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(Mis)Perceptions of the Labor Market

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(Mis)Perceptions of the Labor Market*

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Abstract

Workers and firms make decisions based on what they believe is valued in the labor market. We study whether employers and workers hold accurate perceptions about the preferences of others through a series of incentivized field experiments on one of Europe's largest freelance platforms. We first elicit employer preferences over worker characteristics and worker preferences over job characteristics using evaluations of worker profiles and job offers with randomized characteristics. We then elicit beliefs about these preferences from participants on the other side of the market and test their accuracy. We document that beliefs about some characteristics are fairly accurate on average, but that there exist substantial *perception gaps* about preferences on both sides of the market, including about the value of posted wages, human capital, market reputation, and job amenities. We develop a model showing how these gaps can distort pricing and investment decisions. Consistent with the model, larger *perception gaps* are associated with worse market outcomes, and counterfactual exercises imply that eliminating these gaps would increase matching and match quality. Finally, providing workers with information about actual market preferences changes their behavior and appears to improve their subsequent job outcomes. Our findings highlight misperceptions about what others value as a source of information frictions with important economic consequences.

JEL CODES: J24, J31, J63, D83, D84, C93

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1 Introduction

Workers and firms make decisions based on what they think is valued in the labor market. Workers choose which skills to invest in and which jobs to apply to. Firms choose what to pay and which amenities to offer. When these beliefs are inaccurate, workers may not invest in the characteristics firms value most, while firms may not design compensation packages to effectively attract workers.

A growing literature studies whether workers and firms hold accurate beliefs about labor market conditions, including wages, outside options, and employment opportunities. Yet knowing which opportunities are available is distinct from understanding how the market values worker and job characteristics. Even when information about available workers and jobs is readily accessible, observed wages, credentials, amenities, and matches need not reveal underlying preferences: characteristics are chosen endogenously, and market outcomes reflect the beliefs and decisions of both sides. Consequently, market participants may misunderstand the returns to their own choices, leading them to inefficiently set prices or invest in characteristics that others value less than anticipated. Whether such misperceptions are widespread and constitute an economically important source of labor market frictions remains largely unexplored.

In this paper, we conduct incentivized field experiments on one of Europe's largest freelance job platforms to identify *perception gaps* – discrepancies between the preferences of market participants and beliefs about these preferences – within a common experimental framework and for a rich set of worker, employer, and job characteristics. The platform we study focuses on skilled, project-based work in software development, marketing, and communications. Jobs vary in duration and working conditions, with the average job lasting approximately one month and involving several thousand euros in wages.

In the *Evaluation* experiments, we present employers with hypothetical worker profiles that closely resemble those shown on the platform when contacting workers and present workers with hypothetical job offers that closely resemble those shown to workers when they are contacted. Participants first select a job category and then evaluate 25 profiles or offers tailored to this category. Within each profile and offer, we independently randomize characteristics drawn from real platform data. Worker profiles vary human

capital, market reputation, work preferences, demographics, and asked wages. Job offers vary offered wages, employer characteristics and reputation, non-wage amenities, job duration, and employer demographics. Participants report both their interest in hiring a worker or accepting a job and their perceived likelihood of receiving a positive response from the other side of the market. 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 or jobs. This design allows us to causally identify how each characteristic affects evaluations while preserving realism and relevance.

In the *Prediction* experiments, we recruit other employers and workers to predict the evaluations of participants from the *Evaluation* experiments, within their own job category. Using the same profiles and offers, we elicit workers' beliefs about employers' preferences for worker characteristics and employers' beliefs about workers' preferences for job characteristics. Participants each make 25 predictions about average evaluations, incentivized based on their accuracy using a binarized scoring rule (Healy and Leo, 2025). Comparing estimates between the *Evaluation* and *Prediction* experiments identifies *perception gaps* on each side of the market.

Our analysis proceeds in two steps. We first establish whether workers and employers accurately understand what the other side values. We then investigate whether misperceptions are reflected in observed choices and outcomes in the market, and whether providing information about actual preferences changes these choices and outcomes.

We find that the value of some characteristics is accurately anticipated, but that the value of others is substantially misperceived, generating large average prediction errors. First, there are substantial misperceptions about employers' preferences for worker characteristics. Employers respond negatively to higher asked wages, although higher wages also signal competence, partially offsetting the negative price effect. Strikingly, workers substantially underestimate employers' sensitivity to asked wages. Employers also value market reputation and work experience, but workers overestimate the extent to which they do, including platform-specific and general work experience as well as prestigious experience credentials. Moreover, workers incorrectly believe that there is a penalty for

signaling a preference for remote work on their profiles. These gaps are economically substantial, with misperceptions about certain characteristics equivalent to differences in employers' valuations of around €1,000 per month of full-time equivalent wages. Workers thus misunderstand the market value of their own characteristics and the trade-offs between asked wages and signals of worker quality, potentially leading them to misprice their services and misallocate investments in human capital and reputation. Lastly, we find no evidence of gender discrimination and limited evidence of discrimination against workers of Middle Eastern and North African (MENA) origin, although workers of MENA origin anticipate discrimination against MENA profiles.[1]

We also document substantial misperceptions about workers' preferences. Workers are highly responsive to offered wages and attach substantial value to working conditions, particularly remote work and avoiding jobs with tight deadline requirements, while placing relatively little weight on employer characteristics and reputation. Yet employers overestimate workers' responsiveness to offered wages and valuation of longer jobs, while underestimating their valuation of remote work. Magnitudes are again economically meaningful. For example, the *perception gap* regarding remote work corresponds to an underestimation of workers' willingness to forego earnings for remote work by around €400 per month. Employers thus misunderstand how workers trade off wages and non-wage amenities, potentially leading them to set wages inefficiently and provide working conditions that do not reflect workers' preferences.

Misperceptions about employers' preferences are generally larger than those about workers' preferences, although they are substantial across both sides, driving average prediction errors of approximately one point on a ten-point Likert scale, equivalent to roughly half of a standard deviation in evaluation ratings. *Perception gaps* vary considerably across individuals, with a sizable share holding inaccurate beliefs about any given characteristic. Since misperceptions distort behavior at the individual level, this highlights that they can have important consequences even when average gaps are modest. Misperceptions also do not appear smaller among more experienced market participants, suggesting that they may not be eliminated through experience alone.[2] Moreover, using

[1] Employer evaluations indicate similar interest in hiring ethnic minority profiles, but they are evaluated slightly more negatively (5% of a standard deviation) on the likelihood that they would accept a job offer.

[2] Learning could be particularly slow given the noisiness and complexity of the information environ-

an additional prediction experiment, we show that employers and workers also misperceive the preferences of their own side of the market, i.e., their competitors, although beliefs are more accurate than for the other side of the market.

Estimated *perception gaps* are robust to a number of measurement and interpretation considerations. One concern is the relevance of misperceptions about average preferences for market decisions. If there is preference heterogeneity within job categories, then the average preference may not represent the market return to that characteristic, and misperceptions about the mean may be less consequential if agents target a specific market segment. We provide direct evidence from a complementary experiment that workers' beliefs about the preferences of the specific employers they target and about perceived hiring returns closely track their beliefs about average employer preferences.

The economic importance of these *perception gaps* depends on whether they affect the decisions workers and employers make. We therefore examine their implications for pricing, investment, and matching, combining a theoretical framework, administrative evidence on market behavior, and an information treatment. First, we present a model highlighting two channels through which gaps distort outcomes: 1) holding market participants' characteristics fixed, they distort how participants price their characteristics and 2) allowing for investments in characteristics, gaps distort investment decisions. These distortions can reduce matching and match quality from realized matches.

Second, consistent with the model, *perception gaps* predict actual behavior and outcomes in the market. Workers are more likely to overestimate employers' valuation of characteristics they possess, while employers are more likely to overestimate workers' valuation of amenities they offer, consistent with investment distortions. Moreover, workers who overestimate their value to employers or underestimate employers' wage sensitivity ask higher wages, while employers who overestimate the attractiveness of their offers or underestimate workers' wage sensitivity offer lower wages, consistent with pricing distortions. Larger pricing distortions are associated with worse outcomes, including fewer matches, lower worker earnings, and higher wages paid by employers. A quantification

ment: each side potentially misperceives the other side and others' misperceptions. Moreover, as we discuss below, systematic misperceptions could persist because observed outcomes from market interactions provide misleading information, for example due to endogenous decisions or confounding, or because psychological biases such as overconfidence or projection distort how information is interpreted.

exercise suggests that eliminating *perception gaps* would increase job matching by 2.9% and match quality by 3.6%.[3]

Third, we investigate whether providing personalized information about actual market preferences to participants changes their behavior. Most participants report finding this information useful and intend to change their behavior. We test whether worker intentions translate to real changes using daily data on profile content within a Differences-in-Differences design using non-contacted workers as a comparison group.[4] We document a 4.4-percentage-point or 489% increase in the rate of workers in the treatment group updating their profile specifically on the day of the experiment. Workers were particularly likely to modify their asked wage, specifically in the direction suggested by the information, leading to a net decrease in asked wages. Furthermore, we find evidence of increased demand for workers who received the information: a 15% increase in the probability of receiving a job offer in the three months following the treatment. Together, these results indicate that *perception gaps* are economically consequential, that participants respond to information about market preferences, and that correcting misperceptions may meaningfully affect labor market outcomes.

This paper contributes to four strands of literature. Our main contribution is to identify *perception gaps* about the preferences of other market participants, document their prevalence on both sides of the labor market, and investigate their economic consequences.

First, we contribute to the literature on labor market preferences and beliefs about these preferences. A longstanding literature estimates the returns to worker characteristics, including human capital and demographics (Topel, 1991; Card, 2001; Charles and Guryan, 2011), while a growing literature examines workers' valuation of wages and non-wage amenities (Caldwell et al., 2025; Humlum et al., 2025; Mas, 2025; Adrjan et al., 2026). Yet market participants make decisions based not only on these preferences, but also on their subjective beliefs about what others value. Measuring actual and perceived preferences within a common framework is therefore important, but empirically challenging

[3]This exercise focuses on pricing distortions since we do not observe investment decisions or costs. The exercise also holds constant the number of job offers, since we have data on offers made but not on the decision to make an offer. These two restrictions could lead us to estimate a lower bound on total gains from eliminating *perception gaps*, although the exercise is partial equilibrium and considers match quality for workers and employers, abstracting from surplus of the platform itself.

[4]Non-contacted workers were randomly ordered near the end of our recruitment list for the experiments and we reached our pre-registered number of participants before contacting them.

(Fuster and Zafar, 2023). Recent studies have begun addressing this challenge. Exley et al. (2024) and Caron and Erda (2026) compare college students' beliefs about employers' valuation of selected resume characteristics to experimentally elicited employer preferences, while Cordes and Müller (2026) study employers' beliefs about workers' valuation of non-wage amenities using unincentivized survey vignettes.[5]

We extend this literature in three ways. First, we study misperceptions about preferences on both sides of an active labor market, covering wages, human capital, market reputation, and job amenities. Second, we combine experimentally identified preferences with incentivized predictions within a common framework, allowing us to measure and compare *perception gaps* across characteristics and market participants. We find substantial misperceptions on both sides, including among experienced participants, although employers generally have more accurate beliefs about workers' preferences than workers have about employers' preferences. Third, we link these experimentally measured gaps to actual market decisions and outcomes, and examine how participants respond to personalized information about market preferences.

Our analysis also extends beyond beliefs about the other side of the market to beliefs about competitors. Market returns depend not only on demand for characteristics, but also on their supply from competing workers and firms. Recent research highlights the importance of beliefs about competitors for market behavior (He et al., 2023; Bertheau and Hoeck, 2025; Cullen et al., 2025b), and we provide rare experimental evidence on their accuracy.[6] We find that misperceptions are qualitatively similar but generally smaller than those concerning the other side of the market.

Second, we contribute to the literature on information frictions and their consequences. Existing work documents inaccurate beliefs about market conditions like wages and job opportunities, among workers (Conlon et al., 2018; Mueller et al., 2021; Bryan et al., 2022; Sockin and Sojourner, 2023; Jäger et al., 2024; Miano, 2025; Sockin et al., 2026) and firms (Friedrich and Zator, 2024; Abebe et al., 2025), as well as misperceptions about others'

[5]Exley et al. (2024) and Caron and Erda (2026) use incentivized resume ratings with college employers to study beliefs about the importance of GPA and other resume characteristics. Angeli et al. (2023) and Lepage et al. (2025) provide related evidence on anticipated discrimination. Russell and Shah (2025) use an incentivized rating experiment in India to study firms' disclosure of amenities valued by workers.

[6]A broader literature in industrial organization examines firms' biased beliefs about competitors. See Aguirregabiria and Jeon (2020) for a review.

beliefs and behavior (Bursztyn and Yang, 2022; Bursztyn et al., 2023; Exley et al., 2025).

We identify a distinct information friction: workers and firms misunderstand the market value of characteristics they can choose or offer. Unlike misperceptions about available opportunities or market conditions, these beliefs directly concern the returns to agents' own decisions, potentially distorting behavior and outcomes even when information about jobs and workers is readily accessible. For example, Cullen et al. (2025a) find that workers are willing to forgo substantial earnings for remote work, yet employers offer similar wages for comparable remote and in-person jobs, consistent with firms failing to account for workers' valuation of this amenity. We also go beyond identifying *perception gaps* to document that they have important consequences by combining a model, administrative data, and an information treatment. More generally, our findings suggest that similar misperceptions could contribute to phenomena including wage premia, labor shortages, and imperfect compensating differentials for firms, as well as skill mismatch, over-credentialing, and wage inequality among workers.

Third, we extend the IRR methodology by eliciting preferences and predictions for large samples of both workers and employers, across a rich set of characteristics, with profiles and offers tailored to job categories and participants' needs. The platform collaboration allows us to implement the experiments without deception, while avoiding awareness of participation in academic research (Agan et al., 2023), and to use administrative records to assess representativeness, validate estimates, and investigate market behavior.[7] This combination is particularly useful for studying misperceptions, which are difficult to infer from observed market outcomes alone. Our approach complements correspondence studies (Bertrand and Mullainathan, 2004; Kline et al., 2022) by measuring evaluations along a detailed scale and multiple dimensions rather than a binary callback decision.[8] It also complements vignette studies (Maestas et al., 2023) by incentivizing evaluations of realistic profiles and offers, mitigating recent concerns with discrete choice experiments focusing on few characteristics (Adrjan et al., 2026).

Fourth, we contribute to the literature on online labor markets, platforms, and free-

[7]See Deschamps et al. (2025) for another example of combining administrative data with experiments on both sides of a market to study safety concerns in carpooling.

[8]Correspondence studies are less suited to examining both sides of the market. In our setting, firms contact workers, precluding a study sending profiles to firms. In other settings, workers are typically not contacted by firms without first applying, precluding a study sending job offers to workers.

lancing. Freelancing and platform markets account for a substantial, growing share of economic activity (Upwork Research Institute, 2023) and most workers in our experiments report freelancing as their main source of income. Existing research emphasizes the importance of platforms in facilitating matches between users (Cullen and Farronato, 2021; Echenique et al., 2023). We highlight a distinct obstacle: even when platforms make information about workers and jobs available, users may misunderstand what others value and consequently make suboptimal decisions about their own characteristics and prices. Our findings suggest that platforms can potentially improve matching by informing users about market preferences, for example through pricing guidance or personalized feedback.[9] The relevance of these findings likely extends beyond online markets. The platform we study features skilled work, substantial financial stakes, frequent interactions, and relatively rich information about other market participants. The existence of substantial misperceptions in this environment suggests that similar information frictions may also matter in traditional labor markets, where learning about market preferences could be even more difficult.

The rest of the paper is organized as follows. Section 2 introduces the platform and administrative data. Section 3 describes the experimental design and empirical strategy. Section 4 presents the results of the *Evaluation* experiments. Section 5 presents the results of the *Prediction* experiments and evidence on *perception gaps*. Section 6 investigates the consequences of these gaps, presenting the model followed by quantification exercises and results of the information treatment. Section 7 presents evidence on *perception gaps* about the preferences of competitors. Section 8 discusses potential sources of *perception gaps*. Section 9 concludes.

2 The platform

We study one of the largest platforms for freelance work in Europe. Founded over 10 years ago, it operates in over 15 countries and generated approximately €1 billion in revenue in 2025. We focus on its largest market, France. The platform covers a range of mostly

[9] Roussille (2024) illustrates the importance of information-based platform design for reducing gender differences in asking wages. Misperceptions may also distort entry into freelance markets relative to traditional employment (Pires, 2022; Freeland et al., 2026).

high-skilled jobs which vary in duration (typically from one day to six months), daily wages (€125 to €1,200), weekly hours (part-time or full-time), and working conditions (remote or in person). The average job has a wage budget of several thousand euros and lasts around one month, indicating that jobs are economically meaningful. For 75% of workers in our experiments, freelancing is their main source of income. As detailed below, we focus on eight of the most popular job categories on the platform: five in software development (front-end, back-end, full-stack, mobile, and integration/content management system (CMS)/webmaster), two in communications (copywriting and social media/community management), and growth marketing.

We refer to freelancers as "workers," though they are 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 flexible arrangements. Once a worker completes their profile and it is approved, the profile becomes visible to employers.[10] As is common in online labor markets, employers initiate contact after viewing profiles, including asked wages (Roussille, 2024).[11]

Employers are typically representatives of firms or organizations who create recruiter accounts on the platform. For the rest of the paper, we thus refer to employers as "recruiters," though these could represent firm owners, managers, project leaders, etc. Organizations on the platform range from single-person businesses to the largest French firms with tens of thousands of workers. Each account is tied to a specific individual recruiter, with an organization having multiple accounts if they have multiple recruiters.

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

[10] 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 jobs.

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

provide as an incentive for their evaluations.

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

2.1 Administrative data

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

We present an overview of the platform's French activity for 2025 in Table 1, restricted to our eight job categories. For confidentiality reasons, some summary statistics are reported as 10th-90th percentile ranges rather than means and some observation counts are reported as broad indicative ranges. Panel (a) summarizes workers, restricted to profiles active and visible to recruiters for at least three months during the year. Workers are in their mid thirties on average, have been on the platform for just over four years, and have slightly more than 10 years of work experience. The 10th percentile has completed 0 jobs and the 90th percentile has completed 6, while workers in the top 10% have often completed dozens of jobs. The average daily asked wage is €442. Most workers report being available full time and for in-person work. Just over 70% have completed at least a Master's degree, slightly less than one third of them are female, and slightly less than 15% are classified as being of MENA origin.[12]

[12]Gender and ethnicity are not included in the platform data. We impute them from users' first names. For ethnic origin, we use the INSEE national first-name database, *Fichier des prénoms* (available

We consider offers made by recruiters during the year in Panel (b). Recruiters who made at least one job offer have been on the platform for just over two years on average, with most of them having offered between 1 and 5 jobs. Wage budgets vary widely, between €230 and €14,420, while jobs last approximately one month on average. Averaging across recruiters, just under 40% of offers require full-time work and around 10% require on-site work. We do not provide a breakdown of firm size for confidentiality reasons, but most recruiter accounts are associated with smaller firms, consistent with 90% of French firms having less than 10 employees (Institut national de la statistique et des études économiques, Insee), although larger firms are slightly overrepresented on the platform.

