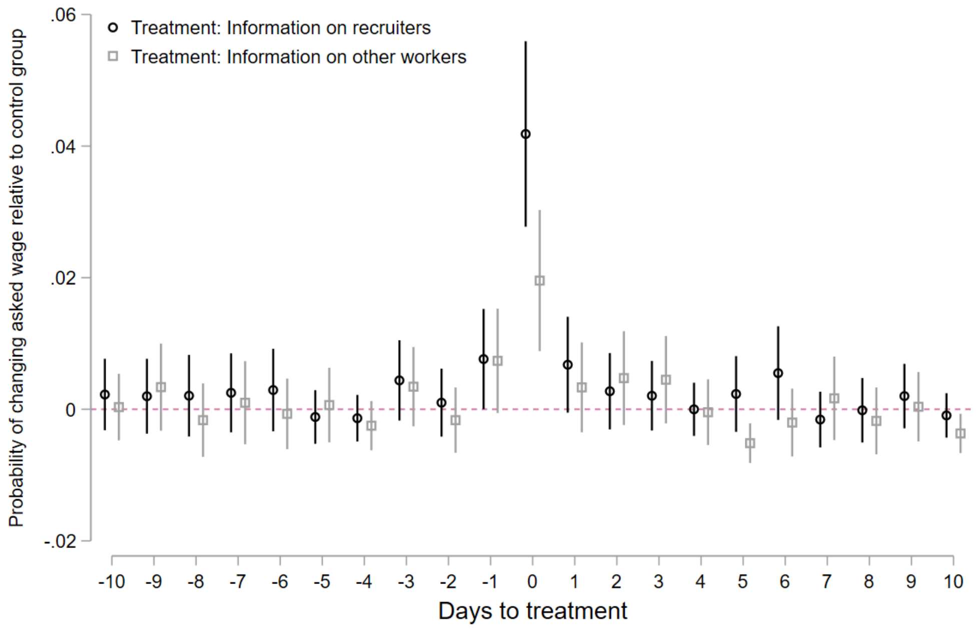
Predictor:	Recruiters		Workers	
Object:	Offers			
Dependent variable:	Accept (estimated and predicted)			
	(1)	(2)	(3)	(4)
Daily wage (100s) × P_i	0.193***	0.105*	0.167***	0.218***
	(0.054)	(0.061)	(0.047)	(0.043)
At least one job × P_i	0.101	0.115	0.134	-0.017
	(0.094)	(0.120)	(0.094)	(0.080)
Number of jobs (10s) × P_i	-0.044	0.023	0.005	0.054
	(0.053)	(0.063)	(0.053)	(0.042)
Share reviews × P_i	-0.020	0.066	-0.027	0.042
	(0.056)	(0.068)	(0.055)	(0.049)
Prestigious × P_i	0.215***	0.311***	0.081	0.092
	(0.071)	(0.074)	(0.070)	(0.066)
Remote × P_i	-0.068	-0.114	-0.008	-0.258***
	(0.099)	(0.104)	(0.105)	(0.082)
Full time × P_i	-0.012	0.053	0.045	0.039
	(0.067)	(0.077)	(0.067)	(0.057)
Duration (months) × P_i	0.058***	0.004	0.060***	0.060***
	(0.018)	(0.024)	(0.018)	(0.016)
Teamwork required × P_i	0.018	0.087	-0.028	0.077
	(0.068)	(0.079)	(0.072)	(0.059)
Tight deadlines × P_i	-0.034	0.095	-0.240***	-0.110*
	(0.076)	(0.085)	(0.079)	(0.063)
MENA origin × P_i	-0.028	-0.144*	0.056	-0.061
	(0.073)	(0.080)	(0.069)	(0.061)
Female × P_i	0.061	-0.003	-0.018	-0.052
	(0.059)	(0.067)	(0.061)	(0.053)
Observations	24,750	23,100	27,850	31,475
Number of predictors	201	135	325	470
Number of evaluators	789	789	789	789
Evaluator outcome standard deviation	2.549	2.549	2.549	2.549
Work on site	No	Some	No	Yes

Notes: This table reports OLS estimates of Equation 4 using participants from both the *Evaluation* and *Prediction* experiments and augmented by interacting each characteristic with an indicator for whether the participant was part of the *Prediction* experiments. The estimates shown represent the interaction terms, corresponding to the differences between the predicted impact of each characteristic by participants of the *Prediction* experiments and the estimated impact of each characteristic on evaluations by participants in the *Evaluation* experiments. Estimates correspond to those from Table B.24, but splitting predictors by whether recruiters ever asked for on site work in their past past job offers, or by their declared willingness to work on site for workers. See Table B.24 for more details. All specifications include respondent fixed effects. Standard errors are clustered at the respondent level. $*p < 0.10, **p < 0.05, ***p < 0.01$.

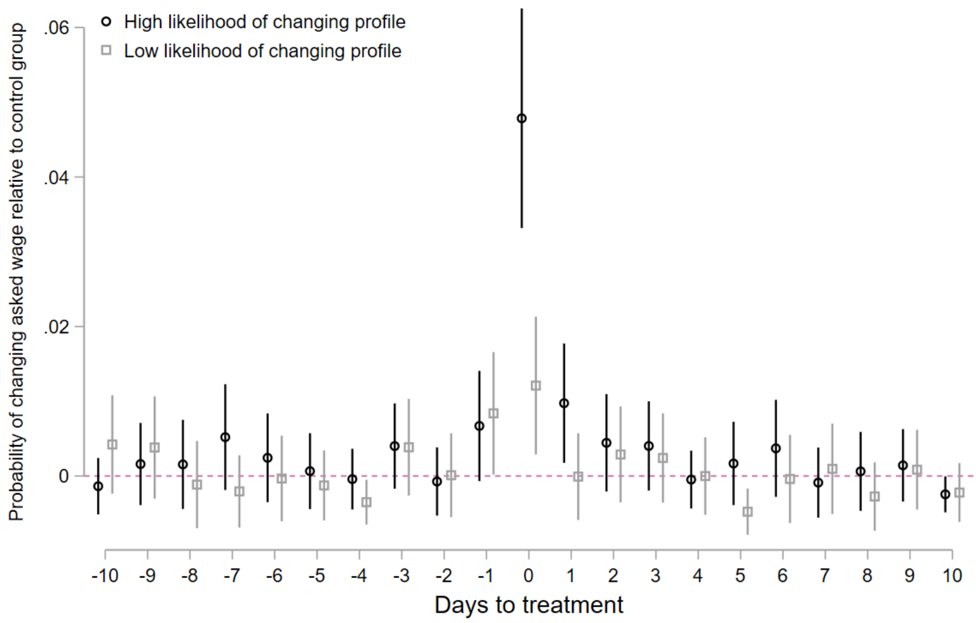
B.3 Information treatment

Figure B.7: Differences-in-Differences estimates of changes in asked wages following the information treatment

(a) By whether information related to recruiters or other workers



(b) By self-reported likelihood of changing their profile in the experiment



Notes: This figure shows estimates from Figure 4b but restricting to changes in the asked wage rather than other profile characteristics. Baseline rate of updating for workers before the experiment is 0.5%. See Figure 4b for details. Bars represent 95 % confidence intervals.

C Theoretical framework details

C.1 Proposition 1

C.1.1 Assumptions

For Parts 1 and 3 of the proof we fix a worker with true value v and a recruiter with true job utility u. Part 2 considers how match probabilities vary across the distribution of recruiter types specified in Assumption 5.

Assumption 1 (Recruiter pricing regularity)**.** *For any* (v, u, w) *and any perceived* $\hat{u}$*, the recruiter's objective*

$$p \;\mapsto\; \sigma(\hat{u} + p - w)(v - p)$$

has a unique maximiser $p^{\star}(w; v, u)$ *under correct beliefs* $(\hat{u} = u)$ *and a unique maximiser* $p^{\Gamma}(w; v, \hat{u})$ *under belief* $\hat{u}$*. These maximisers are interior.*

Assumption 2 (Strict optimality of recruiter pricing)**.** *The recruiter's true expected surplus*

$$T(p; v, u, w) \;\equiv\; \sigma(u + p - w)(v - p)$$

is strictly maximised at $p^{\star}(w; v, u)$*.*

Assumption 3 (Worker offer-probability monotonicity)**.** *The perceived probability of receiving an offer* $\hat{q}^{\Gamma}(w; \hat{v})$ *is strictly decreasing in* w*, strictly increasing in* $\hat{v}$*, and has increasing differences in* $(w, \hat{v})$*.*

Assumption 4 (Worker optimality)**.** *The worker's true expected payoff under correct beliefs has a unique maximiser* $w^{\star}(v)$*.*

Assumption 5 (Continuity and nondegeneracy)**.** *The distribution of recruiter characteristics is such that* $\Pi^{\star}(w; v, u)$ *and* $\Pi^{\Gamma}(w; v, \hat{u})$ *vary continuously in* w*, and there is positive probability mass of recruiter types* u *arbitrarily close to the offer cutoff* c*.*

C.1.2 Proof

Part 1: Price-setting distortions. *Recruiter wages.* Fix (v, w) and consider the recruiter's problem under belief $\hat{u}$:

$$\max_{p \geq 0} \sigma(\hat{u} + p - w)(v - p).$$

Let $a \equiv \hat{u} - w$. By Assumption 1, the optimum p^Γ is interior and satisfies the first-order condition

$$\sigma'(a + p)(v - p) - \sigma(a + p) = 0. \tag{6}$$

Because σ is the logistic function, (6) can be rewritten as $(v - p^\Gamma)\big(1 - \sigma(a + p^\Gamma)\big) = 1$. Differentiating both sides with respect to a and collecting terms:

$$-\frac{\partial p^\Gamma}{\partial a}\big(1 - \sigma(a + p^\Gamma)\big) \;+\; (v - p^\Gamma)\big(-\sigma'(a + p^\Gamma)\big)\left(1 + \frac{\partial p^\Gamma}{\partial a}\right) = 0.$$

Using $(v - p^\Gamma)\sigma'(a + p^\Gamma) = (v - p^\Gamma)\sigma(a + p^\Gamma)\big(1 - \sigma(a + p^\Gamma)\big)$ and the identity $(v - p^\Gamma)(1 - \sigma) = 1$, this simplifies to

$$\frac{\partial p^\Gamma}{\partial a} \;=\; -\,\sigma(a + p^\Gamma) \;<\; 0,$$

since $\sigma(\cdot) \in (0, 1)$. Hence the optimal offered wage is strictly decreasing in $\hat{u} = u + \Gamma$. If $\Gamma > 0$ the recruiter posts a wage strictly below the correct-beliefs benchmark; if $\Gamma < 0$, strictly above it.

