(Mis)perceptions of the Labor Market*

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Abstract

Workers' investment and job search are shaped by their perceived market returns, which depend on the preferences of firms and competing workers. Similarly, firm compensation and amenity provision are shaped by perceived returns which depend on the preferences of workers and competing firms. We study whether employers and workers hold accurate perceptions about the preferences of others in the labor market. We conduct a series of incentivized field experiments on one of Europe's largest freelance platform to measure the causal returns to a rich set of worker, employer, and job characteristics and then to measure market participants' beliefs about those returns. First, we elicit employers' and workers' preferences 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 systematic *perception gaps* on both sides of the market, including about the value of posted wages, human capital, market reputation, work arrangements, 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, reducing match rates and surplus. Our findings highlight an important source of information frictions in labor markets and its economic consequences.

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1 Introduction

Workers invest in human capital and search for jobs based on the labor market returns they expect, such as the wage premium to additional education. Firms, in turn, set wages and workplace amenities based on the expected returns from attracting and retaining workers. These expectations govern investment decisions, compensation, and the allocation of talent.

Yet, estimating returns to specific worker, firm, and job characteristics is difficult because these characteristics are endogenously acquired, priced, and advertised. Valuations also likely vary across individuals, jobs, and market conditions. A central question is therefore whether workers and firms hold accurate beliefs about the preferences of other market participants. If beliefs are systematically biased, investment, search and matching, and pricing decisions may be distorted, with important implications for policy and welfare.

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

We study perception gaps arising from agents misperceiving the preferences of 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 other recruiters' preferences for worker characteristics; and (iv) workers' beliefs about other workers' preferences for recruiter and job characteristics. Together, these tests provide a comprehensive assessment of perception gaps on both sides of the labor market.

In the *Evaluation* experiments, we present recruiters with hypothetical worker profiles that closely resemble what recruiters see on the platform when contacting a worker and workers with hypothetical job offers that closely resemble what workers see when con-

tacted. Recruiters (workers) evaluate 25 profiles (offers) within one of 9 job categories 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 the recruiter would offer them the job). Profiles and offers are tailored to each job category and to participants' stated hiring needs, based on information from real profiles and offers on the platform. For example, recruiters seeking translation services are shown translator profiles with the relevant language expertise and with real corresponding work experiences from translators on the platform, while translators are shown translation job offers consistent with their own expertise.

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, working conditions, 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 clear negative responses to asked wages, although these also act as signals of competence, attenuating the negative price effect. Recruiters also value market reputation and work experience, but not 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 freelancers of Middle Eastern and North African (MENA) origin. Recruiter evaluations indicate similar interest in hiring these ethnic minorities, 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 perception gaps across and within each side of the market.

The results reveal several economically meaningful perception gaps on both sides of the market. On average, participants make prediction errors of approximately 1.68 points on a 10-point scale — roughly two thirds of a standard deviation in evaluations — and over half of these errors are explained by misperceptions about the specific randomized characteristics we consider. Recruiters' beliefs about worker preferences are the most accurate, although they misread worker preferences consequentially on wages and working conditions: they overestimate how reactive workers are to offered wages relative to non-wage amenities and underestimate how much workers value remote work, especially for tech jobs. These gaps can be quite substantial in terms of valuation, with the perception gap for remote work preferences corresponding to a misjudgment of workers' willingness to forego wages for remote work of around €300 per month. Workers' predictions of recruiter preferences are the least accurate. They strikingly underestimate the negative effect of higher asked wages on recruiter interest and substantially overestimate the returns to market reputation, work experience, and prestigious credentials, while expecting recruiters to discriminate against workers of MENA origin. Predictions about competitors follow similar patterns, indicating that market participants are similarly misinformed about both

sides of the labor market. In addition, we find little evidence that perception gaps are smaller for more experienced market participants.

Beyond these average gaps, distributions of individual-level prediction errors suggest that aggregate results conceal substantial heterogeneity. Since perception gaps distort behavior and outcomes at the individual level, even an aggregate market perception gap of 0 can be associated with important efficiency losses. While individual-level prediction errors are noisy, we estimate substantial perception gaps and implied errors in ranking characteristics and identifying subsets of the most important characteristics, in any order.

After making predictions, participants receive personalized feedback to correct perceptions about each characteristic. This information treatment examines whether correcting perceptions changes subsequent platform behavior and provides evidence on whether market participants themselves recognize the importance of these information frictions and the value of the information generated from our experiments.

A large majority of participants report finding the personalized feedback useful to inform their activity on the platform, especially information on the effects of wages, and intend to change their market behavior in response, with workers most likely to intend modifying their profiles and recruiters most likely to intend revising their job offer descriptions. We test these intentions using daily data on workers' profile updating around the time of the survey. We find an increase in the rate of workers updating their profiles and their asked wages of around 5-10 and 1-4 percentage points in the day of the experiment and the following day, corresponding to 50-100% and 100-400% increases, respectively.

To interpret our findings, 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 perception gaps distort market outcomes. First, holding characteristics fixed, perception gaps distort pricing decisions. Second, allowing investment in characteristics (e.g., organizing production for remote work), the same gaps distort investments. In both cases, perception gaps reduce expected surplus by lowering match rates and 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.

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, it relates to work on how workers' search and skill investments respond to expected labor market returns. Estimating such returns 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, largely self-contained labor market.

More importantly, we contribute to the smaller literature comparing subjective expectations of returns to their realized counterparts. Because investment and search decisions depend on beliefs rather than objective returns, measuring both is essential but empirically challenging (Fuster and Zafar, 2023; Caldwell et al., 2025; Lepage et al., 2025). Even for characteristics that are fixed after labor market entry, subjective beliefs matter because they influence related behavior like pricing. Existing evidence is limited in scope and typically focuses on a narrow set of characteristics or settings outside of labor markets.[1] By jointly eliciting causal returns and incentivized beliefs about these returns within a single market, we provide a comprehensive assessment of expectation gaps. Our results show that workers 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. Again, more importantly, estimating employers' expectations of these returns in an incentivized way and comparing them to realized returns has rarely been

[1] Exley et al. (2024) uses results from an IRR to incentivize student college predictions about the impact of omitting GPAs on employers' CV evaluations. Angeli et al. (2023) find that residents of Brazilian favelas overestimate the extent of discrimination they may face, which distorts their job application behavior.

feasible, even though such comparisons are central to understanding how compensation policies translate into hiring outcomes. The only related paper of which we are aware is Cordes and Müller (2026), which presents survey evidence that firms underestimate workers' valuation for 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 be inaccurate (He et al., 2023; Bertheau and Hoeck, 2025; Cullen et al., 2025).[2] To our knowledge, we are the first to experimentally estimate expectation gaps about competitors' preferences in the labor market.

Taking our results on both sides of the market together makes clear how complex coordination failures arising from these information frictions can be. Since each side can missperceive both their own side as well as the other side, it appears exceedingly complex for even sophisticated agents to correctly learn from observed outcomes. The set of market participants, equilibrium prices and investments, and matching can all be distorted by the expectation gaps we document.[3]

Fourth, we contribute to a broader literature on information frictions and their implications for market efficiency and welfare. A large literature documents that agents routinely hold missperceptions about others (Bursztyn and Yang, 2022; Bursztyn et al., 2023; Exley et al., 2025) and that workers (Conlon et al., 2018; Mueller et al., 2021; Bryan et al., 2022; Sockin and Sojourner, 2023; Jäger et al., 2024; Miano, 2025) and firms (Friedrich and Zator, 2024; Abebe et al., 2025) have inaccurate beliefs about the labor market. We focus on expectation gaps about other market participants' preferences, for which evidence is much rarer. As our theoretical framework and information treatment make clear, inefficient pricing and investment decisions can arise solely because of these gaps, even absent commonly studied frictions such as search or bargaining. Expectation gaps thus provide an information microfoundation for labor market frictions and could constitute a source of monopsony power for better-informed agents.

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

[3] An unexpected outcome could depend on own misperceptions about preferences of either side of the market or on others' misperceptions, with potential for multiple self-confirming equilibria.

Fifth, we implement incentivized field experiments without deception, combining strengths from different approaches used in prior work. Our collaboration with the platform provides rich administrative data on profiles, job offers, and outcomes, near-universal access to users, and the ability to recommend real workers and jobs. This extends the IRR literature by estimating preferences on both sides of the market, with larger samples of participants and tailored profiles and offers within narrowly defined job categories. It also enables us to assess the representativeness of our participant pool and validate our experimental results using data on behavior and realized outcomes on the platform, a key advantage of our setting.[4]

Our collaboration also allows us to conduct experiments under the truthful guise of the platform conducting studies to improve its matching services, rather than mentioning to participants that they are part of an academic study, mitigating recent concerns with experimenter demand bias (Agan et al., 2023). Doing so while still using the IRR methodology has some advantages over common approaches like correspondence studies (Bertrand and Mullainathan, 2004; Kline et al., 2022). Our design allows each participant to evaluate multiple profiles or offers on detailed scales and across more than one dimension, rather than relying on binary callback outcomes.[5] In that sense, our *Evaluation* experiments share similarities with vignette experiments (Maestas et al., 2023), but are conducted in a realistic, high-stakes market setting, with the average job on the platform carrying a wage budget of €6,170. More importantly, this design allows us to go beyond estimating preferences and use evaluations to incentivize the *Prediction* experiments and identify market perception gaps, the paper's central goal. Our empirical approach could be applied to measure information frictions in other important settings, including housing, consumer, and capital markets.

Sixth, we contribute to the literature on online labor markets and freelancing, sectors of rapidly growing economic importance, especially following the COVID-19 pandemic. For example, 38% of the U.S. workforce performed some freelance work in 2023, for a

[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.

[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.

total of 1.27 trillion in annual earnings (Upwork Research Institute, 2023). The ability of online platforms to successfully match their users is key for success, whether for freelancing, traditional job and unemployment boards, or rental and marketplaces (Cullen and Farronato, 2021; Echenique et al., 2023). Our results indicate that platforms lose out on beneficial matches simply because users misperceive preferences of other users, leading them to behave inefficiently.[6] Our results indicate scope for changes in the design and recommendation algorithms of matching platforms with the notion of providing additional information to users, whether through pricing guidance, algorithmic nudges, or the provision of information on job-level outcomes. Relative to traditional labor markets, the environment we study provides richer information to users, features frequent interactions over shorter-term contracts, and involves narrowly defined tasks, suggesting that the perception gaps we document could be even more important in traditional market 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 the evidence on perception gaps. In section 6, we present the results of the information treatment to correct perceptions. In section 7, we present the theoretical framework. Section 8 concludes.

2 The platform

We study one of the largest online platforms for freelance work in Europe. Founded over 10 years ago, it operates in over 15 countries. We focus on its largest market, France.

The platform hosts a wide range of mostly high-skilled occupations, including technology (e.g., developers) as well as other jobs like marketing and communication. Jobs vary substantially in duration (from a few hours to six months), daily wage rates (€125 to

[6]Entry in these markets may also be distorted by the perception gaps we document, both in terms of who and how many enter. Our results provide a channel through which some workers may overestimate the returns to freelancing or gig work relative to more traditional salaried work (Pires, 2022; Freeland et al., 2026).

€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 €6,100 and lasts one month, indicating that jobs are economically meaningful and high stakes. For 75% of workers in our experiments, freelancing is their main source of income.

We refer to freelancers as "workers," though they are legally independent contractors under French law, rather than employees. Jobs do not constitute employment contracts, and standard regulations regarding salaries, benefits, dismissals, etc. typically do not apply, resulting in highly 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 employing tens of thousands of workers, but are mostly made up of small and medium businesses. Each account is usually 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 functions.

To join the platform, workers and recruiters create a free account and profile. Once completed and approved, worker profiles become visible to recruiters.[7] As is common in online labor markets, recruiters initiate contact after viewing profiles, including their asked wage (Roussille, 2024). Moreover, 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).

Recruiters search for workers using keywords and filters that generate customized lists of profiles. They can then contact workers by sending a "job offer," which specifies the job description and 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 primarily 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. Moreover, the existence of this paid service highlights recruiters' willingness to pay for targeted recommendations, which we use to incentivize recruiter evaluations in the experiment.

[7]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.

When contacted—either directly 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 the first two margins of the process: (i) how recruiters evaluate worker profiles when deciding whom to contact (hire), and (ii) how freelancers evaluate job offers when deciding whether to submit a quote (accept the job).

2.1 Administrative data

We have access to administrative data covering all platform activity between 2021 and March 2026, including the full content of profiles, job offers, and realized job outcomes.

We use these data for three main purposes. First, they inform the experimental design by allowing 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 and validate experimental findings against observed behavior and realized outcomes. Third, this linkage allows us to examine whether our information treatment affects real behavior, in particular changes to workers' profile content.

We present an overview of the platform's activity in 2025 in Table 1. We begin in Panel A with the universe of worker profiles, restricted to those active and visible to recruiters at least at some point during the year, yielding 229 thousand workers. Workers are in their mid thirties on average, have an average of 1.5 completed jobs (though there is stark heterogeneity along this dimension, as discussed below), have been on the platform for just over two and a half years, and have slightly more than 11 years of work experience. The average daily asked wage is around €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.

We then consider the universe of offers by recruiters during the year in Panel B,

totaling 48 thousand offers. Recruiters have been on the platform for just over two years on average, with each having offered an average of 2 jobs on the platform. The average budget for a job is €6,100 for an average duration of one month. Just under 40 percent of offers require full-time work and around 17% require on-site work. The bulk of recruiter accounts are associated with small firms with at most 10 employees, though medium and large firms are actually overrepresented on the platform, since over 90% of firms in the French labor market have less than 10 employees (Institut national de la statistique et des études économiques , Insee).

3 Experimental design

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

3.1 Job categories

The experiments focus on some of the largest job categories 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, remote work), and involve workers and recruiters who differ in terms of characteristics like gender.

We partition these broad categories into narrower job categories. Development is divided into front-end, back-end, full-stack, mobile, and integration/CMS/webmaster; communication into content redaction as well as social media and community management. 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. For example, mobile developers typically specialize in operating-system-specific applications (e.g., iOS), while back-end developers focus on server-side architecture and databases. See Appendix D for a short description of each job category as provided to participants in the experiment.

Profiles and job offers are constructed at the job-category level and 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 misperceptions 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).

Finally, we focus on these categories for two practical 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, hiring decisions in these categories rely primarily on traditional characteristics included on profiles and offers. In contrast, some creative jobs (e.g., graphic design) depend heavily on individualized portfolios, which would be difficult to randomize while preserving realism.

See Table B.1 for summary statistics by job category.

3.2 Constructing profiles and offers

Profiles and offers are designed to closely replicate the format, layout, and content observed on the platform. They appear nearly identical to actual profiles and offers, but are streamlined and standardized.

The content and distribution of each randomized characteristic are informed by administrative data and constructed separately by job category. For example, the range of asked wages on profiles reflects the true range of the empirical distribution of asked wages within the relevant category; the content of listed work experiences is drawn from real descriptions of worker experiences in that category; and the share of offers indicating part-time work requirements is based on the corresponding platform frequency in that category. All attributes are independently randomized across profiles and offers, with the exception of a few characteristics which are only defined for profiles and recruiters with at least one completed job, 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 detailed descriptions 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.[8] Profiles are also indicated to be currently available, as signaled on the platform through an "availability badge." These design choices ensure that recruiters evaluate profiles based on underlying attributes rather than concerns about geographic accessibility or platform activity.[9]

Asked wage. Each profile includes a randomized daily asked wage. In the experiment, we fix the asked wage on a profile as the wage that a recruiter would have to pay to recruit the worker.[10]

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

Each experience includes the name of the firm worked at and a short 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 randomly display one or two experiences per profile.[11]

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 are manually reviewed

[8] 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.

[9] While existing work has shown 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.

[10] In practice, asked wages are a strong predictor of realized wages (correlation of 0.93), consistent with prior evidence (Roussille, 2024), and can also serve as a signal of quality (Wolinsky, 1983). Anecdotal evidence suggests that the platform even cautions workers against setting rates that are too low to avoid signaling low quality.

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

by the research team and by the platform to ensure relevance for the job category and to remove references to gender, ethnicity, or senior managerial roles.

A subset of experiences is classified as "prestigious" based on the associated firm, which corresponds to large, well-known organizations. Prestigious firms include 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).[12] Prestige is assigned at the profile level: profiles display either no prestigious experiences 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) prestigious experiences.

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

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

Market reputation. Profiles include the number of completed platform jobs, 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 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

[12]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.

while assigning a constant average rating of 5 to reviewed profiles.[13]

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.[14]

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 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. We randomize both dimensions. 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.[15] 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.[16] Names are randomly assigned to profiles from these lists.

Each name is paired with a corresponding profile 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.[17]

Some results described below indicate that gender and ethnicity were salient, since participants anticipated discrimination against certain groups on the platform, but did not indicate to participants that the study's purpose related to discrimination. Indeed, only one participant out of 69 in our piloting included discrimination as a potential purpose of the study when prompted using an open-ended question, consistent with our communication of the experiment as a platform-driven initiative to understand its matching.

We test the impact of both signaled gender and ethnicity (independently) on evalua-

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

[14]Recruiters can infer that the badge signals platform success, but do not observe the precise criteria for its assignment.

[15]Profile pictures on the platform must correspond to the individual and typically consist of a professional headshot.

[16]Individuals of MENA origin represent France's largest ethnic minority and have been the primary focus of the French literature on discrimination (Laouénan and Rathelot, 2022).

[17]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 approximately that of real profiles on the platform.

tions.

Expertise keywords. Profiles include a list of specific 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 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.[18] Other 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.

Unlike worker profiles, job offers contain substantial 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, while standardizing their format to systematically vary specific characteristics. Each constructed offer corresponds to a job located in France, specifically in the participating freelancer's region, with a start date listed as "as soon as possible," the most common option on the platform. Recall that it is recruiters who contact workers with offers. As such, there are typically no mentions of hard requirements that are easy to assess from a worker's profile, like experience or education, since workers would presumably not receive an offer for which they do not qualify along those margins. In contrast, other aspects like willingness to work in person or specific technical skills can be more difficult to assess with confidence from a profile and are therefore mentioned on offers.

Offers include a description of the tasks to be performed. We build a category-specific

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

pool of task descriptions based on condensed and standardized versions of real offers. While we do not test hypotheses related to task content, including realistic task descriptions enhances engagement and external validity. All descriptions were reviewed by both the platform and the research team to ensure relevance and consistency within each job category.

Offered wage. Each offer includes a randomized daily offered wage. Recruiters typically observe a worker's asked wage before making contact, yet offers may be made both below and above the ask, and final wages can be negotiated. In the experiment, we fix the offered wage as the wage that a worker would receive if they accept. Endogenous price-setting and bargaining makes it difficult to identify price sensitivity using observational data. In contrast, exogenous wage variation in our experimental design allows us to isolate responsiveness to wages.

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 for a job in the past) and (ii) reviews from workers for those jobs. We follow the same approach as for worker 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.

As for profiles, 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 of completed jobs for which a review was left.

Recruiter prestige. As on the platform, 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 worker profiles, relying on the same classification of "prestigious" firms described above. 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 firm." Because prestige is highly correlated with organization size, we

do not attempt to separately identify their effects.

Work conditions. Each offer randomizes job duration, remote versus in-person requirements, and requirement for full versus part-time availability (2–3 days per week). Job duration varies substantially, including across categories, ranging from less than one week to 180 days.

In addition, some job characteristics are occasionally mentioned in free text. We standardize and randomize two of the most common: whether the work is performed independently or as part of a team, and whether the job involves tight or pressing deadlines. The former relates to flexibility and autonomy—often cited as key motivations for freelance work—while the latter captures preferences over stressful or high-pressure environments.

We test the impact of the following five work arrangements on evaluations: duration (in months), remote (yes versus no), full-time versus part time, teamwork requirement versus no requirement regarding task coordination or reporting, and tight deadline requirement versus no timeline requirement.

Demographics. Offers include the first name of the recruiter but no profile picture. This name corresponds to the individual responsible for hiring rather than the firm itself. As with worker profiles, we randomize recruiter names using job-category-specific lists and distinguish four groups: men and women of European origin, and men and women of MENA origin.

Since job offers and recruiter profiles have no pictures, similarity in results on the impact of demographic characteristics of workers on profiles and recruiters on job offers highlights that the results below are unlikely to be driven by experimental choices regarding the inclusion of pictures in experimental profiles.

Expertise keywords. Offers include a set of required expertise keywords. Because it would be implausible for workers to receive and accept 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 never the latter. To ensure internal consistency, we construct category- and expertise-specific pools of task descriptions, so that required

expertise aligns naturally with the content of the offer.

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 recruited through their email address, late in fall 2025, restricting to participants recently active on the platform, meaning recruiters who contacted at least one worker about a job and workers available to be recruited.[19] We contacted participants using a platform email address and formatted the look and content of the email to mirror an official communication.[20] The stated purpose was to participate in a study by the platform to improve matching by better understanding how workers select jobs and how recruiters select workers.

There was no mention of academic research or the researchers, although it was mentioned that the platform reserves the rights to share study data with its associated researchers and that results could be released publicly. This mitigates potential concerns regarding experimenter demand effects from being aware of being in an academic study, while avoiding deception.

Recruiters (workers) received €50 (20) for completing the experiment – which lasted an average of 16 minutes for recruiters and 17 minutes for workers, not counting outliers taking over an hour – along with a chance to win one randomly-drawn prize of €1000.

[19] 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.

[20] We were unable to include the very largest firms in our set of recruiters (6% of the recruiter pool) because their account is handled directly by platform representatives. Since these firms would have made up a 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 to indicate other required expertise not included in the provided list.[21] 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, as explained below.

Next, participants are given instructions for making 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 normal and 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 large pools of workers and recruiters on the platform. This design choice increases statistical power, reduces scope for experimental fatigue, and makes results less sensitive to a few potential outliers. Having fewer evaluations per participant does reduce precision when estimating individual-level preferences, but as we discuss next, recommendations made based on individual preferences were seen as highly relevant to participants

[21] 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.

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 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. 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. See Appendix A for details on the mapping from evaluations to recommendations.

These recommendations are of high value to participants. As mentioned previously, recruiters can pay the platform to avoid searching and receive personalized recommendations. We provide a similar service, basing recommendations on their evaluations. Similarly, it is often believed (and we show below) that workers can improve their profile by completing jobs, and the average value of a job in terms of total wages is €6,100.[22]

We also surveyed recruiters after sending them their recommendations to inquire about their relevance. 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 constitutes the first evidence on the IRR methodology's incentivization procedure and it speaks against potential concerns that having 25 evaluations could have led to low-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:

[22]Some third-party services sell profile advice and tips to workers for the platform, suggesting workers attach value to optimizing their profile and motivating the value of the information treatment we implement.

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?

Participants are informed that their evaluation of both dimensions are factored in their recommendations.[23] Although the first question we ask 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"), participants are incentivized through recommendations to report their preferences for a profile or job, taking into account their perceived likelihood of success when trying to recruit or obtain such a profile or job (the second question). 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 matched to recruiters by the platform's matching service may prefer the absolute best job available, they face higher competition for such jobs. In correspondence studies, a lack of call back can also 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.

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.

[23] A third question about competence - perceived competence of a profile by recruiters and self-assessed competence for a job by workers - is also included but not incentivized. We use this dimension below to help interpret some of our results.

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.[24] The stated purpose was to participate in a platform study to improve its matching services by understanding how preferences of recruiters and freelancers align. Again, there was no mention of the researchers or of academic research.

Participants were mostly 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 €1000.

3.4.2 Predictions and incentivization

Participants first choose a job category using the same process as in the *Evaluation* experiments. 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.[25]

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

[24] Again, we restricted the respondent pool to recently-active accounts, excluding large 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 them to predict preferences of the other side of the market. In practice, these repeat participants account for a minority of the participant samples and exhibit similar perception gaps as participants who did not complete the *Evaluation* experiments, so we pool and present both together. Participants were not eligible to predict both the other side of the market and competitors.

[25] Unlike in the *Evaluation* experiments, participants are not seeking certain workers or jobs. For example, it is recruiters who may be shown job offers and workers who may be shown profiles. 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 a worker to code in Python or Java, but they do 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 below when analyzing data from 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 these keywords.

evaluations from the *Evaluation* experiments 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 profiles (competitors). Similarly, half of workers are tasked with predicting evaluations of recruiters for profiles (the other side of the market), while the other half is tasked with predicting evaluations of workers for offers (competitors). 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.[26]

To incentivize accurate predictions, payoffs depend on the accuracy of predictions using a binarized scoring rule (Healy and Leo, 2025). For five randomly-selected profiles or briefs, recruiters (workers) receive a bonus of €5 (2) with probability increasing in the accuracy of their prediction. See Appendix A for details. 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.

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 predictions about each characteris-

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

tic. These predictions were also incentivized using a similar binarized scoring rule (see Appendix A for details). After making their predictions, participants are provided with tables summarizing their predictions next to the true values. Whenever a prediction falls within the 90% confidence interval of the true value estimated from the *Evaluation* experiments, participants are told that their beliefs are fairly accurate.[27] When outside the confidence interval, they are explained the potential consequences of having incorrect beliefs about the characteristic's effect and given advice on potential changes they could make regarding their behavior on the platform. For example, freelancers who overestimated recruiters' sensitivity to asked wages are told that they may be able to increase the ask on their profile while remaining more competitive than they thought. See Appendix A for the advice given and Appendix D for the instructions.