3 Experimental design

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

3.1 Constructing profiles and offers

Profiles and offers are designed to closely follow the format, layout, and content observed on the platform. They were constructed at the job-category level to reflect how recruiters usually search for workers and to mirror each participant's relevant market, increasing realism and relevance.[13] Job categories span tasks that differ in skill requirements, wages, and work conditions (e.g., duration), but within a category, workers perform similar tasks using comparable skills.[14] See Appendix E for a description of each job category as provided to participants.

at `https://www.data.gouv.fr/datasets/fichier-des-prenoms-depuis-1900`), augmented with data from Jouniaux (2001) and Hawramani (2015). This methodology has been used in previous work (e.g., Algan et al. (2022); Laouénan and Rathelot (2022)). Individuals of MENA origin represent the largest ethnic minority in France and have been the main focus of the French literature on discrimination. Regarding gender, we use the tool Genderize (available at `https://genderize.io/`), which infers the gender statistically most likely to be associated with a first name based on large-scale online data.

[13] This ensures that the perception gaps we document capture participants' beliefs about their relevant job and market. In contrast, prior work typically considers broader categories like groupings of college majors or occupations.

[14] The *Evaluation* experiments also included a ninth category, translation, but it was selected by too few recruiters (6) to be used in the *Prediction* experiments. We omit these jobs from the main analysis, but show below that preference estimates are similar when including them.

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

3.1.1 Freelancer profiles

We briefly summarize the characteristics included on profiles. More details are provided in Appendix A, along with an example of an experimental profile translated into English and the original French version.

All profiles are constructed to be located in France, specifically in the participating recruiter's region, fluent in French, and proficient in English.[15] All profiles also indicate being currently available. These choices ensure profiles are evaluated based on their attributes, rather than geographic accessibility or market activity.[16]

Asked wage. We fix the daily asked wage on a profile as the wage that a recruiter would have to pay to recruit the worker. In practice, asked wages are a strong predictor of realized wages (correlation of 0.94), consistent with prior evidence (Roussille, 2024).

Experience. Experience is indicated through years of experience (on and off the platform) and a description of some specific past experiences. Each profile lists either one or two specific experiences, including the name of the firm worked for, as well as a summary of tasks and achievements.

We identify a subset of experiences as "prestigious" based on the associated firm, corresponding to French firms among the top 40 by market capitalization and foreign firms of comparable or greater size. Prestige is randomized at the profile level: profiles display either no prestigious experience or exclusively prestigious experiences (one or two).

[15] Most workers report at least working proficiency in English on their profile, and virtually all report being fluent in French, including MENA profiles.

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

Education. We include one of the following highest completed degrees, which are most common: higher technician certificate (BTS in France), university vocational diploma (DUT in France), bachelor's degree (license in France), and Master's.

Market reputation. A substantial share of active workers have never completed a job on the platform. To reflect this, we randomize a point mass at zero completed jobs and draw positive counts of completed jobs for remaining profiles.

As is common in online markets, reviews are almost universally 5 out of 5, but there is variation in the share of completed jobs that receive a review across workers, suggesting that this could be a relevant margin through which satisfaction is signaled. Accordingly, we randomize this share while assigning an average rating of 5 to reviewed profiles.

Lastly, we randomize the presence of a reputation badge awarded to workers who complete jobs exceeding a certain value over a given period.[17]

Work conditions. Profiles indicate availability only for remote work or also in person, and full-time versus part-time availability.

Demographics. Gender and MENA origin are signaled through first names and profile pictures.

3.1.2 Job offers

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

Job offers contain free text, similar to a job advertisement, which we base on the content and structure of real offers. Each offer corresponds to a job located in the participating worker's region, with a start date listed as "as soon as possible".[18] To enhance realism, offers include a task description drawn from job category-specific pools adapted from real descriptions.

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

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

[18] Since recruiters contact workers, there is typically no mention of hard requirements that can be assessed from a profile, like experience or education, since workers would presumably not receive an offer for which they do not qualify.

Market reputation. Recruiter reputation is signaled through the number of completed jobs (i.e., the number of times they hired a worker) and reviews from workers, constructed analogously as for profiles.

Recruiter prestige. Each offer begins with an introduction of the recruiter and/or firm and also lists organization size and industry. We introduce firm prestige analogously to profiles, relying on the same classification of "prestigious" firms.[19] Prestige is highly correlated with organization size, so we do not attempt to separately identify their effect.

Work conditions. Each offer randomizes job duration (less than one week to six months), remote versus in-person requirement, and full versus part-time requirement.

We also randomize two other common conditions in the task description: whether the task involves teamwork and whether it involves tight deadlines.

Demographics. Gender and MENA origin are signaled through first names.

3.2 *Evaluation* experiments

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

3.2.1 Recruitment

In line with the platform's usual communication, participants were contacted through their email address, late in fall 2025, restricting to users recently active on the platform in the relevant job categories.[20] The look and content of the recruitment email mirrored official communication.

The stated purpose was to participate in a study by the platform to improve its matching by better understanding how workers select jobs and recruiters select workers. There was no mention of academic research or of the researchers, beyond a disclaimer that the platform reserves the right to share study data. This mitigates potential concerns from

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

[20] The very largest firms are excluded because their accounts are handled directly by platform representatives. Since these firms would have made up a very small fraction of respondents, it should not meaningfully affect our results.

experimenter demand effects while mitigating concerns from deception.

Recruiters (workers) received €50 (€20) for completing the experiment – which lasted on average 17 minutes – along with a chance to win one prize of €1,000.

3.2.2 Evaluations and incentivization

Participants first choose a job category. For recruiters, this is the category in which they expect to hire next. For workers, this is the primary category in which they offer their services.[21] If a recruiter or worker indicates that none of the listed categories are relevant for them, they are screened out of the experiment. Second, participants select expertise keywords relevant to their hiring needs or skills, which we use to tailor the profiles and offers they evaluate. This ensures that evaluations concern workers and jobs relevant to participants and mirrors the platform's operations. See Appendix A.1 for details.

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

Each participant makes 25 evaluations.[22] To incentivize truthful evaluations, 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 for one job based on their evaluations. Accordingly, the more careful and honest their evaluations are, the more valuable their recommendations are.[23] See Appendix A.2 for details on the mapping from evaluations to recommendations.

These recommendations should be valuable to participants: some recruiters already pay the platform for personalized recommendations, while the average job is worth sev-

[21] 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.

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

[23] Workers were told that they would only be recommended for one job to avoid incentives to maximize their number of recommendations, for example by evaluating positively jobs that are common, regardless of their preferences.

eral thousand euros to workers. To investigate recommendation quality, we surveyed recruiters after sending them their recommendations. Although the sample is limited to 60 recruiters who answered this follow-up survey, 96% of them indicated that at least one recommendation was relevant or very relevant for their next job. This provides direct evidence on the quality of recommendations generated through the IRR approach and supports the effectiveness of our implementation.

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

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

and

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

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

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

and

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

Participants are informed that their evaluations on both dimensions are factored into their recommendations.[24] The first question explicitly abstracts from likelihood of acceptance or offering ("Suppose that they would accept an offer if you contacted them" and "If you were contacted for this job"). Factoring the second question into recommendations incentivizes reporting preferences while taking into account the perceived likelihood of success. This presumably yields more meaningful estimates for understanding behavior. For example, while a recruiter with an unattractive job may unconditionally "prefer" hiring the absolute best candidate, they are unlikely to pursue such a candidate in practice.

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

Similarly, while workers may unconditionally prefer the absolute best job, they likely face higher competition for such a job. In correspondence studies, a lack of callback can indicate either too low or too high perceived quality, but we can separate both margins.

3.3 Prediction experiments

The *Prediction* 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 others and to conduct an information treatment. See Appendix E for recruitment messages and experimental instructions.

3.3.1 Recruitment

A new group of recently active users was recruited early in spring 2026, again through their email address and mirroring official communication.[25] The stated purpose was to participate in a platform study to improve its matching by understanding how preferences of recruiters and workers align. Again, there was no mention of an academic study.

Participants were paid based on their predictions as described below, but recruiters (workers) also received €10 (€5) for completing the experiment, which lasted an average of 17 minutes, along with a chance to win one prize of €1,000.

3.3.2 Predictions and incentivization

Participants first choose a job category and are told how participants in the *Evaluation* experiments were incentivized through recommendations. They are then given information about participants in the *Evaluation* experiments within their job category, including the sample size and recent platform activity. Workers receive information about recruiters' average job budgets and organizational size, while recruiters receive information about workers' average asking wages, completed jobs, and years of experience.

Each participant makes 25 predictions about the average evaluation that a given profile or offer received, from 1 to 10, including up to one decimal point. The randomized characteristics of profiles and offers are identical to those in the *Evaluation* experiments.

[25] We separated the list of all eligible platform users in two random groups before launching the *Evaluation* experiments, so similar users were contacted to be part of the *Evaluation* and *Prediction* experiments.

For simplicity, participants are only asked to predict the average 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 evaluators.[26]

To incentivize accurate predictions, payoffs depend on prediction accuracy using a binarized scoring rule (Healy and Leo, 2025). Participants are told that their expected payoff is maximized by truthfully reporting their best estimate of the average evaluation that a profile or offer received. See Appendix A.3 for details.

These experiments ask for predictions about average preferences in a given job category. The mean is an intuitive quantity to predict. Our model shows why average preferences matter for market decisions, while our focus on narrow job categories makes these averages more representative of the market participants face. Still, participants may segment their market on specific characteristics, either due to preferences (e.g., working remotely) or competitive forces (e.g., specializing into certain more niche tasks), which would decrease the conceptual relevance of mean preferences as a benchmark. After we present our main results, we validate their relevance using an additional experiment showing that workers strongly expect average recruiter preferences to reflect their relevant market and to capture market returns.

3.3.3 Information treatment

After making predictions, participants are informed about the characteristics that were randomized on profiles or offers and asked to predict each characteristic's marginal effect on evaluations. We asked these additional predictions to make the information treatment more salient by explicitly showing participants their predictions compared to estimated preferences and giving them information about what their mistakes could imply.[27] For example, workers who overestimate recruiters' sensitivity to asked wages were told that they might be able to increase their asked wage while remaining more competitive than

[26]It could have seemed unnatural for recruiters and workers to predict how likely a recruiter or worker in the *Evaluation* experiments would have perceived themselves to have their offer accepted or receive a given offer without information on individual respondents. Also recall that questions on hiring and acceptance interest explicitly assume that the worker would accept/that the recruiter would make the offer, allowing predictors to abstract from the other dimension.

[27]Whenever a prediction falls within the 90% confidence interval of the estimated preference, participants are told that their beliefs are fairly accurate. When the estimated effect of a characteristic on evaluations is itself not statistically significantly different from 0, that is also indicated to participants.

they thought. These predictions were also incentivized (see Appendix A).

Participants are asked how useful the information is and about their intentions to modify their behavior (e.g., profile content). We test whether respondents actually change their behavior using daily data on worker profiles and trace out impacts on job offers.[28]

3.4 Empirical strategy

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

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

$$\begin{aligned} R_{ip} = \beta_0 &+ \beta_1 \, DailyWage_{ip} + \beta_2 \, AtLeastOneJob_{ip} + \beta_3 \, NumberOfJobs_{ip} \\ &+ \beta_4 \, ShareReviews_{ip} + \beta_5 \, ReputationBadge_{ip} + \beta_6 \, YearsOfExperience_{ip} \\ &+ \beta_7 \, SecondExperience_{ip} + \beta_8 \, Prestigious_{ip} + \beta_9 \, Master_{ip} + \beta_{10} \, Remote_{ip} \\ &+ \beta_{11} \, FullTime_{ip} + \beta_{12} \, Female_{ip} + \beta_{13} \, MENA_{ip} + \alpha_i + \varepsilon_{ip} \end{aligned} \tag{1}$$

where $DailyWage$ is the asked wage, $AtLeastOneJob$ is an indicator for having completed at least one job, $NumberOfJobs$ is the number of completed jobs, $ShareReviews$ is the share of jobs with reviews, $ReputationBadge$ is whether the profile has a reputation badge, $YearsOfExperience$ is the years of work experience, $SecondExperience$ 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's degree, $Remote$ is whether the profile indicates a preference for working remotely, and $FullTime$ is whether it indicates availability to work five days a week (rather than 2-3 days). $Female$ and $MENA$ are whether the

[28] We did not know whether these data would be available at the time of pre-registration, so we did not pre-register these analyses. We did pre-register that we intended to perform additional analyses combining experimental and platform data, pending availability.

profile indicates the given gender and ethnic origin, and α_i are participant fixed effects. Standard errors are clustered at the participant level.

We set $ShareReviews$, $ReputationBadge$, and $NumberOfJobs$ to 0 when $AtLeastOneJob$ is equal to 0. We center $ShareReviews$ at its sample mean of 60%. Hence, β_2 captures the discrete premium associated with having completed at least one job, beyond the linear contribution of the number of completed jobs. The total effect of going from zero to one completed job, holding the badge absent and the review share at its mean, is $\beta_2 + \beta_3$. 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_5 reflects the impact of having a reputation badge, holding constant completed jobs and share of reviews.

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

$$\begin{aligned} R_{io} = \beta_0 &+ \beta_1 \, DailyWage_{io} + \beta_2 \, AtLeastOneJob_{io} + \beta_3 \, NumberOfJobs_{io} \\ &+ \beta_4 \, ShareReviews_{io} + \beta_5 \, Prestigious_{io} + \beta_6 \, Remote_{io} + \beta_7 \, FullTime_{io} \\ &+ \beta_8 \, Duration_{io} + \beta_9 \, Teamwork_{io} + \beta_{10} \, TightDeadlines_{io} \\ &+ \beta_{11} \, RecruiterFemale_{io} + \beta_{12} \, RecruiterMENA_{io} + \alpha_i + \varepsilon_{io} \end{aligned} \tag{2}$$

where $DailyWage$ is the offered wage, $Prestigious$ is whether the firm is signaled as prestigious, $Remote$ is whether the job can be done remotely, $FullTime$ is whether availability five days a week is required (rather than 2-3), $Duration$ is the indicated length of the job, $Teamwork$ is whether the offer mentions teamwork, and $TightDeadlines$ is whether it mentions tight deadlines. $RecruiterFemale$ and $RecruiterMENA$ are whether the recruiter's name indicates the given gender and ethnic origin. We again include participant fixed effects, and standard errors are clustered at the participant level.

To estimate perception gaps, we jointly consider evaluations and predictions by augmenting Equations (1) and (2) with interaction terms between each randomized characteristic and an indicator variable P_i for whether the rating is from the *Prediction* experiments. We also reweight observations from the *Prediction* experiments to match the distribution of job categories from the *Evaluation* experiments to avoid perception gaps potentially

arising from imbalance in job categories across the two experiments.

In particular, we estimate the following regression model:

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

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

4 Results of the *Evaluation* experiments

Our pre-registered recruitment target was 350 recruiters and 800 workers, after excluding participants not hiring in or working within the job categories in the experiment as well as participants who spent on average fewer than 10 seconds per profile or offer.[29] After applying our exclusion criteria and removing translation jobs, we are left with 342 recruiters and 771 workers.[30] We additionally exclude eight recruiter evaluations for which profile names and pictures were incorrectly displayed.

Table 2 reports estimates from equations (1) and (2). Columns 1 and 2 present the estimated effects of profile characteristics on recruiters' hiring interest and on their assessment of the likelihood that the worker would accept an offer from them, respectively. Columns 3 and 4 report the estimated effects of job offer characteristics on workers' interest in accepting the job and on their assessment of the likelihood of receiving such an offer, respectively. All specifications include respondent fixed effects, so we compare how the same respondent evaluates different profiles or offers controlling for potential differences in how respondents use the rating scale (i.e., being more or less severe). To help interpret magnitudes, we also express preferences in monetary terms by rescaling each coefficient

[29] 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 of time spent on CVs, ranging from 7 to 45 seconds (Culwell-Block and Sellers, 1994; Dishman, 2018).

[30] Results are similar when including translation jobs (Table B.10), but we exclude them for consistency since they are not part of the *Prediction* experiments.

relative to the corresponding wage coefficient (Figure 1).

Figure B.1 shows the distribution of raw ratings given by evaluators, documenting substantial mass across the Likert scale and showing that profiles and offers appeared relevant to participants on average.

4.1 Recruiter preferences

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

Asked wage. Since we ask recruiters their hiring interest at the specific conditions listed on the profile, the asked wage can be interpreted as the price to pay. As expected, higher asked wages reduce hiring interest. Moving from the 25th to the 75th percentile of the randomized wage distribution, corresponding to €270, decreases recruiters' hiring interest by 21% of a standard deviation in profile evaluations.[31]

The relationship is non-linear; asked wage increases have little effect over the lower half of the distribution but a large effect at higher levels (Figure B.3). This pattern aligns with recruiters' hiring budgets for their next job. Within their budgets, recruiters evaluate profiles with higher asking wages more positively, consistent with wages signaling competence (Wolinsky, 1983). Above their budgets, however, higher asking wages sharply reduce hiring interest: a €270 increase reduces interest by 57% of a standard deviation (Table B.1). This correspondence between experimental estimates and budget constraints supports the validity of the design. Further supporting this interpretation, recruiters rate profiles with higher asking wages as more competent. Controlling for perceived competence increases the magnitude of the negative wage coefficient by roughly 40% (Table B.2). Moreover, profiles with higher asks are expected to be less likely to accept a job offer, as shown in column 2 of Table 2.

Market reputation. Market experience also plays an important role in evaluations. Profiles with at least one completed job receive an advantage of 12% of a standard deviation, consistent with the well-documented "cold start" problem in labor markets (Pallais,

[31] In Figure B.2, we split profiles in quartiles of predicted quality based on recruiter evaluations, omitting the ask, and show a negative effect of a higher ask on evaluations within each quartile.

2014; Stanton and Thomas, 2016), where new entrants often struggle to get a first job.[32] Profiles with a completed job are also marginally expected to be more likely to accept an offer, indicating that it may act as a signal of commitment or dependability. Additional completed jobs 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 an offer.

The reputation badge—used by the platform as a signal of success—generates a similar increase in interest as completing a first job, while the share of completed jobs with reviews has little effect on evaluations, consistent with recruiters either overlooking this information or viewing the absence of reviews as uninformative about worker quality.

Human capital. General experience is also valued. Moving from the 25th to the 75th percentile of the randomized distribution of years of experience increases interest by 14% of a standard deviation and profiles displaying two prior work experiences rather than one receive an increase in hiring interest of 24% of a standard deviation. In contrast, experience at prestigious firms has little effect on hiring interest, even though recruiters appear to notice the signal: they perceive these workers as less likely to accept an offer. We also show below that prestigious experiences do impact the probability that a profile is rated particularly highly, even if it appears to have little effect on average ratings.