Worker asks. The worker chooses w to maximise perceived expected payoff

$$\widetilde{W}(w; \hat{v}) \;=\; \hat{q}^\Gamma(w; \hat{v}) \cdot \mathbb{E}\Big[A\big(p^\Gamma(w; v, \hat{u});\, u,\, w\big)\big(u + p^\Gamma(w; v, \hat{u}) - w\big) \;\Big|\, \Pi^\Gamma(w; v, \hat{u}) \geq c\Big].$$

By Assumption 3, $\widetilde{W}$ has increasing differences in $(w, \hat{v})$, so by standard monotone comparative statics the optimal ask is increasing in $\hat{v}$. Hence workers who overestimate their market value ($\Delta > 0$) post asks that are too high, while workers who underestimate it post asks that are too low.

Part 2: Matching effects of pricing distortions. We analyse the recruiter-side and worker-side effects in turn.

Recruiter perception gaps ($\Delta = 0$, $\Gamma \neq 0$). For a recruiter drawn from the distribution in Assumption 5 with true utility u, and with the worker's ask fixed at $w^\star(v)$, the match outcome is

$$M^\Gamma \;=\; \mathbf{1}\big\{\Pi^\Gamma(w^\star; v, \hat{u}) \geq c\big\} \cdot A\big(p^\Gamma(w^\star; v, \hat{u});\, u,\, w^\star\big)\,.$$

We compare this to the correct-beliefs outcome M^0 by examining the two components separately.

Offer probability. By the envelope theorem applied to the recruiter's maximisation problem,

$$\frac{\partial\, \Pi^\Gamma(w; v, \hat{u})}{\partial\, \hat{u}} \;=\; \sigma'\big(\hat{u} + p^\Gamma - w\big)\big(v - p^\Gamma\big) \;>\; 0,$$

since $v > p^\Gamma$ at any interior optimum (from the first-order condition (6), $(v - p^\Gamma) = \sigma/\sigma' > 0$). Hence Π^Γ is strictly increasing in $\hat{u} = u + \Gamma$.

When $\Gamma > 0$: $\Pi^\Gamma(w^\star; v, \hat{u}) > \Pi^\star(w^\star; v, u)$. By Assumption 5, there exist recruiter types u for which $\Pi^\star(w^\star; v, u) < c \leq \Pi^\Gamma(w^\star; v, \hat{u})$, so the recruiter makes an offer under distorted beliefs but would not under correct beliefs. Hence the offer probability is strictly higher when $\Gamma > 0$. Symmetrically, when $\Gamma < 0$: $\Pi^\Gamma < \Pi^\star$, and by Assumption 5 there exist types for which $\Pi^\Gamma(w^\star; v, \hat{u}) < c \leq \Pi^\star(w^\star; v, u)$, so the offer probability is strictly lower.

Conditional acceptance probability. From Part 1, $p^\Gamma < p^\star$ when $\Gamma > 0$. The true acceptance probability conditional on an offer is

$$A(p^\Gamma;\, u,\, w^\star) \;=\; \sigma(u + p^\Gamma - w^\star) \;<\; \sigma(u + p^\star - w^\star) \;=\; A(p^\star;\, u,\, w^\star),$$

since σ is strictly increasing and $p^\Gamma < p^\star$. Hence conditional acceptance is strictly lower when $\Gamma > 0$. Symmetrically, $p^\Gamma > p^\star$ when $\Gamma < 0$ gives strictly higher conditional acceptance.

This establishes the recruiter-side claims of Proposition 1, Part 2.

Worker perception gaps ($\Gamma = 0$, $\Delta \neq 0$). From Part 1, $w^\Delta > w^\star(v)$ when $\Delta > 0$ and $w^\Delta < w^\star(v)$ when $\Delta < 0$. We consider both components.

Offer probability. $\Pi^\star(w; v, u) = \max_{p \geq 0} \sigma(u + p - w)(v - p)$. The same FOC identity gives $p^\star$ as a function of w. Differentiating that identity with respect to w yields $dp^\star/dw =$

$\sigma(u + p^\star - w) \in (0, 1)$. By the envelope theorem,

$$\frac{\partial\,\Pi^\star(w; v, u)}{\partial\,w} \;=\; -\sigma'(u + p^\star - w)(v - p^\star) \;<\; 0,$$

so $\Pi^\star$ is strictly decreasing in w. When $\Delta > 0$, $w^\Delta > w^\star$ implies $\Pi^\star(w^\Delta; v, u) < \Pi^\star(w^\star; v, u)$. By Assumption 5, there exist recruiter types for which the recruiter makes an offer under the correct ask ($\Pi^\star(w^\star; v, u) \geq c$) but not under the inflated ask ($\Pi^\star(w^\Delta; v, u) < c$). Hence the offer probability is strictly lower when $\Delta > 0$. When $\Delta < 0$, $w^\Delta < w^\star$ implies $\Pi^\star(w^\Delta; v, u) > \Pi^\star(w^\star; v, u)$, so the offer probability weakly increases (strictly so for recruiter types near the cutoff c under Assumption 5).

Conditional acceptance probability. The net effect on acceptance works through $u + p^\star(w) - w$. Since $dp^\star/dw = \sigma \in (0, 1)$, we have

$$\frac{d}{dw}[u + p^\star(w) - w] \;=\; \frac{dp^\star}{dw} - 1 \;=\; \sigma - 1 \;<\; 0.$$

Hence $u + p^\star(w) - w$ is strictly decreasing in w, so the true conditional acceptance probability $A(p^\star(w); u, w) = \sigma(u + p^\star(w) - w)$ is strictly decreasing in w. When $w^\Delta > w^\star$ ($\Delta > 0$) the conditional acceptance probability strictly falls; when $w^\Delta < w^\star$ ($\Delta < 0$) it strictly rises.

Combining the two components. When $\Delta > 0$, both the offer probability and the conditional acceptance probability strictly fall, so the overall match probability strictly decreases. When $\Delta < 0$, both weakly increase (with the offer probability strictly increasing for recruiter types near the cutoff), so the overall match probability weakly increases.

This establishes the worker-side claims of Proposition 1, Part 2.

Part 3: Private expected-payoff loss. *Recruiters.* We consider three mutually exclusive cases according to whether distorted beliefs change the offer decision, and whether an offer is made under both or neither regime.

Case (i): Offer made under both correct and distorted beliefs, but at a different wage ($p^\Gamma \neq p^\star$). Under correct beliefs, $p^\star(w; v, u)$ uniquely maximises true expected surplus $T(p; v, u, w)$. Under misperception the recruiter chooses $p^\Gamma \neq p^\star$. By Assumption 2, $T(p^\star; v, u, w) > T(p^\Gamma; v, u, w)$, so the recruiter's true expected payoff strictly falls.

Case (ii): Offer made under distorted beliefs but not under correct beliefs ($\Gamma > 0$ with $\Pi^\star(w; v, u) < c \leq \Pi^\Gamma(w; v, \hat{u})$). Under correct beliefs the recruiter's payoff is 0 (no offer). Under distorted beliefs, the recruiter incurs the fixed cost c and earns true surplus $T(p^\Gamma; v, u, w)$. By Assumption 2, $T(p^\Gamma; v, u, w) \leq T(p^\star; v, u, w) = \Pi^\star(w; v, u) < c$, so the true net payoff from making the offer is $T(p^\Gamma) - c < 0$. The recruiter's payoff therefore strictly falls relative to the correct-beliefs outcome of 0.

Case (iii): No offer made under distorted beliefs but offer made under correct beliefs ($\Gamma < 0$ with $\Pi^\Gamma(w; v, \hat{u}) < c \leq \Pi^\star(w; v, u)$). Under distorted beliefs the recruiter's payoff is 0 (no offer). Under correct beliefs the recruiter would earn $\Pi^\star(w; v, u) - c \geq 0$. Since $\Pi^\star(w; v, u) \geq c$, the correct-beliefs payoff is non-negative, and strictly positive whenever $\Pi^\star(w; v, u) > c$. By Assumption 5 there exist recruiter types with $\Pi^\star(w; v, u) > c$, so the recruiter's payoff strictly falls for such types.

In all three cases the recruiter's true expected payoff strictly falls whenever perception gaps alter pricing or offer decisions.

Workers. By Assumption 4, the worker's true expected payoff is uniquely maximised at $w^\star(v)$. When misperceptions cause the worker to choose $w^\Delta \neq w^\star(v)$, strict optimality implies a strictly lower true expected payoff.

Combining these arguments establishes all three claims of Proposition 1. $\square$

C.2 Proposition 2

C.2.1 Assumptions

Assumption 6 (Monotone returns of characteristics)**.** *The baseline (correct-beliefs) expected payoff functions satisfy*

$$J(1) > J(0) \qquad \textit{and} \qquad \Pi(1) > \Pi(0).$$

Moreover, the perceived payoff differences $\hat{J}(1) - \hat{J}(0)$ and $\hat{\Pi}(1) - \hat{\Pi}(0)$ are strictly increasing in $(v_1 + \Delta)$ and $(u_1 + \Gamma)$, respectively.

Assumption 7 (Cost distributions)**.** *Worker skill costs κ_x are independently drawn from a continuous distribution G_x with support $\mathbb{R}_+$, and recruiter amenity costs κ_y are inde-*

pendently drawn from a continuous distribution G_y with support $\mathbb{R}_+$. Both distributions are strictly increasing on their supports (no atoms).

Assumption 8 (Efficient pricing conditional on characteristics)**.** *Conditional on (x, y), pricing, offer, and acceptance decisions follow the baseline model under correct beliefs. In particular, conditional on characteristics, recruiters correctly forecast worker acceptance using $u(y)$ and workers correctly forecast recruiters' offer behaviour using $v(x)$. Under Assumption 8, $\hat{J}(x)$ and $\hat{\Pi}(y)$ are therefore well-defined finite scalars for each $x, y \in \{0, 1\}$.*

Assumption 9 (Nondegeneracy for matching effects)**.** *There exists a set of characteristic pairs (x, y) such that under correct beliefs these pairs match with strictly positive probability and generate strictly positive expected surplus. Moreover, the probability of such pairs occurring in the market is strictly increasing in the prevalence of $x = 1$ alone, strictly increasing in the prevalence of $y = 1$ alone, and strictly increasing in the joint prevalence of $x = 1$ and $y = 1$.*

Discussion. Assumptions 6–8 ensure that wedges operate only through the ex ante investment margin and that characteristic choices follow cutoff rules. Assumption 9 rules out knife-edge cases. The strengthened single-margin monotonicity conditions in Assumption 9 are used to establish the over-investment direction of Part 2 when only one side of the market is distorted.