Lastly, participants are asked how useful they find the information we provide them and about their intentions to modify their behavior along different dimensions (e.g., content of profile or offers, work conditions of their jobs, or selection of workers/jobs), which constitutes our main outcome of interest for the information treatment, along with a test of these intentions using real data on profile modifications by workers.

3.5 Empirical strategy

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

When analyzing both *Evaluation* and *Prediction* experiments, we estimate the following ordinary least squares (OLS) regression model for participant i's rating or prediction of profile p

[27] 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.

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

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 displayed work experiences were at a prestigious firm, *Master* is whether the profile's highest completed education is a Master' 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 origin* 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

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

where *Daily wage* is the offered wage, *Prestigious* is whether the firm is described 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 origin* are whether the recruiter's name indicates the given gender and ethnic origin. We again include participant fixed effects, and standard errors are again clustered at the participant level.

Our primary contribution is to identify four types of perception gaps, between: i) recruiter preferences and worker beliefs about these preferences, ii) worker preferences and recruiter beliefs about these preferences, iii) recruiter preferences and recruiter beliefs about these preferences, and iv) worker preferences and worker beliefs about these preferences.

To estimate perception gaps, we jointly consider evaluations and predictions and simply augment Equations 1 and 2 with an interaction term between each randomized characteristic and whether the observation is an evaluation from the *Evaluation* experiments or a predicted evaluation from the *Prediction* experiments. We also reweight observations from the *Prediction* experiments to match the distribution of job categories across participants from the *Evaluation* experiments to avoid perception gaps potentially arising from imbalance in job categories across the two sets of experiments.

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.[28] In total, 459 recruiters and 1007 workers completed the experiment and, after applying our exclusion criteria, we are left with 348 recruiters and 824 workers. We additionally exclude eight recruiter evaluations in 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 workers would accept an offer, 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 while controlling for potential differences in how respondents use the rating scale (i.e. being systematically more or less severe).[29] Estimates are precise: for characteristics with no statistically significant effect, we can generally rule out economically large impacts on evaluations.

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 (or reservation wage) rather than as a reference point that may be negotiated. As expected, higher asked wages reduce hiring interest. Moving from the 25th to the 75th percentile of the randomized

[28] 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).

[29] Participant fixed effects also purge the impact of expertise keyword(s) on the evaluation of profiles and offers, since these keywords are constant within participant.

wage distribution, corresponding to €300, decreases recruiters' hiring interest by 24% of a standard deviation in profile evaluations.

As shown in Figure 2, the relationship is non-linear. Asked wage increases have very 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 more positively profiles with higher asked wages when they fall within their budget and strongly penalize profiles with asked wages that exceed it, with a €300 increase in that region reducing hiring interest by 65% of a standard deviation (B.10). This correspondence between experimentally recovered preferences and actual budget constraints supports the validity of the design.

Asked wages also appear to function as a signal of competence, partially offsetting their direct price effect. As shown in Table B.2, 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%.[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.

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, where new entrants often struggle to get a first job.[31] 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 simple signal of platform success—generates a similar increase in interest as obtaining a first completed

[30] Although recruiters were asked to rate competence, this dimension was not incentivized in the recommendation mechanism to preserve incentives to trade off hiring interest against the likelihood of a successful match.

[31] Table B.8 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.

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.

Traditional experience signals are 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 the total number of past experiences, since recruiters are informed that only a representative subset is shown on profiles. A second experience may also provide additional job-relevant information about the worker's capabilities and fit.

In contrast, whether past experience occurred at a prestigious firm has little effect on hiring interest. This is despite evidence that the signal was salient, since profiles with prestigious work experiences were rated as less likely to accept a job offer. This muted effect may reflect the composition of recruiters in our sample—few represent large firms (around 5%)—or the fact that platform jobs are narrowly defined around specific skills, limiting the value of broad prestige signals.

A Master's degree has little effect on evaluations, consistent with general ability signals providing limited information.[32] Recruiters appear to prioritize task-specific experience and market reputation over broader educational credentials. 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 signaling 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 a few hours to a few days per week. As a result, variation along these margins generates limited differentiation in hiring interest. Consistent with this, for the

[32]It also has little effect on evaluations of profiles with no completed projects (Table B.8).

[33]In exploratory analyses, we further distinguish degrees obtained from prestigious institutions and find little evidence that even these materially affect evaluations. Results are available upon request.

small 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 mostly being available remotely (B.11). 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 for workers.

Finally, we find no evidence of gender discrimination and little evidence of ethnic 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 productivity-related concerns, although the estimated difference is relatively small. We also find little evidence that other characteristics on a profile are evaluated differently depending on the gender or ethnicity signaled on it (Table B.9).[34]

Our results align with much of the correspondence study literature for gender, but differ from studies documenting substantial discrimination against workers of MENA origin in France.[35] Since callback rates obtained from correspondence studies conflate the hiring interest and acceptance margins, our results are qualitatively consistent with those studies, but estimated magnitudes appear smaller.

This is consistent with the view that freelancing reduces exposure to discriminatory barriers. Jobs are often defined around specific tasks, reducing uncertainty about productivity given rich targeted information included on profiles. Interactions are also typically shorter-term, remote, and more transactional, limiting concerns about other aspects like personal fit. In addition, although budgets for jobs on the platform are economically meaningful, the contractual stakes are much lower than for traditional employment relationships—there are no long-term commitments, dismissal costs, or broader legal liabilities—which may further reduce discriminatory screening (Benson and Lepage, 2024). It seems quite unlikely that these results are driven by demographics not being salient

[34]Exploratory analyses comparing profiles and offers from the greater Paris area versus the rest of France also suggested 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).

or participants anticipating that demographics would not factor in their recommendations, because as we show below, discrimination against MENA profiles was anticipated by participants in the *Prediction* experiments.

4.2 Worker preferences

Workers' interest in accepting a job is also shaped by several offer characteristics, though the relevant dimensions are different from those driving recruiters' 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 features of the job itself, particularly work conditions.

The offered wage is by far 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, this relationship appears approximately linear across the wage distribution (Figure 2). 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.[36] We find a strong discontinuity at the point where the wage on an experimental offer crosses the participating worker's asked wage indicated on their real profile (B.10). 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 reservation point. The fact that preferences estimated in our experiments strongly relate in an intuitive way to real market outcomes 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

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

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 on platforms like Amazon's Mechanical Turk (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.2 indicates that this effect is largely driven by workers feeling less qualified for these jobs. Moreover, some traditional 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 prestigious organizations, reinforcing the interpretation that such jobs are perceived as less attainable. This result potentially reflects the fact that most workers on the platform have limited experience, given evidence below that this penalty is not present among workers with substantial experience.

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. Workers also report a higher perceived likelihood of receiving such jobs. Workers who indicate such a preference on their profile are also estimated to have a markedly higher preference for remote jobs in the experiment, although those who indicate being available either remotely or in person also prefer remote jobs to in-person ones (B.11). Again, the alignment between experimentally-estimated preferences and platform outcomes supports the validity of the experimental design.

Workers attach relatively little weight to whether work is described as being performed independently or in teams. In contrast, 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 longer job duration on both acceptance interest and perceived likelihood of receiving the offer, while full-time requirements have no substantive impact. Figure 2 indicates that short

jobs of less than one week are rated substantially lower, with a more muted impact of increasing duration beyond a few weeks.

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.4), replacing respondent fixed effects with job-category fixed effects (Table B.5), and retaining the small subset of respondents who spent on average fewer than 10 seconds per evaluation (Table B.3). Adjustments for multiple hypothesis testing yield nearly-identical results (Table B.12). Reweighting evaluations so that the participant sample is representative of the platform population also has limited impact on the estimates, beyond a few changes in statistical significance mostly for the likelihood of an offer being accepted or received (Table B.14). Estimates are similar when comparing the first (1-12) to the second half (13-25) of evaluations (Table B.7).[37]

Our results are also 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 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.6).

Table 3 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 emphasizing substantial teamwork.

Table B.13 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

[37]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.

candidates.[38] 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.15 presents results separately by participants' platform experience as indicated on their platform account.[39] 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 they don't penalize offers from prestigious firms and also don't expect to be less likely to receive such offers (Table B.18).[40] Lastly, results are also similar when splitting the sample of worker respondents by whether they have below or above-average years of freelancing experience, whether on the platform or not (Table B.19).

Results are largely similar across participant gender and ethnicity (Tables B.16 and B.17).

Lastly, we express estimates in monetary terms by rescaling coefficients relative to that of the wage, purged of the signaling value of the wage for recruiters (Figure 1). Recruiters are willing to pay €2000-3000 more per month for workers with an established platform reputation—measured by completed projects or a badge—and even more for workers with greater experience and a second detailed work experience. Freelancers are willing to forgo roughly €1500 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.

[38] 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.

[39] Our respondent pool is positively selected along this dimension, especially for workers: roughly half of participants have completed at least one job, compared to substantially less than half among all active users.

[40] We do not present the same analysis for recruiters due to relatively few of them having completed many jobs.

5 Results of the *Prediction* experiments and perception gaps

Our pre-registered recruitment target is 350 recruiters and 800 workers for each version of the experiment (own-side and cross-side), 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] In total, 973 recruiters and 1963 workers completed the experiment and, after applying our ore-registered exclusion criteria, we are left with a sample of 706 recruiters and 1618 workers.

On average, participants make large prediction errors of approximately 1.68 per profile or offer in absolute value, on the scale from 1 to 10, even accounting for individual fixed effects to capture the fact that participants, namely between the *Evaluation* and *Prediction* experiments, may differ in their use of the scale. These within-respondent errors correspond to about two thirds of a standard deviation in the evaluations participants make in the *Evaluation* experiments.

Our primary interest is in understanding to what extent these errors are systematically driven by characteristics randomized on profiles and offers. Before looking at each characteristic in turn, we quantify the overall contribution of perception gaps held by participants to their average prediction error. 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 impact of the characteristic from the *Evaluation* experiments.[42] We find that *more than half* of the entire errors individuals make can be explained by systematic perception gaps they hold

[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 10 seconds, because we only ask participants one question per profile or offer, rather than three.

[42] We use ridge regressions to penalize the individual-level regression coefficients to ensure they do not become too large and to avoid overfitting. The optimal penalization parameter is chosen through cross-validation. We then use the ridge regression parameters to recover an estimated prediction at the individual level that depends only on the characteristics of profiles and briefs. To remove prediction errors arising from scale effects across respondents, we then demean the ridge regression prediction, the "true" valuation of a profile using the coefficients from the *Evaluation* experiments and the predictions from the *Prediction* experiment. After this procedure, we recover two prediction errors - the difference between the ridge regression prediction and the actual evaluation, which we call the systematic perception gap, and the difference between the prediction from the experiment and the actual evaluation, which is the sum of both idiosyncratic and systematic errors. We take the ratio of the variance of these two errors to quantify how much of the variance of the prediction error is explained by the systematic error.

about the specific preferences of other market participants for these characteristics.[43]

We next turn to breaking down prediction errors across the different randomized characteristics of interest, first looking at average perception gaps across individuals and job types. Since these may hide substantial heterogeneity that cancels itself out (i.e. overestimation by some and underestimation by others), we then look at variation in these perception gaps across narrower job categories, and then across individuals. These exercises yield strong evidence of substantial perception gaps that imply economically meaningful information frictions in the labor market we study.

5.1 Recruiter predictions perception gaps

5.1.1 Predictions of worker preferences

Column 1 of Table 4 shows estimates of equation 2 where the dependent variable is recruiters' predicted evaluation of job offers by workers. Recruiters predict that workers prefer offers characterized by higher wage, that are posted by a recruiter with at least one completed job on the platform, that allow for remote work, that are longer, that do not mention tight or urgent deadlines, and that are offered by female recruiters. Qualitatively, we did not identify a statistically significant preference among workers for recruiters who completed at least one job on the platform or for female recruiters, and we did identify a negative preference for recruiters from prestigious firms, but recruiters appear able to successfully predict what other characteristics influence the interest of workers for jobs.

Next, we explicitly test for the presence of perception gaps by comparing estimates from the *Evaluation* and the *Prediction* experiments. We augment equation 2 with interactions between each randomized characteristic and a respondent corresponding to a recruiter (from the *Prediction* experiments) rather than a worker (from the *Evaluation* experiments). These interactions identify differences between workers' preferences for

[43]The remaining variation in prediction errors could arise from several sources. For example, some content on profiles and offers is not explicitly captured by the characteristics we test, including a worker's interest in a specific task content, or a recruiter's assessed fit of a worker given their industry-specific experience or tasks described in their past work experiences. It could also arise from model misspecification (our analyses and quantification assume independent linear relationships between each characteristic and a profile or offer's evaluation or predicted evaluation), other factors like idiosyncratic responses to certain combinations of characteristics, or behavioral biases. 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.

characteristics and recruiters' beliefs about these preferences, representing the perception gaps of interest. A positive value means that recruiters overestimate the importance of a characteristic for workers, while a negative one means that they underestimate it. Since evaluations and predictions are made within job category, we also re-weight observations from the *Prediction* experiments to match the share of job categories from the *Evaluation* experiments. Lastly, since perception gaps may not only differ meaningfully by type of job, but cancel out altogether, we also present results separately for tech and non-tech jobs.

Results are shown in Columns 1 and 2 of Table 5. We find evidence of statistically significant perception gaps in at least one type of job for seven out of the twelve randomized offer characteristics. Most gaps arise from misperception regarding the quantitative importance of characteristics which do statistically significantly affect worker evaluations of job offers, but some also arise regarding characteristics for which we do not identify important worker preferences. Conceptually, perception gaps distort recruiter behavior and are therefore important regardless of whether they concern a characteristic that does or does not in fact affect worker evaluations of job offers.

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 job offer's assessment.

Recruiters overestimate the extent to which higher offered wages increase workers' interest in a job, largely driven by non-tech, where the interaction term represents an overestimation of 46% from the corresponding coefficient in Table 3 and implies that recruiters expect each €100 increase in offered wage to increase worker interest by 14% of a standard deviation in worker evaluations of offers more than it does. Recruiters in non-tech also statistically significantly overestimate the importance of reputation, namely a recruiter having already hired for a job on the platform, expecting it to increase worker interest by 9% of a standard deviation more than it does. Recruiters fail to predict the

negative impact of a job offer coming from a prestigious organization, yielding a positive perception gap of around 10% of a standard deviation on average. 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 regarding full-time requirements are both at least marginally statistically significant and correspond to about 6% of a standard deviation, but of opposite signs, with tech recruiters failing to predict the penalty that tech workers attach to these requirements and non-tech recruiters predicting a penalty that we do not identify among non-tech workers. Recruiters also overestimate the positive marginal effect of a longer project by almost double, especially in tech, corresponding to an anticipated return that is 1.5% of a standard deviation higher than the true return for each additional month.

Lastly, we find some evidence suggesting that recruiters incorrectly expect workers to penalize offers from recruiters of MENA origin, namely in tech, while we do not detect a meaningful effect of recruiter ethnicity on worker evaluations. Prediction gaps also vary relatively little by respondent gender and ethnicity (Table B.25).

Some of these perception gaps, when expressed in terms of the monetary value attached to each characteristic from the *Evaluation* experiments, are very substantial, as shown in Fig 4. For example, the underestimation of workers' valuation for longer jobs corresponds to underestimating the value of job duration by €100 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 euro per month. In contrast, the value of offers from recruiters with at least one previous completed job is overestimated by around €300 per month and of offers from prestigious organizations by almost double that amount per month. On average, perception gaps in absolute value amount to misperceptions of €170 *per characteristic*, indicating that they reflect economically important misperceptions about the value of job characteristics to workers.

So far, we have restricted attention to average gaps across broad job types, but these averages are likely to hide heterogeneity across smaller job categories and even more so

across individual predictors. First, in Figure 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. These coefficients tend to be substantially larger than those above, indicating that perception gaps shown above are attenuated since they vary across jobs.

More importantly, perception gaps 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.

Figure 6 presents the distributions of participant-level perception gaps for each characteristic. Some of the distributions are substantially skewed left or right, consistent with the average gaps presented above, but distributions also exhibit substantial variation with pronounced tails on each side. 40% (15%) of participants have prediction errors above 0.6 (1.2) in absolute value on the 10-point likert scale, corresponding to around one quarter (one half) of a standard deviation in worker evaluations of offers and often several times larger than the characteristic's own impact on worker evaluations.

Overall, we thus find evidence of some substantial average gaps, although average beliefs are roughly accurate for several other characteristics, and that these average gaps hide substantial individual heterogeneity. Moreover, as shown below, perceptions of recruiters regarding preferences of workers on job offers are the most accurate of the four sets of beliefs we test, with even more important perception gaps arising among other sets of predictions.

5.1.2 Predictions of other recruiters' preferences

Column 1 of Table 4 shows estimates of equation 1 where the dependent variable is recruiters' predicted evaluation of profiles by other recruiters. Overall, recruiter predictions imply that every randomized characteristic on a profile except the worker's gender meaningfully affects evaluations of other recruiters. While this differs from our qualitative findings in the *Evaluation* experiments, predicted impacts largely go in the correct direction.

When testing explicitly for perception gaps, we find evidence of statistically significant gaps in at least one type of job for seven out of the thirteen randomized profile characteristics. Gaps arise 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.

The first four gaps relate to market reputation, with predictors overestimating the importance of having at least one completed job, the return to additional completed jobs, a higher share of completed jobs with reviews, and the reputation badge. These amount to relative gaps ranging from 50% to several times the size of the estimated preference from evaluators and to prediction errors of 5% (for every ten jobs completed) to 13% of a standard deviation in profile evaluations.

The next two gaps relate to indicating availability for remote-only and full-time work on profiles, especially for recruiters in non-tech. They expect the first to incur a penalty and the second a benefit, while neither are estimated to meaningfully affect evaluations, leading to gaps of around 10% of a standard deviation in evaluations.

Lastly, recruiters, especially in tech jobs, expect other recruiters to discriminate against MENA profiles, contrary to what we document above. The estimated gap amounts to around 10% of a standard deviation in evaluations. These gaps vary relatively little by respondent gender and ethnicity (Table B.26).

Figure 4 shows perception gaps expressed in terms of the monetary value attached to each characteristic from the *Evaluation* experiments. Values are substantial, with recruiters overestimating the increased willingness to pay of other recruiters for workers

with better market reputation and overestimating their decreased willingness to pay for remote or MENA workers, by an average of nearly €2,000 per month. On average, perception gaps in absolute value amount to misperceptions of €1,028 per month *per characteristic*.

Summarizing perception gaps across individual job categories yields differences of around 0.2 on the 10-point scale, corresponding to 10% of a standard deviation in recruiter ratings of profiles, for each characteristic (Figure 3).

Lastly, these average gaps again dissimulate large heterogeneity across individual predictors as shown in Figure 5. 45% (18%) of participants have prediction errors above 0.5 (1) in absolute value on the 10-point likert scale, corresponding to around one quarter (one half) of a standard deviation in recruiter evaluations of profiles and often several times larger than the characteristic's own impact on recruiter evaluations.

5.2 Worker predictions and perception gaps

5.2.1 Predictions of recruiter preferences

Column 2 of Table 4 shows estimates of equation 1 where the dependent variable is workers' predicted evaluation of profiles by recruiters. Worker predictions imply that they expect every randomized characteristic on a profile except the asked wage and the worker's gender to affect evaluations of recruiters, always in the correct estimated direction, except for preferences for remote work, which is predicted to penalize profiles while we find a small positive, non-statistically significant impact in the *Evaluation* experiments.

Looking directly at perception gaps in Columns 1 and 2 of Table 5, we find evidence of statistically significant perception gaps in at least one of tech or non-tech for nine out of the thirteen randomized characteristics. The estimated perception gap on the asked wage is almost of identical 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 do not anticipate this penalty, leading them to overestimate recruiters' evaluation of a profile by 7% of a standard deviation for each additional €100

in asked wages.

Workers tend to overestimate how much recruiters value market reputation, namely the value of having completed a job (tech and non-tech), of having completed more jobs conditional on having completed at least one (tech), and of the badge (tech and non-tech). The statistically significant interaction terms have magnitudes ranging from around 60 to 150% of the true estimated impact, corresponding to an overestimation of the characteristic's impact on evaluations on the 10-point scale of 9 to 22% of a standard deviation in recruiter evaluations.

Workers overestimate the return to experience, especially in tech where the perception gap is around 50% of the estimated coefficient from the *Evaluation* experiments and implies that workers overestimate how recruiters would increase their interest in a profile by 10% of a standard deviation for each additional 10 projects completed. They also vastly overestimate the return to prestigious work experiences by around 200% overall and even more in non-tech, overestimating the marginal benefit of prestigious work experiences on a recruiter's evaluations by 8% of a standard deviation.

Workers also expect a penalty from indicating availability only for remote work and a benefit from indicating full-time availability, but neither characteristic is estimated to meaningfully affect recruiter evaluations (on average).

Lastly, workers expect MENA profiles to be discriminated against, especially in tech where the bulk of MENA workers are, Workers anticipate a lower evaluation by 9% of a standard deviation in recruiter evaluations, in contrast with the small, negligible positive effect of MENA origin on tech recruiter evaluations reported in Table 3. These gaps vary relatively little by respondent gender and ethnicity (Table B.25), beyond noting that anticipated discrimination against MENA workers appears driven specifically by respondents who are themselves of MENA origin.

Figure 4 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. On average, perception gaps in absolute value amount to misperceptions of €1,274 per month *per characteristic*, again much larger than those from predicting worker preferences from job offers.

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 3).

Lastly, these average gaps again dissimulate large heterogeneity across individual predictors as shown in Figure 5. 49% (22%) of participants have prediction errors above 0.5 (1) in absolute value on the 10-point likert scale, corresponding to around one quarter (one half) of a standard deviation in recruiter evaluations of profiles and often several times larger than the characteristic's own impact on recruiter evaluations.

5.2.2 Predictions of other workers' preferences

Column 2 of Table 4 shows estimates of equation 1 where the dependent variable is workers' predicted evaluation of profiles by other workers. Overall, worker predictions imply that they expect the offered wage, at least one previous hire (job completed) by the recruiter, remote status, and job duration to positively affect worker interest, while they expect recruiters at prestigious organizations and job offers mentioning tight deadlines to be penalized. Qualitatively, workers thus have a fairly good understanding of what characteristics their peers value.

Still, we find that, quantitatively, there are sizable perception gaps. Workers overestimate how reactive their peers are to the offered wage on an offer by about 22%, meaning that each €100 increase increases worker interest by 8% of a standard deviation less than they think. Workers in non-tech largely underestimate the penalty attached to prestigious organizations, by around 67%, which implies that such an offer is evaluated 8% of a standard deviation higher than anticipated by other workers.

Workers underestimate how much their peers value remote work, by about 25% or 7% of a standard deviation, but overestimate how much they value longer jobs by about 300% or 1 percentage point per additional month of duration. Lastly, they largely overestimate the penalty attached to offers with mentions of tight or urgent deadlines, by about two

thirds or 2.4% of a standard deviation. These gaps vary relatively little by respondent gender and ethnicity (Table B.26).

Figure 4 shows perception gaps expressed in terms of the monetary value attached to each characteristic from the *Evaluation* experiments. Some values are again substantial, with workers overestimating the value attached by other workers to offers from prestigious organizations and longer jobs by about €200 per month and €150 per month for each additional month of duration and underestimating the value for remote work and offers mentioning tight deadlines by about €400 per month. On average, perception gaps in absolute value amount to misperceptions of €150 per month *per characteristic*, much more accurate than worker predictions of recruiter preferences on profiles.

On average, gaps in absolute value across job categories correspond to a difference of 0.15 to 0.2 on the 10-point scale, corresponding to 6-8% of a standard deviation in worker ratings of offers, for each characteristic (Figure **??**).

Lastly, these average gaps again dissimulate large heterogeneity across individual predictors as shown in Figure 6. 43% (17%) of participants have prediction errors above 0.6 (1.2) in absolute value on the 10-point likert scale, corresponding to around one quarter (one half) of a standard deviation in worker evaluations of offers and often several times larger than the characteristic's own impact on worker evaluations.

5.3 Robustness and heterogeneity

The main results are robust to retaining the small subset of respondents who spent on average fewer than 6 seconds per prediction (Tables B.21 and B.22). Adjustments for multiple hypothesis testing yield nearly-identical results (Tables B.23 and B.24).

Although our focus is on perception gaps for each characteristic, a related, weaker condition to test whether beliefs about the importance of each characteristic are accurate is to test whether predictions imply that participants hold the correct ranking of characteristics in terms of their relative importance. The rank correlation between individual-level predicted effect sizes and the true estimated effect sizes from the *Evaluation* experiments is about 0.25, indicating a positive but somewhat weak relationship between the two. While this may reflect the fact that several characteristics have somewhat similar muted

impacts on evaluations, complicating their ranking, even focusing on subsets of the most important characteristics indicates substantial ranking errors. For example, while 74% of respondents can correctly predict one out of the top three most important characteristics on profiles and offers, only 22% get two out of the top three, and less than 5% get all three.