A Master's degree has little effect on evaluations, consistent with many jobs being quite specialized, leading to job-specific experience and market reputation being prioritized over broader ability signals.[33]

Work conditions. Indicating remote-only or part-time availability has little effect on interest, likely reflecting that many recruiters seek remote arrangements and require less than full-time work. Consistent with this, among recruiters who indicate requiring in-person work for their next job, we find suggestive evidence of a strong remote penalty (Table B.4). Moreover, profiles with full-time availability are expected to be more likely to accept an offer, indicating that it still constitutes an advantage for these profiles.

[32]Table B.3 provides evidence that, in the absence of completed jobs, recruiters place greater weight on experience.

[33]Exploratory analyses that were not pre-registered yield little evidence of heterogeneity by degree institution prestige. Results are available upon request.

Demographics. Finally, we find no evidence of gender discrimination and limited evidence of ethnic discrimination. Profiles of MENA origin do not receive lower hiring interest or assessed competence, but are rated as less likely to accept a job offer (5% of a standard deviation), with the effect seemingly being driven by recruiters of non-MENA origin, as discussed below.[34] These results suggest that, to the extent that ethnic minorities face a disadvantage, it could relate to their perceived responsiveness or reliability. We find little evidence that other profile characteristics are evaluated differently depending on demographics (Table B.6).

These results align with previous IRR evidence and with correspondence studies for gender, but differ from correspondence studies documenting discrimination against MENA workers in France (Dares et al., 2021a,b). This may reflect lower exposure to discrimination in freelancing: jobs involve specific, self-contained tasks, interactions are short-term, often remote, and transactional, and dismissal costs or other legal liabilities are low.[35] In line with this, observational platform data provide limited evidence that MENA origin is associated with a lower probability of having completed a project over our analysis period, after controlling for other profile characteristics (-7% difference, P-value of 0.401).

4.2 Worker preferences

Workers' interest in accepting a job depends on a different set of characteristics than those driving recruiters' hiring interest. Workers place substantial weight on the wage and on job conditions, but little weight on recruiter and firm characteristics.

[34] In Table B.5, we show that this negative effect appears larger among recruiters who attach little importance to diversity in hiring, based on a question asked at the very end of the experiment. Additional exploratory analyses that were not pre-registered yield little evidence of heterogeneity between the Paris area and the rest of France. Results are available upon request.

[35] The results are unlikely to reflect that demographics are not salient, not expected to be used in recommendations, caused by choices related to profile pictures, or social desirability bias. First, there is an effect on the expected probability that MENA profiles would accept an offer and we show below that discrimination against MENA profiles in hiring interest is anticipated by participants. Second, as shown next, results are similar between profiles and offers, with the latter not including profile pictures. Third, participants were not told that they were part of an academic study. Consistent with this, only one participant in our piloting indicated discrimination among a list of potential study purposes when prompted using an open-ended question. While participants might still have expected their experimental decisions to be observable to the platform, that is also true of all their other platform decisions, making the experiment no different along that margin.

Offered wage. Moving from the 25th to the 75th percentile of the randomized offered wage distribution increases acceptance interest by 0.75 standard deviations in worker evaluations. Unlike for recruiters, the relationship appears approximately linear (Figure B.3), but we do find a strong shift at the point where the wage on an experimental offer crosses the participating worker's asked wage indicated on their real profile (Table B.1). Workers are more sensitive to wage increases below their ask and less so to wage increases above it, consistent with the ask acting as a reference or reservation point and again corroborating our experimental design's validity.

Market reputation. Recruiter reputation (completed jobs and review shares) has little discernible effect on evaluations. This could partly arise because, once job contracts are signed, payment for completed work is guaranteed through the platform, mitigating concerns such as payment withholding (Benson et al., 2020). One exception is organizational prestige, which reduces workers' interest by 8% of a standard deviation. Table B.2 suggests that this effect is consistent with workers feeling less qualified for these jobs, in line with workers also reporting being less likely to receive such offers. Consistent with this interpretation, the negative effect appears smaller among workers with stronger platform reputation, as shown below.

Work conditions. Workers value work conditions, most notably remote work. Offers allowing remote work receive 27% of a standard deviation higher evaluations.[36] Workers prefer remote jobs whether their profile indicates availability for in-person work or a preference for remote work, but this preference is stronger among the latter group (Table B.4). Workers attach little weight to whether jobs indicate being performed in teams, but report 10% of a standard deviation lower interest in those mentioning tight deadlines, consistent with willingness to pay to avoid stressful environments or with tight deadlines complicating scheduling across jobs. We find a small, suggestive positive effect of job duration on interest which appears to hinge on jobs lasting less than one week versus at least a few weeks (Figure B.3).

[36]Estimates in Figure 1 suggest that workers are willing to accept around 15% lower wages for remote work, somewhat higher than Mas and Pallais (2017) (8%) and similar to more recent estimates from Cordes et al. (2026) (15%).

Demographics. We find little evidence of worker discrimination.

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.7), replacing respondent fixed effects with job category fixed effects (Table B.8), retaining respondents who spent on average fewer than 10 seconds per evaluation (Table B.9), adjustments for multiple hypothesis testing (Table B.22), and reweighting participants for platform representativeness (Table B.11). Estimates are broadly consistent when comparing the first 12 with the final 13 evaluations (Table B.12).

Patterns are broadly similar across participant gender or ethnicity (Table B.13), although the sample of MENA respondents is small. Results are broadly similar across tech and non-tech jobs (Table B.20),[37] recruiter organization size (Table B.15; not preregistered), and platform experience (B.16 and B.17). Results restricted to workers with greater experience (at least five completed jobs) are also similar, with some evidence that they do not penalize prestigious offers (Table B.18).

Analyses using ordered probit regressions, which relax the linearity assumption along the 10-point scale and only require that participants value higher ratings more favorably on average, yield similar conclusions (Table B.19). Analyses looking at the impact of characteristics on whether profiles and offers are rated particularly highly, rather than average evaluations, generate two insights: smaller benefits of a first completed job, indicating that the "cold start" problem may affect profiles that are otherwise unable to stand out, and prestigious experiences increase the likelihood of a profile being rated highly.[38]

Overall, the *Evaluation* experiments show that recruiters and workers value different combinations of wages, human capital, reputation, and working conditions. These experimentally estimated preferences provide a benchmark for assessing whether market participants correctly anticipate the returns to the characteristics they possess or offer.

[37]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 and project duration more, while non-tech workers respond more negatively to offers signaling teamwork.

[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 can be seen as approximating "hiring", to the extent that a recruiter pursues their top candidate.

5 Results of the *Prediction* experiments and perception gaps

We now examine whether workers and recruiters correctly anticipate the preferences documented in the *Evaluation* experiments, and therefore understand how the market values different worker and job characteristics.

Our pre-registered recruitment target was 350 recruiters and 800 workers, after excluding participants not hiring in or working within the job categories in the experiment and those spending fewer than six seconds per profile or offer on average.[39] After applying our exclusion criteria, we are left with a sample of 345 recruiters and 802 workers.

On average, participants make large prediction errors of around 1.63 per profile or offer on the 10-point Likert scale.[40] Our primary interest is in determining how much of these prediction errors can be attributed to misperceptions about the characteristics randomized on profiles and offers. We first assess their combined contribution before examining perception gaps for individual characteristics.

To do so, for each participant, we estimate the effect they expect each characteristic to have on evaluations as implied by their 25 predictions, minus the true estimated impact from the *Evaluation* experiments. In particular, we estimate respondent-specific coefficients using a hierarchical linear model to recover Empirical Bayes estimates under a Gaussian prior. This procedure shrinks noisy estimates towards the population mean, avoiding overfitting.[41] We find that misperceptions about the randomized characteristics account for substantial prediction errors, averaging approximately half a standard deviation in evaluation ratings, or around one point on the 10-point scale, accounting for most of the total average prediction error of 1.63.

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

[40] See Figure B.4 for the distributions of raw predictions.

[41] Formally, for profile or offer i, we recover $P_i^{eb} = \Sigma_j \beta_{kj}^{eb} X_j$, where β_{kj}^{eb} are the Empirical Bayes coefficients and X_j are randomized characteristics. We then recover the difference between the Empirical Bayes prediction and the actual evaluation ($e_i^{eb} = P^{eb} - \Sigma_j \beta^{ev} X_j$).

5.1 Predicting recruiter preferences

We use Equations (1) and (2) to estimate the effects of individual characteristics on evaluations and predictions, and Equation (3) to test for differences between these estimates. A positive (negative) perception gap indicates that predictors overestimate (underestimate) the effect of a characteristic on evaluations, where effects are measured with their signs. Thus, for characteristics with negative effects, a positive gap corresponds to underestimating the magnitude of the penalty. We interpret gaps in terms of their size relative to estimated preferences, but since some of these coefficients are quite small, resulting gaps can be very large. Accordingly, we also express gaps in terms of their size relative to one standard deviation in evaluation ratings as well as in monetary terms.

Results are presented in columns 1-3 of Table 3. Column 1 reproduces results from Table 2 for convenience, showing the impact of each characteristic on recruiter evaluations. Column 2 presents the impact that workers expect each characteristic to have on recruiter evaluations. Column 3 reports the perception gap, calculated as the predicted effect in column 2 minus the actual effect in column 1. We find several perception gaps, some regarding the importance of characteristics which do affect recruiter evaluations and some regarding characteristics with little observed impact on recruiter evaluations.

Asked wage. Workers substantially underestimate recruiters' sensitivity to asked wages: the perception gap amounts to approximately 81% of the experimentally estimated wage effect, or 6.4% of a standard deviation in evaluations for each additional €100 in asked wages. This suggests that workers may overestimate the signaling component of wages, potentially distorting their ask decision.

Market reputation and human capital. Workers also overestimate the value of reputation and human capital, namely having at least one completed job, the reputation badge, years of experience, and prestigious work experiences. Magnitudes range from 50% to over 100% of the estimated effects on evaluations, corresponding to prediction errors of 8-16% of a standard deviation in evaluations. These results indicate that workers misunderstand how employers trade off wages and signals of worker quality. As the model highlights below, these misperceptions can distort the extent to which workers invest in

acquiring these signals. Moreover, even for signals that workers have less control over (e.g. years of experience), misperceptions can again distort asked wages.

Work conditions. Workers expect that profiles indicating a remote-work preference are penalized and those indicating availability for full-time work are favored, although we find that neither affects evaluations on average, leading to gaps that are several times larger than estimated preferences for the characteristics or 6-8% of a standard deviation in evaluations. These misperceptions indicate that workers do not understand the trade-off between their preferred working conditions and recruiters' willingness to hire them, which could affect both matching and match quality.

Demographics. There is little average anticipated gender or ethnic discrimination, though MENA workers do anticipate discrimination against MENA profiles.[42] Otherwise, results are broadly consistent across respondent gender and ethnicity (Table B.23).

Figure 2 quantifies perception gaps relative to the monetary value attached to each characteristic in the *Evaluation* experiments. These estimates express workers' misperceptions about recruiters' valuation of different characteristics in monthly full-time-equivalent wage terms. Amounts are substantial, on average amounting to misperceptions of €605 per month of full-time equivalent wages per characteristic.

These magnitudes underscore that workers' misperceptions concern economically important trade-offs between asking wages and other characteristics. As a result, inaccurate beliefs may affect not only how workers assess their market value, but also the wages and characteristics they choose to offer.

5.2 Predicting worker preferences

Results regarding recruiter predictions of worker preferences are presented in columns 4-6 of Table 3. We find fewer large, statistically significant perception gaps than for recruiter preferences, suggesting that recruiters generally have more accurate beliefs about what workers value than workers have about what recruiters value. Still, there are a handful of key misperceptions.

[42] Recent work finds evidence that individuals overestimate the extent of discrimination they might face (Angeli et al., 2023; Brouard et al., 2024; Lepage et al., 2025).

Offered wage. Recruiters overestimate workers' responsiveness to offered wages. For each additional €100, recruiters overestimate the effect by about 15% relative to the actual effect, a gap equivalent to 5% of a standard deviation in evaluations. As with the wage-sensitivity gap documented above, this implies a distortion in offered wages. Holding constant the other characteristics of their job, recruiters may expect that they need to offer more than they do in order to hire a worker.

Market reputation. The negative impact of offers from prestigious organizations on worker valuations is entirely unanticipated by recruiters, yielding a gap of 9% of a standard deviation. Otherwise, recruiters generally anticipate the relative lack of importance of recruiter reputation to workers.

Work conditions. Recruiters underestimate workers' valuation of remote work by more than 23% of its estimated effect, equivalent to 6% of a standard deviation in evaluations. Conversely, they overestimate the positive effect of longer jobs by more than a factor of two, yielding a gap of 1.3% of a standard deviation for each additional month of duration. Taken together, these results imply that recruiters misunderstand how workers trade off wages and non-wage amenities, again potentially impacting wage setting but also the extent to which recruiters efficiently adapt their job conditions.

Demographics. There is little evidence of anticipated discrimination by recruiters, consistent with results on worker evaluations.

Some of these gaps are substantial in monetary terms, again rescaling by the coefficient on offered wage from the *Evaluations* experiment, as shown in Figure 2. On average, gaps in absolute value amount to misperceptions of approximately €165 per month. In particular, the overestimation of workers' valuation of offers from prestigious firms and the underestimation of their valuation of remote work correspond to misperceiving the value of these amenities by €600 and €400 per month of full-time equivalent wages. These gaps suggest that recruiters misunderstand the wage adjustments needed to attract workers with particular job conditions.

5.3 Heterogeneity and robustness

The accuracy of individual beliefs matters even when average perceptions are correct. Average perception gaps can conceal heterogeneity across job categories and particularly across individual predictors. An average gap close to zero could reflect either broadly accurate beliefs or overestimation by some offset by underestimation among others. For example, take two workers, one who overestimates recruiters' price sensitivity and the other who underestimates it. Average beliefs are accurate, but one might set their ask too high, potentially decreasing their employment opportunities, while the other might set their ask too low, potentially decreasing their earnings. In both cases, misperceptions matter even in the absence of an average gap.

Accordingly, although we have limited power to test for differences between jobs, we investigate how perception gaps differ across job categories and individuals. Table B.24 conducts the analysis by tech and non-tech jobs, suggesting heterogeneity across types of work, with perception gaps sometimes offsetting one another. Calculating gaps at the level of the eight job categories instead and averaging them in absolute value yields average gaps of 0.15-0.2 on the 10-point scale or 6-10% of a standard deviation in evaluations per characteristic. These estimates are substantially larger than the size of the average perception gap documented above and we can reject that the impact of certain characteristics is equal across categories, namely asked and offered wages, suggesting some meaningful heterogeneity (Figure B.5).

Calculating gaps at the individual level in Figure 3 also yields large apparent heterogeneity and substantial shares of predictors with large misperceptions.[43] Across characteristics, around one third of workers and 20% of recruiters on average have prediction errors above one half of a standard deviation in evaluations.

Perception gaps do not appear to diminish with platform experience (Tables B.25, B.26). As shown below, they are also systematically related to predictors' own characteristics, consistent with the model in Section 6.1. For example, workers with higher asks underestimate recruiters' price sensitivity by more and workers who report being available

[43]To increase precision, we use the direct predictions of each characteristic's marginal impact on evaluations asked of respondents after they made their profile predictions. There is a very strong relationship between the two prediction measures (Figure B.6).

in person overestimate the penalty recruiters attach to remote-only profiles by more. Recruiters with larger budgets overestimate workers' price sensitivity by more and recruiters hiring for in-person jobs underestimate workers' preference for remote work by more.

Results are robust to retaining respondents who spent on average fewer than 6 seconds per prediction (Table B.27), adjustments for multiple hypothesis testing (Table B.22), ordered probit estimation (except the gap on worker wage sensitivity, Table B.28), and reweighting either evaluators or predictors for platform representativeness (Table B.29).

5.4 Additional experiment: market segmentation and returns

Our main experiments measure beliefs about average preferences within narrow job categories. For these beliefs to be economically relevant, they should be informative about the preferences of recruiters and workers that workers and recruiters actually target and about the characteristics participants believe improve their market prospects. We investigate this in an additional experiment with 150 workers.

Before making predictions, workers describe in detail the types of jobs and recruiters they target along all dimensions included on job offers. They then make predictions for 25 worker profiles. For each profile, they predict (i) the hiring interest of recruiters in their target market, (ii) the hiring interest of recruiters in their job category on average, and (iii) the likelihood that the profile would receive a job offer within the following three months, taking into account both recruiter demand and competition from other workers.[44]

Comparing the first two measures tests whether beliefs about average preferences mask substantially different beliefs about the recruiters workers actually target. Comparing the last two measures tests whether beliefs about average recruiter preferences predict workers' perceived hiring prospects, which may also depend on competition from other workers. For example, a characteristic valued by relatively few recruiters could still improve hiring prospects if few workers possess it.

Appendix Figure B.7 shows that these different objects are closely aligned. At the

[44]Predictions of average recruiter interest were incentivized based on accuracy, while predictions of target-market interest were incentivized through platform recommendations to recruiters matching workers' stated target markets. The third question on the likelihood of receiving a job offer was not incentivized. Participants received a fixed payment of €10 and could earn a bonus of up to €5 based on prediction accuracy. This experiment was not included in our original pre-registration and was done after the fact to investigate robustness of our results.

profile level, predicted average recruiter interest is strongly related to predicted target-market interest, with a slope of 0.86 (s.e. 0.01). Perceived hiring likelihood is similarly strongly related to predicted average recruiter interest, with a slope of 0.89 (s.e. 0.01). The relationship is also apparent when considering predictions associated with each randomized characteristic separately (Appendix Figures B.8 and B.9). Thus, workers appear to believe that average recruiter preferences are broadly representative of both the preferences of recruiters in their target markets and the characteristics that improve their hiring prospects. These results support our baseline analysis using beliefs about average preferences as an economically relevant benchmark.

6 Consequences of perception gaps

We now investigate whether misperceptions about market preferences translate into economically consequential decisions. We first develop a model showing how perception gaps can distort behavior, then examine how gaps relate to actual market behavior and outcomes. Finally, we investigate whether providing information about market preferences changes participants' behavior and subsequent job outcomes.

6.1 Theoretical framework

We present a model in which two sources of distortion arise when subjective expectations of agents about the preferences of others are inaccurate. First, even when worker and job characteristics are fixed, misperceptions distort pricing. Second, when agents can invest in characteristics, misperceptions distort investments (see Appendix C.2 for a version of the model studying investment). These distortions can lead some matches to fail to occur and matches that do occur to generate less surplus.

6.1.1 Baseline model

There is a continuum of workers indexed by $i \in [0, 1]$ and a continuum of recruiters indexed by $j \in [0, 1]$. Each worker i has observable characteristics x_i that map into a value to recruiters $v_i \equiv v(x_i)$, interpreted as expected productivity. Each recruiter j has

observable characteristics y_j that map into a value to workers $u_j \equiv u(y_j)$, interpreted as non-wage utility. For now, consider v_i and u_j as fixed.