C.2.2 Proof

Part 1: Investment distortions. *Workers.* Given belief wedge Δ, the worker chooses $x = 1$ if and only if

$$\hat{J}(1) - \hat{J}(0) \geq \kappa_x.$$

By Assumption 8, $\hat{J}(x)$ is well-defined for each $x \in \{0, 1\}$, so the perceived payoff difference $\hat{J}(1) - \hat{J}(0)$ is a well-defined finite scalar. By Assumption 7, this implies a cutoff rule: there exists a unique threshold

$$\kappa_x^{\Delta} \equiv \hat{J}(1) - \hat{J}(0)$$

such that workers invest ($x = 1$) if and only if $\kappa_x \leq \kappa_x^{\Delta}$. Hence the prevalence of skilled workers is $\Pr(x = 1) = G_x(\kappa_x^{\Delta})$.

By Assumption 6, κ_x^{Δ} is strictly increasing in $(v_1 + \Delta)$, hence strictly increasing in Δ. Therefore $\Pr(x = 1)$ is strictly increasing in Δ. Relative to correct beliefs ($\Delta = 0$), workers with $\Delta > 0$ over-invest (choose $x = 1$ too often), while workers with $\Delta < 0$ under-invest.

Recruiters. Similarly, by Assumption 8, $\hat{\Pi}(y)$ is well-defined for each $y \in \{0, 1\}$. Recruiters choose $y = 1$ if and only if

$$\hat{\Pi}(1) - \hat{\Pi}(0) \geq \kappa_y.$$

By Assumption 7, there exists a unique threshold

$$\kappa_y^{\Gamma} \equiv \hat{\Pi}(1) - \hat{\Pi}(0),$$

so that $y = 1$ if and only if $\kappa_y \leq \kappa_y^{\Gamma}$, and thus $\Pr(y = 1) = G_y(\kappa_y^{\Gamma})$.

By Assumption 6, κ_y^{Γ} is strictly increasing in $(u_1 + \Gamma)$ and thus in Γ. Therefore $\Pr(y = 1)$ is strictly increasing in Γ. Relative to correct beliefs ($\Gamma = 0$), recruiters with $\Gamma > 0$ over-provide amenities, while recruiters with $\Gamma < 0$ under-provide them.

This establishes Part 1.

Part 2: Matching effects. By Assumption 8, conditional on (x, y) the matching, pricing, and acceptance outcomes coincide with the baseline model under correct beliefs. Thus belief wedges can affect matching only by changing the distribution of characteristics in the market.

From Part 1, $\Delta < 0$ (resp. $\Gamma < 0$) strictly reduces the prevalence of high-x workers (resp. high-y recruiters) relative to correct beliefs, while $\Delta > 0$ and $\Gamma > 0$ increase those prevalences.

Under-investment direction ($\Delta < 0$ or $\Gamma < 0$). By Assumption 9, the probability that a random worker–recruiter pair draws characteristics yielding a mutually acceptable match with positive expected surplus is strictly increasing in the prevalence of $x = 1$ alone and in the prevalence of $y = 1$ alone. Hence reducing either prevalence strictly reduces match probability. There therefore exist worker–recruiter pairs that would match under correct beliefs but do not occur (and therefore do not match) under distorted investment choices.

Over-investment direction ($\Delta > 0$ or $\Gamma > 0$). By Assumption 9, increasing the prevalence of $x = 1$ alone or $y = 1$ alone strictly increases the probability that a random pair achieves a match with positive expected surplus. Hence over-investment weakly—and, for at least one side of the market, strictly—increases match probability.

This establishes Part 2.

Part 3: Private expected-payoff loss. *Workers.* Let $B \equiv J(1) - J(0) > 0$ be the worker's true incremental benefit of investing in $x = 1$ (positive by Assumption 6). Under correct beliefs the worker invests if and only if $B \geq \kappa_x$, giving the privately optimal rule $x^\star = \mathbf{1}\{\kappa_x \leq B\}$. Under belief wedge Δ, the worker uses threshold $\hat{B} \equiv \hat{J}(1) - \hat{J}(0)$ and chooses $x^\Delta = \mathbf{1}\{\kappa_x \leq \hat{B}\}$.

If $\Delta \neq 0$ and behavior changes, then $\hat{B} \neq B$ and by continuity of G_x there exists a non-null set of costs κ_x for which $x^\Delta \neq x^\star$. For any such worker:

- If $x^\Delta = 1$ but $x^\star = 0$, then $\kappa_x > B$ and the true net gain from investing is $B - \kappa_x < 0$.
- If $x^\Delta = 0$ but $x^\star = 1$, then $\kappa_x < B$ and the true net gain $B - \kappa_x > 0$ is foregone.

In either case the worker's true expected payoff net of investment costs is strictly lower under the distorted choice than under the correct-beliefs choice.

Recruiters. An analogous argument applies. Let $D \equiv \Pi(1) - \Pi(0) > 0$ be the recruiter's true incremental benefit of providing $y = 1$ (positive by Assumption 6). Under correct beliefs the privately optimal rule is $y^\star = \mathbf{1}\{\kappa_y \leq D\}$, while under wedge Γ the recruiter uses $\hat{D} \equiv \hat{\Pi}(1) - \hat{\Pi}(0)$ and chooses $y^\Gamma = \mathbf{1}\{\kappa_y \leq \hat{D}\}$. If $\Gamma \neq 0$ and behavior changes, then $\hat{D} \neq D$ and by continuity of G_y there exists a non-null set of costs for which $y^\Gamma \neq y^\star$, implying a strict loss in true payoff net of costs by the same case analysis as above.

This establishes Part 3 and completes the proof. $\square$

C.3 Extension: competitor *perception gaps*

This appendix modifies the theoretical framework by introducing misperceptions about competitors' preferences. All timing, matching, pricing conditional on (x, y), and the investment structure from the framework remain unchanged.

C.3.1 Competitors and residual demand

In the baseline framework, workers and recruiters draw heterogeneous investment costs $\kappa_x \sim G_x$ and $\kappa_y \sim G_y$. We interpret these heterogeneous costs as reflecting heterogeneous preferences over the relevant job attribute (e.g., disutility of full-time work for workers or disutility of remote production for recruiters).

Let

$$m_x \equiv \Pr(x = 1), \qquad m_y \equiv \Pr(y = 1)$$

denote the equilibrium fractions of workers and recruiters investing.

We now allow the incremental return to investment to depend on the fraction of competitors who invest. Specifically, let

$$\Delta J(m_x) \equiv J(1; m_x) - J(0; m_x), \tag{7}$$

$$\Delta \Pi(m_y) \equiv \Pi(1; m_y) - \Pi(0; m_y), \tag{8}$$

with

$$\Delta J'(m_x) < 0, \qquad \Delta \Pi'(m_y) < 0.$$

Thus an investment yields higher returns when it is relatively scarce among competitors. All other elements of the framework remain unchanged.

C.3.2 *Perception gaps* about competitors' cost distributions

Agents correctly perceive payoffs conditional on (x, y) but may misperceive the distribution of competitors' investment costs. Let $\widehat{F}_W$ and $\widehat{F}_E$ denote agents' beliefs about the cost distributions of competing workers and recruiters, respectively. These beliefs induce perceived investment fractions

$$\hat{m}_x = \widehat{F}_W\big(\Delta J(\hat{m}_x)\big), \qquad \hat{m}_y = \widehat{F}_E\big(\Delta\Pi(\hat{m}_y)\big),$$

where the fixed-point expressions follow from the cutoff investment rules evaluated under perceived returns. Workers make investment decisions using $\Delta J(\hat{m}_x)$, and recruiters use $\Delta\Pi(\hat{m}_y)$.

C.3.3 Proposition

Proposition 3 (Distortionary effects of competitor-preference misperceptions)**.** *Consider the extension in which workers and recruiters choose characteristics prior to matching, and suppose that pricing and acceptance decisions are efficient conditional on these choices.*

1. ***Investment distortions.*** *Workers who overestimate the scarcity of competitors investing in $x = 1$ over-invest in x, while workers who underestimate this scarcity under-invest. Symmetrically, recruiters who overestimate the scarcity of competitors investing in $y = 1$ over-provide y, while recruiters who underestimate this scarcity under-provide it.*

2. ***Matching effects.*** *Under-investment reduces the prevalence of high-productivity workers and high-utility jobs, causing some matches that would occur under correct beliefs to fail to occur. In contrast, over-investment increases the market value of workers and jobs, weakly increasing the probability of match.*

3. ***Private expected-payoff loss.*** *Whenever competitor-preference wedges alter characteristic choices, they strictly reduce the agent's own true expected payoff net of investment costs.*

Proof. The proof follows the proof of Proposition 2, after the substitution that the perceived incremental benefits are shifted by perceived competitor scarcity rather than by wedges on (v_1, u_1).

In Proposition 2, the worker uses $\hat{B}_x \equiv \hat{J}(1) - \hat{J}(0)$ and the recruiter uses $\hat{B}_y \equiv$

$\hat{\Pi}(1) - \hat{\Pi}(0)$. Here, define instead

$$\hat{B}_x \equiv \Delta J(\hat{m}_x), \quad B_x^\star \equiv \Delta J(m_x^\star), \quad \hat{B}_y \equiv \Delta\Pi(\hat{m}_y), \quad B_y^\star \equiv \Delta\Pi(m_y^\star),$$

where $\hat{m}_x$ (resp. $\hat{m}_y$) is the agent's belief about the prevalence of competitors investing in $x = 1$ (resp. $y = 1$), and $(m_x^\star, m_y^\star)$ is the correct-beliefs equilibrium prevalence.

Part 1. By Assumption 7, investment follows a cutoff rule with cutoff equal to the perceived incremental benefit, exactly as in Proposition 2. Since $\Delta J' < 0$, overestimating scarcity (i.e. believing fewer competitors invest, $\hat{m}_x < m_x^\star$) implies $\Delta J(\hat{m}_x) > \Delta J(m_x^\star)$, hence $\hat{B}_x > B_x^\star$ and therefore over-investment. The reverse inequality $\hat{m}_x > m_x^\star$ implies $\hat{B}_x < B_x^\star$ and under-investment. The recruiter-side argument is symmetric using $\Delta\Pi' < 0$.

Parts 2–3. Given Part 1, the distribution of types in the market is shifted exactly as in Proposition 2, with $\hat{B}$ replaced by $\Delta(\cdot)$ evaluated at perceived $\hat{m}$. Parts 2 and 3 then follow verbatim from the proof of Proposition 2 using Assumptions 8–9 and the same case analysis for strict private losses. $\square$

D Experimental material

D.1 Recruitment

Figure D.1: Recruitment email, recruiters - English

[PLATFORM LOGO]

Your opinion matters! Help us improve [PLATFORM]: 50€ gift card + entry to a 1000€ lottery + personalized selection of freelance profiles

Hello,

You use [PLATFORM] to find the best freelance talent. Today, we would like to request your expertise to help us make our platform even more efficient and tailored to *your* needs.

How? By participating in a short survey of approximately **15 minutes** where you will evaluate 25 **freelance profiles.**

For your participation you will receive:

1. A **personalized selection of five freelance profiles**
2. An Amazon gift card worth **50€**
3. Entry to a **1000€ lottery**

Click here to participate in the survey

The compensation and recommendations will be awarded subject to eligibility and full participation in the study. They will be sent to the email address of your choice.