6 Results of the information treatment

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 for male and ethnic majority 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 behavior in the marketplace 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 sample of participants is quite limited. In contrast, workers profiles are continuously active and visible on the platform, so a worker intending to change their behavior would likely to do by modifying their profile after the information treatment.

We test this using daily data on profile modifications of workers. For every day in the five days surrounding the day in which they take the experiment (these correspond

to different days for different participants), we create a balanced panel with indicator variables for whether a worker's profile or asked wage was modified that day.

The results are shown in Figure 7. The daily frequency of profile and asked wage modifications is relatively flat in the five days before participants complete the experiment and increases markedly for the days of the experiment and the day that follows it, before returning around the pre-treatment baseline. Estimated increases of around 0.05-0.08 percentage points in panel (a) correspond to increases of around 50-100% from the baseline probability and are stronger for the information treatment about recruiter preferences than that about other workers' preferences. The patterns are similar for panel (b), indicating increases of 0.01-0.04 percentage points or 100-400% from the baseline probability.

Overall, while fewer workers change their profile than would be expected from intentions stated during the experiment, there is clear evidence of some behavioral changes by treated workers consistent with them attempting to optimize based on their updated perceptions of the market.

7 Theoretical framework

7.1 Intuitive overview

The framework provides a simple way to interpret the empirical findings by focusing on how beliefs about others' preferences shape behavior in the market.[44] In the model, 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 the true preferences of others, but make decisions based on their subjective expectations about those preferences. If these expectations are wrong, which we refer as perception gaps, their choices can deviate from what would be optimal under correct information.

The model highlights two main mechanisms through which perception gaps distort

[44]See Appendix C for an extension of the framework to perception gaps about the preferences of competitors.

market outcomes. First, even when worker and job characteristics are fixed, perception gaps distort pricing decisions. For example, a worker who overestimates how much recruiters value their skills may set an asked wage that is too high, while a recruiter who overestimates workers' preferences for the amenities they offer may offer a wage that is too low. Second, when agents can invest in characteristics—such as acquiring skills or designing jobs with certain working conditions—perception gaps lead to inefficient investment choices. Agents invest too much in characteristics whose returns they overestimate and too little in characteristics whose returns they underestimate

As a result, perception gaps reduce expected efficiency in the labor market. Matches that would have generated value may fail to occur because workers and recruiters make decisions based on incorrect expectations about each other. Moreover, even when matches still occur, they generate less surplus than they would if agents have accurate beliefs. The model helps connect the findings to well-known labor market phenomena. For workers, perception gaps can contribute to skill mismatch, excessive credential acquisition, unemployment, and wage inequality. For firms, they can contribute to wage premia, compensating wage differentials, and labor shortages.

7.2 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).

7.2.1 Objective functions and payoffs

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.

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

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

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

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 with higher u have more attractive non-wage amenities and can 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 mechanically 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 with higher v can also ask for more while preserving the probability of getting an offer and securing a higher payoff conditional on accepting an offer.

7.3 Pricing distortions

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 perception gap.

We abstract from modeling uncertainty about x_i and from learning about it to focus on the simplest setting that allows us to show how perception gaps can distort behavior. A dynamic model would be substantially more complicated, namely because it would need to consider simultaneous perception gaps on both sides of the market.

7.3.1 Modified objective functions and payoffs

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 recruiters' valuation of the match, and therefore both the likelihood of receiving an offer for a given asked wage, and the wage that they would be offered conditional on receiving an offer.

7.3.2 Model predictions: pricing

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 to workers 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.*** *Belief-induced 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 perception gaps 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. □

Recruiters who overestimate (underestimate) the attractiveness of their job make offers that are too low (high), because they think such an offer is still likely enough to be accepted (is necessary to have a sufficient chance of being accepted). Similarly, workers who overestimate (underestimate) their attractiveness to recruiters ask wages that are too high (low), because they think such an ask is still likely enough to yield an offer (is necessary to have a sufficient chance of receiving an offer). Intuitively, agents are pricing

based on a wrongly-perceived demand curve, which naturally affects the likelihood of matching.

The distortions described in Proposition 1 aggregate to the market level in a straightforward way. Because matching occurs pairwise and perception gaps operate at the individual level, aggregate match rates equal the cross-sectional average of individual match probabilities. Hence a reduction in individual match probabilities translates directly into lower aggregate matching. Pricing distortions can reduce the probability of a match and lower expected total surplus both by preventing some mutually beneficial matches and by reducing surplus in matches that do occur. The model generates unmatched workers and unfilled jobs—interpretable as unemployment and vacancies—even in the absence of bargaining or search frictions. Perception gaps also generate excess dispersion in posted asks and offers relative to the correct-beliefs benchmark. Over- and underpricing coexist in the market even among agents with identical characteristics, potentially providing a microfoundation for firm pay premia, mismatches, and wage inequality.

In this partial-equilibrium framework, because distortions operate through beliefs about how characteristics are valued, information that shifts beliefs toward the truth—such as our information treatment— could increase both matches and surplus.

7.4 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

[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 seems expositionally less relevant for characteristics like education.

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:

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

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, it seems natural to expect that perception gaps would 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 $\hat{u}(y)$.

7.4.1 Model predictions: investment

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 who overestimate the return to productivity-enhancing characteristics over-invest in skills, while those who underestimate these returns under-invest. Symmetrically, recruiters who overestimate the value of job amenities over-provide them, while those who underestimate this value under-provide them.*

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 worker skills and job amenities, depending on the average direction of belief wedges. Intuitively, when agents overestimate (underestimate) the returns to investment, then too many (few) invest. This also distorts the probability of matching, with net aggregate effects depending on the distribution of perception gaps.

At the individual level, these distortions relate intuitively to important policy challenges like labor shortages and over-education. Our framework intuitively implies that firms who under-invest in non-wage amenities could struggle to attract workers, while those who over-invest would likely be unable to recoup their costs by offering lower wages, leading to an apparent lack of compensating differential. Similarly, workers who under-invest in skills or credentials could struggle to find work (especially in their intended

occupation) while those who over-invest would struggle to find wages high enough to justify their investments.

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 perception 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.

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 plausibly 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.

References

Abebe, Girum, A Stefano Caria, Marcel Fafchamps, Paolo Falco, Simon Franklin, Simon Quinn, and Forhad Shilpi, "Matching frictions and distorted beliefs: Evidence from a job fair experiment," *The Economic Journal*, 2025, *135* (671), 2089–2121.

Agan, Amanda, Bo Cowgill, and Laura Gee, "The Tradeoffs of Transparency: Measuring Discrimination When Subjects Are Told They Are in an Experiment," 2023.

_ , _ , and Laura Katherine Gee, "Do workers comply with salary history bans? a survey on voluntary disclosure, adverse selection, and unraveling," 2020, *110*, 215–219.

Aguirregabiria, Victor and Jihye Jeon, "Firms' beliefs and learning: Models, identification, and empirical evidence," *Review of Industrial Organization*, 2020, *56* (2), 203–235.

Angeli, Deivis, Ieda Matavelli, and Fernando Secco, "Expected discrimination and job search," 2023.

Barbanchon, Thomas Le, Roland Rathelot, and Alexandra Roulet, "Gender differences in job search: Trading off commute against wage," *The Quarterly Journal of Economics*, 2021, *136* (1), 381–426.

Benson, Alan, Aaron Sojourner, and Akhmed Umyarov, "Can reputation discipline the gig economy? Experimental evidence from an online labor market," *Management Science*, 2020, *66* (5), 1802–1825.

_ and Louis Pierre Lepage, "Learning to Discriminate on the Job," *Available at SSRN 4155065*, 2024.

Bertheau, Antoine and Christian Philip Hoeck, "Firms' Beliefs About Wage Setting," 2025.

Bertrand, Marianne and Sendhil Mullainathan, "Are Emily and Greg more employable than Lakisha and Jamal? A field experiment on labor market discrimination," *American economic review*, 2004, *94* (4), 991–1013.

Bryan, Kevin A, Mitchell Hoffman, and Amir Sariri, "Information frictions and employee sorting between startups," 2022.

Bursztyn, Leonardo, Alexander W Cappelen, Bertil Tungodden, Alessandra Voena, and David H Yanagizawa-Drott, "How are gender norms perceived?," 2023.

_ **and David Y Yang**, "Misperceptions about others," *Annual review of economics*, 2022, *14* (1), 425–452.

Caldwell, Sydnee, Ingrid Haegele, and Jörg Heining, "Firm pay and worker search," 2025.

Card, David, "Estimating the return to schooling: Progress on some persistent econometric problems," *Econometrica*, 2001, *69* (5), 1127–1160.

Charles, Kerwin Kofi and Jonathan Guryan, "Studying discrimination: Fundamental challenges and recent progress," *Annu. Rev. Econ.*, 2011, *3* (1), 479–511.

Conlon, John J, Laura Pilossoph, Matthew Wiswall, and Basit Zafar, "Labor market search with imperfect information and learning," 2018.

Cordes, Simon and Max Müller, "Do Firms Know What Workers Want?," 2026.

Cullen, Zoë and Chiara Farronato, "Outsourcing tasks online: Matching supply and demand on peer-to-peer internet platforms," *Management Science*, 2021, *67* (7), 3985–4003.

_ **, Shengwu Li, and Ricardo Perez-Truglia**, "What's my employee worth? the effects of salary benchmarking," *Review of Economic Studies*, 2025.

Culwell-Block, Beverly and Jean Anna Sellers, "Résumé content and format—Do the authorities agree?," *The Bulletin of the Association for Business Communication*, 1994, *57* (4), 27–30.

Dares, ISM Corum, and IPP, "Discrimination à l'embauche des personnes d'origine supposée maghrébine : quels enseignements d'une grande étude par testing ?," Research Report Note IPP n°76, Institut des politiques publiques (IPP) 2021.

_ , _ , and _ , "Discrimination à l'embauche selon le sexe : les enseignements d'un testing de grande ampleur," Research Report Note IPP n°67, Institut des politiques publiques (IPP) 2021.

Deschamps, Pierre, Dylan Glover, Xavier Lambin, Laouénan Laouénan, and Guillaume Chapelle, "Safety First: Gender Differences in Screening on an Online Platform," 2025.

Dishman, Lydia, "Your Resume Only Gets 7.4 Seconds to Make an Impression—Here's How to Stand Out," November 2018.

Echenique, Federico, Nicole Immorlica, and Vijay V. Vazirani, *Online and Matching-Based Market Design*, Cambridge, UK: Cambridge University Press, 2023.

Exley, Christine L, Oliver P Hauser, Molly Moore, and John-Henry Pezzuto, "Believed gender differences in social preferences," *The Quarterly Journal of Economics*, 2025, *140* (1), 403–458.

_ , Raymond Fisman, Judd B Kessler, Louis-Pierre Lepage, Xiaomeng Li, Corinne Low, Xiaoyue Shan, Mattie Toma, and Basit Zafar, "Information-optional policies and the gender concealment gap," 2024.

Freeland, Edward, Andrew Garin, and Dmitri K Koustas, "How Do Workers Think About The Costs and Benefits of Freelance Work? New Evidence From a Survey Experiment," 2026.

Friedrich, Benjamin U and Michał Zator, "Price Discovery in Labor Markets: why do Firms say They Cannot Find Workers?," 2024.

Fuster, Andreas and Basit Zafar, "Survey experiments on economic expectations," 2023, pp. 107–130.

He, Haoran, Marcus Roel, and Qian Weng, "How Many Others Apply for the Jobs I Am Applying for? The Effect of Perceived Labor Market Competition on Job Search," *SSRN*, 2023.

Healy, Paul J and Greg Leo, "Belief elicitation: a user's guide," in "Handbook of Experimental Methodology," Vol. 1, North-Holland, 2025, pp. 81–162.

Institut national de la statistique et des études économiques (Insee), "Le tissu productif français par catégorie d'entreprises en 2023," 2025. Accessed: 2026-03-16.

Jäger, Simon, Christopher Roth, Nina Roussille, and Benjamin Schoefer, "Worker beliefs about outside options," *The Quarterly Journal of Economics*, 2024, *139* (3), 1505–1556.

Kessler, Judd B, Corinne Low, and Colin D Sullivan, "Incentivized resume rating: Eliciting employer preferences without deception," *American Economic Review*, 2019, *109* (11), 3713–3744.

Kline, Patrick, Evan K Rose, and Christopher R Walters, "Systemic discrimination among large US employers," *The Quarterly Journal of Economics*, 2022, *137* (4), 1963–2036.

Laouénan, Morgane and Roland Rathelot, "Can information reduce ethnic discrimination? Evidence from Airbnb," *American Economic Journal: Applied Economics*, 2022, *14* (1), 107–132.

Lepage, Louis-Pierre, Xiaomeng Li, and Basit Zafar, "Anticipated discrimination and major choice," 2025.

Maestas, Nicole, Kathleen J Mullen, David Powell, Till Von Wachter, and Jeffrey B Wenger, "The value of working conditions in the United States and implications for the structure of wages," *American Economic Review*, 2023, *113* (7), 2007–2047.

Mas, Alexandre, "Non-wage amenities," *Handbook of Labor Economics*, 2025, *6*, 373–446.

Miano, Armando, "Search costs, outside options, and on-the-job search," 2025.

Mueller, Andreas I, Johannes Spinnewijn, and Giorgio Topa, "Job seekers' perceptions and employment prospects: Heterogeneity, duration dependence, and bias," *American Economic Review*, 2021, *111* (1), 324–363.

Pires, Pedro, "How much can you make? misprediction and biased memory in gig jobs," 2022.

Roussille, Nina, "The role of the ask gap in gender pay inequality," *The Quarterly Journal of Economics*, 2024, *139* (3), 1557–1610.

Sockin, Jason and Aaron Sojourner, "What's the inside scoop? challenges in the supply and demand for information on employers," *Journal of Labor Economics*, 2023, *41* (4), 1041–1079.

Topel, Robert, "Specific capital, mobility, and wages: Wages rise with job seniority," *Journal of political Economy*, 1991, *99* (1), 145–176.

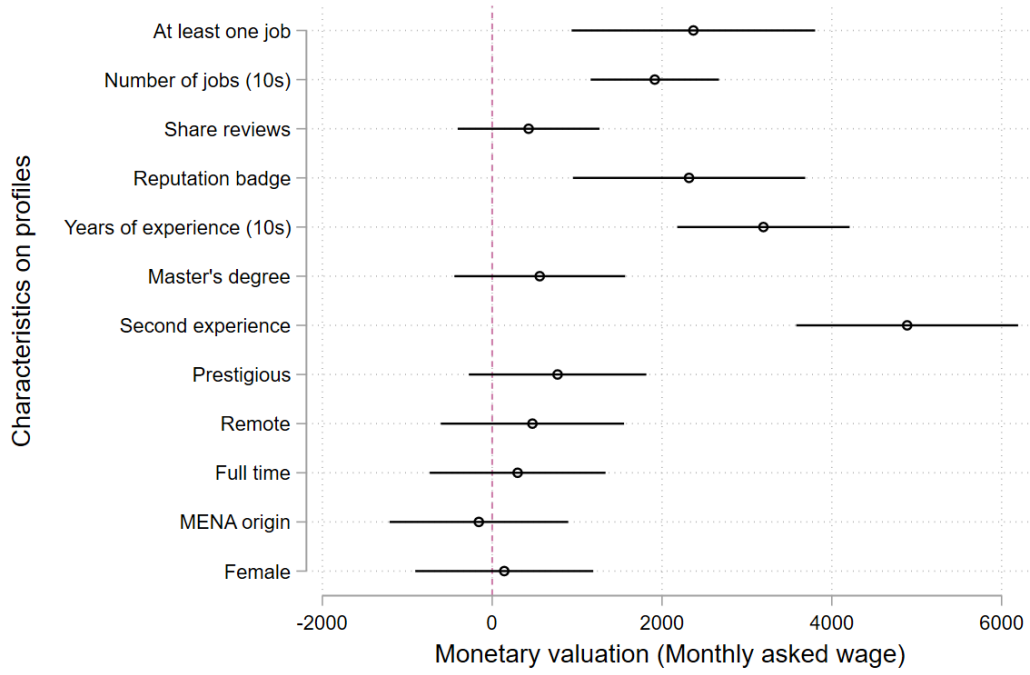
Upwork Research Institute, "Freelance Forward 2023 Research Report," December 2023. Accessed: 2026-03-03.

Wolinsky, Asher, "Prices as signals of product quality," *The review of economic studies*, 1983, *50* (4), 647–658.

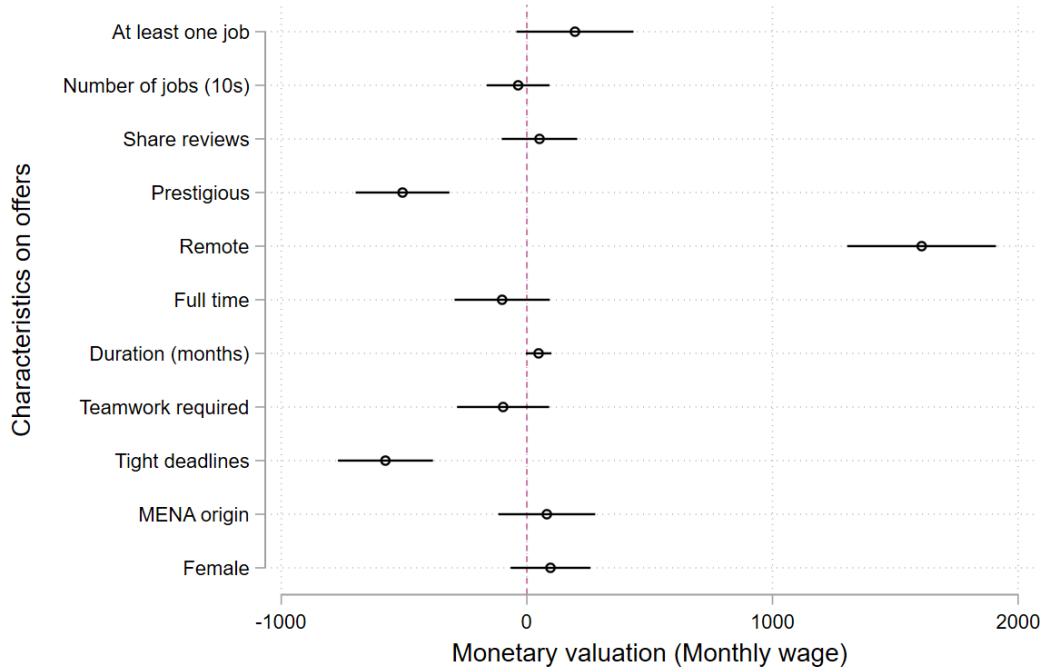
Figures

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

(a) Recruiters



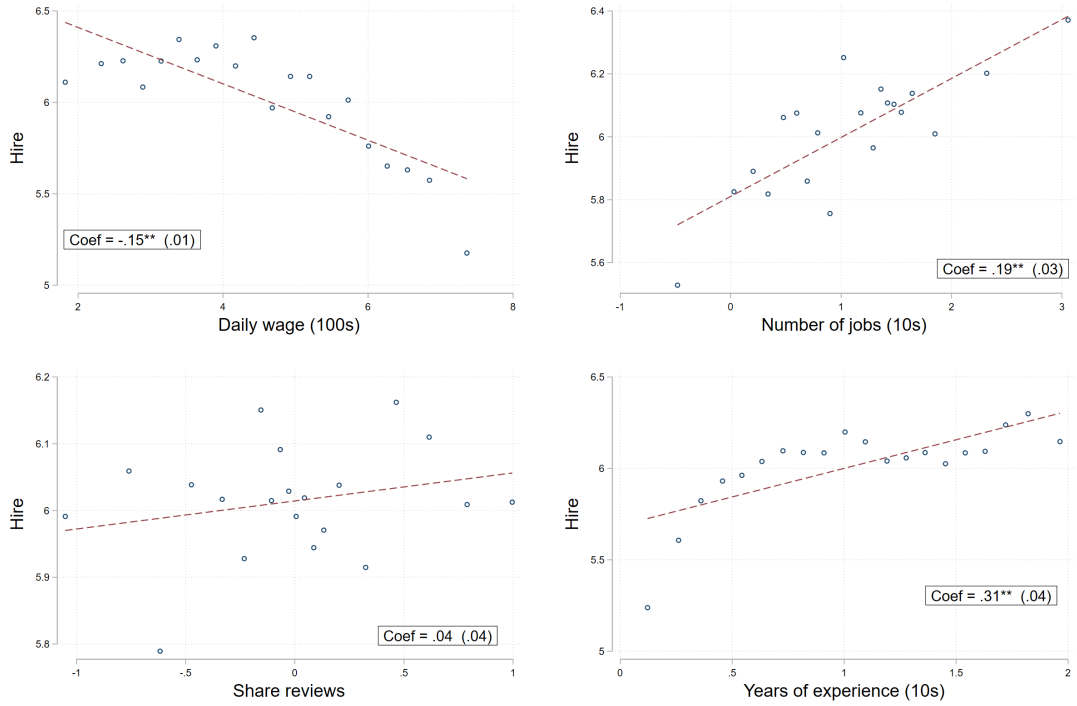
(b) Workers



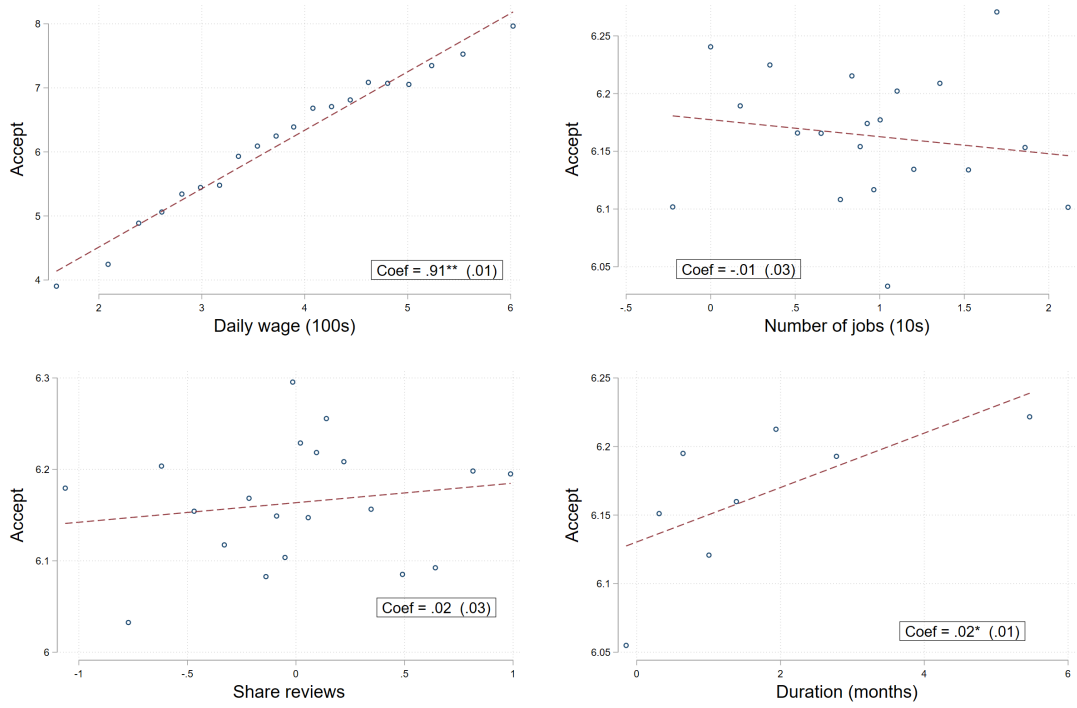
Notes: This figure presents estimates of monetary valuations for each characteristic x randomized on profiles and offers, computed as β_x/β_z, where βs refer to regression coefficients from equations 1 and 2. In Panel (a), β_z refers to the estimated asked wage coefficient from equation 1 but controlling for the reported competence of a profile to purge the signaling component of the asked wage and isolate the price effect (Table B.2). 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: Estimated impact of continuous characteristics on evaluations