Timing

1. Worker i publicly posts an ask $w_i \geq 0$.
2. Each worker is randomly matched to a single recruiter j. The recruiter observes (x_i, w_i) and chooses whether to make an offer and, if so, offers wage $p \geq 0$.
3. The worker accepts or rejects the offer (if any). If an offer is accepted, a match occurs and the wage equals p (there is no bargaining).

Worker acceptance. Given an offer p, the worker accepts whenever

$$u + p - w + \varepsilon \geq 0,$$

where ε is an i.i.d. logit acceptance shock (scale normalized to 1) capturing idiosyncratic, match-specific variation in the acceptance decision that does not affect payoff conditional on acceptance. We interpret w as a publicly posted asking wage that serves as a reference point when evaluating an offer. Job-specific non-wage utility shifts the effective acceptance threshold, so a worker may accept an offer with a wage below their posted ask.

The probability of acceptance is

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

If an offer is accepted, the worker's payoff is $u + p$. Otherwise, their payoff is 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

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

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 that probability be defined as

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

Conditional on making an offer, increasing p 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 a 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.

Worker problem. The worker chooses w to maximize expected payoff:

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

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

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

Workers are willing to accept lower wages for jobs with higher u. Workers with higher v are more attractive to recruiters, increasing their wages and offer probabilities; under the regularity conditions stated in Appendix C, they also optimally post higher asks.

6.1.2 Pricing distortions

We now introduce inaccurate beliefs about the preferences of the other side of the market.

Workers may misperceive how recruiters value their characteristics x_i:

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

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

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

where $\Gamma \in \mathbb{R}$ is the recruiter's gap.

For expositional simplicity, we study the two perception gaps separately.[45] This isolates the consequences of each first-order perception gap without higher-order beliefs about the other side's misperceptions. We also abstract from modeling uncertainty and learning about v and u to focus on the simplest setting showing how perception gaps distort behavior. Although we model misperceptions about how worker and job characteristics are valued, misperceptions could also arise from inaccurate beliefs about the characteristics of workers and jobs themselves (Sockin and Sojourner, 2023; Andresen et al., 2026), suggesting that the framework could be applied to study other types of information frictions.

Recruiter problem A recruiter with perception gap Γ solves their problem forecasting acceptance using $\hat{u}$:

$$\widehat{A}(p; \hat{u}, w) = \sigma(\hat{u} + p - w).$$

Let

$$p^{\Gamma}(w; v, \hat{u}) \in \arg\max_{p \geq 0} \widehat{A}(p; \hat{u}, w)(v - p)$$

and

$$\Pi^{\Gamma}(w; v, \hat{u}) = \max_{p \geq 0} \widehat{A}(p; \hat{u}, w)(v - p).$$

The recruiter makes an offer whenever $\Pi^{\Gamma}(w; v, \hat{u}) \geq c$. Recruiters therefore misperceive

[45] When analyzing worker gaps, workers misperceive how recruiters value their characteristics but abstract from the possibility that recruiters themselves hold inaccurate beliefs about worker preferences. Conversely, when analyzing recruiter gaps, recruiters misperceive how workers value their job characteristics but abstract from the possibility that workers' posted asks themselves reflect inaccurate beliefs about recruiter preferences.

how their job characteristics affect workers' valuation and hence acceptance, which can distort both the decision to make an offer and the offer itself.

Worker problem A worker with perception gap Δ expects a recruiter with job value u to offer $p^*(w;\hat{v},u)$ whenever $\Pi^*(w;\hat{v},u) \geq c$. The worker therefore perceives the probability of receiving an offer as $\widehat{q}(w;\hat{v}) = \Pr(\Pi^*(w;\hat{v},u) \geq c)$, and chooses the ask to solve

$$\max_{w \geq 0} \widehat{q}(w;\hat{v}) \cdot \mathbb{E}\left[A(p^*(w;\hat{v},u);u,w)\,(u + p^*(w;\hat{v},u)) \mid \Pi^*(w;\hat{v},u) \geq c\right].$$

Let $w^{\Delta}(v)$ denote the resulting ask. Workers form distorted expectations about the likelihood of receiving an offer and the offered wage conditional on receiving one. Realized recruiter decisions following the worker's choice of $w^{\Delta}(v)$ are determined by the true value v, according to $p^*(w^{\Delta}(v);v,u)$ and $\Pi^*(w^{\Delta}(v);v,u)$.

Proposition 1. *Consider each perception gap separately and compare the resulting choices and outcomes with the correct-beliefs benchmark.*

1. ***Pricing.*** *For recruiters, $\Gamma > 0$ leads them to offer lower wages than under correct beliefs; $\Gamma < 0$ leads them to offer higher wages. For workers, $\Delta > 0$ leads them to ask higher wages; $\Delta < 0$ leads them to ask lower wages.*

2. ***Matching and expected payoff.*** *For workers, $\Delta > 0$ raises the worker's ask, reducing the probability of receiving an offer. Among recruiter types that make an offer under both the distorted- and correct-beliefs asks, the higher ask also reduces the probability of acceptance. Hence matching falls; the reverse holds for $\Delta < 0$.*

   For recruiters, $\Gamma > 0$ lowers the offered wage and raises the perceived profitability of making an offer, so the probability of making an offer increases. Among recruiter types that make an offer under both distorted and correct beliefs, the lower offered wage reduces the probability of acceptance. The reverse holds for $\Gamma < 0$.

   Whenever a perception gap alters pricing or offer decisions, the resulting distortion reduces the agent's expected payoff relative to the correct-beliefs benchmark.

Proof. See Appendix C. □

6.1.3 Broader labor market implications

The pricing model and its investment extension (Appendix C.2) highlight how perception gaps can contribute to some broader labor market phenomena.

Unemployment. The model generates unmatched workers—interpretable as unemployment. Under-investment in characteristics valued by recruiters lowers workers' probability of being hired, while pricing misperceptions can also change the likelihood of being hired through asked wages.

Labor shortages. The model generates unfilled jobs—interpretable as vacancies. Under-investment in amenities valued by workers lowers firms' probability of filling jobs, while pricing misperceptions can additionally affect offer and acceptance decisions.

(Lack of) Compensating differentials. Firms that under-invest in amenities may need to increase their wages to compensate, but those that over-invest may not be able to recoup their costs through lower wages, creating an apparent lack of compensating differentials. Moreover, employers may not know how to accurately price their amenities after acquiring them, also muting compensating differentials.

Pay differences and wage inequality. Mispricing generates excess wage dispersion. Over- and underpricing coexist even among agents with identical characteristics, contributing to observed pay differences among similar employers and workers.

Credentialing and skills mismatch. Workers may underinvest or overinvest in credentials like education, potentially generating either over-credentialing or skill shortages. Workers who acquire "too much" of a credential may find themselves employed in jobs that don't use it and employers who offer the wrong amenity levels for the workers they seek may attract other workers instead, creating mismatches.

Imperfect competition. Employers who better understand worker preferences can more effectively set pay and amenities to attract and retain workers, contributing to variation in market power.

6.2 Perception gaps and market outcomes

The model predicts that misperceptions about market preferences can distort the characteristics and prices agents choose, with consequences for matching. We investigate these

predictions using participants' experimental perception gaps linked to their administrative records, examining three outcomes: the characteristics they possess or offer, their pricing decisions, and their market outcomes.

The investment extension in Appendix C.2 shows that agents who overestimate the return to a characteristic should be more likely to invest in that characteristic. We do not observe investment decisions, but we can test whether perception gaps predict the characteristics agents possess or offer. We estimate whether a participant's gap for a characteristic, estimated using the Empirical Bayes procedure from Section 5, predicts the presence of that characteristic on their profile or offers. Columns 1 and 3 of Panel (a) of Table 4 show that, for both workers and recruiters, overestimating the value of a characteristic is positively correlated with their profile or offers containing that characteristic.

Next, we study the correlation between perception gaps and pricing. Using estimated preferences from the *Evaluation* experiments, we estimate a market value for each profile and offer on the platform, excluding the wage, approximating ν and u in the framework.[46] We combine these estimates with participants' predicted market values of their own profile to employers or offer to workers. Using Empirical Bayes estimates, we compute predicted ratings $\hat{\nu}$ and $\hat{u}$ by taking the sum of the predicted impact of each characteristic multiplied by the quantity of that characteristic on the profile or offer. We then standardize ν, u, $\hat{\nu}$ and $\hat{u}$ across job categories for comparability. We construct the perception gaps Δ and Γ as the difference between participants' predicted market values and their experimentally estimated market values, capturing the extent to which they overestimate or underestimate the value of their non-wage characteristics.

Consistent with the model, columns 2 and 4 of Panel (a) of Table 4 show that workers who overestimate their value to recruiters set higher asks, while recruiters who overestimate the attractiveness of their offers set lower offered wages, controlling for experimentally estimated market values. Effects are sizable. A one-standard-deviation increase in overestimation is associated with an increase of 13% of a standard deviation in workers' asking wages and a decrease of 4.7% of a standard deviation in recruiters' offered wages. Although not included in the model, we also document impacts of misperceptions regard-

[46] Market value is the sum of estimated preferences for all randomized characteristics, each multiplied by the quantity of the characteristic on the given profile or offer.

ing wage sensitivity: workers who underestimate recruiters' price sensitivity ask higher wages, while recruiters who overestimate workers' price sensitivity offer higher wages.

Perception gaps also correlate with job outcomes, as shown in Panel (b) of Table 4. Workers with larger misperceptions in absolute value about the value of their non-wage characteristics have fewer successful matches and lower earnings, with decreases of 8% and 13% of a standard deviation for a one standard deviation increase in perception gaps. Similarly, recruiters with larger gaps have fewer accepted job offers and, conditional on hiring, pay higher wages (effects of 12% and 24% of a standard deviation in the outcomes, with only the second being statistically significant). Effects of misperceptions regarding wage sensitivity also go in the predicted direction and are statistically significant when looking at the number of jobs completed, suggesting that pricing distortions from these misperceptions can affect matching.

These results show that perception gaps are systematically associated with pricing decisions and market outcomes, consistent with the mechanisms highlighted by the model. To assess their potential economic magnitude, we next use the estimated pricing relationships in a stylized counterfactual exercise that corrects perception gaps, assuming that the associations between perceptions and wages capture how market participants would adjust their pricing decisions if their beliefs changed.

We provide a high-level summary here, with details provided in Appendix D. We first estimate the relationship between perception gaps and pricing and adjust asked and offered wages for counterfactual correction rates ranging from 0% to 100%. We abstract from investment distortions due to lack of data on investment choices. Next, we estimate how these wage changes affect market outcomes. For each job posted by a recruiter in the *Prediction* experiments, we identify workers in the *Prediction* sample who were eligible and available when the job was posted. We then estimate how the recruiter would allocate contacts among these workers under the counterfactual wages. We hold fixed the total number of offers made for each job but allow their allocation across workers to change, since our data do not identify how recruiters' decisions about the number of offers would respond to wage changes. Lastly, for each offer, we calculate the probability that the worker would accept.

Estimates in Table D.1 compare outcomes under different levels of perception gaps.[47] We find that closing pricing distortions entirely would have substantial impacts, increasing matches by 2.9% and match quality by 3.6%, largely due to decreased asked wages.

6.3 Information treatment

The preceding analyses show that perception gaps are associated with economic decisions and outcomes, but these relationships do not by themselves establish that inaccurate beliefs drive behavior. The information treatment provides complementary evidence by allowing us to examine whether participants adjust their market decisions after receiving personalized information about actual preferences.

In the experiment, over 85% of workers and recruiters reported that the information was useful, especially that on wages. A majority of participants also reported intending to change their behavior in response to the information, most frequently job offer content for recruiters and profile content for workers.

Since worker profiles can continuously be updated, a worker intending to change their behavior due to the information could readily modify their profile after the experiment.[48] We test this using daily data on profile modifications during the ten days before and after each participant completes the experiment. As a comparison group, we use workers who were included in the pool of potential predictors, but were not contacted since we reached our pre-registered number of participants before contacting them (the order of participants within the contact list is random). We estimate the following equation:

$$\text{Change}_{it} = \sum_{\substack{d=-10 \\ d\neq -1}}^{10} \beta_d \left(\text{Treat}_i \times \mathbb{1}\{t - \tau_i = d\}\right) + \alpha_i + \delta_t + \varepsilon_{it} \tag{4}$$

where Change_{it} is an indicator equal to one if worker i changes their profile on day t. Treat_i is an indicator for workers who participated in the experiment, while τ_i denotes worker i's treatment date. For comparison workers, we assign a placebo treatment date randomly drawn from the distribution of actual treatment dates. The indicator $\mathbb{1}\{t-\tau_i =$

[47] We focus on expected match quality of workers and recruiters, abstracting from modeling the platform itself as a market participant.

[48] Testing whether intentions translated to behavioral changes for recruiters is challenging since we have fewer respondents and job offers are less frequent.

$d\}$ is equal to one when day t is d days relative to treatment, with $d = -1$ omitted. The coefficient β_d captures the difference in the probability of changing one's profile between treated and comparison workers at event time d. The terms α_i and δ_t denote worker and calendar-day fixed effects, respectively. Standard errors are clustered at the worker level.

Figure 4 shows the results. The relative frequency of profile modifications is fairly flat in the days before the experiment and increases markedly on the day of the experiment. The estimated 4.4-percentage-point increase corresponds to an increase of almost 500% from the baseline probability. Figure B.10 indicates particularly large increases for those who reported intending to change their profile in the experiment, though results are somewhat noisy, and large increases when restricting to changes in asked wages rather than any profile characteristic. The concentration of profile updates immediately after participation strongly suggests that these changes were triggered by the experiment, especially given that participants do not log into the platform to take the experiment.

Importantly, Table B.30 shows that workers were more likely to change their wage specifically in the direction indicated by the treatment, namely to decrease it when informed that they underestimate recruiters' wage sensitivity, overestimate the value of their own profile characteristics, or both. On average, wages decrease by 4% following the treatment, in line with workers being ex ante more likely to under- than overestimate the negative effect of a higher ask on recruiter evaluations. These results are consistent with the model and quantification exercise. Moreover, the fact that wage adjustments follow the direction of participants' personalized feedback makes explanations based solely on selection into the experiment or other aspects of participation less plausible.

Although we have limited power to trace out treatment effects on eventual job outcomes since only a subset of the relatively small treatment group modified their profile, we estimate the following equation:

$$\text{Offer}_{it} = \sum_{\substack{m=-3 \\ m\neq -1}}^{3} \beta_m \left(\text{Treat}_i \times \mathbb{1}\{t - \tau_i = m\}\right) + \alpha_i + \delta_t + \varepsilon_{it}, \tag{5}$$

where Offer_{it} is an indicator equal to one if worker i receives at least one job offer during period t. We define event time in four-week intervals relative to the date of the information treatment, with $m = 0$ corresponding to the first four weeks following

treatment. For comparison workers, we assign a placebo treatment date randomly drawn from the distribution of actual treatment dates. The coefficients β_m capture differences in the probability of receiving at least one job offer between treated and comparison workers, relative to the four weeks preceding treatment ($m = -1$). The terms α_i and δ_t denote worker and calendar-month fixed effects. Standard errors are clustered at the worker level.

Panel (b) of Figure 4 shows evidence that participation in the experiment is followed by an increase of about 15% in the probability of receiving a job offer in the months following the experiment, namely among workers who modified their profiles. This pattern is consistent with observed wage adjustments improving workers' hiring prospects, although we cannot strictly separate the contribution of the information from other aspects of participation. Together, the immediate, directionally consistent pricing responses and subsequent increase in job offers provide evidence that misperceptions about market preferences impact economic decisions and outcomes.

7 Perception gaps about competitor preferences

Our main analysis focuses on misperceptions about the preferences of the other side of the market. However, pricing and investment decisions may also depend on participants' beliefs about their competitors, since the returns to characteristics depend partly on what other workers and recruiters offer. We therefore conducted an additional prediction experiment eliciting beliefs about the preferences of participants on the same side of the market. This allows us to test the accuracy of two more sets of beliefs: recruiters' beliefs about other recruiters' preferences, and workers' beliefs about other workers' preferences.

After applying the same sample restrictions described above, we recruited 339 recruiters and 776 workers to make these predictions. Results are shown in Table 5. Perception gaps are generally smaller than for beliefs about the other side of the market. The difference is statistically significant for recruiter preferences ($p = 0.02$), but not for worker preferences ($p = 0.18$), suggesting that participants tend to understand the preferences of their competitors more accurately. Still, there are several sizable perception gaps that tend to be directionally similar to those held by the other side of the market.

Specifically, recruiters underestimate other recruiters' wage sensitivity, overestimate

their valuation of market reputation and human capital, and anticipate that they discriminate against MENA profiles. Workers overestimate other workers' wage sensitivity, overestimate their valuation of offers from prestigious organizations and for longer jobs, while they underestimate their valuation of remote jobs. In addition, they overestimate the penalty that other workers attach to job offers with tight deadline requirements.

These misperceptions may further distort market decisions. For example, workers who misperceive other workers' wage sensitivity or preferences for job amenities may misjudge the competition they face for particular jobs. More generally, these findings suggest that market participants misunderstand not only the demand for characteristics, but also the competitive environment in which they make decisions. Correcting beliefs about one side of the market may therefore not be sufficient to eliminate market distortions.

8 Sources of perception gaps

Although we do not identify the sources of perception gaps, several mechanisms could prevent market participants from learning the returns to worker and job characteristics. First, learning may be slow because market interactions provide limited, noisy information. Workers observe the interest they receive, but not how recruiters would have responded to different wages or profile characteristics. Similarly, recruiters observe workers' responses, but not how those same workers would respond to alternative offers. Even repeated interactions provide limited information about the relative importance of characteristics, since several dimensions of profiles and offers vary simultaneously. Learning is further complicated because outcomes reflect the interaction of multiple misperceptions from both sides of the market. Accordingly, learning is challenging even when participants update their beliefs rationally from available information.

Second, the information participants acquire may itself be misleading, biasing learning. Beliefs influence decisions, which in turn determine the information individuals observe, potentially generating self-confirming beliefs (Fudenberg and Levine, 1993; Lepage, 2024). Moreover, outcomes reflect the joint determination of characteristics and choices rather than their causal effects (Spiegler, 2026). High-wage or high-reputation workers likely also possess better unobserved characteristics, potentially leading participants to under-

estimate recruiters' wage sensitivity and overestimate their valuation of market reputation. Finally, information acquired through networks may propagate inaccurate beliefs (Graeber et al., 2024). For example, anecdotal evidence from the platform suggests frequent emphasis on not asking wages that are too low to avoid signaling low quality.

Third, psychological biases may distort how participants form beliefs and interpret feedback. Overconfidence may lead individuals to misattribute outcomes to the preferences of others rather than their own quality (Heidhues et al., 2018; Lepage et al., 2026). Participants may also project their preferences onto others, assuming that others place similar values on particular characteristics (Ross et al., 1977; Cordes and Müller, 2026). Relatedly, motivated beliefs may lead individuals to overestimate the market value of characteristics they possess or have invested in and to discount information that challenges these beliefs (Bénabou and Tirole, 2002; Eil and Rao, 2011).