Your feedback is essential for us and for your future projects. It will help us develop features that will save you time and connect you with freelancers even better targeted for the success of your projects.

Thank you in advance for your contribution!

The [PLATFORM] team

You are receiving this email because you are registered on [PLATFORM] as a client. We inform you that your responses are collected by [PLATFORM] for research and service improvement purposes, and you can find our personal data protection charter

If you no longer wish to receive messages similar to this one, click here.

Figure D.2: Recruitment email, recruiters

[LOGO PLATEFORME]

Votre avis compte ! Aidez-nous à améliorer [PLATEFORME]: 50€ offerts + participation à une loterie de 1000€ + une sélection personnalisée de profils freelances

Bonjour,

Vous utilisez [PLATEFORME] pour trouver les meilleurs talents freelance. Aujourd'hui, nous aimerions solliciter votre expertise pour nous aider à rendre notre plateforme encore plus performante et adaptée à *vos* besoins.

Comment ? En participant à une courte enquête d'environ **15 minutes** où vous devrez évaluer 25 **profils freelances.**

Pour votre participation vous recevrez:

1. Une **sélection personnalisée de cinq profils freelances**
2. Un chèque cadeau Amazon de **50€**
3. Une participation à une loterie de **1000€**

Je clique ici pour participer à l'enquête

La gratification et les recommandations seront attribuées sous réserve d'éligibilité et de participation complète à l'étude. Elles seront envoyées à l'adresse email de votre choix.

Vos retours sont essentiels pour nous et pour vos futurs projets. Ils nous aideront à développer des fonctionnalités qui vous feront gagner du temps et vous mettront en relation avec des freelances encore mieux ciblés pour la réussite de vos projets.

Nous vous remercions par avance pour votre contribution !

L'équipe [PLATEFORME]

Vous recevez cet email car vous êtes inscrit sur [PLATEFORME] en tant que client. Nous vous informons que vos réponses sont collectées par [PLATEFORME] à des fins de recherches et d'amélioration de nos services, et vous retrouverez notre charte de protection des données personnelles

Si vous ne voulez plus recevoir de messages similaires à celui-ci, cliquez ici.

Figure D.3: Recruitment email, freelancers - English

[PLATFORM LOGO]

Your opinion matters! Help us improve [PLATFORM]: 20€ gift card + entry to a 1000€ lottery + recommendation for a project

Hello,

You use [PLATFORM] to find the best freelance missions. Today, we would like to request your expertise to help us make our platform even more efficient and tailored to *your* needs.

How? By participating in a short survey of approximately **15 minutes** where you will evaluate **25 typical missions.**

For your participation, you will receive:

1. For 25% of respondents, a **personalized recommendation for a project on [PLATFORM]**
2. An Amazon gift card worth **20€**
3. Entry to a **1000€ lottery**

Click here to participate in the survey

The compensation and recommendation will be awarded subject to eligibility and full participation in the study. The compensation will be sent to the email address of your choice.

Your feedback is essential for us and for your future missions. It will help us develop features that will save you time and connect you with missions even better targeted for the success of your freelance activity.

Thank you in advance for your contribution!

The [PLATFORM] team

You are receiving this email because you are registered on [PLATFORM] as a client. We inform you that your responses are collected by [PLATFORM] for research and service improvement purposes, and you can find our personal data protection charter

If you no longer wish to receive messages similar to this one, click here.

Figure D.4: Recruitment email, freelancers

[LOGO PLATEFORME]

Votre avis compte ! Aidez-nous à améliorer [PLATEFORME]: 20€ offerts + participation à une loterie de 1000€ + recommandation pour un projet

Bonjour,

Vous utilisez [PLATEFORME] pour trouver les meilleures missions freelance. Aujourd'hui, nous aimerions solliciter votre expertise pour nous aider à rendre notre plateforme encore plus performante et adaptée à *vos* besoins.

Comment ? En participant à une courte enquête d'environ **15 minutes** où vous devrez évaluer **25 missions types.**

Pour votre participation, vous recevrez:

1. Pour 25% des répondants, une **recommandation personnalisée pour un projet sur [PLATEFORME]**
2. Un chèque cadeau Amazon de **20€**
3. Une participation à une loterie de **1000€**

Je clique ici pour participer à l'enquête

La gratification et recommandation seront attribuées sous réserve d'éligibilité et de participation complète à l'étude. La compensation sera versée à l'adresse email de votre choix.

Vos retours sont essentiels pour nous et pour vos futures missions. Ils nous aideront à développer des fonctionnalités qui vous feront gagner du temps et vous mettront en relation avec des missions encore mieux ciblées pour la réussite de votre activité freelance.

Nous vous remercions par avance pour votre contribution !

L'équipe [PLATEFORME]

Vous recevez cet email car vous êtes inscrit sur [PLATEFORME] en tant que client. Nous vous informons que vos réponses sont collectées par [PLATEFORME] à des fins de recherches et d'amélioration de nos services, et vous retrouverez notre charte de protection des données personnelles

Si vous ne voulez plus recevoir de messages similaires à celui-ci, cliquez ici.

D.2 Evaluation experiment – recruiter questionnaire

D.2.1 Introduction

Help us better understand your collaboration preferences.

We are conducting a series of surveys to better understand your criteria for selecting freelance talent. Your responses will help us offer more relevant profiles to our users. In addition, we will use your responses to recommend five active freelancers on [the platform] who match your needs.

Survey description.

- Evaluate 25 freelancer profiles.
- For each freelancer, indicate your level of interest in collaborating.
- Estimated time: 15 minutes.

Thank you for your participation.

- A €50 Amazon voucher.
- Entry into a lottery to win €1000.
- Voucher sent within 10 business days following completion of the survey.
- A personalized selection of five active freelancers on [the platform].

*Compensation is subject to eligibility and full participation in the survey. Compensation and recommendations will be sent within 10 business days following your participation. The €1000 lottery prize will also be sent as an Amazon voucher, within two months following the conclusion of the survey. Any compensation will be sent to an email address of your choice.

Data protection. Processing of your data. We will analyze your responses in connection with data from your [the platform] account, including your profile information and your interactions with the platform. This information will be processed confidentially and stored on our secure servers. Only [the platform] and its research partners will have access to it for purposes of analysis and improvement of the user experience. General findings may be shared in our communications or in publications. However, no personal data will be disclosed.

If you wish to leave and return later, please use the same device in order to resume where you left off. Once started, you have one day to complete the survey. To stop receiving our communications, click the unsubscribe links at the bottom of the email you received. Information about [the platform]'s data protection policy, your rights in this regard, and the contact address for questions about the survey can be found in our data protection center.

By clicking "Start the study," you agree to participate in the survey.

D.2.2 Screening Questions

Q1. Which of the following job family would you be most likely to recruit your next freelancer for?

- Tech (Web and Mobile Development, CMS Integration and Development)
- Marketing & Communication (Growth Marketing, Social Media Strategy and Community Engagement, Content Writing)
- Translation
- None of these categories

Q2. *(Asked only if the respondent selected "None of these categories" in Q1 and then ends the survey.)* In which of the following domains would you be most likely to hire a freelancer?

- Strategy Consulting
- Image & Sound
- Support Functions
- Video Games

- Web & Graphic Design
- None of these domains

D.2.3 Preliminary Questions – Marketing & Communication

Q3. *(Asked only if the respondent selected "Marketing & Communication" in Q1 and ends the survey if None of these roles is selected.)* Which of the following roles would you be most likely to hire your next freelancer for? A description of each role is provided below.

- Growth Marketing
- Content Writing
- Social Media Strategy and Community Engagement
- None of these roles

Role descriptions.

- **Growth Marketing:** Develops and implements digital strategies to acquire, retain, and convert customers, while tracking and optimizing performance. Areas of expertise include web marketing strategy, SEO, SEA, analytics, CRM, email marketing, and growth hacking.
- **Content Writing:** Produces content for different formats in order to inform, engage, and persuade, depending on an organization's communication objectives. Areas of expertise include copywriting, web and SEO writing, proofreading and editing, and the writing of articles, newsletters, white papers, and reports.
- **Social Media Strategy and Community Engagement:** Develops and manages a brand's or organization's digital presence on social media by designing strategy and producing engaging content to reach and retain its audience. Areas of expertise include community management and social media management.

Q4. *(Asked only if the respondent selected "Growth Marketing" in Q3.)* Which of the following skills should this freelancer absolutely have? (Select all that apply.)

- Digital acquisition strategy
- Performance analysis and tracking
- Conversion rate optimization (CRO)
- SEO (Search Engine Optimization)
- SEA (Search Engine Advertising)
- Social media advertising
- Demand generation / lead generation
- Email marketing
- CRM & marketing automation
- I do not know / None of the listed skills

Q5. *(Asked only if the respondent selected "Content Writing" in Q3.)* Which of the following skills should this freelancer absolutely have? (Select all that apply.)

- Copywriting / Copy editing
- Web and SEO writing
- Other writing (e.g., reports)
- Proofreading and editing
- I do not know / None of the listed skills

Q6. *(Asked only if the respondent selected "Social Media Strategy and Community Engagement" in Q3.)* Which of the following skills should this freelancer absolutely have? (Select all that apply.)

- Social media
- Community management
- Communication strategy

- Content marketing
- I do not know / None of the listed skills

Q7. *(Asked only if the respondent selected any option other than "None of these roles" in Q3.)* Please specify any additional skill not listed above that you consider absolutely necessary (optional):

D.2.4 Preliminary Questions – Translation

Q8. *(Asked only if the respondent selected "Translation" in Q1.)* Which of the following languages should the freelancer absolutely master, in addition to French? (Select all that apply.)

- German
- English
- Arabic
- Chinese
- Danish
- Spanish
- Greek
- Italian
- Japanese
- Dutch
- Norwegian
- Polish
- Portuguese
- Russian

- Swedish
- Czech
- Turkish
- Vietnamese
- None of the listed languages

Q9. *(Asked only if the respondent selected "Translation" in Q1.)* Please specify any additional language not listed above that you consider absolutely necessary (optional):

D.2.5 Preliminary Questions – Tech

Q10. *(Asked only if the respondent selected "Tech" in Q1 and ends the survey if None of these roles is selected.)* Which of the following roles would you be most likely to hire a freelancer for? (A description of each role is provided below.)

- Front-end developer
- Back-end developer
- Full-stack developer
- Web integration / CMS development / Webmaster
- Mobile developer
- None of these roles

Role descriptions.

- **Front-end developer:** Designs and develops the visible interface of a website or web application to provide a smooth and engaging user experience (e.g., JavaScript, React, Vue, Angular, HTML/CSS integration).
- **Back-end developer:** Develops and maintains the server-side components of a website or application (servers, databases, APIs) to ensure performance and security (e.g., Node.js, Java, Python, PHP).