(a) Recruiters



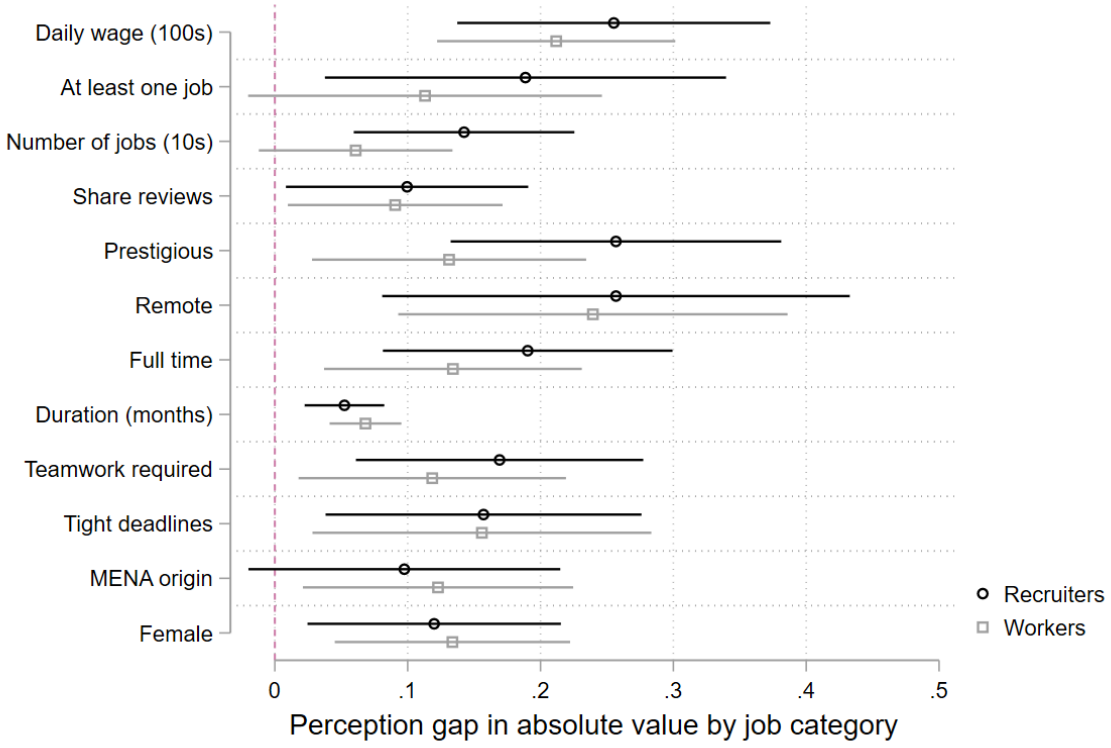
(b) Workers



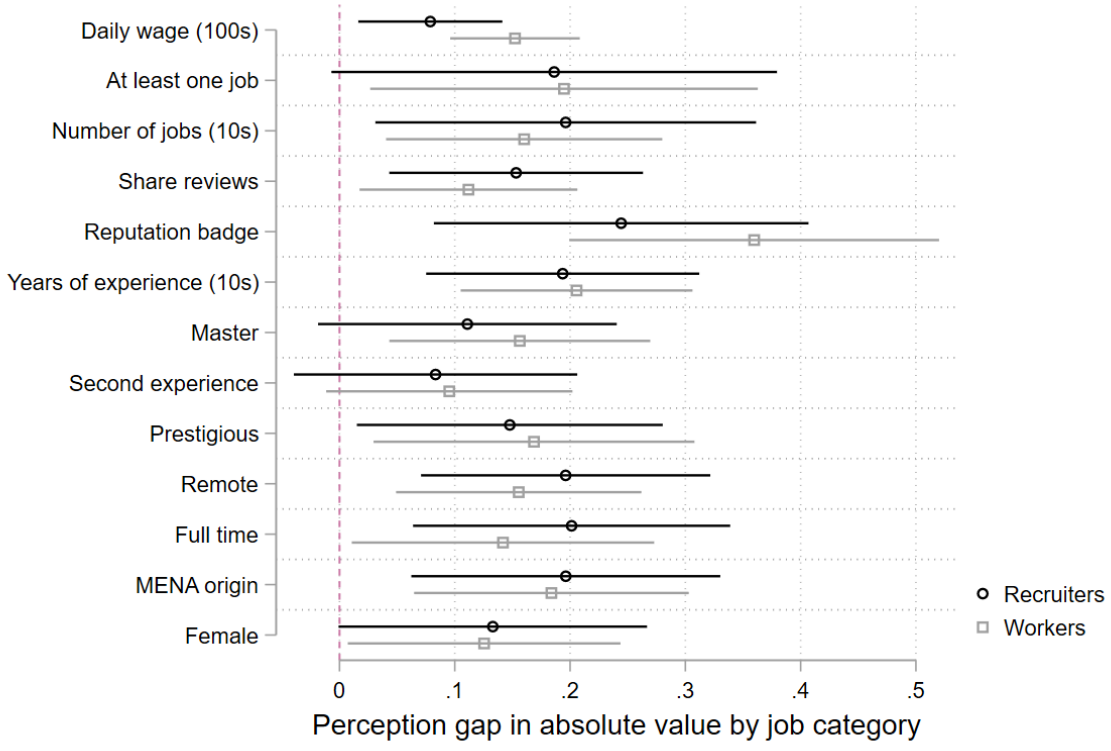
Notes: This figure shows binned scatter plots of the relationship between recruiters' interest in hiring a profile (Panel (a)) or workers' interest in accepting a job (Panel (b)) and the value of continuous randomized characteristics on profiles and briefs, controlling for respondent fixed effects and 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 3: Absolute value of perception gaps by job category from the *Prediction* experiments

(a) Offers



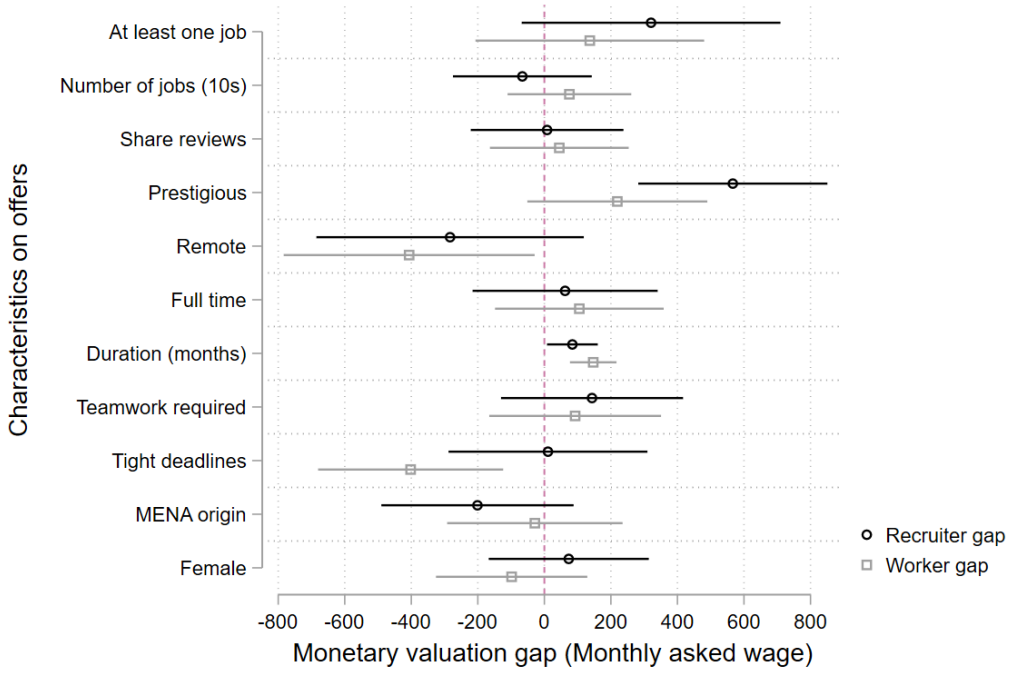
(b) Profiles



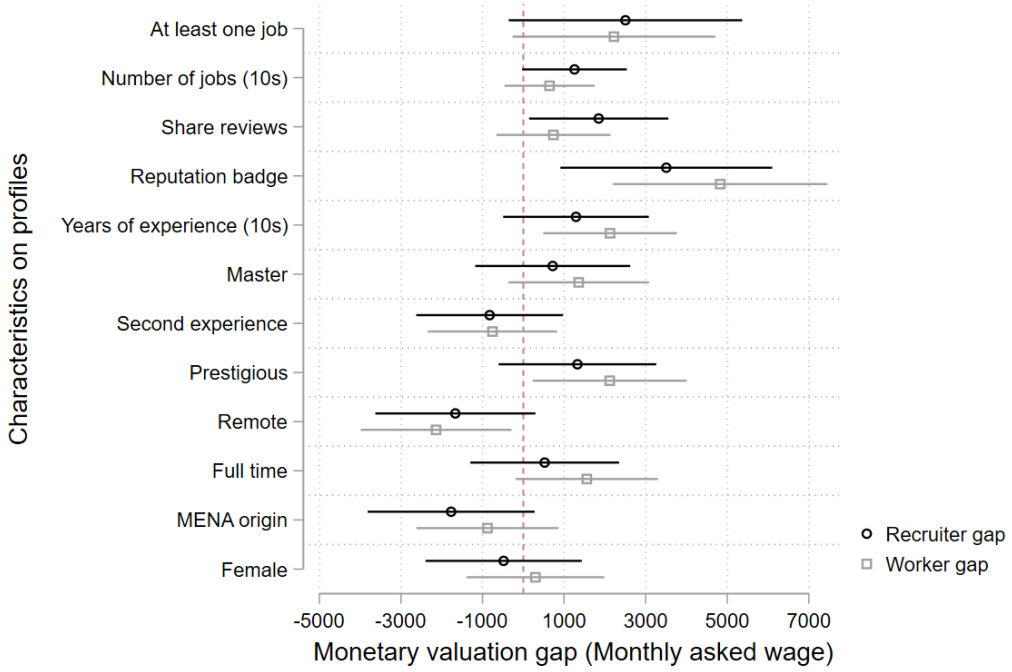
Notes: This figure plots perception gaps estimated at the job category level, transformed to their absolute value, and then average across categories. To recover the average perception gap with standard errors, we use a random effects meta-analysis, which weighs coefficients across different job categories using their inverse variance. Bands represent 95% confidence intervals.

Figure 4: Monetary value of perception gaps

(a) Offers

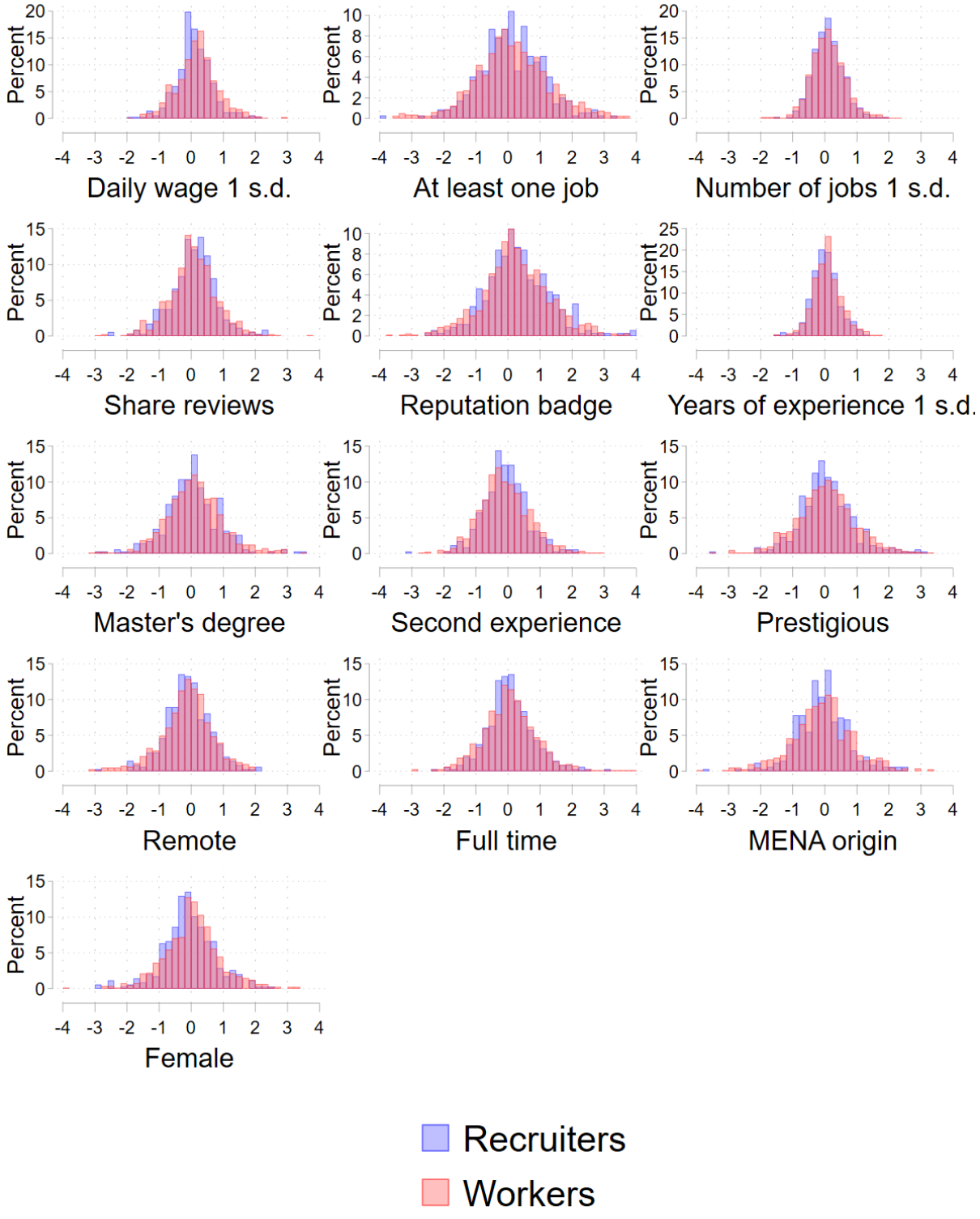


(b) Profiles



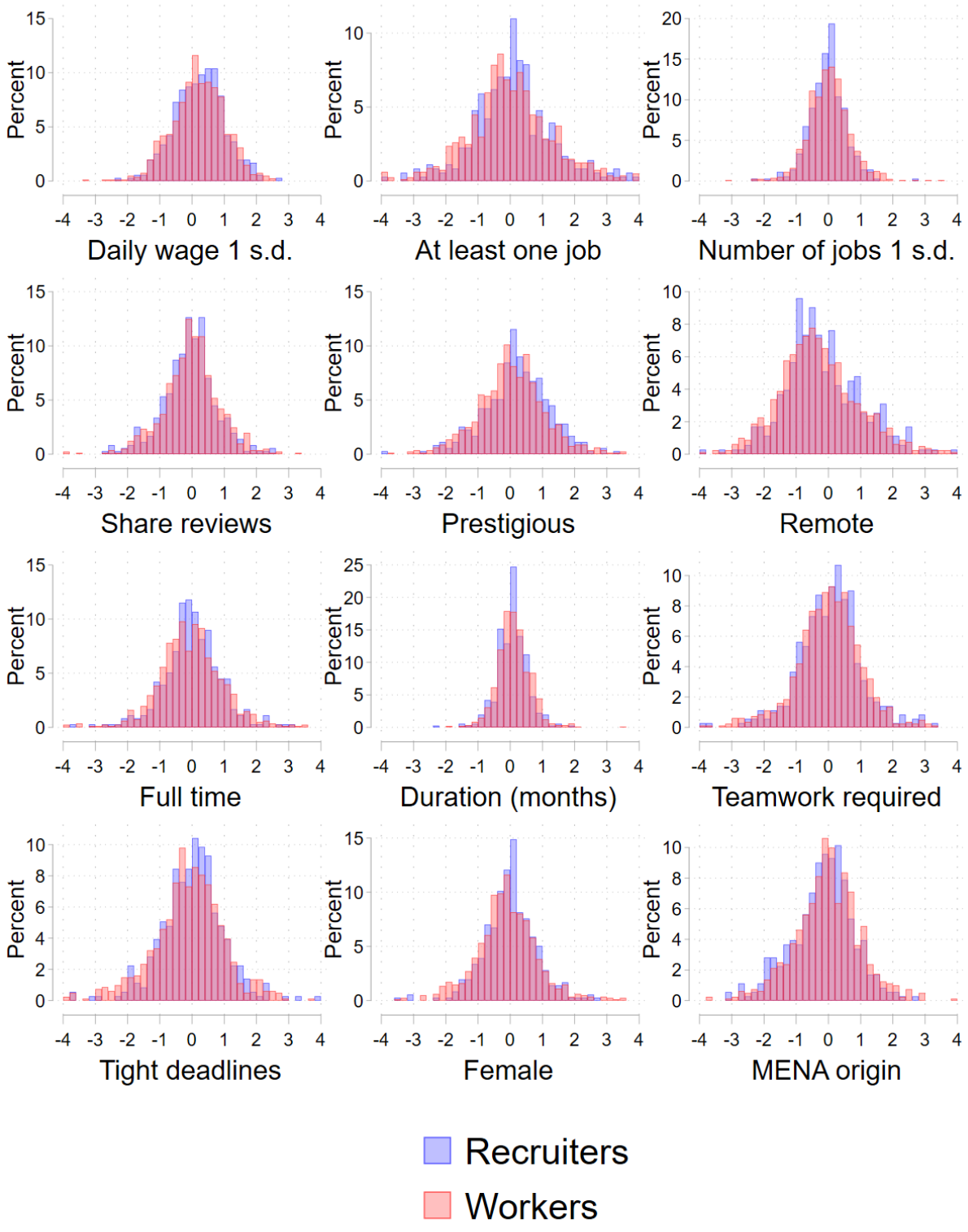
Notes: Each point represents the perception gap for a particular characteristic X, normalized by the daily wage regression coefficient estimated in the *Evaluation* experiments. This valuation is computed as $\frac{\beta_X^p - \beta_X}{\beta_z}$ for offers and as $\frac{\beta_X^p - \beta_X}{-\beta_z}$ 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 but controlling for the reported competence of a profile to purge the signaling component of the asked wage and isolate the price effect (Table B.2). 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 5: Histograms of individual level perception gaps about characteristics on profiles



Notes: Each sub-figure represents a histogram showing the distribution of individual-level perception gaps for a given characteristic, trimming 5% of outliers for each distribution. To compute these perception gaps, we estimate Equation 1 at the individual-level using ridge regressions, where the optimal penalization parameter is obtained through cross-validation. We then compare the obtained ridge regression parameters to the true coefficients estimated in the *Evaluation* experiments.

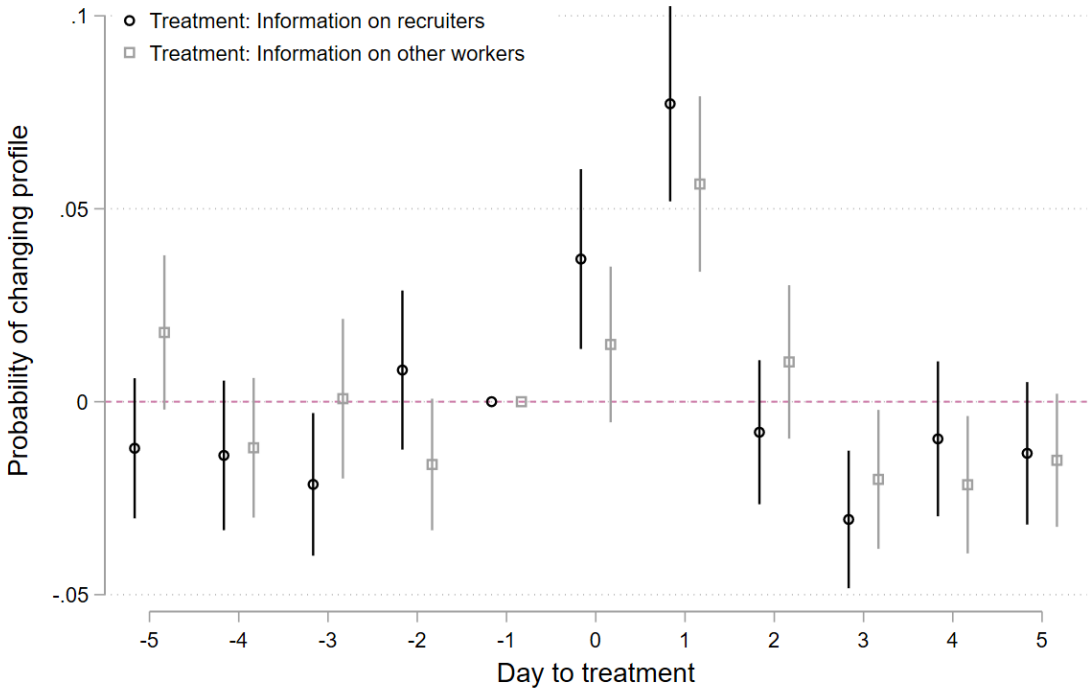
Figure 6: Histograms of individual level perception gaps about characteristics on job offers



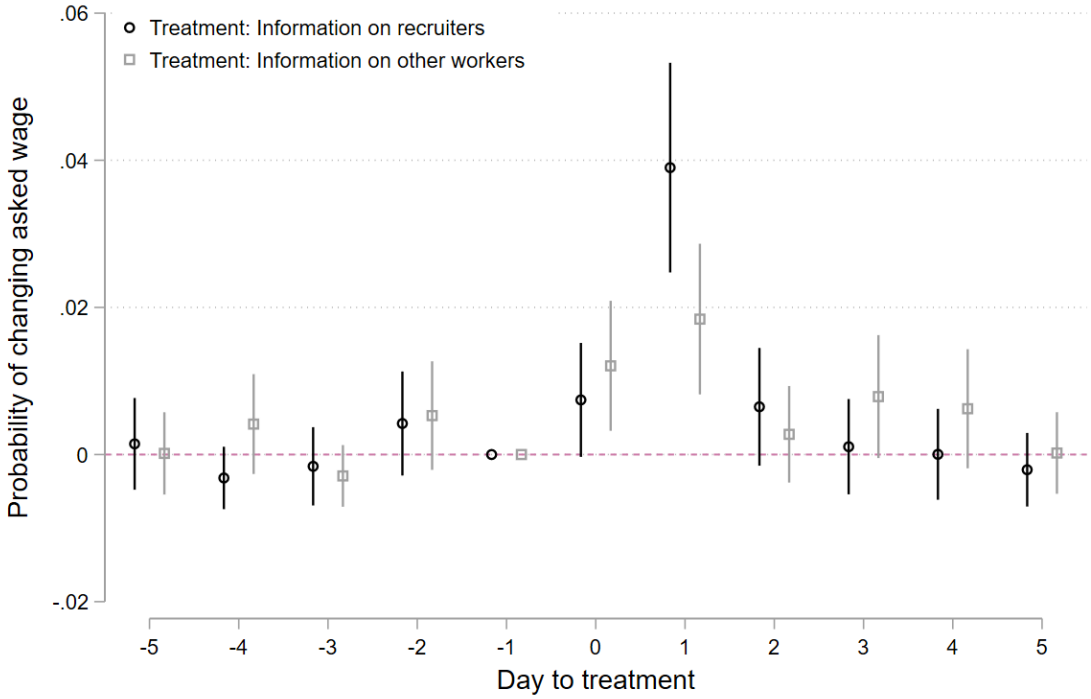
Notes: Each sub-figure represents a histogram showing the distribution of individual-level perception gaps for a given characteristic, trimming 5% of outliers for each distribution. To compute these perception gaps, we estimate Equation 1 at the individual-level using ridge regressions, where the optimal penalization parameter is obtained through cross-validation. We then compare the obtained ridge regression parameters to the true coefficients estimated in the *Evaluation* experiments.

Figure 7: Probability of changing profile for freelancers following the information treatment

(a) Profile change



(b) Asked wage change



Notes: This figure shows the daily probability of a worker changing their profile or specifically the asked wage on their profile on the platform centered around the day in which they received the information treatment (0). Coefficients are normalized to 0 for the day before the information treatment. Bars represent 95 % confidence intervals.

Tables

Table 1: Summary statistics on the market

Panel (a) Workers	
Age	36.19
	(9.47)
Number of jobs	1.46
	(11.57)
Asked wage	462.87
	(244.56)
Years on platform	2.68
	(2.38)
Years of experience	11.17
	(7.25)
Full-time availability (%)	77.1
Remote-only availability (%)	34.4
Master's degree (%)	70.9
Female (%)	40.2
MENA origin (%)	15.2
Number of observations	229,352
Panel (b) Offers by recruiters	
Years on platform	2.08
	(2.19)
Number of offers per recruiter	2.04
	(7.35)
Budget per recruiter (1,000s)	6.17
	(17.24)
Job duration (months)	1.06
	(2.32)
Full-time requirement (%)	39.4
On-site requirement (%)	17.3
Small firm (1–10) (%)	74.5
Medium firm (11–249) (%)	20.6
Large firm (250+) (%)	4.9
Female recruiter (%)	30.9
MENA recruiter (%)	7.7
Number of observations	4,7874

Notes: Panel (a) reports summary statistics for workers visible on the platform for at least one day during the year. Panel (b) reports summary statistics for offers made by recruiters; job-level characteristics are averaged at the recruiter level. Continuous variables are reported as means, with standard deviations in parentheses. Indicator variables are reported as percentages. In Panel (b), offers with budget or duration above the 99th percentile are excluded prior to aggregation. *Number of jobs* refers to the number of jobs completed on the platform. Asked wages corresponds to the wage indicated on workers' profiles. Years of experience corresponds to workers' total years of experience in the labor market. Full-time and remote-only availability are indicator variables for whether workers indicate being available for full time jobs and remote work-only jobs on their profile. Statistics are calculated using data from the 2025 calendar year.