9 Conclusion

Workers and firms make decisions based not only on the opportunities available to them, but also on how they believe the market values the characteristics they possess or offer. This paper documents substantial misperceptions about these valuations on both sides of a large freelance labor market. Using incentivized field experiments, we show that workers misunderstand recruiters' preferences for wages, human capital, and market reputation, while recruiters misperceive workers' preferences for wages and non-wage amenities.

Our findings suggest that these misperceptions matter for economic decisions and outcomes. A theoretical framework shows how inaccurate beliefs can distort pricing and investment choices, potentially reducing matching and match quality. Consistent with these mechanisms, perception gaps are systematically associated with participants' characteristics, wage-setting decisions, and market outcomes. A stylized counterfactual exercise suggests that correcting pricing distortions from these gaps could meaningfully improve matching. Moreover, providing workers with information about recruiters' preferences is followed by immediate wage adjustments in the direction indicated by the information, with evidence of a subsequent increase in the probability of receiving job offers.

One broader implication is that labor market frictions can arise even when information

about jobs and workers is readily accessible. Observing opportunities and their characteristics does not necessarily reveal how others value them or the returns to one's own choices. This distinction is particularly relevant in the relatively information-rich freelance market we study, where participants can observe numerous profiles and job offers yet still hold systematically inaccurate beliefs. Similar frictions may be present in traditional labor markets, where learning about others' preferences could be even more difficult.

These findings point to a role for information-based interventions that go beyond improving access to job opportunities. Providing information about market preferences, pricing guidance, or personalized feedback may help workers and firms make better decisions. More broadly, the approach we develop could be used to investigate similar misperceptions in other markets, including housing, consumer, and capital markets.

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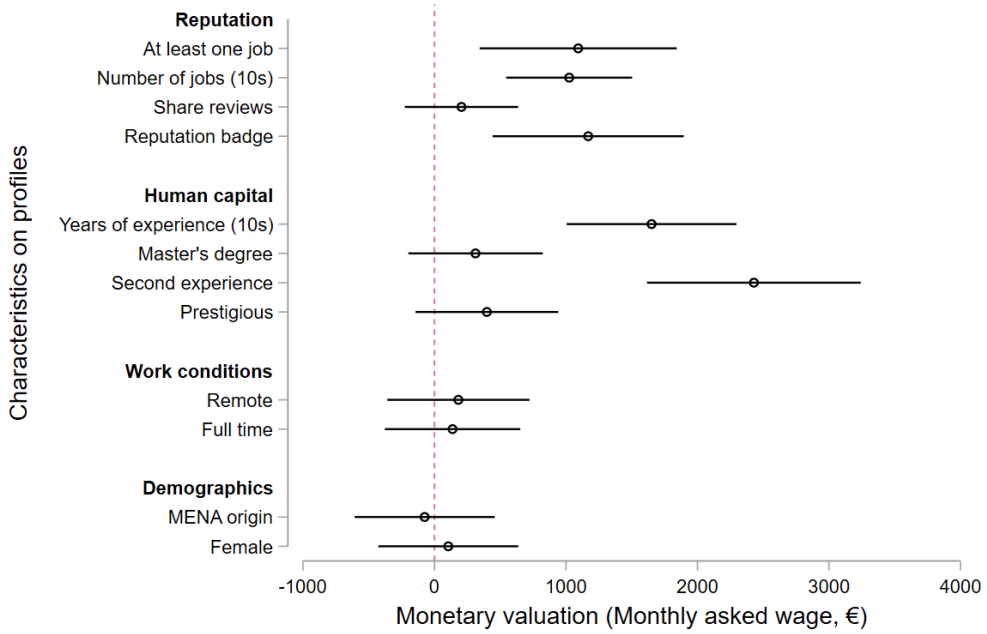
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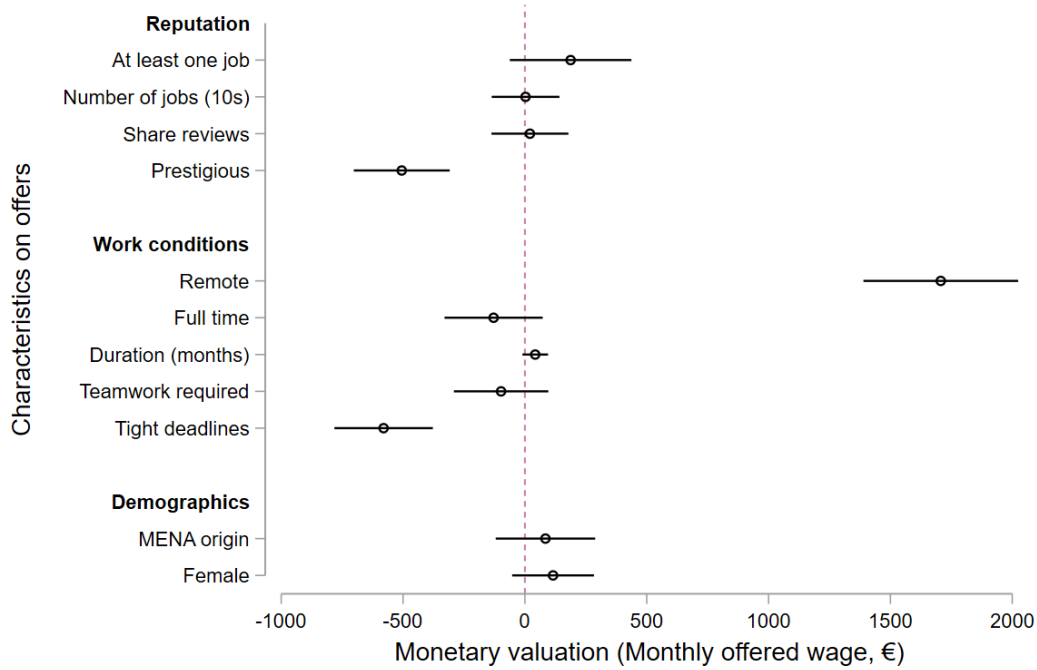
Figures

Figure 1: Monetary value of preferences from the *Evaluation* experiments

(a) Recruiter preferences



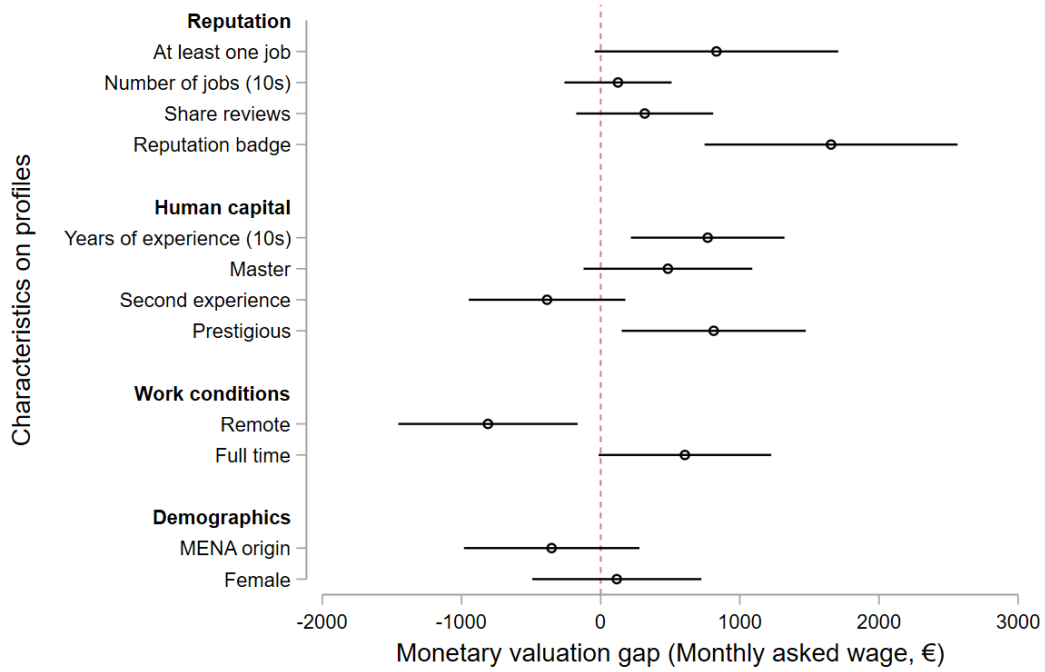
(b) Worker preferences



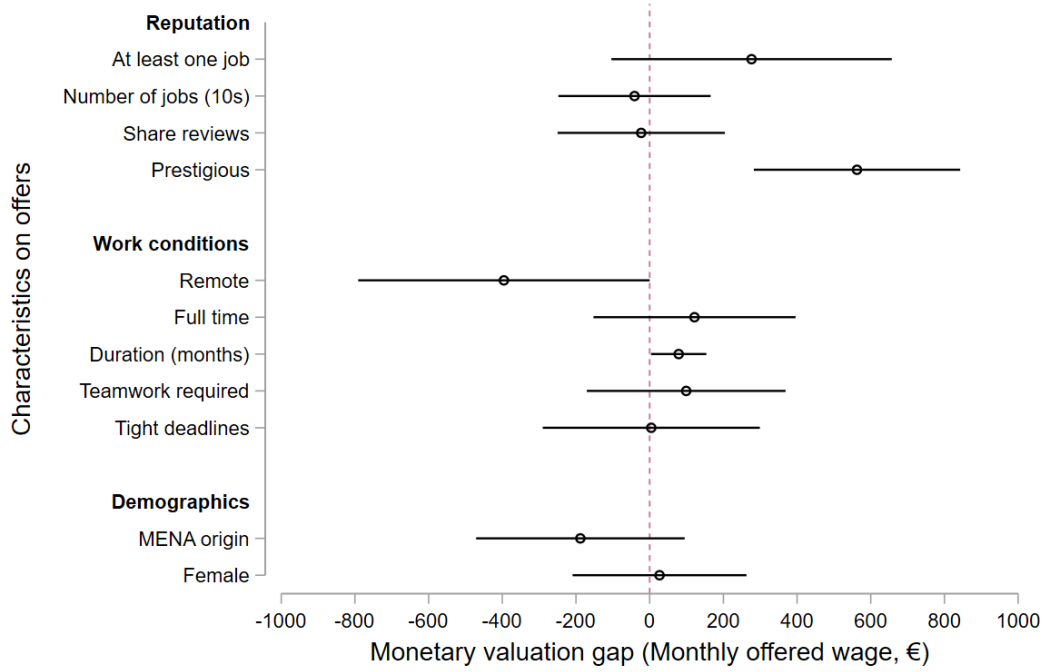
Notes: This figure presents estimates of monetary valuations for each characteristic x randomized on profiles and offers, computed as $-\beta_x/\beta_z$ (Panel a) or β_x/β_z (Panel b), where βs refer to regression coefficients from equations (1) and (2). In Panel (a), we use $\beta_z = -0.43$ which refers to the estimated asked wage coefficient from equation 1, for profiles where the asked wage is above the recruiter's self reported budget, and controlling for the reported competence of a profile to purge the signaling component of the asked wage (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: Monetary value of perception gaps

(a) Perception gaps about recruiter preferences

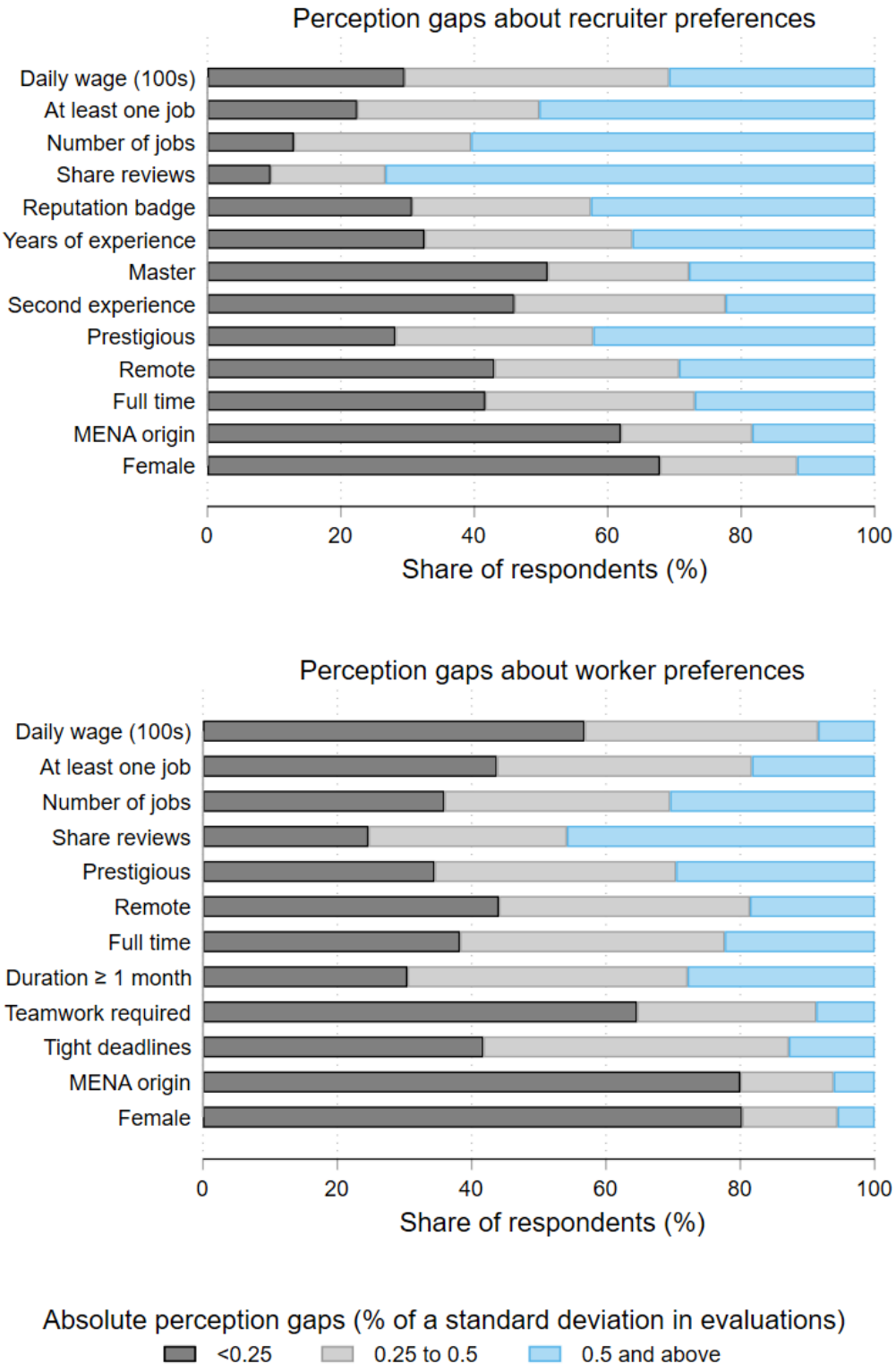


(b) Perception gaps about worker preferences



Notes: Each point represents the perception gap for a particular characteristic x, normalized by the 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* experiments. In Panel (a), we use $\beta_z = -0.43$ which refers to the estimated asked wage coefficient from equation 1, for profiles where the asked wage is above the recruiter's self reported budget, and controlling for the reported competence of a profile to purge the signaling component of the asked wage (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.

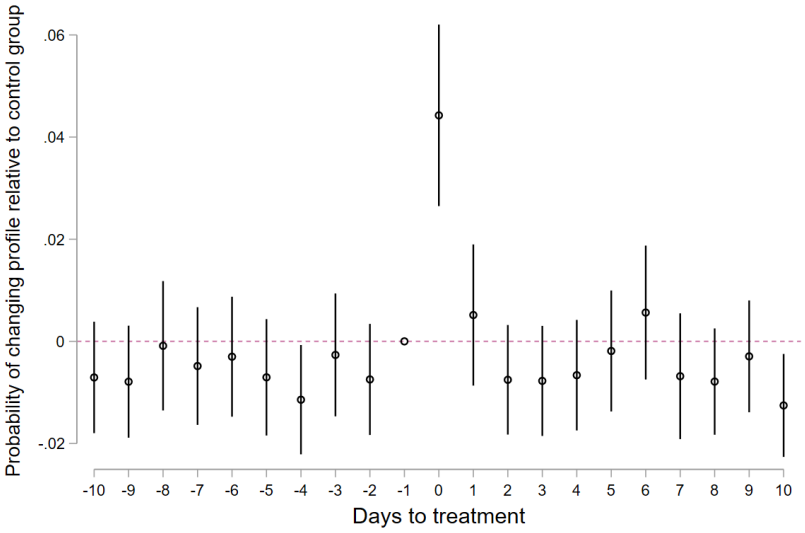
Figure 3: Individual-level perception gaps



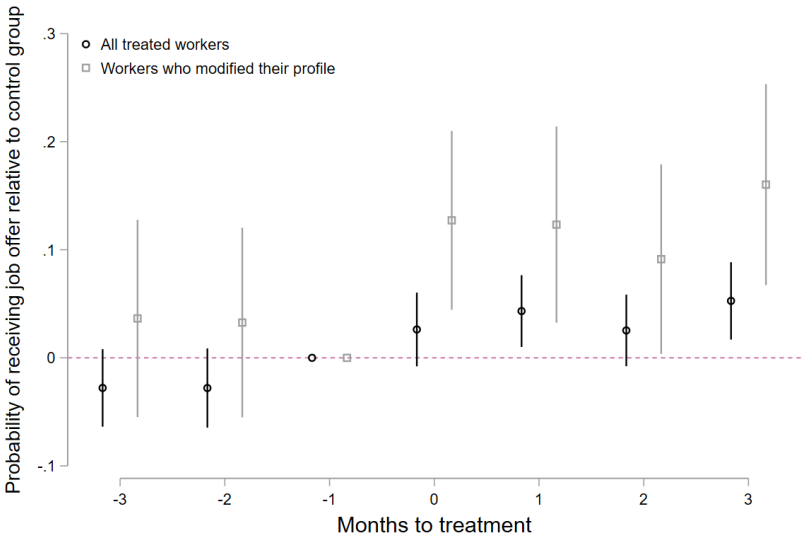
Notes: The figure plots the distribution of individual-level perception gaps for each characteristic. Gaps are computed by subtracting estimated preferences of participants in the *Evaluation* experiments from the prediction of each participant about that characteristic's marginal impact on evaluations from the *Prediction* experiments. Gaps are normalized by the standard deviation of the demeaned outcome variable in the *Evaluation* experiments.