- **Full-stack developer:** Works on both front-end and back-end, capable of building a complete web application end-to-end (e.g., JavaScript, Node.js, React, Angular).
- **Web integration / CMS development / Webmaster:** Builds and customizes websites (showcase or e-commerce), often using CMS platforms, integrating content and functionalities (e.g., WordPress, Shopify, PrestaShop).
- **Mobile developer:** Develops native or hybrid mobile applications for smartphones and tablets (e.g., iOS, Android, Flutter).

Q11. *(Asked only if "Full-stack developer" is selected in Q10.)* Which of the following skills should this developer absolutely have? (Select all that apply.)

- C#, ASP.NET Core
- C/C++
- CSS, Bootstrap
- Java, Hibernate
- Java, Spring
- Java, Spring Boot
- JavaScript/TypeScript, Angular
- JavaScript/TypeScript, AngularJS
- JavaScript/TypeScript, GraphQL
- JavaScript/TypeScript, jQuery
- JavaScript/TypeScript, Next.js
- JavaScript/TypeScript, Node.js
- JavaScript/TypeScript, Nuxt.js
- JavaScript/TypeScript, NestJS

- JavaScript/TypeScript, React.js
- JavaScript/TypeScript, Vue.js
- PHP, Laravel
- PHP, Symfony
- Python, Django
- Tailwind CSS
- Ruby, Ruby on Rails
- I do not know / None of the listed skills

Q12. *(Asked only if "Front-end developer" is selected in Q10.)* Which of the following skills should this developer absolutely have? (Select all that apply.)

- CSS, Bootstrap
- JavaScript/TypeScript, Angular
- JavaScript/TypeScript, AngularJS
- JavaScript/TypeScript, GraphQL
- JavaScript/TypeScript, jQuery
- JavaScript/TypeScript, Next.js
- JavaScript/TypeScript, Nuxt.js
- JavaScript/TypeScript, NestJS
- JavaScript/TypeScript, React.js
- JavaScript/TypeScript, Vue.js
- Tailwind CSS
- I do not know / None of the listed skills

Q13. *(Asked only if "Back-end developer" is selected in Q10.)* Which of the following skills should this developer absolutely have? (Select all that apply.)

- C#, ASP.NET Core
- C/C++
- Java, Hibernate
- Java, Spring
- Java, Spring Boot
- JavaScript/TypeScript, GraphQL
- JavaScript/TypeScript, Next.js
- JavaScript/TypeScript, Node.js
- JavaScript/TypeScript, Nuxt.js
- JavaScript/TypeScript, NestJS
- PHP, Laravel
- PHP, Symfony
- Python, Django
- Ruby, Ruby on Rails
- I do not know / None of the listed skills

Q14. *(Asked only if "Web integration / CMS / Webmaster" is selected in Q10.)* Which of the following skills should this developer absolutely have? (Select all that apply.)

- Web integration and development
- CMS and e-commerce
- SEO

- HTML & CSS
- JavaScript
- PHP
- WordPress
- Drupal
- Elementor
- Shopify
- PrestaShop
- WooCommerce
- Magento
- Webflow
- I do not know / None of the listed skills

Q15. *(Asked only if "Mobile developer" is selected in Q10.)* Which of the following skills should this developer absolutely have? (Select all that apply.)

- iOS
- Swift
- Objective-C
- Android
- Kotlin
- Java
- React Native
- Flutter

- Xamarin
- Ionic
- Firebase
- I do not know / None of the listed skills

Q16. *(Asked only if any role other than "None of these roles" is selected in Q10.)* Please specify any additional skill not listed above that you consider absolutely necessary (optional):

D.2.6 Profile Evaluation Task

Instructions. You will now be presented with 25 freelancer profiles to evaluate.

To complete this evaluation, please imagine that you are in a hiring situation on [the platform] for your company. For each profile, you will be asked three questions to assess your level of interest in a potential collaboration.

The profiles shown are inspired by real freelancers but have been constructed specifically for the purposes of this survey and do not correspond to actual profiles available on the platform. However, your evaluations will be used to recommend five active freelancers on [the platform] who match your needs. Therefore, these recommendations will be most useful and relevant if your evaluations are accurate and sincere.

Please rely on your intuition and answer honestly. There are no right or wrong answers; we are interested in your judgment as a recruiter.

Evaluation (repeated for each profile). For each freelancer profile, respondents answered the following questions:

- **Q17.** To what extent would you like to hire this person under the conditions indicated in their profile? Assume that they would accept an offer if you contacted them.

1 2 3 4 5 6 7 8 9 10

- **Q18.** What is the probability that this person would accept to work with you if you contacted them for a project?

1 2 3 4 5 6 7 8 9 10

- **Q19.** *(Additional question; response does not influence recommendations.)* Do you consider this person competent to carry out a project for you?

1 2 3 4 5 6 7 8 9 10

D.2.7 Additional Questions

Q20. Do you have experience in the field for which you evaluated the profiles?

- Yes
- No

Q21. What are your roles within your company? (Select all that apply.)

- Management and administration
- Human resources
- Sales and marketing
- Product development and operations
- IT
- Communication
- Other:

Q22. Have you previously worked with freelancers?

- Yes, on more than three occasions
- Yes, one to three occasions

- No, never

Q23. Do you plan to hire a freelancer in the short or medium term?

- Yes, in the short term
- Yes, in the medium term
- No, not at the moment

Q24. *(Asked only if the respondent selected either "Yes" option in Q23.)* What is the maximum daily rate you would be willing to pay for a freelancer?

100 210 320 430 540 650 760 870 980 1090 1200

Q25. *(Asked only if the respondent selected either "Yes" option in Q23.)* Should the freelancer have a minimum number of years of professional experience? If yes, please specify the number of years. If not, enter 0.

Q26. *(Asked only if the respondent selected either "Yes" option in Q23.)* Which work arrangement would be absolutely necessary?

- Fully remote
- On-site only
- Hybrid (remote + on-site)
- No preference

Q27. *(Asked only if the respondent selected either "Yes" option in Q23.)* Please specify any additional or more specific skills that a freelancer should have (if applicable):

Q28. *(Asked only if "No preference" is selected in Q26.)* In which city would the assignment take place?

Q29. To what extent is diversity an important criterion in your hiring decisions?

1 2 3 4 5 6 7 8 9 10

D.3 Evaluation experiment – worker questionnaire

D.3.1 Introduction

Help us better understand your collaboration preferences.

We are conducting a series of surveys to better understand your preferences and selection criteria as a freelancer, in order to improve our recommendations. Your responses will help us offer more relevant projects to users. In addition, for 25% of randomly selected respondents, we will use their responses to recommend them for a project on [the platform] that matches their preferences.

Survey description.

- Evaluate 25 project descriptions.
- For each project, indicate your level of interest in collaborating.
- Estimated time: 15 minutes.

Thank you for your participation.

- A €20 Amazon voucher.
- Entry into a lottery to win €1000.
- Voucher sent within 10 business days following completion of the survey.
- A potential recommendation for a project matching your preferences.

*Compensation is subject to eligibility and full participation in the survey. The €1000 lottery prize will also be sent as an Amazon voucher, within two months following the conclusion of the survey. Any compensation will be sent to an email address of your choice.

Data protection. Processing of your data. We will analyze your responses in connection with data from your [the platform] account, including your profile information and your interactions with the platform. These data will be processed confidentially and stored on secure servers. Only [the platform] and its research partners will have access to them for the purposes of analysis and improving the user experience. General findings may be shared in communications or publications. However, no personal data will be disclosed.

Your participation is voluntary and you may leave the survey at any time. If you wish to leave and return later, please use the same device to resume where you left off. Once started, you have one day to complete the survey. To stop receiving our communications, click the unsubscribe links at the bottom of the email you received. You can find information about [the platform]'s data protection policy, your rights in this regard, and contact details for questions about the survey in our data protection center.

By clicking "Start the survey," you agree to participate in the survey.

D.3.2 Screening Question

Q1. [End survey if None is selected] In which job family do you provide the largest share of your services on [the platform]?

- Tech (Web and Mobile Development, CMS Integration and Development)
- Marketing & Communication (Growth Marketing, Social Media Strategy and Community Engagement, Content Writing)
- Translation
- None of these categories

D.3.3 Preliminary Questions – Marketing & Communication

Q2. *(Asked only if "Marketing & Communication" is selected in Q1 and ends survey if None is selected.)* What is your primary area of specialization on [the platform]?

- Growth Marketing
- Content Writing
- Social Media Strategy and Community Engagement
- None of these roles

Role descriptions.

- **Growth Marketing:** Develops and implements digital strategies to acquire, retain, and convert customers, while tracking and optimizing performance. Areas of expertise include web marketing strategy, SEO, SEA, analytics, CRM, email marketing, and growth hacking.
- **Content Writing:** Produces content across different formats to inform, engage, and persuade. Areas of expertise include copywriting, web and SEO writing, proofreading and editing, and writing articles, newsletters, white papers, and reports.
- **Social Media Strategy and Community Engagement:** Develops and manages digital presence on social media by designing strategies and producing engaging content. Areas of expertise include community management and social media management.

Q3. *(Asked only if "Growth Marketing" is selected in Q2.)* Among the following skills, select all that you master.

- Digital acquisition strategy
- Performance analysis and tracking
- Conversion rate optimization (CRO)
- SEO (Search Engine Optimization)
- SEA (Search Engine Advertising)
- Social media advertising
- Demand generation / lead generation
- Email marketing
- CRM & marketing automation
- None of the listed skills

Q4. *(Asked only if "Content Writing" is selected in Q2.)* Among the following skills, select all that you master.

- Copywriting / Copy editing
- Web and SEO writing
- Other writing (e.g., reports)
- Proofreading and editing
- None of the listed skills

Q5. *(Asked only if "Social Media Strategy and Community Engagement" is selected in Q2.)* Among the following skills, select all that you master.

- Social media
- Community management
- Communication strategy
- Content marketing
- None of the listed skills

D.3.4 Preliminary Questions – Translation

Q6. *(Asked only if "Translation" is selected in Q1.)* Which of the following languages do you master, in addition to French? (Select all that apply.)

- German
- English
- Arabic
- Chinese
- Danish

- Spanish
- Greek
- Italian
- Japanese
- Dutch
- Norwegian
- Polish
- Portuguese
- Russian
- Swedish
- Czech
- Turkish
- Vietnamese
- None of the listed languages

D.3.5 Preliminary Questions – Tech

Q7. *(Asked only if "Tech" is selected in Q1 and ends survey if None is selected.)* What is your primary area of specialization on [the platform]?

- Front-end developer
- Back-end developer
- Full-stack developer
- Web integration / CMS development / Webmaster
- Mobile developer
- None of these roles

Role descriptions.