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***
	(0.03)	(0.02)	(0.03)	(0.02)
At least one job	0.232***	0.097*	0.081	0.035
	(0.07)	(0.06)	(0.05)	(0.04)
Number of jobs (10s)	0.187***	0.052**	-0.015	-0.011
	(0.03)	(0.02)	(0.03)	(0.02)
Share reviews	0.042	0.008	0.021	0.003
	(0.04)	(0.03)	(0.03)	(0.02)
Reputation badge	0.227***	0.042		
	(0.07)	(0.05)		
Years of experience (10s)	0.313***	0.006		
	(0.04)	(0.03)		
Master	0.055	-0.049		
	(0.05)	(0.04)		
Second experience	0.478***	0.176***		
	(0.05)	(0.04)		
Prestigious	0.075	-0.126***	-0.210***	-0.160***
	(0.05)	(0.04)	(0.04)	(0.03)
Remote	0.046	0.042	0.667***	0.139***
	(0.05)	(0.04)	(0.06)	(0.03)
Full time	0.029	0.101**	-0.042	0.011
	(0.05)	(0.04)	(0.04)	(0.03)
Duration (months)			0.020*	0.021**
			(0.01)	(0.01)
Teamwork required			-0.040	-0.023
			(0.04)	(0.03)
Tight deadlines			-0.239***	-0.051*
			(0.04)	(0.03)
MENA origin	-0.015	-0.075*	0.034	0.038
	(0.05)	(0.04)	(0.04)	(0.03)
Female	0.014	0.047	0.040	-0.017
	(0.05)	(0.04)	(0.03)	(0.03)
Number of observations	8692	8692	20600	20600
Number of respondents	348	348	824	824
Outcome mean	6.014	6.856	6.164	6.496
Outcome s.d.	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. 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: 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***
	(0.04)	(0.03)	(0.02)	(0.03)	(0.04)	(0.04)	(0.02)	(0.03)
At least one job	0.282***	0.183*	0.018	0.167**	0.100	0.063	0.045	0.017
	(0.09)	(0.11)	(0.08)	(0.08)	(0.07)	(0.07)	(0.05)	(0.06)
Number of jobs (10s)	0.141***	0.220***	0.095***	0.021	-0.003	-0.028	0.020	-0.037
	(0.04)	(0.05)	(0.03)	(0.03)	(0.04)	(0.04)	(0.03)	(0.03)
Share reviews	0.032	0.055	-0.026	0.041	0.038	0.005	0.017	-0.013
	(0.06)	(0.06)	(0.04)	(0.05)	(0.05)	(0.05)	(0.03)	(0.04)
Reputation badge	0.207**	0.254***	0.116*	-0.033				
	(0.09)	(0.09)	(0.07)	(0.07)				
Years of experience (10s)	0.368***	0.262***	0.050	-0.039				
	(0.06)	(0.06)	(0.04)	(0.05)				
Master	0.063	0.054	-0.049	-0.048				
	(0.07)	(0.07)	(0.06)	(0.05)				
Second experience	0.453***	0.506***	0.134***	0.219***				
	(0.06)	(0.07)	(0.05)	(0.06)				
Prestigious	0.118*	0.027	-0.056	-0.198***	-0.127**	-0.292***	-0.111***	-0.210***
	(0.07)	(0.08)	(0.06)	(0.06)	(0.05)	(0.06)	(0.04)	(0.05)
Remote	-0.055	0.148**	0.033	0.050	0.851***	0.477***	0.185***	0.092*
	(0.08)	(0.07)	(0.05)	(0.06)	(0.09)	(0.08)	(0.04)	(0.05)
Full time	0.153**	-0.093	0.161***	0.040	-0.097*	0.021	-0.004	0.031
	(0.07)	(0.07)	(0.06)	(0.06)	(0.06)	(0.06)	(0.03)	(0.05)
Duration (months)					0.037**	0.003	0.021**	0.021
					(0.01)	(0.02)	(0.01)	(0.01)
Teamwork required					0.047	-0.115**	0.004	-0.048
					(0.05)	(0.06)	(0.04)	(0.05)
Tight deadlines					-0.258***	-0.227***	-0.041	-0.063
					(0.06)	(0.06)	(0.04)	(0.05)
MENA origin	0.026	-0.070	-0.079	-0.067	0.080	-0.006	0.030	0.047
	(0.07)	(0.08)	(0.05)	(0.06)	(0.06)	(0.06)	(0.04)	(0.05)
Female	-0.011	0.035	0.056	0.037	0.073	0.015	-0.035	-0.002
	(0.08)	(0.07)	(0.06)	(0.06)	(0.05)	(0.05)	(0.04)	(0.04)
Number of observations	4392	4300	4392	4300	10450	10150	10450	10150
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 s.d.	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 4: Estimates from the *Prediction* experiments

Predictor:	Recruiters		Workers	
Object:	Offers	Profiles	Offers	Profiles
Dependent variable:	Accept	Hire	Accept	Hire
	(1)	(2)	(3)	(4)
Daily rate (100 euros)	1.060***	-0.105***	1.087***	-0.020
	(0.03)	(0.02)	(0.02)	(0.01)
At least one job	0.195***	0.392***	0.140***	0.372***
	(0.06)	(0.07)	(0.05)	(0.05)
Number of jobs (10s)	-0.011	0.289***	0.028	0.246***
	(0.03)	(0.03)	(0.03)	(0.02)
Share reviews	0.012	0.172***	0.028	0.093***
	(0.03)	(0.04)	(0.03)	(0.03)
Reputation badge		0.478***		0.572***
		(0.05)		(0.04)
Years of experience (10s)		0.414***		0.474***
		(0.04)		(0.03)
Master		0.112**		0.158***
		(0.05)		(0.03)
Second experience		0.416***		0.421***
		(0.04)		(0.03)
Prestigious	0.040	0.172***	-0.113***	0.229***
	(0.04)	(0.04)	(0.04)	(0.04)
Remote	0.581***	-0.083**	0.529***	-0.117***
	(0.06)	(0.04)	(0.05)	(0.03)
Full time	-0.025	0.064	-0.009	0.138***
	(0.04)	(0.04)	(0.03)	(0.03)
Duration (months)	0.051***		0.075***	
	(0.01)		(0.01)	
Teamwork required	0.000		-0.015	
	(0.04)		(0.03)	
Tight deadlines	-0.224***		-0.398***	
	(0.05)		(0.04)	
MENA origin	-0.047	-0.140***	0.026	-0.077**
	(0.04)	(0.05)	(0.03)	(0.03)
Female	0.084**	-0.014	0.012	0.042
	(0.04)	(0.04)	(0.03)	(0.03)
Observations	8,900	8,750	20,250	20,200
Number of predictors	356	350	810	808
Outcome variable s.d.	2.050	1.763	2.244	1.782

Notes: This table reports results from estimating Equations 1 and 2 using OLS and participants from the *Prediction* experiments. See Table 2 for further details. Standard errors are clustered at the respondent level. $^{*}p < 0.10$, $^{**}p < 0.05$, $^{***}p < 0.01$.

Table 5: Perception gaps about the preferences of the other side of the market

Evaluator:	Workers			Recruiters		
Predictor:	Recruiters			Workers		
Object:	Offers			Profiles		
Dependent variable:	Accept			Hire		
	(1)	(2)	(3)	(4)	(5)	(6)
Daily wage (100s)	0.171***	0.070	0.355***	0.137***	0.139***	0.135***
	(0.04)	(0.06)	(0.07)	(0.03)	(0.04)	(0.04)
At least one job	0.110	0.006	0.223*	0.158*	0.166	0.119
	(0.08)	(0.10)	(0.13)	(0.09)	(0.11)	(0.13)
Number of jobs (10s)	-0.008	0.002	-0.013	0.046	0.173***	-0.038
	(0.04)	(0.06)	(0.06)	(0.04)	(0.05)	(0.06)
Share reviews	0.002	-0.052	0.061	0.053	0.070	0.029
	(0.05)	(0.07)	(0.07)	(0.05)	(0.06)	(0.08)
Reputation badge				0.343***	0.428***	0.242**
				(0.08)	(0.10)	(0.12)
Years of experience (10s)				0.151***	0.196***	0.095
				(0.05)	(0.07)	(0.08)
Master's degree				0.097	0.094	0.093
				(0.06)	(0.08)	(0.08)
Second experience				-0.054	-0.069	-0.046
				(0.06)	(0.07)	(0.09)
Prestigious	0.241***	0.171**	0.325***	0.151**	0.089	0.211**
	(0.06)	(0.08)	(0.09)	(0.07)	(0.08)	(0.10)
Remote	-0.112	-0.321***	0.131	-0.152**	-0.099	-0.201**
	(0.08)	(0.12)	(0.12)	(0.06)	(0.08)	(0.09)
Full time	0.027	0.157**	-0.142*	0.111*	0.031	0.196**
	(0.06)	(0.08)	(0.08)	(0.06)	(0.09)	(0.08)
Duration (months)	0.036**	0.041*	0.029			
	(0.02)	(0.02)	(0.02)			
Teamwork required	0.052	-0.025	0.136			
	(0.06)	(0.08)	(0.08)			
Tight deadlines	0.011	-0.003	0.028			
	(0.06)	(0.09)	(0.09)			
MENA origin	-0.085	-0.141*	-0.027	-0.062	-0.170**	0.078
	(0.06)	(0.08)	(0.09)	(0.06)	(0.08)	(0.10)
Female	0.032	-0.007	0.068	0.021	0.042	-0.006
	(0.05)	(0.07)	(0.07)	(0.06)	(0.09)	(0.08)
Observations	28,625	15,150	13,475	28,742	17,517	11,225
Number of predictors	356	174	182	808	525	283
Number of evaluators	789	432	357	342	176	166
Evaluator outcome variable s.d.	2.549	2.549	2.549	1.970	1.970	1.970
Job family	All	Tech	Non-tech	All	Tech	Non-tech

Notes: This table reports OLS estimates of Equations 1 and 2 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. Columns 1-3 represent differences between the impact of characteristics on workers' willingness to accept a job offer and the predicted impact of these characteristics by recruiters. Columns 4-6 represent differences between the impact of characteristics on recruiters' willingness to hire a worker and the predicted impact of these characteristics by workers. Observations are reweighted so that chosen job categories in the *Predictions* experiment match the proportions of the *Evaluations* experiment. All regressions control for respondent fixed effects. See Tables 2 and 3 for additional details. Standard errors are clustered at the respondent level. $^{*}p < 0.10$, $^{**}p < 0.05$, $^{***}p < 0.01$.

Table 6: Perception gaps about the preferences of competitors

Evaluator:	Recruiters			Workers		
Predictor:	Recruiters			Workers		
Object:	Profiles			Offers		
Dependent variable:	Hire			Accept		
	(1)	(2)	(3)	(4)	(5)	(6)
Daily wage (100s)	0.052	0.074	0.027	0.198***	0.132***	0.319***
	(0.03)	(0.05)	(0.04)	(0.04)	(0.05)	(0.06)
At least one job	0.178*	0.123	0.242*	0.055	0.036	0.071
	(0.10)	(0.13)	(0.14)	(0.07)	(0.09)	(0.11)
Number of jobs (10s)	0.089**	0.151**	0.040	0.030	0.044	0.019
	(0.05)	(0.06)	(0.06)	(0.04)	(0.05)	(0.06)
Share reviews	0.131**	0.130*	0.132	0.018	-0.012	0.050
	(0.06)	(0.08)	(0.09)	(0.04)	(0.06)	(0.07)
Reputation badge	0.249***	0.298**	0.179			
	(0.09)	(0.12)	(0.12)			
Years of experience (10s)	0.092	0.061	0.113			
	(0.06)	(0.09)	(0.09)			
Master's degree	0.051	0.086	0.005			
	(0.07)	(0.10)	(0.09)			
Second experience	-0.059	-0.085	-0.033			
	(0.06)	(0.09)	(0.09)			
Prestigious	0.094	0.123	0.071	0.089	-0.011	0.208**
	(0.07)	(0.09)	(0.10)	(0.06)	(0.07)	(0.08)
Remote	-0.118*	-0.010	-0.224**	-0.164**	-0.233**	-0.083
	(0.07)	(0.10)	(0.09)	(0.08)	(0.11)	(0.11)
Full time	0.037	-0.123	0.208**	0.042	0.103	-0.038
	(0.07)	(0.09)	(0.09)	(0.05)	(0.07)	(0.08)
Duration (months)				0.059***	0.064***	0.053**
				(0.01)	(0.02)	(0.02)
Teamwork required				0.037	-0.032	0.108
				(0.05)	(0.07)	(0.08)
Tight deadlines				-0.162***	-0.154**	-0.165*
				(0.06)	(0.07)	(0.09)
MENA origin	-0.126*	-0.211**	-0.020	-0.012	-0.108	0.098
	(0.07)	(0.10)	(0.10)	(0.05)	(0.07)	(0.09)
Female	-0.034	-0.079	-0.000	-0.040	-0.080	-0.008
	(0.07)	(0.10)	(0.09)	(0.05)	(0.06)	(0.07)
Observations	17,292	8,767	8,525	39,975	24,275	15,700
Number of predictors	350	175	175	810	539	271
Number of evaluators	342	176	166	789	432	357
Evaluator outcome variable s.d.	1.970	1.970	1.970	2.549	2.549	2.549
Job family	All	Tech	Non-tech	All	Tech	Non-tech

Notes: This table reports OLS estimates of Equations 1 and 2 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. Columns 1-3 represent differences between the impact of characteristics on recruiters' interest in hiring a profile and the predicted impact of these characteristics by other recruiters. Columns 4-6 represent differences between the impact of characteristics on workers' interest in accepting a job and the predicted impact of these characteristics by other workers. All regressions control for respondent fixed effects. See Tables 2 and 3 for additional details. Standard errors are clustered at the respondent level. $^{*}p < 0.10$, $^{**}p < 0.05$, $^{***}p < 0.01$.

A Additional details on the experimental design

A.1 Construction of profiles and offers

A.1.1 Examples

Figure A.1: Worker profile - English

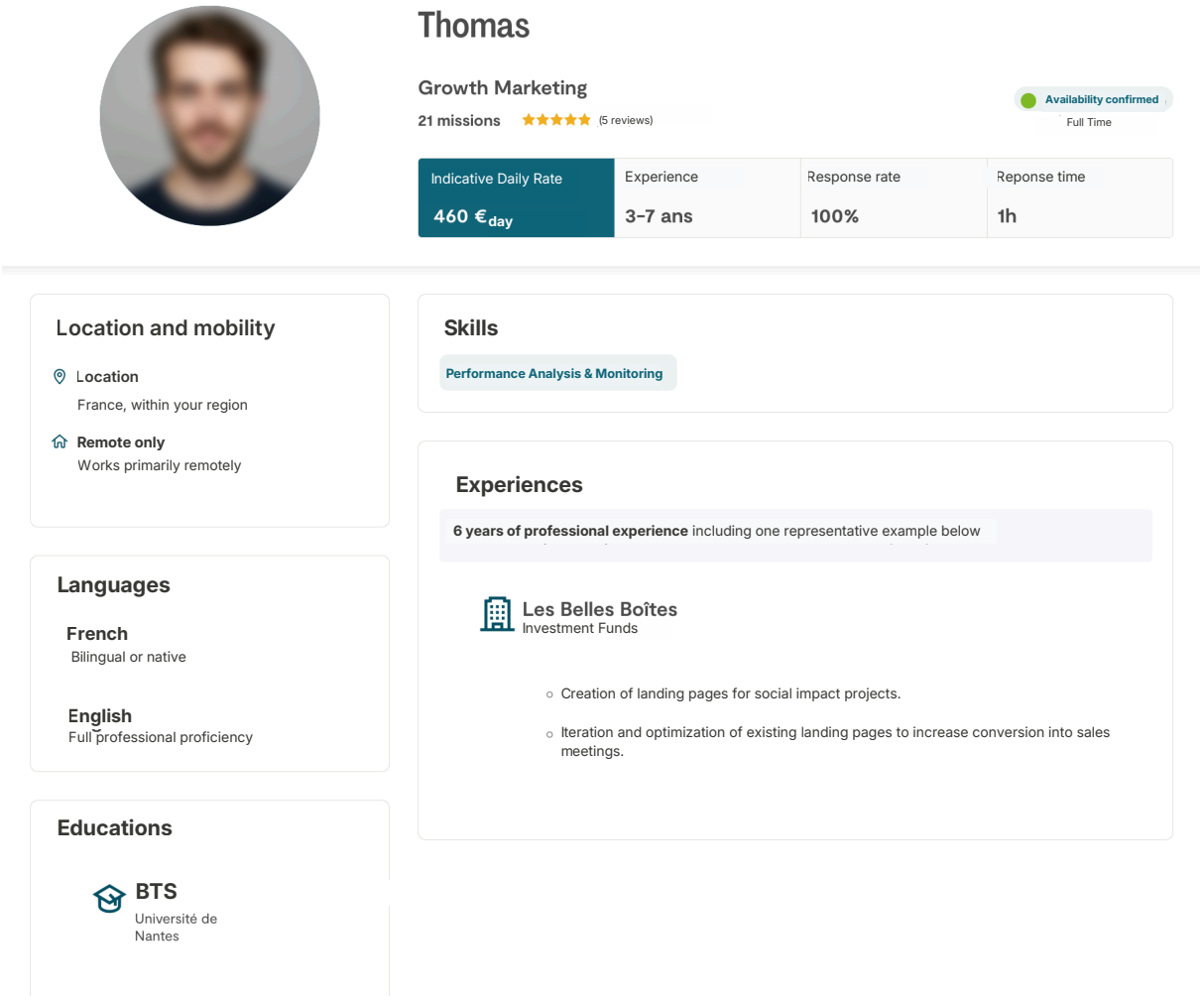


Figure A.2: Worker profile



Thomas

Growth Marketing

21 missions ★★★★★ (5 avis)

Disponibilité confirmée
À temps plein

Tarif indicatif	Expérience	Taux de réponse	Temps de réponse
460 €/ jour	3-7 ans	100%	1h

Localisation et déplacement

Localisation
France, dans dans votre région

En télétravail uniquement
Travaille majoritairement à distance

Langues

Français
Bilingue ou natif

Anglais
Capacité professionnelle complète

Formations

DUT
Université de Nantes

Compétences

Analyse & Suivi de performance

Expériences

6 années d'expérience professionnelle dont voici ci-dessous 1 exemple représentatif

Les Belles Boîtes
Fonds d'investissement

- Création de landing pages pour des projets à impact social.
- Itération sur les landing pages existantes afin d'optimiser les conversions en rendez-vous commerciaux.

Figure A.3: Job offer - English

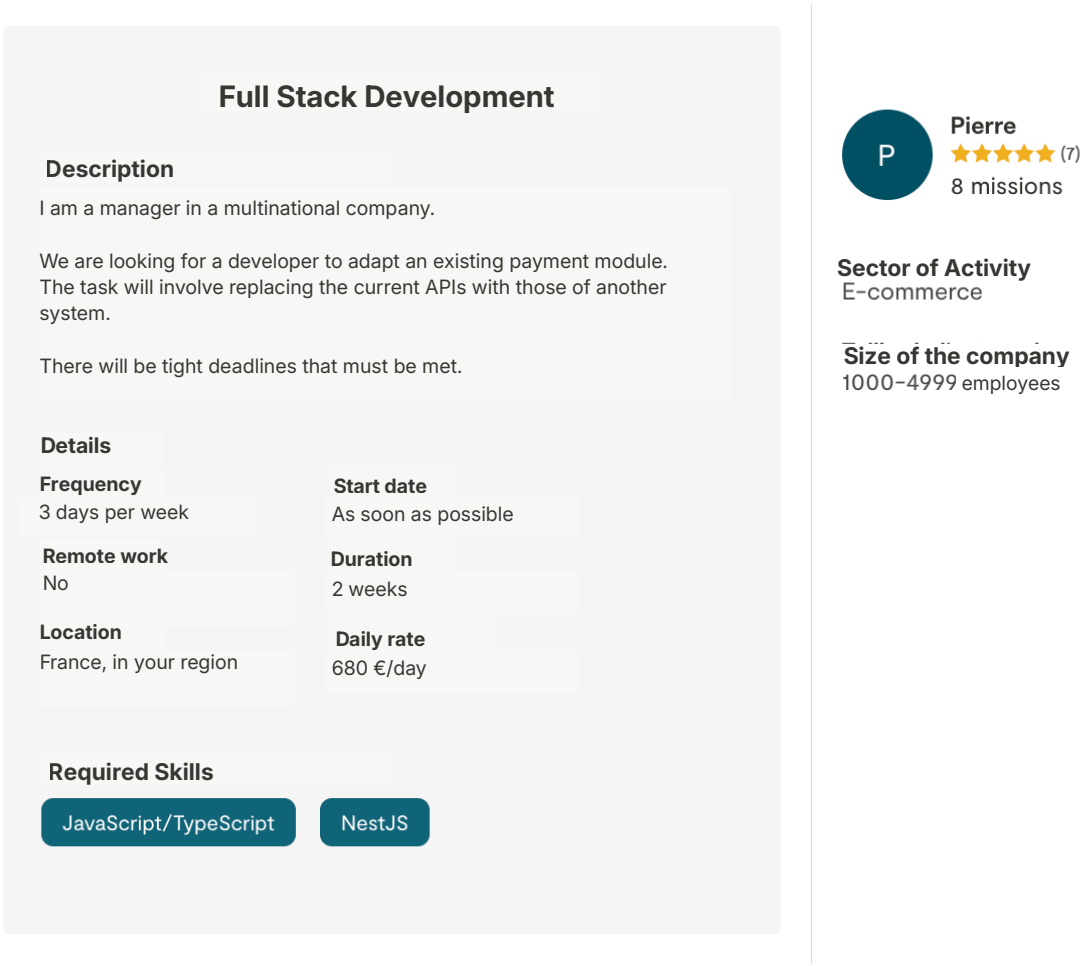
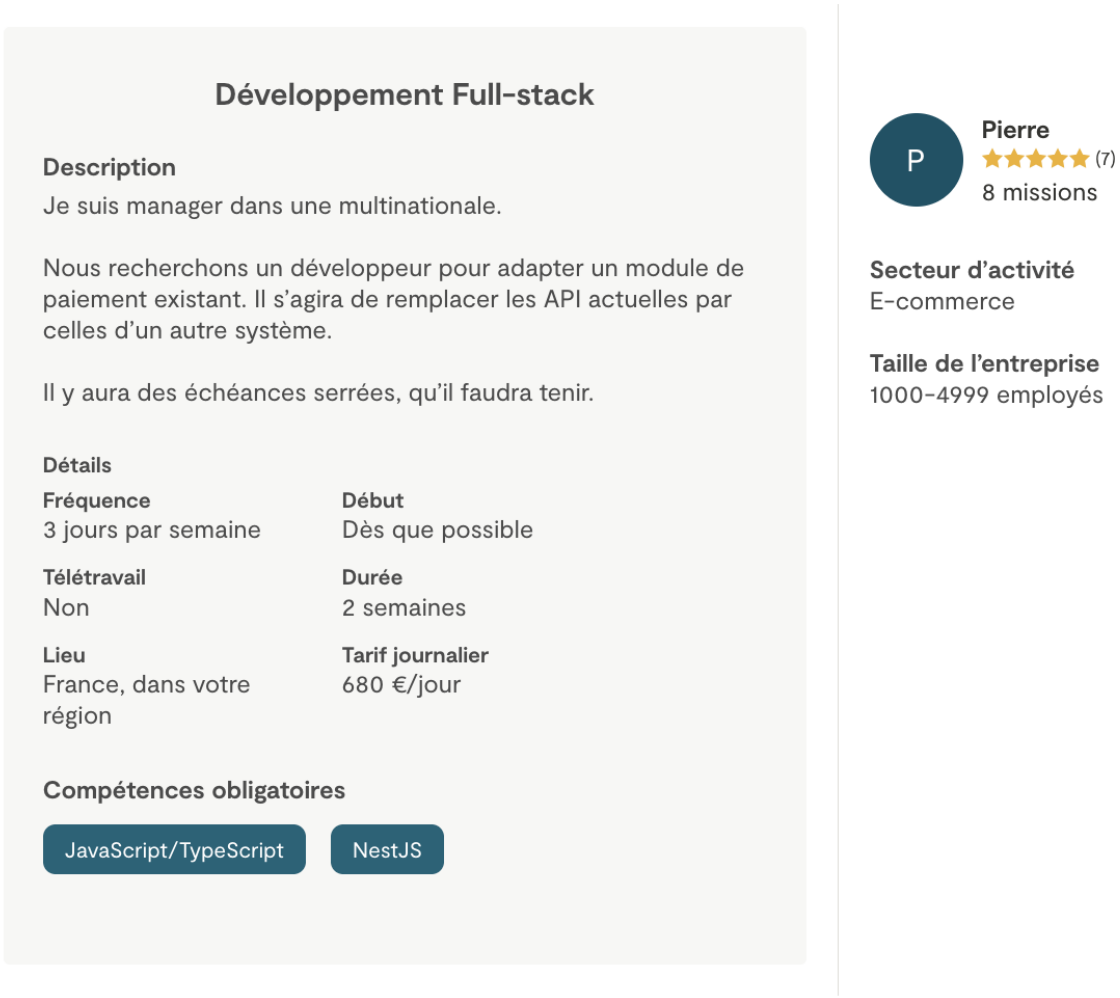


Figure A.4: Job offer



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. 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 corresponding to the 10th and 90th percentiles of asked wages for each job category.