Figure 4: Differences-in-Differences estimates of the information treatment on worker profile changes and job offers received

(a) Worker profile updates



(b) Likelihood of receiving a job offer



Notes: Panel (a) shows the daily differential probability of workers changing their profile in the treatment versus comparison group. Timing is centered around the day in which respondents receive the information treatment (0), controlling for worker and day to treatment fixed effects. We consider the following elements when determining whether a profile was changed: asked wage, availability for on site or remote work, number of educational degrees on profile, number of work experiences, and availability for part-time or full-time work. The sample consists of workers who received information on recruiters (treated group) and of 2,392 workers who were scheduled to be recruited for the experiment but were not contacted since we reached our targeted sample (comparison group). Workers were ordered randomly within the contact list. The comparison group is assigned a random treatment date drawn from the real distribution of treatment dates. Estimates are normalized relative to the day before treatment. The baseline rate of profile updating before the experiment is 0.9%. Bars represent 95 % confidence intervals.
Panel (b) shows the monthly differential probability of receiving at least one job offer. Timing is centered around the day in which respondents receive the information treatment (0), with 0 representing the first four weeks following the information treatment, controlling for worker and month fixed effects. The sample is as defined in panel (a). The comparison group is assigned a random information treatment date drawn from the real distribution of treatment dates. "Workers who modified their profile" corresponds to those who modified their profile in the 2 weeks following the treatment. Estimates are normalized relative to the month before the information treatment takes place.

Tables

Table 1: Summary statistics of the market for 2025

Panel (a) Workers	
Age	34.72
	(8.27)
Number of jobs	[0.00– 6.00]
Asked wage	442.35
	(186.20)
Years on platform	4.11
	(2.46)
Years of experience	10.46
	(6.02)
Full-time availability (%)	72.5
Remote-only availability (%)	43.7
Master's degree (%)	70.2
Female (%)	32.3
MENA origin (%)	14.5
Number of workers	25,000–75,000
Panel (b) Offers by recruiters	
Years on platform	2.29
	(2.35)
Number of offers per recruiter	[1.00– 5.00]
Budget per recruiter (1,000s)	[0.23– 14.42]
Job duration (months)	1.18
	(2.42)
Full-time requirement (%)	38.1
On-site requirement (%)	8.5
Female recruiter (%)	28.4
MENA recruiter (%)	7.6
Number of offers	15,000–50,000

Notes: Panel (a) reports summary statistics for workers in the eight job categories included in the experiments. Workers are included if their profile was created before 2025 and they were visible to recruiters for at least 90 days in 2025. Panel (b) reports summary statistics for offers made by recruiters in the same job categories. Job-level characteristics are averaged at the recruiter level. In Panel (a), "Years of experience" corresponds to workers' total years of experience in the labor market. In Panel (b), offers with budget or duration above the 99th percentile are excluded prior to aggregation. Gender and ethnicity of workers and recruiters are imputed from first names. For confidentiality reasons, some quantities are reported as 10th-90th percentile ranges in square brackets rather than exact values. Numbers of workers and offers are reported as broad ranges.

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)	-0.156***	-0.136***	0.909***	0.173***
	(0.025)	(0.018)	(0.030)	(0.018)
At least one job	0.214***	0.085	0.078	0.010
	(0.070)	(0.055)	(0.053)	(0.043)
Number of jobs (10s)	0.200***	0.063***	0.001	0.013
	(0.033)	(0.024)	(0.029)	(0.023)
Share reviews	0.040	0.010	0.009	-0.005
	(0.042)	(0.034)	(0.033)	(0.025)
Reputation badge	0.228***	0.041		
	(0.066)	(0.050)		
Years of experience (10s)	0.323***	0.008		
	(0.044)	(0.033)		
Master	0.061	-0.045		
	(0.051)	(0.039)		
Second experience	0.475***	0.168***		
	(0.048)	(0.040)		
Prestigious	0.078	-0.123***	-0.209***	-0.164***
	(0.053)	(0.045)	(0.041)	(0.032)
Remote	0.036	0.032	0.706***	0.157***
	(0.054)	(0.037)	(0.063)	(0.034)
Full time	0.027	0.104**	-0.053	0.003
	(0.051)	(0.041)	(0.042)	(0.029)
Duration (months)			0.018	0.019**
			(0.011)	(0.008)
Teamwork required			-0.040	-0.014
			(0.041)	(0.030)
Tight deadlines			-0.240***	-0.047
			(0.042)	(0.031)
MENA origin	-0.015	-0.083*	0.035	0.036
	(0.053)	(0.042)	(0.043)	(0.034)
Female	0.021	0.053	0.048	-0.005
	(0.053)	(0.042)	(0.035)	(0.029)
Number of observations	8,542	8,542	19,275	19,275
Number of respondents	342	342	771	771
Outcome mean	6.018	6.863	6.128	6.473
Outcome standard deviation	1.970	1.520	2.565	1.787

Notes: This table reports results from estimating Equations (1) and (2) by OLS and using evaluations from participants in the *Evaluation* experiments. All regressions control for respondent fixed effects. Outcomes are measured on a 10-point Likert-scale. "Hire" corresponds to a recruiters' stated interest in hiring a given worker profile. "Accept likelihood" corresponds to a recruiter's expected likelihood that a worker with the given profile would accept a job offer from them. "Accept" corresponds to a workers' stated interest in accepting a given job offer. "Offer likelihood" corresponds to a worker's expected likelihood that a recruiter with the given job would offer it to them. Each participating recruiter evaluates 25 randomized worker profiles (columns 1–2) and each participating worker evaluates 25 job offers (columns 3–4). *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* captures the discrete premium associated with having completed at least one job, beyond the linear contribution of the number of completed jobs, while *Number of jobs* captures the intensive margin of additional completed jobs. Further details on the distribution of randomized characteristics can be found in Appendix A. Experimental instructions can be found in Appendix E. Standard errors are clustered at the respondent level. $^{*}p < 0.10$, $^{**}p < 0.05$, $^{***}p < 0.01$.

Table 3: Predictions and perception gaps

Evaluator:	Recruiters			Workers		
Predictor:	Workers			Recruiters		
Object:	Profiles			Offers		
Estimate:	Evaluation	Prediction	Perception gap	Evaluation	Prediction	Perception gap
Dependent variable:	Hire			Accept		
	(1)	(2)	(3)	(4)	(5)	(6)
Daily wage (100s)	-0.156***	-0.031**	0.126***	0.909***	1.041***	0.132***
	(0.025)	(0.014)	(0.029)	(0.030)	(0.032)	(0.044)
At least one job	0.214***	0.376***	0.163*	0.078	0.192***	0.114
	(0.070)	(0.044)	(0.083)	(0.053)	(0.060)	(0.080)
Number of jobs (10s)	0.200***	0.225***	0.024	0.001	-0.016	-0.017
	(0.033)	(0.020)	(0.039)	(0.029)	(0.032)	(0.044)
Share reviews	0.040	0.102***	0.062	0.009	-0.001	-0.009
	(0.042)	(0.025)	(0.049)	(0.033)	(0.035)	(0.048)
Reputation badge	0.228***	0.552***	0.323***			
	(0.066)	(0.038)	(0.076)			
Years of experience (10s)	0.323***	0.473***	0.150***			
	(0.044)	(0.028)	(0.052)			
Master	0.061	0.155***	0.094			
	(0.051)	(0.028)	(0.058)			
Second experience	0.475***	0.399***	-0.075			
	(0.048)	(0.028)	(0.055)			
Prestigious	0.078	0.237***	0.159**	-0.209***	0.024	0.233***
	(0.053)	(0.033)	(0.062)	(0.041)	(0.042)	(0.058)
Remote	0.036	-0.123***	-0.158***	0.706***	0.542***	-0.164**
	(0.054)	(0.026)	(0.060)	(0.063)	(0.054)	(0.083)
Full time	0.027	0.145***	0.118**	-0.053	-0.003	0.050
	(0.051)	(0.029)	(0.059)	(0.042)	(0.039)	(0.058)
Duration (months)				0.018	0.050***	0.033**
				(0.011)	(0.011)	(0.016)
Teamwork required				-0.040	0.001	0.041
				(0.041)	(0.040)	(0.057)
Tight deadlines				-0.240***	-0.238***	0.002
				(0.042)	(0.046)	(0.062)
MENA origin	-0.015	-0.083***	-0.069	0.035	-0.043	-0.078
	(0.053)	(0.032)	(0.062)	(0.043)	(0.041)	(0.060)
Female	0.021	0.043	0.023	0.048	0.059*	0.011
	(0.053)	(0.029)	(0.060)	(0.035)	(0.035)	(0.050)
Observations	8,542	20,050	28,592	19,275	8,625	27,900
Number of evaluators	342		342	771		771
Number of predictors		802	802		345	345
Outcome mean	6.018	6.409	6.292	6.128	5.968	6.079
Evaluator outcome standard deviation	1.970	1.970	1.970	2.565	2.565	2.565

Notes: This table reports results from estimating Equations (1) and (2) by OLS using evaluations from participants in the *Evaluation* experiments (columns 1 and 4) and predictions from participants in the *Prediction* experiments (columns 2 and 5) as well as results from estimating Equation 3 by OLS, using both evaluations from participants in the *Evaluation* experiments and predictions from participants in the *Prediction* experiments (columns 3 and 6). Coefficients shown in columns 3 and 6 correspond to the interaction terms in Equation 3 (γ) between P_i, an indicator variable for whether the participant was part of the *Prediction* experiments, and each randomized characteristic. These estimates correspond to 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. The outcome variable in columns 1-3 is recruiters' interest or predicted interest in hiring a worker and the outcome variable in columns 4-6 is workers' interest or predicted interest in accepting a job. All regressions control for respondent fixed effects. The prediction samples are reweighted so that the frequency of job categories is held constant across participants in the *Evaluation* and *Prediction* experiments. 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: Perception gaps and platform outcomes

Panel (a): Characteristics and pricing

Sample:	Workers		Recruiters	
Dependent variable:	Characteristic on profile (0-1)	Asked wage (std)	Characteristic on offer (0-1)	Offered wage (std)
	(1)	(2)	(3)	(4)
Perception gap on characteristic	0.013**		0.018***	
	(0.006)		(0.005)	
Perception gap in own market value		0.130***		-0.047**
		(0.033)		(0.022)
Perception gap in other side's wage sensitivity		0.138***		0.060***
		(0.031)		(0.022)
Own market value		0.388***		-0.085***
		(0.038)		(0.027)
Observations	7,210	800	8,346	1,034

Panel (b): Job outcomes

Sample:	Workers		Recruiters	
Dependent variable:	Number of jobs (std)	Earnings (std)	Number of jobs (std)	Wages paid (std)
	(1)	(2)	(3)	(4)
Absolute perception gap in own market value	-0.082*	-0.131**	-0.117	0.237**
	(0.049)	(0.055)	(0.079)	(0.096)
Absolute perception gap in other side's wage sensitivity	-0.100**	-0.024	-0.178**	0.098
	(0.048)	(0.055)	(0.076)	(0.116)
Own market value	0.161***	0.170***	0.209***	-0.179**
	(0.045)	(0.043)	(0.059)	(0.088)
Observations	800	800	313	c

Notes: Panel (a) reports OLS estimates of the correlation between perception gaps and participant characteristics as well as pricing. For columns 1 and 3, the dependent variable is whether a characteristic is present on a profile/job offer, excluding characteristics less likely to represent a choice: demographics, share reviews, and years of experience. For columns 2 and 4, the dependent variables are the asked and offered wages, standardized by job category. "Perception gap" denotes the difference between a predictor's predicted impact of a characteristic (estimated via Empirical Bayes) and the estimated impact of the characteristic on evaluations, standardized by characteristic. Continuous variables are rescaled to vary between 0 and 1 for comparability: years of experience (columns 2-4), number of projects and asked wage. "Market value" of a profile/offer is the product of the estimated coefficient from the *Evaluation* experiments for each characteristic and the quantity of the characteristic on a profile/job offer, then summed over all characteristics except wages and standardized by job category. To calculate "Perception gap in market value", we first calculate the product of a predictor's predicted impact of a characteristic (estimated via Empirical Bayes) for each characteristic and the quantity of the characteristic on their profile/offer, then sum over all characteristics except wages and standardize by job category. We then take the difference between this quantity and the profile/offer's "Market value". "Perception gap in wage sensitivity" denotes the difference between a predictor's predicted impact of the wage (estimated via Empirical Bayes) and the estimated impact of the wage from the *Evaluation* experiments. Regressions include job category and characteristic fixed effects. Panel (b) reports OLS estimates of the correlation between perception gaps and job outcomes. For columns 1 and 2, the dependent variables are the number of jobs and earnings, standardized by job category. For columns 3-4, the dependent variables are the number of jobs and average wages paid per job, standardized by job category. "Absolute perception gap in market value" and "Perception gap in wage sensitivity" correspond to absolute value analogues of the quantities described for Panel (a). *c* denotes a suppressed sensitive observation count since the outcome is restricted to the set of participating recruiters with at least one completed job. Regressions include job category fixed effects. Bootstrapped standard errors in parentheses for both panels. $*p < 0.10, **p < 0.05, ***p < 0.01$.

Table 5: Predictions and perception gaps for competitors

Evaluator:	Recruiters			Workers		
Predictor:	Recruiters			Workers		
Object:	Profiles			Offers		
Estimate:	Evaluation	Prediction	Perception gap	Evaluation	Prediction	Perception gap
Dependent variable:	Hire			Accept		
	(1)	(2)	(3)	(4)	(5)	(6)
Daily wage (100s)	-0.156***	-0.101***	0.056*	0.909***	1.081***	0.171***
	(0.025)	(0.021)	(0.033)	(0.030)	(0.022)	(0.037)
At least one job	0.214***	0.395***	0.181*	0.078	0.108**	0.030
	(0.070)	(0.068)	(0.098)	(0.053)	(0.044)	(0.069)
Number of jobs (10s)	0.200***	0.291***	0.090**	0.001	0.027	0.026
	(0.033)	(0.030)	(0.044)	(0.029)	(0.023)	(0.038)
Share reviews	0.040	0.161***	0.121**	0.009	0.021	0.013
	(0.042)	(0.037)	(0.056)	(0.033)	(0.026)	(0.042)
Reputation badge	0.228***	0.478***	0.250***			
	(0.066)	(0.056)	(0.087)			
Years of experience (10s)	0.323***	0.410***	0.087			
	(0.044)	(0.044)	(0.062)			
Master	0.061	0.141***	0.080			
	(0.051)	(0.042)	(0.066)			
Second experience	0.475***	0.440***	-0.034			
	(0.048)	(0.043)	(0.064)			
Prestigious	0.078	0.172***	0.094	-0.209***	-0.096***	0.113**
	(0.053)	(0.044)	(0.069)	(0.041)	(0.034)	(0.053)
Remote	0.036	-0.086**	-0.121*	0.706***	0.527***	-0.179**
	(0.054)	(0.038)	(0.066)	(0.063)	(0.042)	(0.076)
Full time	0.027	0.070	0.043	-0.053	-0.022	0.031
	(0.051)	(0.042)	(0.067)	(0.042)	(0.029)	(0.051)
Duration (months)				0.018	0.074***	0.056***
				(0.011)	(0.009)	(0.014)
Teamwork required				-0.040	-0.023	0.018
				(0.041)	(0.033)	(0.052)
Tight deadlines				-0.240***	-0.362***	-0.122**
				(0.042)	(0.036)	(0.055)
MENA origin	-0.015	-0.167***	-0.152**	0.035	-0.012	-0.047
	(0.053)	(0.046)	(0.070)	(0.043)	(0.032)	(0.053)
Female	0.021	-0.024	-0.044	0.048	-0.000	-0.048
	(0.053)	(0.045)	(0.069)	(0.035)	(0.028)	(0.045)
Observations	8,542	8,475	17,017	19,275	19,400	38,675
Number of evaluators	342		342	771		771
Number of predictors		339	339		776	776
Outcome mean	6.018	6.193	6.109	6.128	5.981	6.054
Evaluator outcome standard deviation	1.970	1.970	1.970	2.565	2.565	2.565

Notes: This table reports results from Table 3, but using predictions made by market competitors rather than the other side of the market. Specifically, they correspond to predictions of recruiters about the evaluations of other recruiters and predictions of workers about the evaluations of other workers. All regressions control for respondent fixed effects. The prediction samples are reweighted so that the frequency of job categories is held constant across participants in the *Evaluation* and *Prediction* experiments. 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