- **Front-end developer:** Designs and develops the visible interface of a website or web application to provide a smooth and engaging user experience. Areas of expertise include JavaScript, React, Vue, Angular, and integration of designs in React or HTML/CSS.
- **Back-end developer:** Develops and maintains the non-visible part of a website or application (servers, databases, APIs) to ensure performance and security. Areas of expertise include Node.js, Java, Python, and PHP.
- **Full-stack developer:** Works on both front-end and back-end and is able to build a complete web application end-to-end. Areas of expertise include JavaScript, Node.js, React, and Angular.
- **Web integration / CMS development / Webmaster:** Builds and customizes showcase or e-commerce websites, often using CMS platforms, with content and feature integration. Areas of expertise include website creation, WordPress, Shopify, and PrestaShop.
- **Mobile developer:** Develops native or hybrid mobile applications for smartphones and tablets. Areas of expertise include iOS, Android, and Flutter.

Q8. *(Asked only if "Full-stack developer" is selected in Q7.)* Among the following skills, select all that you master.

- C#, asp.net core
- C/C++
- CSS, Bootstrap
- Java, Hibernate
- Java, Spring
- Java, Spring Boot

- JavaScript/TypeScript, Angular
- JavaScript/TypeScript, AngularJS
- JavaScript/TypeScript, GraphQL
- JavaScript/TypeScript, jQuery
- JavaScript/TypeScript, Next.js
- JavaScript/TypeScript, Node.js
- JavaScript/TypeScript, Nuxt.js
- JavaScript/TypeScript, NestJS
- JavaScript/TypeScript, React.js
- JavaScript/TypeScript, Vue.js
- PHP, Laravel
- PHP, Symfony
- Python, Django
- Tailwind CSS
- Ruby, Ruby on Rails
- None of the listed skills

Q9. *(Asked only if "Front-end developer" is selected in Q7.)* Among the following skills, select all that you master.

- CSS, Bootstrap
- JavaScript/TypeScript, Angular
- JavaScript/TypeScript, AngularJS
- JavaScript/TypeScript, GraphQL

- JavaScript/TypeScript, jQuery
- JavaScript/TypeScript, Next.js
- JavaScript/TypeScript, Nuxt.js
- JavaScript/TypeScript, React.js
- JavaScript/TypeScript, Vue.js
- Tailwind CSS
- None of the listed skills

Q10. *(Asked only if "Back-end developer" is selected in Q7.)* Among the following skills, select all that you master.

- C#, asp.net core
- C/C++
- Java, Hibernate
- Java, Spring
- Java, Spring Boot
- JavaScript/TypeScript, GraphQL
- JavaScript/TypeScript, Next.js
- JavaScript/TypeScript, Node.js
- JavaScript/TypeScript, Nuxt.js
- JavaScript/TypeScript, NestJS
- PHP, Laravel
- PHP, Symfony
- Python, Django

- Ruby, Ruby on Rails
- None of the listed skills

Q11. *(Asked only if "Web integration / CMS development / Webmaster" is selected in Q7.)* Among the following skills, select all that you master.

- Web integration and development
- CMS and e-commerce
- SEO
- HTML & CSS
- JavaScript
- PHP
- WordPress
- Drupal
- Elementor
- Shopify
- PrestaShop
- WooCommerce
- Magento
- Webflow
- None of the listed skills

Q12. *(Asked only if "Mobile developer" is selected in Q7.)* Among the following skills, select all that you master.

- iOS

- Swift
- Objective-C
- Android
- Kotlin
- Java
- React Native
- Flutter
- Xamarin
- Ionic
- Firebase
- None of the listed skills

D.3.6 Project Evaluation Task

Instructions. You will now be presented with 25 projects to evaluate.

To evaluate these projects, please imagine a typical situation in which you receive project opportunities on [the platform]. For each project, you will be asked three questions to assess your level of interest in a potential collaboration.

The projects shown are inspired by real projects and clients, but have been constructed for the purposes of this survey and do not correspond to actual projects available on the platform. However, your evaluations may be used to recommend your profile to the matching teams if you are among the 25% of selected respondents. In that case, you would only be recommended for one project. Therefore, the sincerity and accuracy of your responses are essential to ensure that this potential recommendation matches your preferences.

Please rely on your intuition and answer honestly. There are no right or wrong answers; we are interested in your true preferences.

Evaluation (repeated for each project). For each project, respondents answered the following questions:

- **Q13.** If you were contacted for this project, to what extent would you be willing to accept it under the stated conditions?

  1 2 3 4 5 6 7 8 9 10

- **Q14.** If this client saw your profile, what is the probability that they would contact you for this project?

  1 2 3 4 5 6 7 8 9 10

- **Q15.** *(Additional question; response does not influence project recommendations.)* Do you feel qualified for this project?

  1 2 3 4 5 6 7 8 9 10

D.3.7 Additional Questions

Q16. How many years of work experience do you have?

- On [the platform]:
- As a freelancer:
- Total (including all work experience):

Q17. Is freelancing your main source of income?

- Yes
- No

Q18. Is [the platform] your main source of income?

- Yes
- No

D.4 Prediction experiment – predicting recruiters

These instructions describe both the prediction experiment in which recruiters predict evaluations of their competitors and workers predict recruiter evaluations. Whenever two statements are inside of brackets, the first refers to the version for recruiters, and the second to the version for workers

D.4.1 Introduction

Help us better understand collaboration preferences.

We are conducting a series of surveys to better understand how clients' preferences match freelancers' preferences on [the platform]. Your responses will help us offer better collaboration opportunities to our users.

Survey description.

- Give your opinion on the collaboration preferences of clients [like you] on the platform.
- Receive information to improve your [profile / project descriptions and freelancer search].
- Estimated time: approximately 20 minutes.

Thank you for your participation.

- An Amazon voucher of [5–19.5 € / 10–50 €], depending on your responses.
- Entry into a lottery to win 1000 €.
- Voucher sent within 10 business days following completion of the survey.

*Compensation is subject to eligibility and full participation in the survey. This compensation will be sent to an email address of your choice.

Data protection. Processing of your data. We will analyze your responses in connection with data from your [the platform] account, including your profile information and your interactions with the platform. These data will be processed confidentially and stored on our secure servers. Only [the platform] and its research partners will have access to them for the purposes of analysis and improvement of the user experience. General findings may be shared in our communications or in publications. However, no personal data will be disclosed.

If you wish to leave and return later, please use the same device to resume where you left off. Once started, you have one week to complete the survey. After this deadline, the survey will automatically close and you will not receive compensation. To stop receiving our communications, click the unsubscribe links at the bottom of the email you received. You can find information about [the platform]'s data protection policy, your rights in this regard, and the contact address for questions about the survey in our data protection center.

By clicking "Start the survey," you agree to participate in the survey.

D.4.2 Preliminary Questions

Q1. End survey if None is selected In which of the following categories [would you be most likely to recruit your next freelancer / do you provide the largest share of your services] on [the platform]?

- Tech (Web and Mobile Development, CMS Integration and Development)
- Marketing & Communication (Growth Marketing, Social Media Strategy and Community Engagement, Content Writing)

Translation

- None of these categories

Q2. *(Asked only if "Marketing & Communication" is selected in Q1 and end survey if None is selected.)* [In which of the following roles would you be most likely to recruit your next freelancer? / What is your main area of specialization on [the platform]?]

- Growth Marketing
- Content Writing
- Social Media Strategy and Community Engagement
- None of these roles

Role descriptions.

- **Growth Marketing:** Develops and implements digital strategies to acquire, retain, and convert customers, while monitoring and optimizing performance. Areas of expertise: web marketing strategy, SEO, SEA, analytics, CRM, email marketing, growth hacking.
- **Content Writing:** Writes content adapted to different formats in order to inform, engage, and persuade, depending on the communication objectives of a company or organization. Areas of expertise: copywriting, web and SEO writing, proofreading and editing, writing articles, newsletters, white papers, and reports.
- **Social Media Strategy and Community Engagement:** Develops and manages the digital presence of a brand or organization on social media by designing strategy and producing engaging content to reach and retain its audience. Areas of expertise: community management, social media management.

Q3. *(Asked only if "Tech" is selected in Q1 and end survey if None is selected.)* [For which of the following roles would you be most likely to recruit your next freelancer? / What is your main area of specialization on [the platform]?]

- Front-end developer
- Back-end developer
- Full-stack developer
- Web integration, CMS development, Webmaster
- Mobile developer
- None of these roles

Role descriptions.

- **Front-end developer:** Designs and develops the visible part of a website or application to provide a smooth and engaging user experience. Areas of expertise: JavaScript, React, Vue, Angular, integration of designs in React or HTML/CSS.
- **Back-end developer:** Develops and maintains the non-visible part of a website or application (servers, databases, APIs) to ensure performance and security. Areas of expertise: Node.js, Java, Python, PHP.
- **Full-stack developer:** Works on both the front-end and the back-end and is able to build a complete web application. Areas of expertise: JavaScript, Node.js, React, Angular.
- **Web integration, CMS development, Webmaster:** Creates and customizes showcase or e-commerce websites, often using CMS tools, with content and feature integration. Areas of expertise: website creation, WordPress, Shopify, PrestaShop.
- **Mobile developer:** Develops native or hybrid mobile applications for smartphones and tablets. Areas of expertise: iOS, Android, Flutter.

D.4.3 Prediction Task – Instructions

In a previous survey, we constructed representative freelancer profiles on [the platform]. These profiles were inspired by real cases, but were created for the purposes of the survey and do not correspond to actual profiles available on the platform.

We then asked active clients on [the platform] to indicate their level of interest, from 1 to 10, in these profiles. They were incentivized to provide sincere evaluations even if profiles were made for the purposes of the survey, because their evaluations were then used to recommend real freelancers matching their preferences.

Each client was shown only profiles whose skills matched those they had themselves indicated as necessary for their next project, in order to ensure the relevance of the profiles shown.

You will now be asked to predict, for 25 of these profiles, the average level of interest expressed by clients for the occupation: `the job category selected by the` `participant`.

Here is some information about the clients who responded to the survey:

clients participated in the survey (all active on [the platform] during the last four months)

% are companies with 1 to 10 employees, [ ]% with 11 to 250 employees, and [ ]% with more than 250 employees

% have completed at least one project on [the platform]

- Average budget for their next project: [ ] € per day

Your compensation.

- Fixed amount: [10 € / 5 €]
- Bonus for your predictions: up to [25 € / 10 €]
- Bonus for other questions later in the survey: up to [15 € / 4.5 €]

We have put in place an incentive procedure: the closer you are to the true average evaluation of the surveyed clients, the greater your chances of increasing your bonus.

{Behind a button that participants must click} Details on the bonus calculation.

We will randomly choose 5 of the profiles that you evaluated. For each of them, we will randomly draw a client from the previous survey and calculate, based on that client's responses, their level of interest in this type of profile (x). The closer your prediction out of 10 (p) is to this value, the greater your chances of receiving [5 € / 2 €]. In particular, you will receive [5 € / 2 €] with a probability calculated according to the following formula:

$$1 - \left(\frac{p - x}{3}\right)^2.$$

D.4.4 Predictions

Q4. According to you, what average level of interest (from 1 to 10) did the surveyed clients express for this profile?