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 using *Gemini* 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 68% of highest credentials correspond to Master's degrees, rounded up to 70% in our randomization. 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 underestimates the true fraction, even for active profiles, which is above 50%. 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 addition, profiles with completed jobs are overrepresented in search results of recruiters, meaning that profiles shown to recruiters in the experiment are more similar to those they would usually see on the platform. 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 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 the middle point of this range at 0.6, and the average share of reviews is roughly constant at 0.6 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 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.[47]

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 actual job offers. Each offer characteristic is adapted to each job category, but again, when differences are minimal, we harmonize the randomization across categories for simplicity. 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 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 of the free text included on offers. In particular, we use the following sentences:[48]

[47] 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.

[48] 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.

- 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.

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 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).

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

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

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.

A.4 Advice shown in the information treatment

For each characteristic about which their prediction was statistically significantly different from the estimated impact of the characteristic from the *Evaluation* experiments, participants received feedback depending on whether they overestimated or underestimated its importance. Characteristics were organized into categories, for example platform reputation, and then, they were given a list of the characteristics in that category that they overestimated with the corresponding advice, and a list of the characteristics in that category that they underestimated, again with the corresponding advice.

A.4.1 Recruiters predicting freelancer preferences

Daily rate

- Overestimation: Freelancers in your sector are **less sensitive** to the daily rate indicated on projects than you thought. You could be competitive even by asking for a higher daily rate or by increasing your requirements.
- Underestimation: Freelancers in your sector are **more sensitive** to the daily rate indicated on projects than you thought. You may need to offer a higher daily rate or reduce your requirements to remain competitive.

Reputation

- Overestimation: These characteristics have a **less positive** effect than you thought on the interest of freelancers. If your client account has these characteristics, you may need to offer a higher daily rate and may find it more difficult to recruit freelancers. If your client account does not have these characteristics, you may be more competitive than you thought.
- Underestimation: These characteristics have a **more positive** effect than you thought on the interest of freelancers. If your client account does not have these characteristics, you may need to offer a higher daily rate and may find it more difficult to recruit freelancers. If your client account has these characteristics, you may be more competitive than you thought.

Working conditions

- Overestimation: These characteristics have a **less positive** effect than you thought on the interest of freelancers. Projects with these characteristics may require a higher daily rate and may be more difficult to fill.
- Underestimation: These characteristics have a **more positive** effect than you thought on the interest of freelancers. Projects without these characteristics may require a higher daily rate and may be more difficult to fill.

Gender / ethnic origin

- Overestimation: Freelancers penalize these projects **more** than you thought. The experience of freelancers with these characteristics may be more difficult than you thought.
- Underestimation: Freelancers penalize these projects **less** than you thought. The experience of freelancers with these characteristics may be less difficult than you thought.

A.4.2 Recruiters predicting recruiter preferences

Daily rate

- Overestimation: Clients in your sector are **more sensitive** to the daily rate indicated on profiles than you thought. You may need to offer a higher daily rate or reduce your requirements.
- Underestimation: Clients in your sector are **less sensitive** to the daily rate indicated on profiles than you thought. You could be competitive even by offering a lower daily rate or by increasing your requirements.

Market reputation / experience / working conditions

- Overestimation: These characteristics have a **less positive** effect than you thought on the interest of clients. Profiles with these characteristics are less valued than you thought and may be less expensive and easier to recruit.
- Underestimation: These characteristics have a **more positive** effect than you thought on the interest of clients. Profiles with these characteristics are more valued than you thought and may be more expensive and more difficult to recruit.

Gender / ethnic origin

- Overestimation: Clients penalize these profiles **more** than you thought. The experience of freelancers with these characteristics may be more difficult than you thought.

- Underestimation: Clients penalize these profiles **less** than you thought. The experience of freelancers with these characteristics may be less difficult than you thought.

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A.4.3 Workers predicting worker preferences

Daily rate

- Overestimation: Freelancers in your sector are **less sensitive** to the daily rate indicated on projects than you thought. You could be competitive even by asking for a higher daily rate or by increasing your requirements.
- Underestimation: Freelancers in your sector are **more sensitive** to the daily rate indicated on projects than you thought. You may need to reduce your daily rate or reduce your requirements.

Market reputation

- Overestimation: These characteristics have a **less positive** effect than you thought on the interest of freelancers. Projects with these characteristics may be less competitive than you thought.
- Underestimation: These characteristics have a **more positive** effect than you thought on the interest of freelancers. Projects with these characteristics may be more competitive than you thought.

Working conditions

- Overestimation: These characteristics have a **less positive** effect than you thought on the interest of freelancers. Projects with these characteristics may be less competitive than you thought.
- Underestimation: These characteristics have a **more positive** effect than you thought on the interest of freelancers. Projects with these characteristics may be more competitive than you thought.

Gender / ethnic origin

- Overestimation: Freelancers penalize these projects **more** than you thought.
- Underestimation: Freelancers penalize these projects **less** than you thought.

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A.4.4 Workers predicting recruiter preferences

Daily rate

- Overestimation: Clients are **more sensitive** than you thought. You may need to lower your rate or reduce your requirements.
- Underestimation: Clients are **less sensitive** than you thought. You may remain competitive with higher rates.

Market reputation / experience / working conditions

- Overestimation: These characteristics have a **less positive** effect than you thought. If you have them, you may need to lower your rate.
- Underestimation: These characteristics have a **more positive** effect than you thought. If you have them, you may remain competitive with higher rates.

Gender / ethnic origin

- Overestimation: Clients penalize these profiles **more** than you thought.
- Underestimation: Clients penalize these profiles **less** than you thought.

B Additional figures and tables

Table B.1: Summary statistics by job category

	Developers	Integration	Translation	Marketing	Copywriting	Content
Budget (1,000s)	12.17	1.58	1.12	4.87	3.94	5.06
	(29.76)	(4.50)	(4.00)	(25.47)	(22.47)	(11.81)
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 jobs (%)	29.0	11.8	11.8	27.0	15.3	5.1

Notes: Entries are means. Standard deviations are shown in parentheses for continuous variables. Indicator variables are reported as percentages. Statistics are calculated for the calendar year 2025.

B.1 *Evaluation* experiments

Table B.2: 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***
	(0.03)	(0.02)	(0.02)	(0.03)	(0.01)	(0.03)
At least one job	0.232***	0.189***	0.081**	0.081	0.063	0.037
	(0.07)	(0.07)	(0.04)	(0.05)	(0.04)	(0.04)
Number of jobs (10s)	0.187***	0.182***	0.043**	-0.015	-0.034	0.009
	(0.03)	(0.03)	(0.02)	(0.03)	(0.02)	(0.02)
Share reviews	0.042	0.003	0.039	0.021	0.002	0.020
	(0.04)	(0.04)	(0.03)	(0.03)	(0.03)	(0.03)
Reputation badge	0.227***	0.228***	0.045			
	(0.07)	(0.06)	(0.04)			
Years of experience (10s)	0.313***	0.375***	0.014			
	(0.04)	(0.04)	(0.03)			
Master	0.055	0.042	0.022			
	(0.05)	(0.05)	(0.03)			
Second experience	0.478***	0.503***	0.078***			
	(0.05)	(0.05)	(0.03)			
Prestigious	0.075	0.070	0.020	-0.210***	-0.158***	-0.098***
	(0.05)	(0.05)	(0.03)	(0.04)	(0.03)	(0.03)
Remote	0.046	0.026	0.025	0.667***	0.072**	0.616***
	(0.05)	(0.05)	(0.04)	(0.06)	(0.03)	(0.05)
Full time	0.029	0.027	0.008	-0.042	-0.021	-0.027
	(0.05)	(0.05)	(0.03)	(0.04)	(0.03)	(0.03)
Duration (months)				0.020*	0.017*	0.008
				(0.01)	(0.01)	(0.01)
Teamwork required				-0.040	-0.003	-0.038
				(0.04)	(0.03)	(0.03)
Tight deadlines				-0.239***	-0.070**	-0.189***
				(0.04)	(0.03)	(0.03)
MENA origin	-0.015	-0.021	0.002	0.034	0.038	0.007
	(0.05)	(0.05)	(0.03)	(0.04)	(0.03)	(0.03)
Female	0.014	0.074	-0.045	0.040	0.040	0.011
	(0.05)	(0.05)	(0.03)	(0.03)	(0.03)	(0.03)
Competence - Likert scale (1-10)			0.795***			0.706***
			(0.01)			(0.01)
Number of observations	8692	8692	8692	20600	20600	20600
Number of respondents	348	348	348	824	824	824
Outcome mean	6.014	6.457	6.014	6.164	7.887	6.164
Outcome s.d.	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 4 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 completed 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.3: 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***
	(0.02)	(0.02)	(0.03)	(0.02)
At least one job	0.202***	0.068	0.088*	0.035
	(0.07)	(0.05)	(0.05)	(0.04)
Number of jobs (10s)	0.187***	0.059**	-0.017	-0.011
	(0.03)	(0.02)	(0.03)	(0.02)
Share reviews	0.030	0.006	0.022	0.003
	(0.04)	(0.03)	(0.03)	(0.02)
Reputation badge	0.226***	0.063		
	(0.06)	(0.05)		
Years of experience (10s)	0.297***	0.022		
	(0.04)	(0.03)		
Master	0.029	-0.047		
	(0.05)	(0.04)		
Second experience	0.447***	0.171***		
	(0.04)	(0.04)		
Prestigious	0.064	-0.120***	-0.202***	-0.159***
	(0.05)	(0.04)	(0.04)	(0.03)
Remote	0.039	0.026	0.655***	0.135***
	(0.05)	(0.04)	(0.06)	(0.03)
Full time	0.017	0.081**	-0.041	0.011
	(0.05)	(0.04)	(0.04)	(0.03)
Duration (months)			0.018	0.020**
			(0.01)	(0.01)
Teamwork required			-0.051	-0.026
			(0.04)	(0.03)
Tight deadlines			-0.235***	-0.045
			(0.04)	(0.03)
MENA origin	-0.025	-0.069*	0.037	0.040
	(0.05)	(0.04)	(0.04)	(0.03)
Female	0.001	0.026	0.045	-0.015
	(0.05)	(0.04)	(0.03)	(0.03)
Number of observations	9542	9542	21075	21075
Number of respondents	382	382	843	843
Outcome mean	6.022	6.799	6.177	6.499
Outcome s.d.	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 2, but without restricting the participant sample to those who spent less than 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.4: 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***
	(0.03)	(0.02)	(0.03)	(0.02)
At least one job	0.225***	0.090	0.082	0.037
	(0.07)	(0.06)	(0.05)	(0.04)
Number of jobs (10s)	0.190***	0.054**	-0.015	-0.011
	(0.03)	(0.02)	(0.03)	(0.02)
Share reviews	0.041	0.009	0.021	0.006
	(0.04)	(0.03)	(0.03)	(0.02)
Reputation badge	0.226***	0.049		
	(0.07)	(0.05)		
Years of experience (10s)	0.314***	0.005		
	(0.04)	(0.03)		
Master	0.050	-0.051		
	(0.05)	(0.04)		
Second experience	0.482***	0.179***		
	(0.05)	(0.04)		
Prestigious	0.072	-0.123***	-0.207***	-0.161***
	(0.05)	(0.04)	(0.04)	(0.03)
Remote	0.049	0.041	0.667***	0.139***
	(0.05)	(0.04)	(0.06)	(0.03)
Full time	0.025	0.107**	-0.041	0.014
	(0.05)	(0.04)	(0.04)	(0.03)
Duration (months)			0.020*	0.020**
			(0.01)	(0.01)
Teamwork required			-0.038	-0.024
			(0.04)	(0.03)
Tight deadlines			-0.238***	-0.050*
			(0.04)	(0.03)
MENA origin	-0.015	-0.075*	0.033	0.042
	(0.05)	(0.04)	(0.04)	(0.03)
Female	0.014	0.041	0.038	-0.017
	(0.05)	(0.04)	(0.03)	(0.03)
Number of observations	8692	8692	20600	20600
Number of respondents	348	348	824	824
Outcome mean	6.014	6.856	6.164	6.496
Outcome s.d.	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 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.5: 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***
	(0.03)	(0.02)	(0.03)	(0.02)
At least one job	0.261***	0.147**	0.040	0.026
	(0.08)	(0.07)	(0.06)	(0.05)
Number of jobs (10s)	0.187***	0.041	0.006	0.012
	(0.04)	(0.03)	(0.03)	(0.03)
Share reviews	0.027	-0.044	-0.002	0.024
	(0.05)	(0.05)	(0.04)	(0.03)
Reputation badge	0.254***	0.036		
	(0.07)	(0.06)		
Years of experience (10s)	0.318***	0.048		
	(0.05)	(0.04)		
Master	0.067	-0.024		
	(0.06)	(0.05)		
Second experience	0.456***	0.142***		
	(0.05)	(0.05)		
Prestigious	0.055	-0.137**	-0.177***	-0.138***
	(0.06)	(0.05)	(0.05)	(0.04)
Remote	0.048	0.042	0.609***	0.085**
	(0.06)	(0.05)	(0.07)	(0.04)
Full time	0.045	0.105**	-0.061	0.009
	(0.06)	(0.05)	(0.05)	(0.04)
Duration (months)			0.017	0.021**
			(0.01)	(0.01)
Teamwork required			-0.071	-0.081**
			(0.05)	(0.04)
Tight deadlines			-0.283***	-0.024
			(0.05)	(0.04)
MENA origin	-0.065	-0.125**	0.045	0.089**
	(0.06)	(0.05)	(0.05)	(0.04)
Female	-0.058	0.017	0.027	-0.009
	(0.06)	(0.05)	(0.04)	(0.04)
Number of observations	8692	8692	20600	20600
Number of respondents	348	348	824	824
Outcome mean	6.014	6.856	6.164	6.496
Outcome s.d.	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 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.6: 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***
	(0.01)	(0.01)	(0.02)	(0.01)
At least one job	0.105***	0.083**	0.036	0.023
	(0.04)	(0.04)	(0.02)	(0.02)
Number of jobs (10s)	0.111***	0.108***	-0.008	-0.009
	(0.02)	(0.02)	(0.01)	(0.01)
Share reviews	0.023	0.024	0.007	0.001
	(0.02)	(0.02)	(0.02)	(0.01)
Reputation badge	0.135***	0.140***		
	(0.04)	(0.04)		
Years of experience (10s)	0.164***	0.188***		
	(0.02)	(0.03)		
Master	0.031	0.055**		
	(0.03)	(0.03)		
Second experience	0.252***	0.220***		
	(0.02)	(0.02)		
Prestigious	0.045	0.102***	-0.093***	-0.091***
	(0.03)	(0.03)	(0.02)	(0.02)
Remote	0.023	0.010	0.306***	0.079***
	(0.03)	(0.03)	(0.03)	(0.02)
Full time	0.018	-0.018	-0.021	0.008
	(0.03)	(0.03)	(0.02)	(0.02)
Duration (months)			0.010**	0.013***
			(0.01)	(0.00)
Teamwork required			-0.016	-0.019
			(0.02)	(0.02)
Tight deadlines			-0.115***	-0.038**
			(0.02)	(0.02)
MENA origin	-0.015	0.014	0.016	0.019
	(0.03)	(0.03)	(0.02)	(0.02)
Female	0.005	-0.012	0.019	-0.013
	(0.03)	(0.03)	(0.02)	(0.02)
Number of observations	8692	8692	20600	20600
Number of respondents	348	348	824	824
Outcome mean	6.014	6.014	6.164	6.496
Outcome s.d.	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 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.7: 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***
	(0.03)	(0.03)	(0.02)	(0.02)	(0.03)	(0.03)	(0.02)	(0.02)
At least one job	0.251**	0.252***	0.077	0.132*	0.067	0.064	0.024	0.033
	(0.10)	(0.10)	(0.07)	(0.08)	(0.08)	(0.07)	(0.06)	(0.05)
Number of jobs (10s)	0.163***	0.171***	0.030	0.051	-0.051	0.020	-0.027	0.007
	(0.04)	(0.05)	(0.03)	(0.04)	(0.04)	(0.04)	(0.03)	(0.03)
Share reviews	-0.014	0.092	0.010	-0.007	0.028	0.030	0.005	0.016
	(0.06)	(0.06)	(0.05)	(0.05)	(0.05)	(0.05)	(0.04)	(0.03)
Reputation badge	0.281***	0.226***	0.023	0.062				
	(0.09)	(0.08)	(0.07)	(0.06)				
Years of experience (10s)	0.465***	0.173***	0.069	-0.045				
	(0.06)	(0.06)	(0.05)	(0.04)				
Master	0.032	0.066	-0.063	-0.027				
	(0.07)	(0.07)	(0.05)	(0.05)				
Second experience	0.357***	0.613***	0.092*	0.271***				
	(0.06)	(0.07)	(0.05)	(0.05)				
Prestigious	0.052	0.088	-0.065	-0.173***	-0.273***	-0.162***	-0.238***	-0.096**
	(0.08)	(0.07)	(0.06)	(0.06)	(0.06)	(0.05)	(0.04)	(0.04)
Remote	0.061	0.048	0.033	0.092**	0.688***	0.675***	0.109**	0.182***
	(0.07)	(0.07)	(0.05)	(0.05)	(0.07)	(0.07)	(0.05)	(0.04)
Full time	0.003	0.061	0.048	0.178***	-0.045	-0.051	0.047	-0.028
	(0.07)	(0.07)	(0.06)	(0.06)	(0.06)	(0.05)	(0.04)	(0.04)
Duration (months)					0.016	0.034**	0.027**	0.020*
					(0.02)	(0.01)	(0.01)	(0.01)
Teamwork required					-0.112*	0.022	-0.092**	0.044
					(0.06)	(0.05)	(0.04)	(0.04)
Tight deadlines					-0.318***	-0.175***	-0.042	-0.042
					(0.06)	(0.05)	(0.04)	(0.04)
MENA origin	-0.044	-0.008	-0.073	-0.092	0.028	0.036	0.022	0.065
	(0.08)	(0.07)	(0.06)	(0.06)	(0.06)	(0.06)	(0.05)	(0.04)
Female	0.004	0.053	0.071	0.010	0.050	0.048	-0.039	0.020
	(0.07)	(0.07)	(0.05)	(0.05)	(0.05)	(0.05)	(0.04)	(0.04)
Number of observations	4176	4516	4176	4516	9888	10712	9888	10712
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 s.d.	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 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.8: 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***
	(0.03)	(0.03)	(0.03)	(0.02)
Number of jobs (10s)		0.190***		0.055**
		(0.03)		(0.02)
Share reviews		0.049		0.005
		(0.04)		(0.03)
Reputation badge		0.236***		0.057
		(0.07)		(0.05)
Years of experience (10s)	0.345***	0.299***	-0.069	0.030
	(0.08)	(0.05)	(0.07)	(0.04)
Master's degree	0.111	0.026	-0.108	-0.025
	(0.09)	(0.06)	(0.07)	(0.04)
Second experience	0.555***	0.441***	0.218***	0.157***
	(0.09)	(0.05)	(0.07)	(0.05)
Prestigious	0.101	0.039	-0.145*	-0.111**
	(0.09)	(0.06)	(0.08)	(0.05)
Remote	0.076	0.012	0.010	0.054
	(0.09)	(0.06)	(0.07)	(0.04)
Full time	-0.053	0.080	0.014	0.124**
	(0.09)	(0.06)	(0.07)	(0.05)
MENA origin	-0.062	0.011	-0.088	-0.042
	(0.09)	(0.06)	(0.08)	(0.05)
Female	0.032	0.020	0.188***	-0.028
	(0.09)	(0.06)	(0.07)	(0.05)
Number of observations	2701	5991	2701	5991
Number of respondents	348	348	348	348
Outcome mean	5.590	6.205	6.701	6.925
Outcome s.d.	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 Equations 1 using OLS and participants from the *Evaluation* experiments. They correspond to those from the first 4 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.9: 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***
	(0.03)	(0.03)	(0.02)	(0.03)	(0.03)	(0.04)	(0.02)	(0.03)
At least one job	0.234***	0.188	0.137**	-0.020	0.189**	0.369***	0.081	0.118
	(0.09)	(0.12)	(0.07)	(0.10)	(0.08)	(0.13)	(0.06)	(0.11)
Number of jobs (10s)	0.178***	0.236***	0.047	0.072*	0.209***	0.109*	0.051*	0.043
	(0.04)	(0.06)	(0.03)	(0.04)	(0.04)	(0.06)	(0.03)	(0.05)
Share reviews	0.028	0.112	0.032	-0.042	0.047	0.022	0.022	-0.011
	(0.05)	(0.07)	(0.04)	(0.06)	(0.05)	(0.10)	(0.04)	(0.08)
Reputation badge	0.270***	0.113	0.096	-0.058	0.219***	0.298**	0.054	-0.018
	(0.08)	(0.11)	(0.06)	(0.08)	(0.07)	(0.13)	(0.05)	(0.10)
Years of experience (10s)	0.317***	0.292***	-0.040	0.104*	0.292***	0.364***	-0.009	0.030
	(0.05)	(0.07)	(0.04)	(0.05)	(0.05)	(0.09)	(0.04)	(0.07)
Master's degree	0.084	-0.022	-0.012	-0.134**	0.063	0.058	-0.046	-0.064
	(0.06)	(0.08)	(0.05)	(0.06)	(0.06)	(0.11)	(0.05)	(0.08)
Second experience	0.442***	0.540***	0.162***	0.190***	0.487***	0.515***	0.156***	0.279***
	(0.06)	(0.08)	(0.05)	(0.07)	(0.05)	(0.10)	(0.04)	(0.08)
Prestigious	0.075	0.078	-0.162***	-0.083	0.037	0.171	-0.164***	0.024
	(0.07)	(0.09)	(0.05)	(0.08)	(0.06)	(0.11)	(0.05)	(0.08)
Remote	0.074	0.038	0.096**	-0.034	0.079	-0.019	0.066	-0.064
	(0.06)	(0.09)	(0.04)	(0.06)	(0.06)	(0.10)	(0.04)	(0.07)
Full time	0.085	-0.051	0.105**	0.125*	0.026	0.080	0.128***	0.025
	(0.07)	(0.08)	(0.05)	(0.07)	(0.06)	(0.11)	(0.05)	(0.09)
MENA origin	0.031	-0.133	-0.064	-0.113				
	(0.06)	(0.10)	(0.05)	(0.08)				
Female					0.040	-0.132	0.042	0.072
					(0.06)	(0.11)	(0.05)	(0.09)
Number of observations	5618	3072	5618	3072	6737	1948	6737	1948
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 s.d.	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 4 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.10: 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***	1.307***	0.218***	0.333***	0.017
	(0.06)	(0.07)	(0.03)	(0.05)	(0.04)	(0.04)	(0.03)	(0.03)
At least one job	0.125	0.292**	0.051	0.160	-0.003	0.186**	-0.007	0.058
	(0.11)	(0.14)	(0.08)	(0.12)	(0.06)	(0.08)	(0.06)	(0.06)
Number of jobs (10s)	0.205***	0.190***	0.098**	0.014	-0.002	-0.044	-0.016	-0.003
	(0.05)	(0.06)	(0.04)	(0.05)	(0.03)	(0.04)	(0.03)	(0.03)
Share reviews	-0.059	0.115	-0.009	0.004	0.035	0.005	0.018	-0.010
	(0.07)	(0.09)	(0.05)	(0.07)	(0.04)	(0.05)	(0.03)	(0.04)
Reputation badge	0.314***	0.267**	-0.009	0.144				
	(0.11)	(0.12)	(0.08)	(0.10)				
Years of experience (10s)	0.331***	0.350***	0.005	0.049				
	(0.07)	(0.09)	(0.05)	(0.07)				
Master	-0.004	0.033	-0.013	-0.172**				
	(0.09)	(0.09)	(0.07)	(0.07)				
Second experience	0.437***	0.497***	0.168**	0.085				
	(0.08)	(0.08)	(0.07)	(0.08)				
Prestigious	0.089	0.045	-0.115	-0.158*	-0.163***	-0.285***	-0.113***	-0.196***
	(0.10)	(0.10)	(0.08)	(0.09)	(0.05)	(0.06)	(0.04)	(0.05)
Remote	-0.013	0.043	-0.053	0.013	0.589***	0.762***	0.155***	0.106**
	(0.08)	(0.11)	(0.06)	(0.09)	(0.07)	(0.10)	(0.04)	(0.05)
Full time	-0.019	0.062	0.022	0.072	-0.004	-0.114*	0.006	0.014
	(0.09)	(0.09)	(0.06)	(0.08)	(0.05)	(0.06)	(0.04)	(0.04)
Duration (months)					0.014	0.023	0.022**	0.019
					(0.01)	(0.02)	(0.01)	(0.01)
Teamwork required					-0.008	-0.121*	-0.037	-0.024
					(0.05)	(0.06)	(0.04)	(0.05)
Tight deadlines					-0.258***	-0.262***	-0.065*	-0.075
					(0.05)	(0.06)	(0.04)	(0.05)
MENA origin	-0.051	-0.116	-0.055	-0.136	0.099*	-0.049	0.089**	-0.030
	(0.09)	(0.10)	(0.07)	(0.09)	(0.05)	(0.07)	(0.04)	(0.05)
Female	-0.002	-0.044	0.086	-0.044	0.050	-0.055	0.010	-0.092**
	(0.10)	(0.08)	(0.08)	(0.07)	(0.04)	(0.06)	(0.04)	(0.05)
Number of observations	2745	2394	2745	2394	12239	8338	12239	8338
Number of respondents	200	186	200	186	769	677	769	677
Outcome mean	6.082	5.665	7.001	6.701	5.365	7.334	6.474	6.529
Outcome s.d.	1.960	2.020	1.454	1.583	2.519	2.457	1.797	1.775
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.11: 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	0.762***	1.007***	0.149***	0.189***
	(0.05)	(0.07)	(0.04)	(0.04)	(0.05)	(0.04)	(0.03)	(0.02)
At least one job	0.318**	-0.140	0.223**	-0.205	0.109	0.066	0.098	-0.005
	(0.14)	(0.18)	(0.11)	(0.16)	(0.08)	(0.07)	(0.07)	(0.05)
Number of jobs (10s)	0.233***	0.165*	0.009	0.143*	-0.042	-0.001	-0.022	-0.004
	(0.06)	(0.10)	(0.04)	(0.08)	(0.04)	(0.04)	(0.03)	(0.03)
Share reviews	0.003	0.105	0.012	0.026	-0.038	0.065	-0.073*	0.054*
	(0.08)	(0.12)	(0.07)	(0.07)	(0.05)	(0.04)	(0.04)	(0.03)
Reputation badge	0.231*	0.212	-0.008	0.160				
	(0.12)	(0.19)	(0.09)	(0.15)				
Years of experience (10s)	0.197**	0.551***	0.057	0.007				
	(0.08)	(0.12)	(0.05)	(0.08)				
Master	0.027	0.102	-0.158***	-0.061				
	(0.09)	(0.17)	(0.06)	(0.10)				
Second experience	0.381***	0.502***	0.061	0.274***				
	(0.09)	(0.11)	(0.07)	(0.09)				
Prestigious	0.045	0.282*	-0.129	-0.009	-0.285***	-0.157***	-0.190***	-0.141***
	(0.09)	(0.16)	(0.09)	(0.09)	(0.06)	(0.05)	(0.05)	(0.04)
Remote	0.148	-0.345*	0.060	-0.061	0.885***	0.528***	0.194***	0.104**
	(0.10)	(0.19)	(0.08)	(0.08)	(0.10)	(0.08)	(0.05)	(0.04)
Full time	0.033	0.053	0.106	0.093	-0.021	-0.056	-0.045	0.047
	(0.09)	(0.13)	(0.07)	(0.11)	(0.06)	(0.05)	(0.04)	(0.04)
Duration (months)					0.016	0.023*	0.032**	0.013
					(0.02)	(0.01)	(0.01)	(0.01)
Teamwork required					-0.056	-0.029	-0.035	-0.017
					(0.07)	(0.05)	(0.05)	(0.04)
Tight deadlines					-0.180***	-0.272***	0.023	-0.097**
					(0.07)	(0.05)	(0.05)	(0.04)
MENA origin	-0.130	0.029	-0.052	-0.084	0.028	0.033	-0.021	0.075*
	(0.10)	(0.15)	(0.08)	(0.12)	(0.07)	(0.05)	(0.06)	(0.04)
Female	-0.114	-0.122	0.052	-0.089	0.024	0.059	-0.030	-0.006
	(0.10)	(0.14)	(0.08)	(0.10)	(0.05)	(0.05)	(0.05)	(0.04)
Number of observations	2597	1275	2597	1275	8150	12450	8150	12450
Number of respondents	104	51	104	51	326	498	326	498
Outcome mean	5.858	6.076	6.817	6.875	6.188	6.147	6.453	6.524
Outcome s.d.	2.036	1.866	1.562	1.753	2.518	2.582	1.848	1.757
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 job (columns 1-4) and by whether the participating worker's own platform profile indicates availability for working in-person or primarily remotely. 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, 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 2, but presenting 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.13: 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***
	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)
At least one job	-0.006	0.007	-0.008	0.002	0.007	0.002	0.006	0.006
	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)
Number of jobs (10s)	0.028***	0.030***	0.011**	0.011**	-0.004	-0.004	-0.002	-0.005
	(0.01)	(0.01)	(0.01)	(0.01)	(0.00)	(0.00)	(0.00)	(0.00)
Share reviews	0.005	0.005	0.010	0.014**	0.002	-0.002	-0.002	-0.002
	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)	(0.00)	(0.00)
Reputation badge	0.047***	0.033***	0.020*	0.012				
	(0.01)	(0.01)	(0.01)	(0.01)				
Years of experience (10s)	0.025***	0.023***	0.004	-0.000				
	(0.01)	(0.01)	(0.01)	(0.01)				
Master	0.004	0.010	-0.011	-0.015*				
	(0.01)	(0.01)	(0.01)	(0.01)				
Second experience	0.040***	0.037***	0.009	0.007				
	(0.01)	(0.01)	(0.01)	(0.01)				
Prestigious	0.019**	0.014*	-0.013	-0.011	-0.021***	-0.017***	-0.018***	-0.012**
	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)
Remote	-0.000	0.003	-0.002	0.009	0.051***	0.060***	0.017***	0.013**
	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)
Full time	0.009	0.004	0.014*	0.018**	-0.000	-0.003	0.003	0.001
	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)
Duration (months)					0.004**	0.004**	0.003*	0.004***
					(0.00)	(0.00)	(0.00)	(0.00)
Teamwork required					-0.001	-0.001	-0.014**	-0.013**
					(0.01)	(0.01)	(0.01)	(0.01)
Tight deadlines					-0.028***	-0.025***	-0.018***	-0.012**
					(0.01)	(0.01)	(0.01)	(0.01)
MENA origin	-0.008	-0.001	-0.013	-0.005	0.009	0.010	0.005	0.006
	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)
Female	0.006	0.005	0.003	0.006	0.006	0.002	-0.007	-0.002
	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)
Outcome mean	.14	.16	.21	.21	.23	.28	.22	.21
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