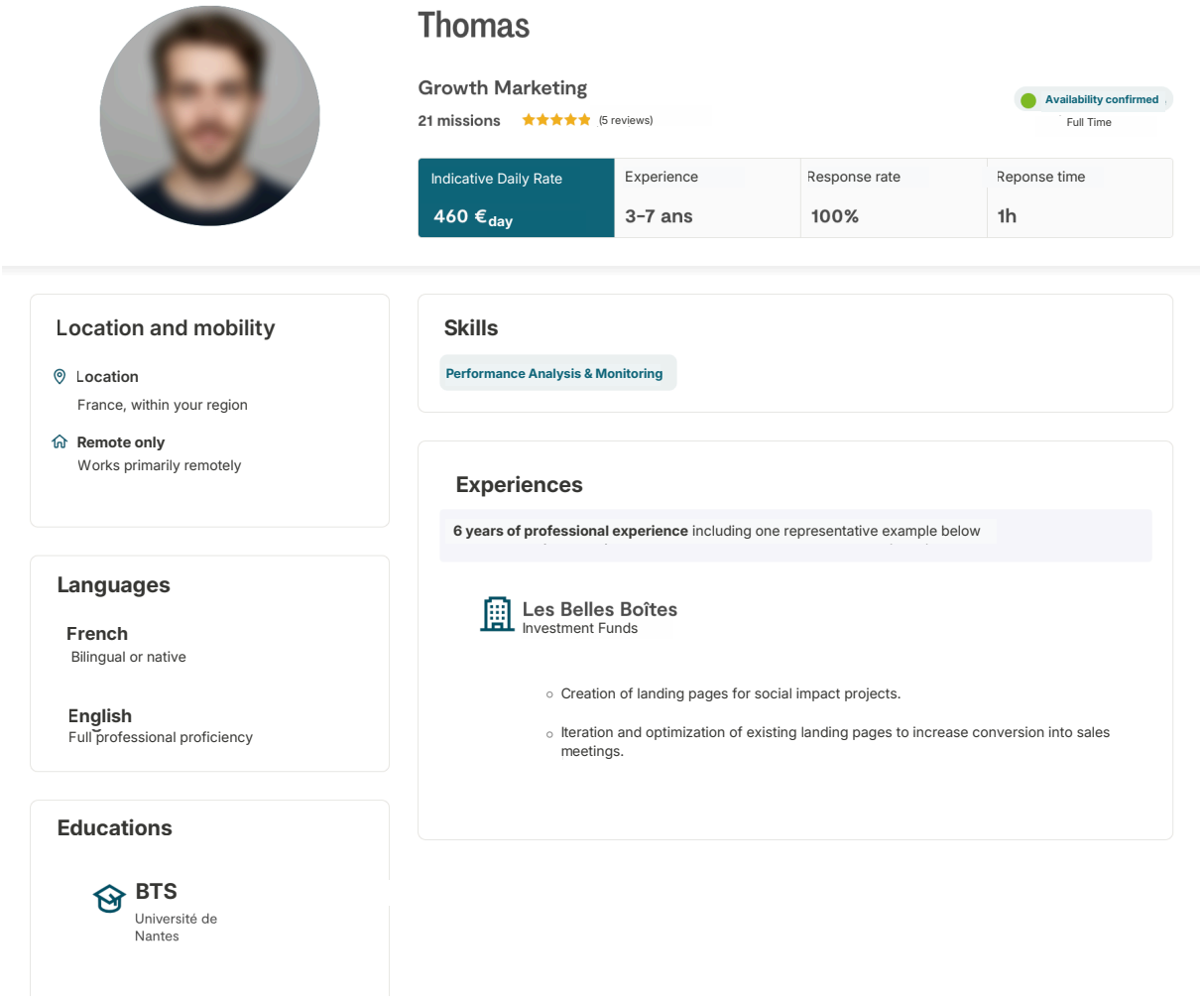


Figure A.2: Worker profile



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

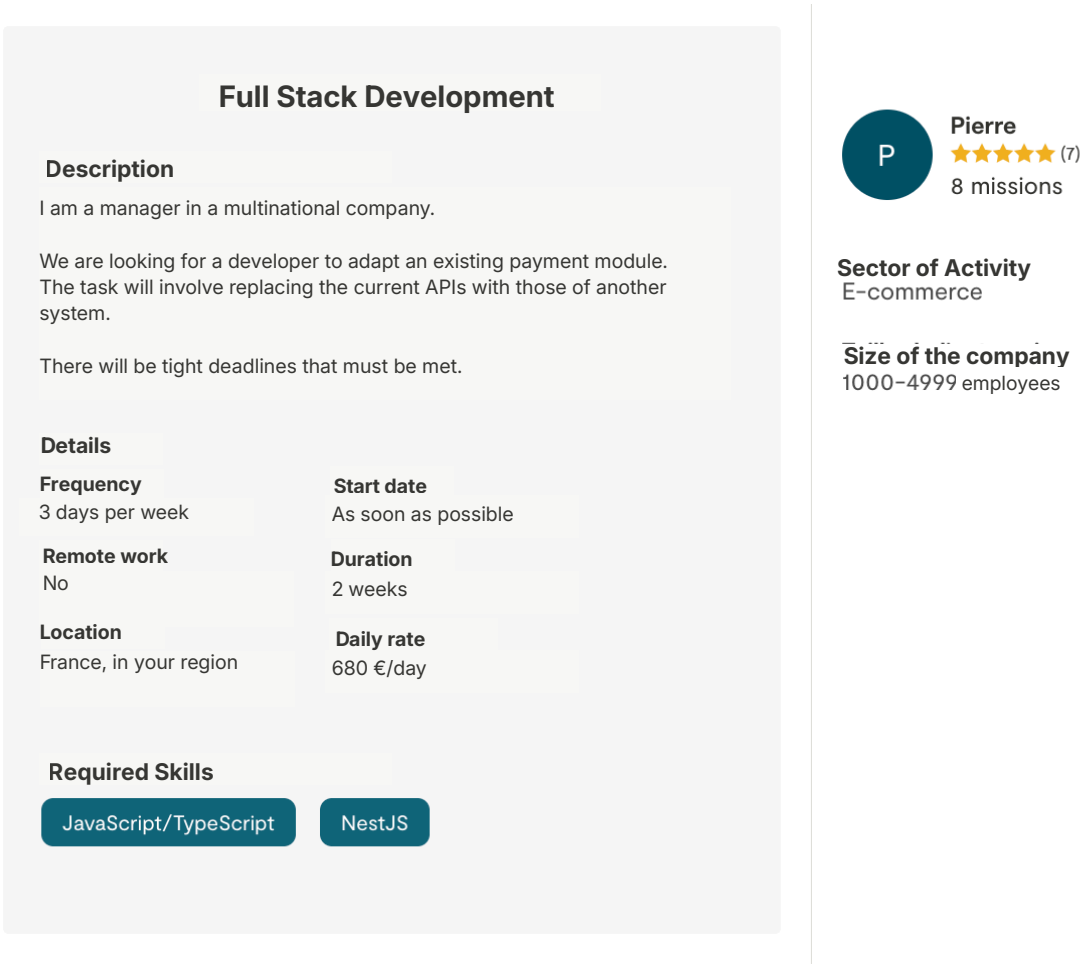
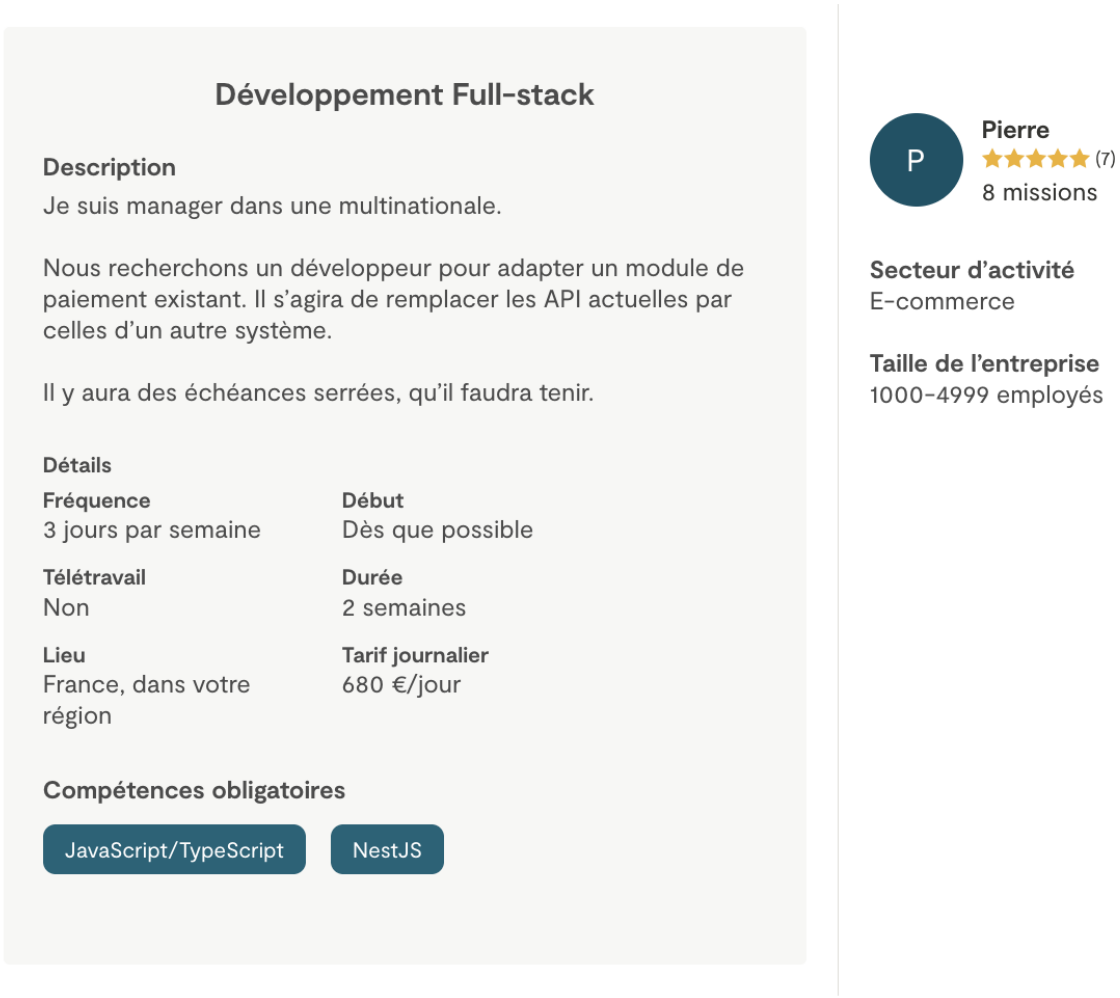


Figure A.4: Job offer



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. We also round frequencies and distributions to the nearest 0.05 value for fractions and the nearest multiple of 5 for integers. See Table A.1 for an overview of randomized characteristics.

Asked wages are drawn from category-specific uniform distributions, with minimum and maximum values based on the 10th and 90th percentiles of asked wages in each category. We use uniform randomization to improve statistical precision across the full range of wages.

Years of experience are displayed using ranges (less than 3 years, 3–7 years, 8–15 years, more than 15 years) along with the exact number shown above the description of specific past experiences. They are drawn from category-specific uniform distributions from 1 to an upper limit equal to the 90th percentile of the distribution for each job category. Since the upper limit is similar across categories, we choose the same value for each category. The number of work experiences shown on a profile was also randomized to be 1 or 2 with equal probability, while the share of workers with prestigious experiences was set at 0.25.

To populate work experiences, we draw a random sample of real experiences in free text format and process each drawn experience to standardize the text and remove mentions of gender, ethnicity, very senior positions, and overly-specific jargon or technical references that would not be relevant to the broader job category. Dates are removed and descriptions are standardized into two bullet points. Every entry was reviewed and edited for quality and consistency. Since displaying only one or two experiences could appear unusual for workers with many years of experience, we explicitly indicate that only a representative subset is shown.

Both the number of experiences and the prestigious classification are uniform across job categories.[49] 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

[49]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.

profiles may have several more, with only one or two being "prestigious", and because we assign prestigious status either to none or to all of the experiences displayed on a profile. These decisions were made to increase power and salience.

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

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

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

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

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

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

to their randomized shares. Part-time availability is indicated as 2–3 days per week, corresponding to the modal part-time arrangement on the platform.

Pictures on the platform must correspond to the individual and typically consist of a professional headshot. For each job category, we compile lists of the 20 most common distinctively male and female French names of European origin and of MENA origin among workers. Names are randomly assigned to profiles from these lists. Each name is paired with a picture matching its gender and ethnic origin. Pictures are AI-generated and blurred to preserve the salience of gender and ethnicity while limiting the transmission of additional signals.[50]

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 accounts 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.[51]

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

A.1.3 Offers

We calculate statistics from existing job offers. Each offer characteristic is adapted to each job category, but again, when differences are small, we harmonize the randomization across categories for simplicity. Again, we also round integers to the nearest multiple

[50]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 approximate that of real profiles on the platform.

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

of 5 and fractions to the nearest 0.05. See Table A.2 for an overview of randomized characteristics.

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

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

Recruiter prestige on the platform would typically be signaled through firm names, but we omit names from offers to avoid 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:[52]

- 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.

[52]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.

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 somewhat 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 set similarly across categories at 0.25. 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 somewhat overrepresented in the experiment, with a share of 0.25 to ensure enough power.

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

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

A.1.4 Expertise keywords

In the *Evaluation* experiments, profiles and offers include expertise keywords, which help determine suitability. For example, for developers, these include programming languages. Since these jobs typically involve specific, relatively short-term tasks, there is limited scope for training workers after hiring. Recruiters are shown only worker profiles that possess the expertise keywords they themselves report as necessary for their next job. Because it would be implausible for workers to receive offers for tasks they cannot perform, we tailor offers to match each participating worker's self-reported expertise. For example, if a worker reports being able to code in Java but not Python, offers shown to them may require the former, but not the latter. Task descriptions are tailored to each job category and expertise keyword to ensure internal consistency.

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. 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.

Recruiters can report that they are unsure about the expertise they need, or indicate other required expertise not included in the provided list. 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 all combinations of expertise keywords. Results are similar when omitting them. All workers selected at least one keyword from our lists.

Expertise keywords are removed from profiles and offers in the *Prediction* experiments since they are not needed to make profiles or offers relevant to participants. Unlike in the *Evaluation* experiments, participants are not seeking workers or jobs. So that omitting expertise keywords does not affect predictions about other characteristics, participants are told that those in the *Evaluation* experiments were only shown profiles or offers with the expertise keyword(s) they had previously selected, allowing predictors to abstract from them entirely. Furthermore, since we include participant fixed effects in our analyses, we purge the effect of expertise keyword(s) since they are constant within participants, so the relevant comparison for predictions is thus a profile or offer without keywords.

Table A.1: Randomization of profile characteristics

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

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

Table A.2: Randomization of job offer characteristics

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

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

A.2 Recommendations in the *Evaluation* experiments

Recommendations are implemented following the procedure established in Kessler et al. (2019). We use ridge regressions, allowing us to estimate preferences for attributes at the individual level while disciplining coefficients by shrinking them towards 0. We select optimal penalty 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 penalty 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 penalty parameters as the optimal penalty 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 based on the 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. 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 job.

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.[53]

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.

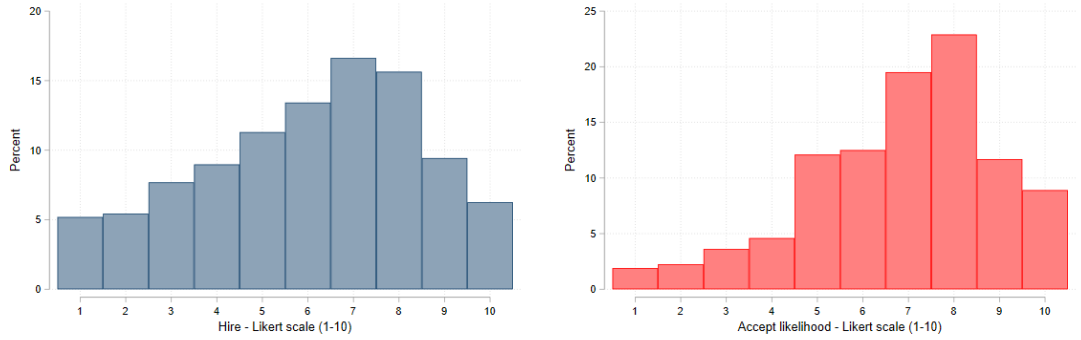
[53]Note: in practice, probabilities were floored at 0. The individual evaluator-specific effects used to calculate bonuses were estimated by OLS, without regularization or shrinkage.

B Additional figures and tables

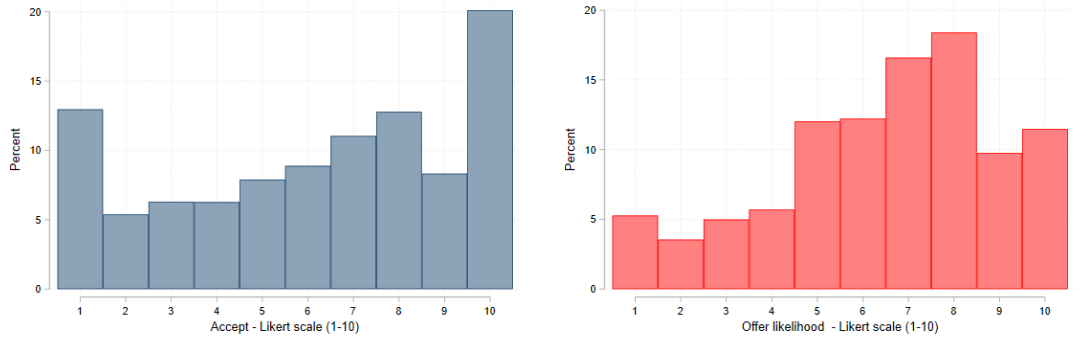
B.1 *Evaluation* experiments

Figure B.1: Distribution of evaluations

(a) Recruiter evaluations

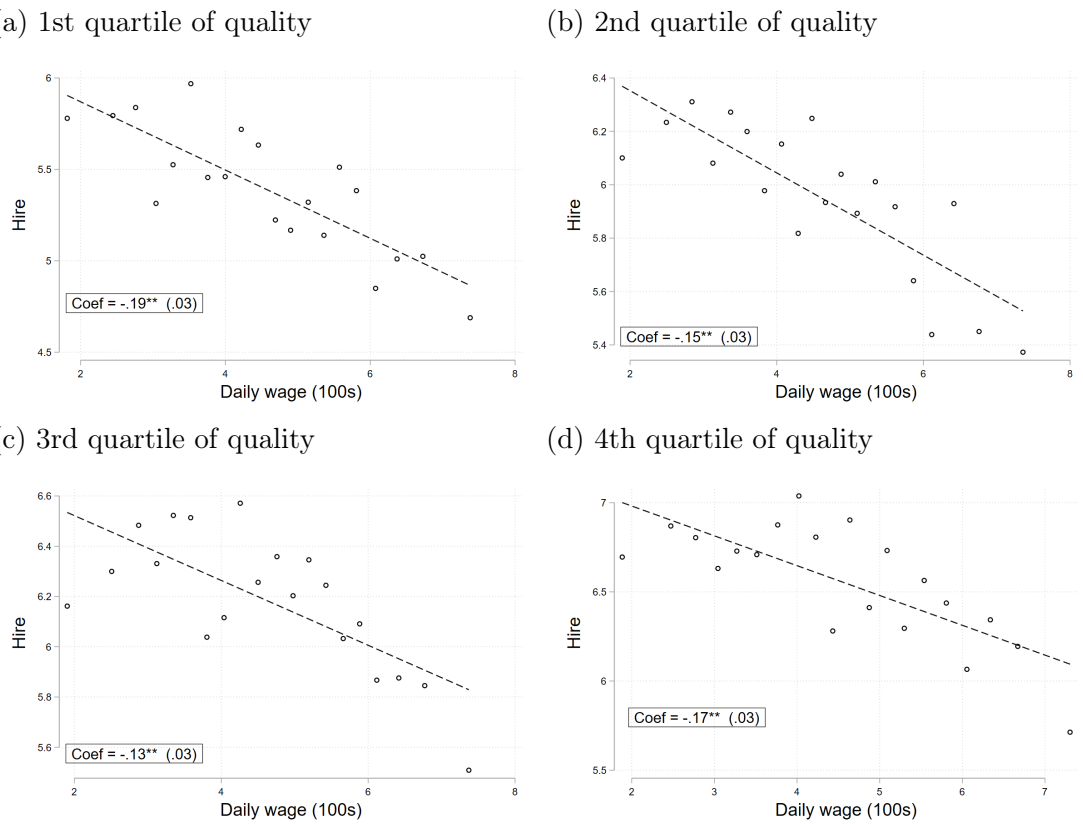


(b) Worker evaluations



Notes: This figure shows histograms plotting the distribution of respondents' evaluations in the *Evaluation* experiments.