For each profile, the following question was asked to the clients:

"To what extent would you like to recruit this person under the conditions indicated on their profile? Suppose that they would accept an offer if you contacted them."

Answer by putting yourself in the place of a client in your job category.

Not at all					Completely				
1	2	3	4	5	6	7	8	9	10

D.4.5 Impact of characteristics

In the profiles that you have just evaluated, we varied different characteristics at random.

The value of each characteristic was assigned independently of the value of the other characteristics of the profile.

For example, the daily rate could change from one profile to another, but this change was not related to the presence of a degree, to experience, or to the other elements of the profile.

We now ask you to predict how each characteristic influenced the evaluation of the clients who responded to the previous survey.

Same reference question: "To what extent would you like to recruit this person under the conditions indicated on their profile? Suppose that they would accept an offer if you contacted them."

Bonus

Bonus for your predictions: up to [15 € / 4.5 €]

We have again put in place an incentive procedure: the closer you are to the true average importance for the surveyed clients, the more your bonus is likely to increase.

{Behind a button that participants must click} Details on the bonus calculation. We will randomly choose 3 of the characteristics that you will have evaluated. For each of these characteristics, we will randomly draw a client from the previous survey and calculate, based on their responses, the importance that they assign to this characteristic (denoted x).

The closer your prediction (p) is to this value, the more likely you are to receive a bonus of [5 € / 1.5 €].

In particular, you will receive a bonus of [5 € / 1.5 €] with a probability equal to:

$$1 - \left(\frac{p - x}{1}\right)^2.$$

How to answer For each characteristic, indicate by how many points it would increase or decrease the average rating given by the clients (on a scale from 1 to 10).

Important

Consider each characteristic independently.

For example, to evaluate the effect of an increase in the daily rate, assume that only the daily rate increases and that all the other characteristics remain the same.

Slider scale: from -2 to +2

+0.3 = the characteristic increases the average rating by 0.3 points (out of 10)

-0.5 = the characteristic decreases the average rating by 0.5 points (out of 10)

0 = the characteristic has no effect on the rating

Q5

Characteristics **Average daily rate**

-2 -1 0 1 2

Increase in the daily rate by 100 euros

Profile reputation

-2 -1 0 1 2

At least one project completed on [the platform] versus none

-2 -1 0 1 2

Ten additional projects completed on [the platform]

-2 -1 0 1 2

All projects completed on [the platform] have a 5/5 review rather than half of the projects having a 5/5 review

-2 -1 0 1 2

A reputation badge

Profile experience

-2 -1 0 1 2

At least one professional experience in a large company (e.g., CAC 40)

-2 -1 0 1 2

Two professional experiences on the profile rather than one

-2 -1 0 1 2

Ten additional years of professional experience

-2 -1 0 1 2

Having a master's degree rather than a bachelor's degree/BTS/DUT

Working arrangements on the profile

-2 -1 0 1 2

Availability to work on your premises

-2 -1 0 1 2

Availability to work only part-time

Origin and gender of the freelancer This survey includes questions on perceived gender and ethnic origin in order to understand whether you think these factors influence the decisions of other clients.

Conducted with independent researchers, these questions aim to assess your perceptions of the presence of discrimination on the platform.

Your answers are confidential and any information on gender or ethnic origin is used exclusively for academic purposes.

Q6 For each characteristic, indicate by how many points it would increase or decrease the average rating given by the other clients (on a scale from 1 to 10).

Origin and gender of the freelancer

-2 -1 0 1 2

Profile with a freelancer with a female-sounding name (first name)

-2 -1 0 1 2

Profile with a freelancer with a MENA-sounding name (first name)

D.4.6 Results

Now discover whether you were correct about the characteristics that influence other clients on the platform.

Daily rate

Characteristic: Increase in the daily rate by 100 euros

Other clients: You: Difference:

Other clients: average impact of the characteristic on the rating of other clients

You: your prediction

Difference: Green = accurate prediction Red = significant deviation

* : we identify little or no significant impact of this variable on the rating of other freelancers

Advice based on prediction errors is shown

Q7 To what extent does the information we have shown you so far seem useful to you as a [client/freelancer] on [the platform]?

Not at all Completely

1 2 3 4 5 6 7 8 9 10

Profile reputation

Characteristic: At least one project completed on [the platform] versus none

Other clients: You: Difference:

Characteristic: Ten additional projects completed on [the platform]

Other clients: You: Difference:

Characteristic: All projects completed on [the platform] have a 5/5 review rather than half of the projects having a 5/5 review

Other clients: You: Difference:

Characteristic: A reputation badge

Other clients: You: Difference:

Other clients: average impact of the characteristic on the rating of other clients

You: your prediction

Difference: Green = accurate prediction Red = significant deviation

* : we identify little or no significant impact of this variable on the rating of other freelancers

Advice based on prediction errors is shown

Q8 To what extent does the information we have shown you so far seem useful to you as a [client/freelancer] on [the platform]?

Not at all Completely

1 2 3 4 5 6 7 8 9 10

Profile experience

Characteristic: At least one professional experience in a large company (e.g., CAC 40)

Other clients: You: Difference:

Characteristic: Two professional experiences on the profile rather than one

Other clients: You: Difference:

Characteristic: Ten additional years of professional experience

Other clients: You: Difference:

Characteristic: Having a master's degree rather than a bachelor's degree/BTS/DUT

Other clients: You: Difference:

Other clients: average impact of the characteristic on the rating of other clients

You: your prediction

Difference: Green = accurate prediction Red = significant deviation

* : we identify little or no significant impact of this variable on the rating of other freelancers

Advice based on prediction errors is shown

Q9 To what extent does the information we have shown you so far seem useful to you as a [client/freelancer] on [the platform]?

Not at all Completely

1 2 3 4 5 6 7 8 9 10

Working arrangements on the profile

Characteristic: Availability to work on your premises

Other clients: You: Difference:

Characteristic: Availability to work only part-time

Other clients: You: Difference:

Other clients: average impact of the characteristic on the rating of other clients

You: your prediction

Difference: Green = accurate prediction Red = significant deviation

* : we identify little or no significant impact of this variable on the rating of other freelancers

Advice based on prediction errors is shown

Q10 To what extent does the information we have shown you so far seem useful to you as a [client/freelancer] on [the platform]?

Not at all Completely

1 2 3 4 5 6 7 8 9 10

Origin and gender of the freelancer

Characteristic: Profile with a freelancer with a female-sounding name (first name)

Other clients: You: Difference:

Characteristic: Profile with a freelancer with a Maghrebi-sounding name (first name)

Other clients: You: Difference:

Other clients: average impact of the characteristic on the rating of other clients

You: your prediction

Difference: Green = accurate prediction Red = significant deviation

* : we identify little or no significant impact of this variable on the rating of other freelancers

Advice based on prediction errors is shown

Q11 To what extent does the information we have shown you so far seem useful to you as a [client/freelancer] on [the platform]?

Not at all Completely

1 2 3 4 5 6 7 8 9 10

Q12 Following this information, do you expect to modify:

[Very unlikely, Unlikely, Neither likely nor unlikely, Likely, Very likely]

- Your project descriptions / Your profile description

- Your criteria for selecting freelancers / Your criteria for selecting projects
- The conditions of your projects / The conditions of the projects you accept

Q13 Please briefly indicate what lesson(s) you take from this information (optional):

D.4.7 Additional questions - recruiters

Q14 Do you have experience in the occupation for which you evaluated the profiles?

- Yes
- No

Q15 What are your roles in your company? Select all relevant options.

- Management and administration
- Human resources
- Sales and marketing
- Product development and operations
- IT
- Communication
- Other

Q16 Have you already worked with freelancers?

- Yes, on more than three occasions
- Yes, on between one and three occasions
- No, never

D.4.8 Additional questions - workers

Q14 How many years of work experience do you have?

Number of years of experience On [the platform] As a freelancer In total, including all your work experience

Q15 Is freelancing your main source of income?

- Yes
- No

Q16 Is [the platform] your main source of income?

- Yes
- No

D.5 Prediction experiment – predicting workers

These instructions describe both the prediction experiment in which recruiters predict worker evaluations and workers predict evaluations of other workers. Whenever two statements are inside of brackets, the first refers to the version for recruiters, and the second to the version for workers.

D.5.1 Introduction

Help us better understand collaboration preferences.

We are conducting a series of surveys to better understand how clients' preferences match freelancers' preferences. Your responses will help us offer better collaboration opportunities to our users.

Survey description.

- Give your opinion on the collaboration preferences of freelancers [on the platform / like you on the platform].
- Receive information to improve your [project descriptions and freelancer search / profile].

- Estimated time: approximately 20 minutes.

Thank you for your participation.

- An Amazon voucher of [10–50 € / 5–19.5 €], depending on your responses.
- Entry into a lottery to win 1000 €.
- Voucher sent within 10 business days following completion of the survey.

*Compensation is subject to eligibility and full participation in the survey. This compensation will be sent to an email address of your choice.

Data protection. Processing of your data. We will analyze your responses in connection with data from your [the platform] account, including your profile information and your interactions with the platform. These data will be processed confidentially and stored on our secure servers. Only [the platform] and its research partners will have access to them for the purposes of analysis and improvement of the user experience. General findings may be shared in our communications or in publications. However, no personal data will be disclosed.

If you wish to leave and return later, please use the same device to resume where you left off. Once started, you have one week to complete the survey. After this deadline, the survey will automatically close and you will not receive compensation. To stop receiving our communications, click the unsubscribe links at the bottom of the email you received. You can find information about [the platform]'s data protection policy, your rights in this regard, and the contact address for questions about the survey in our data protection center.

By clicking "Start the survey," you agree to participate in the survey.

D.5.2 Preliminary Questions

Q1. End survey if None is selected In which of the following categories [would you be most likely to recruit your next freelancer / do you provide the largest share of your services] on [the platform]?

- Tech (Web and Mobile Development, CMS Integration and Development)
- Marketing & Communication (Growth Marketing, Social Media Strategy and Community Engagement, Content Writing)

Translation

- None of these categories

Q2. *(Asked only if "Marketing & Communication" is selected in Q1 and end survey if None is selected.)* [In which of the following roles would you be most likely to recruit your next freelancer? / What is your main area of specialization on [the platform]?]

- Growth Marketing
- Content Writing
- Social Media Strategy and Community Engagement
- None of these roles

Role descriptions.