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 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.14: 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)	-0.200***	-0.131***	0.820***	0.136***
	(0.03)	(0.02)	(0.05)	(0.03)
At least one job	0.162*	0.072	0.137*	0.018
	(0.10)	(0.07)	(0.07)	(0.06)
Number of jobs (10s)	0.208***	0.051	-0.045	0.039
	(0.04)	(0.03)	(0.04)	(0.04)
Share reviews	0.032	0.010	-0.038	0.002
	(0.06)	(0.04)	(0.05)	(0.05)
Reputation badge	0.274***	0.121*		
	(0.09)	(0.07)		
Years of experience (10s)	0.414***	0.094**		
	(0.06)	(0.04)		
Master	0.035	-0.101**		
	(0.07)	(0.05)		
Second experience	0.440***	0.232***		
	(0.07)	(0.05)		
Prestigious	0.066	-0.077	-0.297***	-0.157***
	(0.08)	(0.06)	(0.06)	(0.05)
Remote	-0.060	-0.032	0.615***	0.066
	(0.07)	(0.05)	(0.08)	(0.05)
Full time	0.070	0.163***	-0.145*	-0.020
	(0.07)	(0.05)	(0.07)	(0.05)
Duration (months)			0.019	0.014
			(0.02)	(0.01)
Teamwork required			-0.065	-0.045
			(0.06)	(0.04)
Tight deadlines			-0.248***	-0.116**
			(0.05)	(0.05)
MENA origin	-0.039	-0.076	-0.015	0.003
	(0.09)	(0.06)	(0.06)	(0.05)
Female	-0.017	0.056	0.016	-0.051
	(0.07)	(0.05)	(0.06)	(0.05)
Number of observations	8692	8692	20600	20600
Number of respondents	348	348	824	824
Outcome mean	6.004	6.930	6.321	6.229
Outcome s.d.	1.960	1.501	2.453	1.740

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 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.15: 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***	0.985***	0.154***	0.194***
	(0.03)	(0.04)	(0.03)	(0.02)	(0.04)	(0.04)	(0.03)	(0.02)
At least one job	0.202**	0.274***	0.112	0.091	0.082	0.077	0.025	0.041
	(0.10)	(0.10)	(0.08)	(0.07)	(0.07)	(0.08)	(0.06)	(0.06)
Number of jobs (10s)	0.193***	0.180***	0.040	0.059*	-0.013	-0.017	0.026	-0.044
	(0.05)	(0.04)	(0.04)	(0.03)	(0.04)	(0.04)	(0.03)	(0.03)
Share reviews	0.009	0.077	-0.008	0.027	-0.012	0.062	-0.042	0.049
	(0.06)	(0.06)	(0.05)	(0.05)	(0.05)	(0.04)	(0.04)	(0.03)
Reputation badge	0.302***	0.141	0.034	0.044				
	(0.09)	(0.10)	(0.07)	(0.07)				
Years of experience (10s)	0.323***	0.305***	-0.017	0.038				
	(0.06)	(0.07)	(0.05)	(0.05)				
Master	0.015	0.102	-0.005	-0.095*				
	(0.07)	(0.07)	(0.05)	(0.05)				
Second experience	0.466***	0.493***	0.199***	0.149***				
	(0.07)	(0.07)	(0.06)	(0.05)				
Prestigious	0.131*	0.012	0.004	-0.270***	-0.264***	-0.157***	-0.159***	-0.161***
	(0.07)	(0.08)	(0.06)	(0.06)	(0.06)	(0.05)	(0.04)	(0.05)
Remote	0.051	0.044	0.106**	-0.031	0.683***	0.634***	0.118***	0.154***
	(0.08)	(0.07)	(0.05)	(0.05)	(0.09)	(0.08)	(0.05)	(0.05)
Full time	0.006	0.062	0.118**	0.082	-0.116*	0.023	-0.016	0.031
	(0.07)	(0.08)	(0.06)	(0.06)	(0.06)	(0.06)	(0.04)	(0.04)
Duration (months)					0.033**	0.006	0.034***	0.007
					(0.02)	(0.01)	(0.01)	(0.01)
Teamwork required					-0.037	-0.046	-0.057	0.008
					(0.05)	(0.06)	(0.04)	(0.05)
Tight deadlines					-0.227***	-0.247***	-0.071*	-0.032
					(0.06)	(0.06)	(0.04)	(0.04)
MENA origin	-0.089	0.064	-0.119*	-0.037	0.044	0.038	0.079*	0.007
	(0.07)	(0.08)	(0.06)	(0.06)	(0.06)	(0.06)	(0.04)	(0.05)
Female	0.088	-0.073	0.123**	-0.040	0.045	0.041	-0.023	-0.010
	(0.07)	(0.07)	(0.06)	(0.06)	(0.05)	(0.05)	(0.04)	(0.04)
Number of observations	4672	4020	4672	4020	10150	10375	10150	10375
Number of respondents	187	161	187	161	406	415	406	415
Outcome mean	5.922	6.121	6.654	7.090	6.266	6.078	6.264	6.727
Outcome s.d.	1.980	1.962	1.565	1.477	2.511	2.596	1.729	1.847
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. 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 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***
	(0.03)	(0.05)	(0.02)	(0.04)	(0.04)	(0.05)	(0.02)	(0.03)
At least one job	0.253***	0.178	0.113*	0.061	0.126**	0.001	-0.008	0.117
	(0.09)	(0.12)	(0.07)	(0.10)	(0.06)	(0.09)	(0.05)	(0.08)
Number of jobs (10s)	0.192***	0.189***	0.065**	0.029	-0.010	-0.026	0.008	-0.047
	(0.04)	(0.06)	(0.03)	(0.04)	(0.03)	(0.04)	(0.03)	(0.04)
Share reviews	0.091*	-0.074	0.016	-0.017	0.050	-0.035	0.033	-0.059
	(0.05)	(0.08)	(0.04)	(0.05)	(0.04)	(0.06)	(0.03)	(0.04)
Reputation badge	0.351***	-0.062	0.116**	-0.120				
	(0.08)	(0.10)	(0.06)	(0.09)				
Years of experience (10s)	0.316***	0.306***	-0.022	0.076				
	(0.05)	(0.08)	(0.04)	(0.06)				
Master	0.054	0.051	-0.080*	0.012				
	(0.06)	(0.09)	(0.05)	(0.06)				
Second experience	0.427***	0.601***	0.116**	0.316***				
	(0.06)	(0.09)	(0.05)	(0.07)				
Prestigious	0.042	0.138	-0.098*	-0.194**	-0.139***	-0.339***	-0.143***	-0.190***
	(0.06)	(0.09)	(0.05)	(0.08)	(0.05)	(0.07)	(0.04)	(0.06)
Remote	0.019	0.120	0.044	0.045	0.682***	0.638***	0.137***	0.146**
	(0.06)	(0.11)	(0.04)	(0.07)	(0.08)	(0.10)	(0.04)	(0.06)
Full time	-0.001	0.092	0.051	0.221***	-0.076	0.029	-0.020	0.074
	(0.06)	(0.08)	(0.05)	(0.07)	(0.05)	(0.07)	(0.03)	(0.05)
Duration (months)					0.033**	-0.005	0.022**	0.018
					(0.01)	(0.02)	(0.01)	(0.02)
Teamwork required					0.028	-0.155**	0.018	-0.096*
					(0.05)	(0.07)	(0.04)	(0.05)
Tight deadlines					-0.217***	-0.284***	-0.034	-0.081
					(0.05)	(0.07)	(0.04)	(0.05)
MENA origin	-0.084	0.134	-0.097**	-0.027	0.120**	-0.117	0.062	-0.004
	(0.06)	(0.10)	(0.05)	(0.08)	(0.05)	(0.07)	(0.04)	(0.06)
Female	-0.013	0.063	0.038	0.068	0.032	0.056	-0.050	0.042
	(0.06)	(0.09)	(0.05)	(0.07)	(0.04)	(0.06)	(0.03)	(0.05)
Number of observations	6021	2671	6021	2671	13375	7225	13375	7225
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 s.d.	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. 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: ethnic 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**
	(0.03)	(0.07)	(0.02)	(0.06)	(0.03)	(0.13)	(0.02)	(0.09)
At least one job	0.226***	0.389	0.100*	0.052	0.079	0.127	0.025	0.181
	(0.07)	(0.32)	(0.06)	(0.20)	(0.05)	(0.28)	(0.04)	(0.20)
Number of jobs (10s)	0.186***	0.205**	0.049*	0.103	-0.008	-0.103	-0.001	-0.169
	(0.03)	(0.09)	(0.03)	(0.10)	(0.03)	(0.13)	(0.02)	(0.10)
Share reviews	0.039	0.106	0.006	0.040	0.032	-0.144	-0.008	0.158
	(0.04)	(0.24)	(0.03)	(0.12)	(0.03)	(0.14)	(0.02)	(0.14)
Reputation badge	0.212***	0.525	0.040	0.139				
	(0.07)	(0.33)	(0.05)	(0.21)				
Years of experience (10s)	0.296***	0.604***	0.011	-0.097				
	(0.04)	(0.18)	(0.03)	(0.15)				
Master	0.060	-0.022	-0.047	-0.072				
	(0.05)	(0.18)	(0.04)	(0.10)				
Second experience	0.485***	0.328**	0.180***	0.134				
	(0.05)	(0.12)	(0.04)	(0.11)				
Prestigious	0.073	0.159	-0.125***	-0.142	-0.240***	0.278*	-0.177***	0.091
	(0.05)	(0.23)	(0.05)	(0.20)	(0.04)	(0.16)	(0.03)	(0.17)
Remote	0.021	0.526*	0.027	0.311	0.678***	0.478**	0.143***	0.071
	(0.05)	(0.26)	(0.04)	(0.21)	(0.06)	(0.23)	(0.03)	(0.13)
Full time	0.033	0.028	0.129***	-0.381*	-0.053	0.158	-0.002	0.218
	(0.05)	(0.32)	(0.04)	(0.20)	(0.04)	(0.17)	(0.03)	(0.14)
Duration (months)					0.019*	0.024	0.022***	-0.003
					(0.01)	(0.04)	(0.01)	(0.03)
Teamwork required					-0.029	-0.217	-0.017	-0.135
					(0.04)	(0.18)	(0.03)	(0.14)
Tight deadlines					-0.237***	-0.263	-0.037	-0.259*
					(0.04)	(0.16)	(0.03)	(0.14)
MENA origin	-0.021	0.054	-0.085**	0.068	0.029	0.094	0.032	0.129
	(0.05)	(0.18)	(0.04)	(0.19)	(0.04)	(0.22)	(0.03)	(0.16)
Female	0.013	0.028	0.061	-0.222	0.049	-0.108	-0.011	-0.126
	(0.05)	(0.25)	(0.04)	(0.14)	(0.04)	(0.16)	(0.03)	(0.14)
Number of observations	8192	500	8192	500	19325	1275	19325	1275
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 s.d.	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 ethnic origin. 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.18: 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***
	(0.06)	(0.03)
At least one job	-0.028	-0.063
	(0.10)	(0.08)
Number of jobs (10s)	0.022	0.040
	(0.06)	(0.04)
Share reviews	-0.017	-0.002
	(0.06)	(0.05)
Prestigious	-0.067	-0.063
	(0.07)	(0.06)
Remote	0.673***	0.127*
	(0.13)	(0.07)
Full time	-0.008	0.002
	(0.08)	(0.06)
Duration (months)	0.011	0.007
	(0.02)	(0.02)
Teamwork required	-0.076	0.006
	(0.08)	(0.06)
Tight deadlines	-0.272***	-0.008
	(0.08)	(0.06)
Female	0.108*	-0.002
	(0.06)	(0.06)
MENA origin	0.060	0.061
	(0.08)	(0.07)
Number of observations	5325	5325
Number of respondents	213	213
Outcome mean	5.999	6.898
Outcome s.d.	2.625	1.812
Projects	≥ 5	≥ 5

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 5-8 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. 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, 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***
	(0.04)	(0.04)	(0.02)	(0.02)
At least one job	0.096	0.075	0.071	0.004
	(0.08)	(0.07)	(0.06)	(0.05)
Number of jobs (10s)	-0.047	0.006	-0.011	-0.010
	(0.04)	(0.03)	(0.03)	(0.03)
Share reviews	-0.050	0.081*	-0.019	0.023
	(0.05)	(0.04)	(0.03)	(0.03)
Prestigious	-0.216***	-0.203***	-0.165***	-0.157***
	(0.06)	(0.06)	(0.04)	(0.04)
Remote	0.571***	0.742***	0.113**	0.159***
	(0.09)	(0.08)	(0.05)	(0.04)
Full time	-0.087	-0.004	0.057	-0.025
	(0.06)	(0.06)	(0.04)	(0.04)
Duration (months)	-0.002	0.039**	-0.000	0.039***
	(0.01)	(0.02)	(0.01)	(0.01)
Teamwork required	0.018	-0.089	0.018	-0.059
	(0.06)	(0.06)	(0.04)	(0.04)
Tight deadlines	-0.179***	-0.284***	-0.081*	-0.025
	(0.06)	(0.06)	(0.05)	(0.04)
Female	0.016	0.058	-0.036	-0.004
	(0.05)	(0.05)	(0.04)	(0.04)
MENA origin	0.018	0.049	-0.015	0.082*
	(0.06)	(0.06)	(0.05)	(0.04)
Number of observations	9075	11525	9075	11525
Number of respondents	363	461	363	461
Outcome mean	6.319	6.042	6.215	6.718
Outcome s.d.	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 5-8 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. $*p < 0.10, **p < 0.05, ***p < 0.01$.

Table B.20: 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*
	(0.03)	(0.05)	(0.02)	(0.05)
At least one job	0.274***	0.055	0.131**	-0.043
	(0.08)	(0.17)	(0.06)	(0.12)
Number of jobs (10s)	0.186***	0.195**	0.037	0.105*
	(0.04)	(0.08)	(0.03)	(0.05)
Share reviews	0.047	0.047	0.016	-0.004
	(0.05)	(0.09)	(0.04)	(0.06)
Reputation badge	0.256***	0.175	0.061	-0.028
	(0.08)	(0.11)	(0.06)	(0.10)
Years of experience (10s)	0.286***	0.417***	0.035	-0.062
	(0.05)	(0.10)	(0.04)	(0.08)
Master's degree	0.097*	-0.030	-0.045	-0.013
	(0.06)	(0.11)	(0.04)	(0.07)
Second experience	0.445***	0.579***	0.133***	0.345***
	(0.05)	(0.12)	(0.04)	(0.10)
Prestigious	0.070	0.021	-0.135***	-0.115
	(0.06)	(0.12)	(0.05)	(0.09)
Remote	0.078	-0.102	0.051	-0.028
	(0.06)	(0.15)	(0.04)	(0.06)
Full time	0.046	0.001	0.098**	0.098
	(0.06)	(0.12)	(0.05)	(0.08)
MENA origin	-0.060	0.102	-0.072	-0.103
	(0.06)	(0.13)	(0.05)	(0.09)
Female	0.034	-0.081	0.054	-0.007
	(0.06)	(0.12)	(0.05)	(0.10)
Number of observations	6842	1650	6842	1650
Number of respondents	274	66	274	66
Outcome mean	6.085	5.758	6.835	6.982
Outcome s.d.	1.961	2.013	1.529	1.525
Firm size	≤10 employees	>10 employees	≤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 1-4 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. $*p < 0.10, **p < 0.05, ***p < 0.01$.

B.2 *Prediction* experiments and perception gaps

Table B.21: Perception gaps about the preferences of the other side of the market, including fast respondents

Evaluator:	Workers			Recruiters		
Predictor:	Recruiters			Workers		
Object:	Offers			Profiles		
Dependent variable:	Accept			Hire		
	(1)	(2)	(3)	(4)	(5)	(6)
Daily wage (100s)	0.119***	0.017	0.304***	0.138***	0.142***	0.133***
	(0.05)	(0.06)	(0.07)	(0.03)	(0.04)	(0.04)
At least one job	0.084	-0.034	0.214*	0.169**	0.159	0.154
	(0.08)	(0.10)	(0.13)	(0.09)	(0.11)	(0.13)
Number of jobs (10s)	0.019	0.035	0.010	0.040	0.167***	-0.048
	(0.04)	(0.06)	(0.06)	(0.04)	(0.05)	(0.06)
Share reviews	-0.010	-0.074	0.062	0.050	0.072	0.022
	(0.05)	(0.06)	(0.07)	(0.05)	(0.06)	(0.07)
Reputation badge				0.340***	0.412***	0.254**
				(0.08)	(0.10)	(0.12)
Years of experience (10s)				0.138***	0.181**	0.083
				(0.05)	(0.07)	(0.08)
Master's degree				0.093	0.086	0.093
				(0.06)	(0.08)	(0.08)
Second experience				-0.064	-0.081	-0.055
				(0.06)	(0.07)	(0.09)
Prestigious	0.253***	0.171**	0.349***	0.148**	0.093	0.202**
	(0.06)	(0.08)	(0.09)	(0.06)	(0.08)	(0.10)
Remote	-0.156*	-0.351***	0.075	-0.152**	-0.092	-0.210**
	(0.08)	(0.12)	(0.12)	(0.06)	(0.08)	(0.09)
Full time	0.022	0.137*	-0.129	0.113*	0.019	0.213***
	(0.06)	(0.08)	(0.08)	(0.06)	(0.08)	(0.08)
Duration (months)	0.027*	0.026	0.025			
	(0.02)	(0.02)	(0.02)			
Teamwork required	0.055	-0.018	0.132			
	(0.06)	(0.08)	(0.08)			
Tight deadlines	0.036	0.041	0.030			
	(0.06)	(0.09)	(0.09)			
MENA origin	-0.089	-0.168**	-0.004	-0.060	-0.168**	0.079
	(0.06)	(0.08)	(0.09)	(0.06)	(0.08)	(0.10)
Female	0.014	-0.033	0.058	0.023	0.031	0.007
	(0.05)	(0.07)	(0.07)	(0.06)	(0.09)	(0.08)
Observations	29,275	15,475	13,800	29,767	18,242	11,525
Number of predictors	382	187	195	849	554	295
Number of evaluators	789	432	357	342	176	166
Evaluator outcome variable s.d.	2.549	2.549	2.549	1.970	1.970	1.970
Job family	All	Tech	Non-tech	All	Tech	Non-tech

Notes: This table reports OLS estimates of Equations 1 and 2 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 5, 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 5 for additional details. Standard errors are clustered at the respondent level. $^{*}p < 0.10$, $^{**}p < 0.05$, $^{***}p < 0.01$.