- **Growth Marketing:** Develops and implements digital strategies to acquire, retain, and convert customers, while monitoring and optimizing performance. Areas of expertise: web marketing strategy, SEO, SEA, analytics, CRM, email marketing, growth hacking.
- **Content Writing:** Writes content adapted to different formats in order to inform, engage, and persuade, depending on the communication objectives of a company or organization. Areas of expertise: copywriting, web and SEO writing, proofreading and editing, writing articles, newsletters, white papers, and reports.
- **Social Media Strategy and Community Engagement:** Develops and manages the digital presence of a brand or organization on social media by designing strategy and producing engaging content to reach and retain its audience. Areas of expertise: community management, social media management.

Q3. *(Asked only if "Tech" is selected in Q1 and end survey if None is selected.)* [For which of the following roles would you be most likely to recruit your next freelancer? / What is your main area of specialization on [the platform]?]

- Front-end developer
- Back-end developer
- Full-stack developer
- Web integration, CMS development, Webmaster
- Mobile developer
- None of these roles

Role descriptions.

- **Front-end developer:** Designs and develops the visible part of a website or application to provide a smooth and engaging user experience. Areas of expertise: JavaScript, React, Vue, Angular, integration of designs in React or HTML/CSS.
- **Back-end developer:** Develops and maintains the non-visible part of a website or application (servers, databases, APIs) to ensure performance and security. Areas of expertise: Node.js, Java, Python, PHP.
- **Full-stack developer:** Works on both the front-end and the back-end and is able to build a complete web application. Areas of expertise: JavaScript, Node.js, React, Angular.
- **Web integration, CMS development, Webmaster:** Creates and customizes showcase or e-commerce websites, often using CMS tools, with content and feature integration. Areas of expertise: website creation, WordPress, Shopify, PrestaShop.
- **Mobile developer:** Develops native or hybrid mobile applications for smartphones and tablets. Areas of expertise: iOS, Android, Flutter.

D.5.3 Prediction Task – Instructions

In a previous survey, we constructed representative project descriptions on [the platform]. These projects were inspired by real cases, but were created for the purposes of the survey and do not correspond to actual projects available on the platform.

We then asked active freelancers on [the platform] to indicate their level of interest, from 1 to 10, in these projects. They were incentivized to provide sincere evaluations even if the projects were made for the purposes of the survey, because their evaluations were then used to recommend them to our matching specialists for a project on the platform.

Each freelancer was shown only projects for which they had themselves indicated having the required skills, in order to ensure the relevance of the projects shown.

You will now be asked to predict, for 25 of these projects, the average level of interest expressed by freelancers for the occupation: `the job category selected by the participant`.

Here is some information about the freelancers who responded to the survey:

freelancers participated in the survey (all active on [the platform] during the last three months)

% have completed at least one project on [the platform]

- They have on average [ ] years of freelancing experience
- Average daily rate on their profiles: [ ] € per day

Your compensation.

- Fixed amount: [10 € / 5 €]
- Bonus for your predictions: up to [25 € / 10 €]
- Bonus for other questions later in the survey: up to [15 € / 4.5 €]

We have put in place an incentive procedure: the closer you are to the true average evaluation of the surveyed freelancers, the greater your chances of increasing your bonus.

{Behind a button that participants must click} Details on the bonus calculation.

We will randomly choose 5 of the projects that you evaluated. For each of them, we will randomly draw a freelancer from the previous survey and calculate, based on that freelancer's responses, their level of interest in this type of project (x). The closer your prediction out of 10 (p) is to this value, the greater your chances of receiving [5 € / 2 €]. In particular, you will receive [5 € / 2 €] with a probability calculated according to the following formula:

$$1 - \left(\frac{p - x}{3}\right)^2.$$

D.5.4 Predictions

Q4. According to you, what average level of interest (from 1 to 10) did the surveyed freelancers express for this project?

For each project, the following question was asked to the freelancers:

> "If you were contacted for this project, to what extent would you be willing to accept it under the stated conditions?"

Answer by putting yourself in the place of freelancers in your job category.

Not at all Completely

1 2 3 4 5 6 7 8 9 10

D.5.5 Impact of characteristics

In the projects that you have just evaluated, we varied different characteristics at random.

The value of each characteristic was assigned independently of the value of the other characteristics of the project.

For example, the daily rate could change from one project to another, but this change was not related to the type of company, the duration of the project, or the other elements of the project.

We now ask you to predict how each characteristic influenced the evaluation of the freelancers who responded to the previous survey.

Same reference question: "If you were contacted for this project, to what extent would you be willing to accept it under the stated conditions?"

Bonus

Bonus for your predictions: up to [15 € / 4.5 €]

We have again put in place an incentive procedure: the closer you are to the true average importance for the surveyed freelancers, the more your bonus is likely to increase.

{Behind a button that participants must click} Details on the bonus calculation. We will randomly choose 3 of the characteristics that you will have evaluated. For each of these characteristics, we will randomly draw a freelancer from the previous survey and calculate, based on their responses, the importance that they assign to this characteristic (denoted x).

The closer your prediction (p) is to this value, the more likely you are to receive a bonus of [5 € / 1.5 €].

In particular, you will receive a bonus of [5 € / 1.5 €] with a probability equal to:

$$1 - \left(\frac{p - x}{1}\right)^2.$$

How to answer For each characteristic, indicate by how many points it would increase or decrease the average rating given by the freelancers (on a scale from 1 to 10).

Important

Consider each characteristic independently.

For example, to evaluate the effect of an increase in the daily rate, assume that only the daily rate increases and that all the other characteristics remain the same.

Slider scale: from -2 to +2

+0.3 = the characteristic increases the average rating by 0.3 points (out of 10)

-0.5 = the characteristic decreases the average rating by 0.5 points (out of 10)

0 = the characteristic has no effect on the rating

Q5

Characteristics **Average daily rate**

-2 -1 0 1 2

Increase in the daily rate by 100 euros

Client reputation

-2 -1 0 1 2

The client has completed at least one project on [the platform] versus none

-2 -1 0 1 2

The client has completed 10 additional projects on [the platform]

-2 -1 0 1 2

The client has all completed projects on [the platform] with a 5/5 review rather than half of their projects with a 5/5 review

-2 -1 0 1 2

The client is part of a large company (e.g., CAC 40)

Working arrangements of the project

-2 -1 0 1 2

The project is offered on-site only

-2 -1 0 1 2

The project is offered full-time

-2 -1 0 1 2

Duration longer than one month versus one month or less

-2 -1 0 1 2

Mentions teamwork

-2 -1 0 1 2

Mentions tight deadlines

Origin and gender of the client This survey includes questions on perceived gender and ethnic origin in order to understand whether you think these factors influence the decisions of other freelancers.

Conducted with independent researchers, these questions aim to assess your perceptions of the presence of discrimination on the platform.

Your answers are confidential and any information on gender or ethnic origin is used exclusively for academic purposes.

Q6 For each characteristic, indicate by how many points it would increase or decrease the average rating given by the other freelancers (on a scale from 1 to 10).

Origin and gender of the client

-2 -1 0 1 2

Project with a client with a female-sounding name (first name)

-2 -1 0 1 2

Project with a client with a Maghrebi-sounding name (first name)

D.5.6 Results

Now discover whether you were correct about the characteristics that influence other freelancers on the platform.

Daily rate

Characteristic: Increase in the daily rate by 100 euros

Other freelancers: You: Difference:

Other freelancers: average impact of the characteristic on the rating of other freelancers

You: your prediction

Difference: Green = accurate prediction Red = significant deviation

* : we identify little or no significant impact of this variable on the rating of other freelancers

Advice based on prediction errors is shown

Q7 To what extent does the information we have shown you so far seem useful to you as a [client / freelancer] on [the platform]?

Not at all					Completely				
1	2	3	4	5	6	7	8	9	10

Client reputation

Characteristic: The client has completed at least one project on [the platform] versus none

Other freelancers: You: Difference:

Characteristic: The client has completed 10 additional projects on [the platform]

Other freelancers: You: Difference:

Characteristic: The client has all completed projects on [the platform] with a 5/5 review rather than half of their projects with a 5/5 review

Other freelancers: You: Difference:

Characteristic: The client is part of a large company (e.g., CAC 40)

Other freelancers: You: Difference:

Other freelancers: average impact of the characteristic on the rating of other freelancers

You: your prediction

Difference: Green = accurate prediction Red = significant deviation

* : we identify little or no significant impact of this variable on the rating of other freelancers

Advice based on prediction errors is shown

Q8 To what extent does the information we have shown you so far seem useful to you as a [client / freelancer] on [the platform]?

Not at all Completely

1 2 3 4 5 6 7 8 9 10

Working arrangements of the project

Characteristic: The project is offered on-site only

Other freelancers: You: Difference:

Characteristic: The project is offered full-time

Other freelancers: You: Difference:

Characteristic: Duration longer than one month versus one month or less

Other freelancers: You: Difference:

Characteristic: Mentions teamwork

Other freelancers: You: Difference:

Characteristic: Mentions tight deadlines

Other freelancers: You: Difference:

Other freelancers: average impact of the characteristic on the rating of other freelancers

You: your prediction

Difference: Green = accurate prediction Red = significant deviation

* : we identify little or no significant impact of this variable on the rating of other freelancers

Advice based on prediction errors is shown

Q9 To what extent does the information we have shown you so far seem useful to you as a [client / freelancer] on [the platform]?

Not at all Completely

1 2 3 4 5 6 7 8 9 10

Origin and gender of the client

Characteristic: Project with a client with a female-sounding name (first name)

Other freelancers: You: Difference:

Characteristic: Project with a client with a Maghrebi-sounding name (first name)

Other freelancers: You: Difference:

Other freelancers: average impact of the characteristic on the rating of other freelancers

You: your prediction

Difference: Green = accurate prediction Red = significant deviation

* : we identify little or no significant impact of this variable on the rating of other freelancers

Advice based on prediction errors is shown

Q10 To what extent does the information we have shown you so far seem useful to you as a [client / freelancer] on [the platform]?

Not at all Completely

1 2 3 4 5 6 7 8 9 10

Q11 Following this information, do you expect to modify:

[Very unlikely, Unlikely, Neither likely nor unlikely, Likely, Very likely]

- Your [project descriptions / profile]
- Your criteria for selecting [freelancers / projects]
- The [conditions of your projects / terms of your collaborations]

Q12 Please briefly indicate what lesson(s) you take from this information (optional):

D.5.7 Additional questions - recruiters

Q13 Do you have experience in the occupation for which you evaluated the profiles?

- Yes
- No

Q14 What are your roles in your company? Select all relevant options.

- Management and administration
- Human resources
- Sales and marketing
- Product development and operations
- IT
- Communication
- Other

Q15 Have you already worked with freelancers?

- Yes, on more than three occasions
- Yes, on between one and three occasions
- No, never

D.5.8 Additional questions - workers

Q13 How many years of work experience do you have?

Number of years of experience

On [the platform]

As a freelancer

In total, including all your work experience

Q14 Is freelancing your main source of income?

- Yes
- No

Q15 Is [the platform] your main source of income?

- Yes
- No