Table B.22: Perception gaps about the preferences of competitors, including fast respondents

Evaluator:	Recruiters			Workers		
Predictor:	Recruiters			Workers		
Object:	Profiles			Offers		
Dependent variable:	Hire			Accept		
	(1)	(2)	(3)	(4)	(5)	(6)
Daily wage (100s)	0.056*	0.084*	0.028	0.189***	0.120**	0.315***
	(0.03)	(0.05)	(0.04)	(0.04)	(0.05)	(0.06)
At least one job	0.194**	0.133	0.263*	0.055	0.033	0.073
	(0.10)	(0.13)	(0.14)	(0.07)	(0.09)	(0.11)
Number of jobs (10s)	0.072	0.147**	0.014	0.032	0.044	0.022
	(0.05)	(0.06)	(0.06)	(0.04)	(0.05)	(0.06)
Share reviews	0.140**	0.136*	0.146*	0.026	-0.010	0.066
	(0.06)	(0.08)	(0.08)	(0.04)	(0.06)	(0.07)
Reputation badge	0.288***	0.328***	0.229*			
	(0.09)	(0.12)	(0.12)			
Years of experience (10s)	0.066	0.039	0.086			
	(0.06)	(0.09)	(0.09)			
Master's degree	0.055	0.096	0.003			
	(0.07)	(0.10)	(0.09)			
Second experience	-0.066	-0.087	-0.048			
	(0.06)	(0.09)	(0.09)			
Prestigious	0.096	0.148	0.047	0.093*	0.001	0.202**
	(0.07)	(0.09)	(0.10)	(0.06)	(0.07)	(0.08)
Remote	-0.123*	-0.015	-0.229**	-0.187**	-0.242**	-0.120
	(0.07)	(0.09)	(0.09)	(0.08)	(0.11)	(0.11)
Full time	0.040	-0.109	0.198**	0.042	0.101	-0.036
	(0.06)	(0.09)	(0.09)	(0.05)	(0.07)	(0.08)
Duration (months)				0.057***	0.064***	0.049**
				(0.01)	(0.02)	(0.02)
Teamwork required				0.042	-0.044	0.132
				(0.05)	(0.07)	(0.08)
Tight deadlines				-0.145***	-0.143*	-0.140
				(0.06)	(0.07)	(0.09)
MENA origin	-0.135*	-0.227**	-0.028	-0.021	-0.113	0.080
	(0.07)	(0.10)	(0.10)	(0.05)	(0.07)	(0.08)
Female	-0.042	-0.069	-0.025	-0.038	-0.087	0.001
	(0.07)	(0.10)	(0.09)	(0.05)	(0.06)	(0.07)
Observations	17,867	9,017	8,850	40,675	24,550	16,125
Number of predictors	373	185	188	838	550	288
Number of evaluators	342	176	166	789	432	357
Evaluator outcome variable s.d.	1.970	1.970	1.970	2.549	2.549	2.549
Job family	All	Tech	Non-tech	All	Tech	Non-tech

Notes: This table reports OLS estimates of Equations 1 and 2 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 6, 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 6 for additional details. Standard errors are clustered at the respondent level. $^{*}p < 0.10$, $^{**}p < 0.05$, $^{***}p < 0.01$.

Table B.23: Perception gaps about the preferences of the other side of the market, corrected for multiple hypothesis testing

Evaluator:	Workers			Recruiters		
Predictor:	Recruiters			Workers		
Object:	Offers			Profiles		
Dependent variable:	Accept			Hire		
	(1)	(2)	(3)	(4)	(5)	(6)
Daily wage (100s)	0.171***	0.070	0.355***	0.137***	0.139***	0.135***
	[0.00]	[0.40]	[0.00]	[0.00]	[0.00]	[0.00]
At least one job	0.110	0.006	0.223	0.158**	0.166	0.119
	[0.31]	[1.00]	[0.10]	[0.05]	[0.18]	[0.67]
Number of jobs	-0.008	0.002	-0.013	0.046	0.173***	-0.038
	[0.99]	[1.00]	[0.95]	[0.37]	[0.00]	[0.78]
Share reviews	0.002	-0.052	0.061	0.053	0.070	0.029
	[0.99]	[0.82]	[0.64]	[0.40]	[0.46]	[0.82]
Freelancer badge				0.343***	0.428***	0.242**
				[0.00]	[0.00]	[0.03]
Years of experience (10s)				0.151***	0.196***	0.095
				[0.00]	[0.00]	[0.42]
Master's degree				0.097	0.094	0.093
				[0.10]	[0.46]	[0.51]
Second experience				-0.054	-0.069	-0.046
				[0.40]	[0.46]	[0.82]
Prestigious	0.241***	0.171**	0.325***	0.151***	0.089	0.211**
	[0.00]	[0.02]	[0.00]	[0.00]	[0.46]	[0.03]
Remote	-0.112	-0.321***	0.131	-0.152***	-0.099	-0.201***
	[0.30]	[0.00]	[0.48]	[0.00]	[0.45]	[0.00]
Full time	0.027	0.157**	-0.142	0.111**	0.031	0.196***
	[0.93]	[0.03]	[0.14]	[0.05]	[0.73]	[0.00]
Duration (months)	0.036**	0.041	0.029			
	[0.01]	[0.11]	[0.28]			
Teamwork required	0.052	-0.025	0.136			
	[0.74]	[0.99]	[0.14]			
Tight deadlines	0.011	-0.003	0.028			
	[0.99]	[1.00]	[0.95]			
Arab origin	-0.085	-0.141	-0.027	-0.062	-0.170**	0.078
	[0.30]	[0.11]	[0.95]	[0.40]	[0.01]	[0.70]
Female	0.032	-0.007	0.068	0.021	0.042	-0.006
	[0.91]	[1.00]	[0.64]	[0.59]	[0.73]	[0.91]
Observations	28625	15150	13475	28742	17517	11225
Number of predictors	356	174	182	808	525	283
Number of evaluators	789	432	357	342	176	166
Evaluator outcome variable s.d.	2.549	2.549	2.549	1.970	1.970	1.970
Job family	All	Tech	Non-tech	All	Tech	Non-tech

Notes: This table reports OLS estimates of Equations 1 and 2 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 5, but presenting p-values corrected for multiple-hypothesis testing using the Romano-Wolf method with 1,000 replications in square brackets. See Table 5 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.24: Perception gaps about the preferences of competitors, corrected for multiple hypothesis testing

Evaluator:	Recruiters			Workers		
Predictor:	Recruiters			Workers		
Object:	Profiles			Offers		
Dependent variable:	Hire			Accept		
	(1)	(2)	(3)	(4)	(5)	(6)
Daily wage (100s)	0.052	0.074	0.027	0.198***	0.132***	0.319***
	[0.11]	[0.16]	[0.92]	[0.00]	[0.00]	[0.00]
At least one job	0.178*	0.123	0.242	0.055	0.036	0.071
	[0.07]	[0.60]	[0.11]	[0.82]	[0.95]	[0.82]
Number of jobs	0.089**	0.151***	0.040	0.030	0.044	0.019
	[0.04]	[0.00]	[0.92]	[0.82]	[0.67]	[0.87]
Share reviews	0.131**	0.130	0.132	0.018	-0.012	0.050
	[0.01]	[0.11]	[0.18]	[0.82]	[0.95]	[0.82]
Reputation badge	0.249***	0.298***	0.179			
	[0.00]	[0.00]	[0.34]			
Years of experience (10s)	0.092	0.061	0.113			
	[0.16]	[0.60]	[0.99]			
Master's degree	0.051	0.086	0.005			
	[0.61]	[0.60]	[0.98]			
Second experience	-0.059	-0.085	-0.033			
	[0.52]	[0.58]	[0.97]			
Prestigious	0.094	0.123	0.071	0.089	-0.011	0.208***
	[0.21]	[0.34]	[0.92]	[0.15]	[0.95]	[0.01]
Remote	-0.118*	-0.010	-0.224***	-0.164**	-0.233**	-0.083
	[0.07]	[0.87]	[0.01]	[0.02]	[0.02]	[0.82]
Full time	0.037	-0.123	0.208***	0.042	0.103	-0.038
	[0.64]	[0.34]	[0.01]	[0.82]	[0.20]	[0.87]
Duration (months)				0.059***	0.064***	0.053***
				[0.00]	[0.00]	[0.01]
Teamwork required				0.037	-0.032	0.108
				[0.82]	[0.95]	[0.35]
Tight deadlines				-0.162***	-0.154**	-0.165*
				[0.00]	[0.03]	[0.07]
MENA origin	-0.126*	-0.211**	-0.020	-0.012	-0.108	0.098
	[0.07]	[0.02]	[0.99]	[0.82]	[0.36]	[0.48]
Female	-0.034	-0.079	-0.000	-0.040	-0.080	-0.008
	[0.64]	[0.60]	[0.99]	[0.82]	[0.20]	[0.87]
Observations	17,292	8,767	8,525	39,975	24,275	15,700
Number of predictors	350	175	175	810	539	271
Number of evaluators	342	176	166	789	432	357
Evaluator outcome variable s.d.	1.970	1.970	1.97	2.549	2.549	2.549 0
Job family	All	Tech	Non-tech	All	Tech	Non-tech

Notes: This table reports OLS estimates of Equations 1 and 2 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 6, but presenting p-values corrected for multiple-hypothesis testing using the Romano-Wolf method with 1,000 replications in square brackets. See Table 6 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.25: Perception gaps about the preferences of the other side of the market, by participant gender and ethnicity

Evaluator:	Workers				Recruiters			
Predictor:	Recruiters				Workers			
Object:	Offers				Profiles			
Dependent variable:	Accept				Hire			
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Daily wage (100s)	0.168***	0.174**	0.182***	0.016	0.141***	0.128***	0.135***	0.167***
	(0.05)	(0.07)	(0.05)	(0.08)	(0.03)	(0.04)	(0.03)	(0.05)
At least one job	0.146	-0.011	0.073	0.630***	0.148*	0.236*	0.187**	0.025
	(0.09)	(0.12)	(0.08)	(0.16)	(0.09)	(0.13)	(0.09)	(0.14)
Number of jobs (10s)	-0.002	-0.014	0.021	-0.427***	0.045	0.026	0.036	0.071
	(0.05)	(0.06)	(0.05)	(0.11)	(0.04)	(0.05)	(0.04)	(0.07)
Share reviews	0.020	-0.045	0.010	-0.055	0.070	-0.010	0.052	0.030
	(0.05)	(0.07)	(0.05)	(0.13)	(0.05)	(0.07)	(0.05)	(0.09)
Reputation badge					0.326***	0.374***	0.383***	-0.032
					(0.08)	(0.11)	(0.08)	(0.12)
Years of experience (10s)					0.166***	0.052	0.120**	0.272**
					(0.06)	(0.07)	(0.05)	(0.11)
Master's degree					0.103	0.062	0.063	0.356***
					(0.06)	(0.07)	(0.06)	(0.12)
Second experience					-0.093	0.022	-0.070	0.006
					(0.06)	(0.08)	(0.06)	(0.11)
Prestigious	0.248***	0.224**	0.256***	0.096	0.145**	0.157*	0.154**	0.095
	(0.06)	(0.09)	(0.06)	(0.16)	(0.07)	(0.09)	(0.07)	(0.14)
Remote	-0.126	-0.073	-0.125	0.047	-0.166***	-0.116	-0.149**	-0.184*
	(0.09)	(0.12)	(0.08)	(0.19)	(0.06)	(0.08)	(0.06)	(0.10)
Full time	0.021	0.041	0.017	0.136	0.118*	0.096	0.105*	0.159
	(0.06)	(0.09)	(0.06)	(0.17)	(0.06)	(0.08)	(0.06)	(0.10)
Duration (months)	0.037**	0.032	0.029*	0.110**				
	(0.02)	(0.02)	(0.02)	(0.04)				
Teamwork required	0.016	0.139*	0.030	0.325**				
	(0.06)	(0.08)	(0.06)	(0.14)				
Tight deadlines	0.015	0.002	0.020	-0.030				
	(0.07)	(0.09)	(0.06)	(0.17)				
MENA origin	-0.130*	0.040	-0.082	-0.171	-0.099	0.061	-0.041	-0.224*
	(0.07)	(0.09)	(0.06)	(0.21)	(0.06)	(0.09)	(0.06)	(0.12)
Female	0.076	-0.090	0.052	-0.230*	0.029	0.011	0.024	-0.000
	(0.05)	(0.07)	(0.05)	(0.12)	(0.06)	(0.08)	(0.06)	(0.11)
Observations	26,100	22,250	28,050	20,300	25,467	12,842	27,292	11,017
Number of predictors	255	101	333	23	677	172	750	99
Number of evaluators	789	789	789	789	342	342	342	342
Evaluator outcome variable s.d.	2.549	2.549	2.549	2.549	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 Equations 1 and 2 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 5, but splitting respondents by their gender and ethnic origin. See Table 5 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 about the preferences of competitors, by participant gender and ethnicity

Evaluator:	Recruiters				Workers			
Predictor:	Recruiters				Workers			
Object:	Profiles				Offers			
Dependent variable:	Hire				Accept			
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Daily wage (100s)	0.055	0.040	0.052	0.065	0.194***	0.209***	0.203***	0.172**
	(0.03)	(0.05)	(0.03)	(0.14)	(0.04)	(0.06)	(0.04)	(0.07)
At least one job	0.136	0.309**	0.181*	0.049	0.040	0.080	0.032	0.206
	(0.11)	(0.16)	(0.10)	(0.31)	(0.08)	(0.09)	(0.07)	(0.15)
Number of jobs (10s)	0.077	0.117*	0.094**	0.035	0.058	-0.018	0.038	-0.023
	(0.05)	(0.07)	(0.05)	(0.13)	(0.04)	(0.05)	(0.04)	(0.08)
Share reviews	0.123**	0.162*	0.134**	0.108	0.002	0.049	0.026	-0.042
	(0.06)	(0.08)	(0.06)	(0.19)	(0.05)	(0.06)	(0.04)	(0.08)
Reputation badge	0.242***	0.276**	0.251***	0.244				
	(0.09)	(0.13)	(0.09)	(0.25)				
Years of experience (10s)	0.109	0.034	0.086	0.262				
	(0.07)	(0.10)	(0.06)	(0.26)				
Master's degree	0.049	0.055	0.056	-0.034				
	(0.07)	(0.11)	(0.07)	(0.20)				
Second experience	-0.061	-0.049	-0.034	-0.623**				
	(0.07)	(0.10)	(0.06)	(0.25)				
Prestigious	0.075	0.145	0.097	0.115	0.115*	0.045	0.095*	0.032
	(0.07)	(0.11)	(0.07)	(0.17)	(0.06)	(0.08)	(0.06)	(0.13)
Remote	-0.106	-0.164	-0.123*	-0.004	-0.131	-0.221**	-0.179**	-0.062
	(0.07)	(0.10)	(0.07)	(0.20)	(0.09)	(0.09)	(0.08)	(0.15)
Full time	0.086	-0.106	0.038	0.051	0.050	0.029	0.041	0.061
	(0.07)	(0.09)	(0.07)	(0.12)	(0.06)	(0.07)	(0.05)	(0.12)
Duration (months)					0.075***	0.032*	0.052***	0.112***
					(0.02)	(0.02)	(0.01)	(0.03)
Teamwork required					0.043	0.033	0.031	0.081
					(0.06)	(0.07)	(0.06)	(0.10)
Tight deadlines					-0.155**	-0.176**	-0.183***	-0.025
					(0.06)	(0.08)	(0.06)	(0.10)
MENA origin	-0.167**	0.009	-0.133*	0.044	-0.042	0.041	0.019	-0.220**
	(0.08)	(0.10)	(0.07)	(0.22)	(0.06)	(0.07)	(0.06)	(0.10)
Female	-0.010	-0.103	-0.037	-0.004	-0.040	-0.046	-0.036	-0.062
	(0.07)	(0.10)	(0.07)	(0.22)	(0.05)	(0.06)	(0.05)	(0.09)
Observations	15,167	10,667	16,917	8,917	34,050	25,650	37,000	22,700
Number of predictors	265	85	335	15	573	237	691	119
Number of evaluators	342	342	342	342	789	789	789	789
Evaluator outcome variable s.d.	1.970	1.970	1.970	1.970	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 Equations 1 and 2 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 6, but splitting respondents by their gender and ethnic origin. See Table 6 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.27: Perception gaps about the preferences of the other side, by participant experience on the platform

Evaluator:	Workers		Recruiters	
Predictor:	Recruiters		Workers	
Object:	Offers		Profiles	
Dependent variable:	Accept		Hire	
	(1)	(2)	(3)	(4)
Daily wage (100s)	0.166***	0.177***	0.129***	0.146***
	(0.06)	(0.06)	(0.03)	(0.04)
At least one job	0.040	0.177*	0.107	0.261**
	(0.10)	(0.10)	(0.09)	(0.10)
Number of jobs (10s)	0.035	-0.055	0.008	0.080*
	(0.05)	(0.06)	(0.05)	(0.05)
Share reviews	0.029	-0.022	0.059	0.049
	(0.06)	(0.06)	(0.05)	(0.06)
Reputation badge			0.319***	0.365***
			(0.09)	(0.10)
Years of experience (10s)			0.155***	0.156**
			(0.06)	(0.06)
Master's degree			0.112*	0.081
			(0.07)	(0.07)
Second experience			-0.053	-0.057
			(0.06)	(0.07)
Prestigious	0.199***	0.282***	0.161**	0.125
	(0.07)	(0.08)	(0.07)	(0.08)
Remote	-0.059	-0.168*	-0.126**	-0.167**
	(0.10)	(0.10)	(0.06)	(0.07)
Full time	-0.019	0.072	0.059	0.178**
	(0.07)	(0.07)	(0.07)	(0.07)
Duration (months)	0.017	0.055***		
	(0.02)	(0.02)		
Teamwork required	0.140**	-0.035		
	(0.07)	(0.07)		
Tight deadlines	0.054	-0.032		
	(0.08)	(0.08)		
MENA origin	-0.043	-0.129*	-0.071	-0.054
	(0.08)	(0.07)	(0.07)	(0.07)
Female	0.077	-0.012	0.034	0.007
	(0.06)	(0.06)	(0.07)	(0.07)
Observations	24,250	24,100	20,192	16,892
Number of predictors	181	175	466	334
Number of evaluators	789	789	342	342
Evaluator outcome variable s.d.	2.549	2.549	1.970	1.970
Experience	No jobs	At least one job	No jobs	At least one job

Notes: This table reports OLS estimates of Equations 1 and 2 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 5, but splitting respondents by whether they completed at least one project on the platform or not. See Table 5 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 about the preferences of competitors, by participant experience on the platform

Evaluator:	Recruiters		Workers	
Predictor:	Recruiters		Workers	
Object:	Profiles		Offers	
Dependent variable:	Hire		Accept	
	(1)	(2)	(3)	(4)
Daily wage (100s)	0.054	0.047	0.149***	0.276***
	(0.04)	(0.04)	(0.04)	(0.05)
At least one job	0.199*	0.168	0.029	0.077
	(0.11)	(0.13)	(0.08)	(0.10)
Number of jobs (10s)	0.070	0.110*	0.033	0.041
	(0.05)	(0.06)	(0.04)	(0.05)
Share reviews	0.132**	0.134*	0.007	0.040
	(0.07)	(0.07)	(0.05)	(0.06)
Reputation badge	0.259***	0.247**		
	(0.10)	(0.11)		
Years of experience (10s)	0.100	0.098		
	(0.08)	(0.07)		
Master's degree	0.049	0.056		
	(0.08)	(0.08)		
Second experience	-0.022	-0.096		
	(0.08)	(0.08)		
Prestigious	0.079	0.118	0.083	0.101
	(0.08)	(0.09)	(0.06)	(0.08)
Remote	-0.153*	-0.077	-0.171*	-0.151
	(0.08)	(0.08)	(0.09)	(0.09)
Full time	0.029	0.042	0.040	0.040
	(0.08)	(0.08)	(0.06)	(0.07)
Duration (months)			0.070***	0.042**
			(0.02)	(0.02)
Teamwork required			0.028	0.054
			(0.06)	(0.06)
Tight deadlines			-0.164**	-0.148*
			(0.06)	(0.08)
MENA origin	-0.138*	-0.119	-0.033	0.023
	(0.08)	(0.09)	(0.06)	(0.07)
Female	0.046	-0.132	-0.022	-0.064
	(0.08)	(0.09)	(0.05)	(0.06)
Observations	13,342	12,442	32,200	27,425
Number of predictors	192	156	499	308
Number of evaluators	342	342	789	789
Evaluator outcome variable s.d.	1.970	1.970	2.549	2.549
Experience	No jobs	At least one job	No jobs	At least one job

Notes: This table reports OLS estimates of Equations 1 and 2 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 6, but splitting respondents by whether they have completed at least one job on the platform or not. See Table 6 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 workers with substantial experience on the platform

Evaluator:	Recruiters	Workers
Predictor :	Workers	
Object:	Profiles	Offers
Dependent variable:	Hire	Accept
	(1)	(2)
Daily wage (100s)	0.176***	0.332***
	(0.04)	(0.06)
At least one job	0.290**	0.028
	(0.14)	(0.14)
Number of jobs (10s)	0.060	0.042
	(0.06)	(0.07)
Share reviews	-0.027	-0.029
	(0.09)	(0.07)
Reputation badge	0.446***	
	(0.11)	
Years of experience (10s)	0.075	
	(0.08)	
Master's degree	0.031	
	(0.09)	
Second experience	-0.056	
	(0.08)	
Prestigious	0.148	0.082
	(0.12)	(0.08)
Remote	-0.180**	-0.283**
	(0.09)	(0.11)
Full time	0.225**	0.041
	(0.09)	(0.09)
Duration (months)		0.042*
		(0.02)
Teamwork required		0.057
		(0.08)
Tight deadlines		-0.140
		(0.12)
MENA origin	-0.051	0.008
	(0.09)	(0.09)
Female	0.087	-0.149*
	(0.09)	(0.09)
Observations	12,117	23,075
Number of predictors	143	134
Number of evaluators	342	789
Evaluator outcome variable s.d.	1.970	2.549
Experience	$\geq$ 5 jobs	$\geq$ 5 jobs

Notes: This table reports OLS estimates of Equations 1 and 2 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 5, but restricting to workers with at least 5 completed jobs on the platform. See Table 5 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.30: Perception gaps for workers, by self-reported freelancing experience

Evaluator:	Recruiters		Workers	
Predictor :	Workers			
Object:	Profiles		Offers	
Dependent variable:	Hire		Accept	
	(1)	(2)	(3)	(4)
Daily wage (100s)	0.133***	0.142***	0.138***	0.283***
	(0.03)	(0.03)	(0.04)	(0.04)
At least one job	0.132	0.192*	0.087	0.022
	(0.10)	(0.10)	(0.08)	(0.09)
Number of jobs (10s)	0.037	0.055	0.046	0.018
	(0.05)	(0.04)	(0.05)	(0.05)
Share reviews	0.034	0.075	-0.023	0.061
	(0.05)	(0.06)	(0.05)	(0.05)
Reputation badge	0.366***	0.315***		
	(0.09)	(0.09)		
Years of experience (10s)	0.184***	0.114*		
	(0.06)	(0.06)		
Master's degree	0.098	0.096		
	(0.07)	(0.07)		
Second experience	-0.043	-0.068		
	(0.06)	(0.06)		
Prestigious	0.139*	0.164**	0.062	0.085
	(0.08)	(0.08)	(0.07)	(0.07)
Remote	-0.139**	-0.167**	-0.149*	-0.180*
	(0.07)	(0.07)	(0.09)	(0.09)
Full time	0.127*	0.089	-0.004	0.106*
	(0.07)	(0.07)	(0.06)	(0.06)
Duration (months)			0.073***	0.044***
			(0.02)	(0.02)
Teamwork required			0.075	-0.007
			(0.07)	(0.06)
Tight deadlines			-0.171**	-0.158**
			(0.07)	(0.07)
MENA origin	-0.009	-0.129*	-0.036	0.022
	(0.07)	(0.07)	(0.06)	(0.06)
Female	0.043	-0.003	-0.048	-0.039
	(0.07)	(0.07)	(0.06)	(0.06)
Observations	19,242	18,042	30,075	29,125
Number of predictors	428	380	414	376
Number of evaluators	342	342	789	789
Evaluator outcome variable s.d.	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 1 and 2 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 5, but splitting workers by whether their self-reported years of freelance experience is above or below the median. See Table 5 for more details. All specifications include respondent fixed effects. Standard errors are clustered at the respondent level. $*p < 0.10, **p < 0.05, ***p < 0.01$.

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

$$\sigma'(a + p)(v - p) - \sigma(a + p) = 0. \tag{3}$$

Because σ is the logistic function, (3) 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 (3), $(v - p^\Gamma) = \sigma/\sigma' > 0$). 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. □

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 behaviour 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 behaviour 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. □

C.3 Extension: competitor wedges

This appendix modifies Section 7 by introducing belief wedges about competitors' preferences. All timing, matching, pricing conditional on (x, y), and the investment structure from Section 7 remain unchanged.

C.3.1 Competitors and residual demand

In Section 7, 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

$$\Delta J(m_x) \equiv J(1; m_x) - J(0; m_x), \tag{4}$$

$$\Delta \Pi(m_y) \equiv \Pi(1; m_y) - \Pi(0; m_y), \tag{5}$$

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 Section 7 remain unchanged.

C.3.2 Belief wedges 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 of Section 7 evaluated under perceived returns. Workers make investment decisions using $\Delta J(\hat{m}_x)$, and recruiters use $\Delta \Pi(\hat{m}_y)$. Cutoff rules are otherwise identical to Section 7.

C.3.3 Proposition

Proposition 3 (Distortionary effects of competitor-preference wedges)**.** *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. □

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