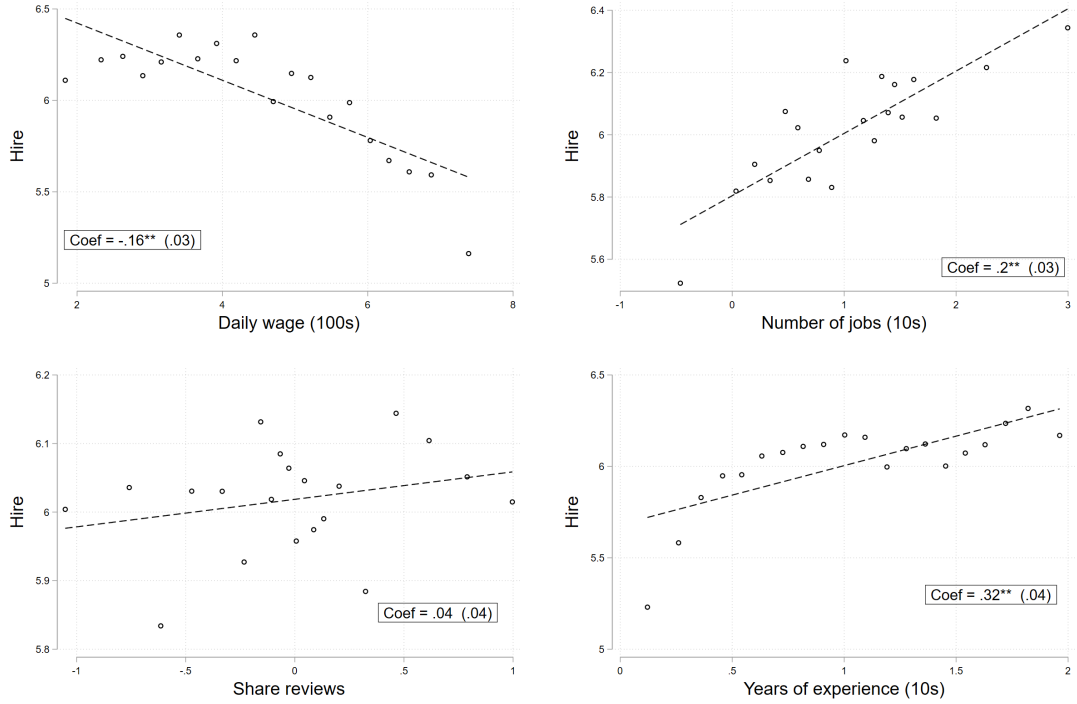
Figure B.2: Effect of asked wages on recruiter evaluations by profile quality



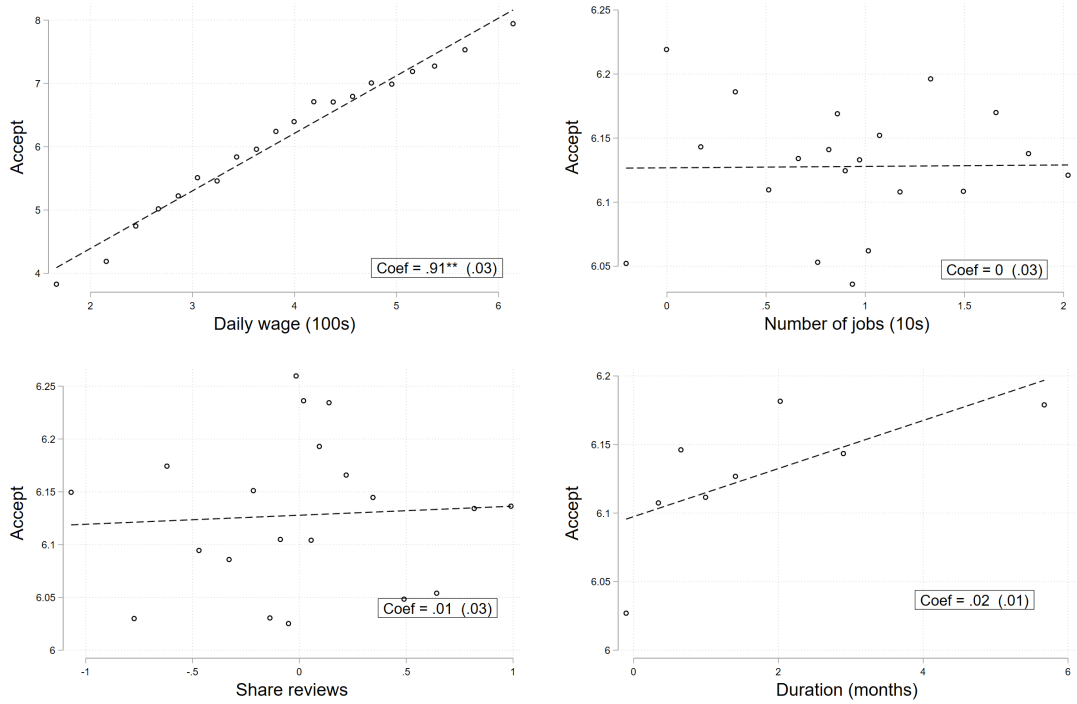
Notes: This figure shows binned scatter plots of the relationship between recruiters' interest in hiring a profile and the value of the asked wage on the profile, for different quartiles of profile quality. Quality is computed as predicted values of recruiter evaluations for a given profile, omitting the asked wage. Dashed black lines represent fitted slopes, with corresponding regression coefficients and standard errors included in the text boxes.

Figure B.3: Estimated impact of continuous characteristics on evaluations

(a) Recruiter evaluations



(b) Worker evaluations



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

Table B.1: Estimated preferences from the *Evaluation* experiments by wage relative to recruiter budget and worker 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)	0.209***	-0.428***	-0.010	-0.224***	1.237***	0.240***	0.304***	0.038
	(0.056)	(0.072)	(0.032)	(0.047)	(0.041)	(0.041)	(0.030)	(0.028)
At least one job	0.126	0.286**	0.049	0.156	-0.019	0.198**	-0.023	0.030
	(0.107)	(0.144)	(0.082)	(0.120)	(0.063)	(0.088)	(0.056)	(0.062)
Number of jobs (10s)	0.210***	0.196***	0.109***	0.019	0.024	-0.045	0.008	0.021
	(0.048)	(0.063)	(0.040)	(0.045)	(0.034)	(0.050)	(0.031)	(0.035)
Share reviews	-0.059	0.108	-0.007	0.002	0.018	0.021	0.013	-0.009
	(0.068)	(0.090)	(0.050)	(0.075)	(0.040)	(0.055)	(0.032)	(0.039)
Reputation badge	0.305***	0.288**	-0.013	0.149				
	(0.109)	(0.115)	(0.084)	(0.098)				
Years of experience (10s)	0.339***	0.344***	0.014	0.048				
	(0.073)	(0.090)	(0.045)	(0.069)				
Master	0.000	0.038	-0.011	-0.172**				
	(0.090)	(0.088)	(0.066)	(0.068)				
Second experience	0.433***	0.498***	0.163**	0.084				
	(0.083)	(0.085)	(0.066)	(0.079)				
Prestigious	0.085	0.051	-0.108	-0.155*	-0.184***	-0.272***	-0.142***	-0.165***
	(0.098)	(0.096)	(0.078)	(0.085)	(0.050)	(0.065)	(0.041)	(0.050)
Remote	-0.010	0.042	-0.053	0.014	0.636***	0.823***	0.182***	0.129**
	(0.077)	(0.106)	(0.063)	(0.088)	(0.069)	(0.099)	(0.043)	(0.053)
Full time	-0.028	0.063	0.015	0.074	-0.013	-0.116*	-0.007	0.010
	(0.086)	(0.094)	(0.060)	(0.076)	(0.050)	(0.068)	(0.038)	(0.045)
Duration (months)					0.008	0.031*	0.021**	0.019
					(0.013)	(0.017)	(0.011)	(0.012)
Teamwork required					-0.013	-0.108*	-0.024	-0.017
					(0.049)	(0.065)	(0.040)	(0.047)
Tight deadlines					-0.251***	-0.243***	-0.060	-0.060
					(0.049)	(0.066)	(0.039)	(0.052)
MENA origin	-0.043	-0.117	-0.058	-0.132	0.073	-0.006	0.069	-0.007
	(0.091)	(0.102)	(0.075)	(0.086)	(0.053)	(0.072)	(0.043)	(0.056)
Female	0.002	-0.048	0.090	-0.041	0.040	-0.048	0.020	-0.079*
	(0.096)	(0.085)	(0.078)	(0.074)	(0.044)	(0.058)	(0.037)	(0.046)
Number of observations	2,731	2,383	2,731	2,383	11,835	7,422	11,835	7,422
Number of respondents	199	185	199	185	732	613	732	613
Outcome mean	6.089	5.665	7.004	6.705	5.365	7.343	6.445	6.517
Outcome standard deviation	1.961	2.021	1.455	1.585	2.534	2.446	1.801	1.740
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 Table 2, but splitting evaluations by whether the asked wage on a hypothetical worker profile is above the participating recruiter's daily budget (columns 1-4) and by whether the offered wage on a hypothetical job offer is above or below the participating worker's asked wage on their profile (columns 5-8). See Table 2 for more details. All specifications include respondent fixed effects. Standard errors are clustered at the respondent level. $*p < 0.10, **p < 0.05, ***p < 0.01$.

Table B.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)	-0.156***	0.076***	-0.216***	0.909***	0.036***	0.884***
	(0.025)	(0.018)	(0.019)	(0.030)	(0.014)	(0.028)
At least one job	0.214***	0.166**	0.082*	0.078	0.058	0.037
	(0.070)	(0.072)	(0.042)	(0.053)	(0.045)	(0.043)
Number of jobs (10s)	0.200***	0.196***	0.045**	0.001	-0.018	0.014
	(0.033)	(0.029)	(0.019)	(0.029)	(0.025)	(0.024)
Share reviews	0.040	-0.000	0.040	0.009	-0.013	0.018
	(0.042)	(0.041)	(0.029)	(0.033)	(0.026)	(0.027)
Reputation badge	0.228***	0.232***	0.045			
	(0.066)	(0.064)	(0.040)			
Years of experience (10s)	0.323***	0.386***	0.017			
	(0.044)	(0.042)	(0.029)			
Master	0.061	0.044	0.026			
	(0.051)	(0.047)	(0.033)			
Second experience	0.475***	0.499***	0.079***			
	(0.048)	(0.047)	(0.030)			
Prestigious	0.078	0.070	0.022	-0.209***	-0.162***	-0.096***
	(0.053)	(0.049)	(0.032)	(0.041)	(0.033)	(0.033)
Remote	0.036	0.011	0.027	0.706***	0.082**	0.648***
	(0.054)	(0.045)	(0.037)	(0.063)	(0.033)	(0.057)
Full time	0.027	0.024	0.008	-0.053	-0.025	-0.035
	(0.051)	(0.047)	(0.034)	(0.042)	(0.032)	(0.034)
Duration (months)				0.018	0.014	0.008
				(0.011)	(0.009)	(0.009)
Teamwork required				-0.040	0.000	-0.040
				(0.041)	(0.032)	(0.033)
Tight deadlines				-0.240***	-0.059*	-0.198***
				(0.042)	(0.034)	(0.034)
MENA origin	-0.015	-0.022	0.003	0.035	0.043	0.005
	(0.053)	(0.048)	(0.034)	(0.043)	(0.035)	(0.036)
Female	0.021	0.082*	-0.044	0.048	0.052*	0.012
	(0.053)	(0.048)	(0.035)	(0.035)	(0.030)	(0.030)
Competence - Likert scale (1-10)			0.792***			0.701***
			(0.015)			(0.013)
Number of observations	8,542	8,542	8,542	19,275	19,275	19,275
Number of respondents	342	342	342	771	771	771
Outcome mean	6.018	6.463	6.018	6.128	7.906	6.128
Outcome standard deviation	1.970	1.836	1.970	.	1.871	.

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 Table 2 for convenience, while columns 2 and 5 show results using an auxiliary measure of perceived competence: how competent recruiters consider a given profile in column 2 and how competent freelancers would feel to complete the offered job in column 5. Columns 3 and 6 include the reported competence rating as a control variable to investigate the role of perceived competence in driving hiring interest and job acceptance. 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 by number of jobs shown on a profile

Evaluator:	Recruiters			
Object:	Profiles			
Dependent variable:	Hire		Accept likelihood	
	(1)	(2)	(3)	(4)
Daily wage (100s)	-0.153***	-0.171***	-0.173***	-0.131***
	(0.034)	(0.028)	(0.027)	(0.019)
Number of jobs (10s)		0.203***		0.064***
		(0.033)		(0.024)
Share reviews		0.045		0.005
		(0.042)		(0.034)
Reputation badge		0.240***		0.056
		(0.066)		(0.050)
Years of experience (10s)	0.365***	0.304***	-0.052	0.026
	(0.076)	(0.051)	(0.067)	(0.038)
Master's degree	0.107	0.040	-0.119	-0.015
	(0.091)	(0.058)	(0.073)	(0.044)
Second experience	0.567***	0.434***	0.225***	0.144***
	(0.087)	(0.054)	(0.070)	(0.047)
Prestigious	0.094	0.046	-0.144*	-0.109**
	(0.092)	(0.064)	(0.079)	(0.051)
Remote	0.063	0.003	-0.000	0.043
	(0.090)	(0.059)	(0.069)	(0.041)
Full time	-0.058	0.083	0.004	0.134***
	(0.087)	(0.060)	(0.073)	(0.049)
MENA origin	-0.053	0.007	-0.086	-0.054
	(0.094)	(0.062)	(0.078)	(0.048)
Female	0.047	0.024	0.208***	-0.029
	(0.091)	(0.061)	(0.071)	(0.050)
Number of observations	2,648	5,894	2,648	5,894
Number of respondents	342	342	342	342
Outcome mean	5.598	6.207	6.713	6.931
Outcome standard deviation	1.987	1.937	1.581	1.488
Number of jobs	None	At least one	None	At least one

Notes: This table reports results from estimating Equation (1) using OLS and participants from the *Evaluation* experiments. They correspond to those from the first 2 columns of Table 2, but splitting evaluations between those of profiles that displayed no completed job on the platform 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.4: Estimated preferences from the *Evaluation* experiments by requirement and preference 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	0.775***	0.990***	0.156***	0.183***
	(0.046)	(0.070)	(0.035)	(0.037)	(0.048)	(0.037)	(0.030)	(0.022)
At least one job	0.318**	-0.140	0.223**	-0.205	0.144*	0.043	0.091	-0.038
	(0.139)	(0.178)	(0.107)	(0.161)	(0.083)	(0.068)	(0.072)	(0.052)
Number of jobs (10s)	0.233***	0.165*	0.009	0.143*	-0.039	0.019	-0.004	0.022
	(0.057)	(0.098)	(0.038)	(0.076)	(0.046)	(0.038)	(0.039)	(0.029)
Share reviews	0.003	0.105	0.012	0.026	-0.029	0.034	-0.078*	0.039
	(0.078)	(0.118)	(0.069)	(0.073)	(0.055)	(0.041)	(0.041)	(0.031)
Reputation badge	0.231*	0.212	-0.008	0.160				
	(0.124)	(0.192)	(0.088)	(0.154)				
Years of experience (10s)	0.197**	0.551***	0.057	0.007				
	(0.079)	(0.118)	(0.054)	(0.083)				
Master	0.027	0.102	-0.158***	-0.061				
	(0.091)	(0.169)	(0.059)	(0.097)				
Second experience	0.381***	0.502***	0.061	0.274***				
	(0.085)	(0.111)	(0.070)	(0.093)				
Prestigious	0.045	0.282*	-0.129	-0.009	-0.298***	-0.151***	-0.209***	-0.138***
	(0.092)	(0.162)	(0.086)	(0.094)	(0.062)	(0.053)	(0.055)	(0.040)
Remote	0.148	-0.345*	0.060	-0.061	0.916***	0.579***	0.193***	0.136***
	(0.100)	(0.194)	(0.077)	(0.082)	(0.109)	(0.076)	(0.056)	(0.043)
Full time	0.033	0.053	0.106	0.093	-0.036	-0.064	-0.047	0.033
	(0.092)	(0.131)	(0.066)	(0.110)	(0.069)	(0.053)	(0.046)	(0.038)
Duration (months)					0.012	0.021	0.030**	0.012
					(0.019)	(0.013)	(0.015)	(0.010)
Teamwork required					-0.052	-0.031	-0.016	-0.013
					(0.072)	(0.049)	(0.053)	(0.037)
Tight deadlines					-0.211***	-0.252***	0.025	-0.088**
					(0.072)	(0.051)	(0.052)	(0.039)
MENA origin	-0.130	0.029	-0.052	-0.084	0.056	0.018	0.007	0.053
	(0.095)	(0.151)	(0.078)	(0.117)	(0.071)	(0.054)	(0.056)	(0.043)
Female	-0.114	-0.122	0.052	-0.089	0.017	0.073	-0.030	0.013
	(0.095)	(0.145)	(0.081)	(0.103)	(0.053)	(0.047)	(0.048)	(0.036)
Number of observations	2,597	1,275	2,597	1,275	7,375	11,900	7,375	11,900
Outcome mean	5.858	6.076	6.817	6.875	6.176	6.098	6.463	6.479
Outcome standard deviation	2.036	2.041	1.562	1.518	2.529	2.588	1.836	1.755
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 Table 2, but splitting evaluations by whether the participating recruiter reports requiring in-person work for their next job (columns 1-4) and by whether the participating worker's profile indicates availability for working in-person or primarily remotely (columns 5-8). See Table 2 for more details. All specifications include respondent fixed effects. Standard errors are clustered at the respondent level. $*p < 0.10, **p < 0.05, ***p < 0.01$.

Table B.5: Estimated preferences from the *Evaluation* experiments, by recruiter preference for diversity

Evaluator:	Recruiters			
Object:	Profiles			
Dependent variable:	Hire		Accept likelihood	
	(1)	(2)	(3)	(4)
Daily wage (100s)	-0.187***	-0.131***	-0.156***	-0.119***
	(0.039)	(0.033)	(0.025)	(0.026)
At least one job	0.049	0.338***	0.049	0.108
	(0.112)	(0.089)	(0.080)	(0.076)
Number of jobs (10s)	0.264***	0.156***	0.088**	0.047
	(0.054)	(0.042)	(0.038)	(0.031)
Share reviews	0.073	0.014	-0.006	0.020
	(0.067)	(0.054)	(0.051)	(0.045)
Reputation badge	0.229*	0.238***	-0.018	0.094
	(0.120)	(0.072)	(0.083)	(0.060)
Years of experience (10s)	0.215***	0.404***	-0.047	0.048
	(0.062)	(0.060)	(0.048)	(0.045)
Master's degree	0.030	0.078	-0.082	-0.019
	(0.079)	(0.066)	(0.057)	(0.054)
Second experience	0.441***	0.502***	0.121**	0.209***
	(0.067)	(0.066)	(0.057)	(0.056)
Prestigious	0.029	0.120*	-0.160**	-0.088
	(0.084)	(0.066)	(0.067)	(0.059)
Remote	-0.120	0.157**	-0.087	0.126***
	(0.089)	(0.063)	(0.055)	(0.048)
Full time	-0.003	0.050	0.089	0.115**
	(0.084)	(0.064)	(0.066)	(0.053)
MENA origin	-0.104	0.061	-0.146**	-0.030
	(0.084)	(0.067)	(0.064)	(0.056)
Female	-0.087	0.114	0.060	0.049
	(0.078)	(0.072)	(0.061)	(0.058)
Number of observations	3,825	4,717	3,825	4,717
Number of respondents	153	189	153	189
Outcome mean	5.636	6.329	6.796	6.918
Outcome standard deviation	2.079	1.877	1.562	1.485
Preference for diversity	Low	High	Low	High

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

Table B.6: Estimated preferences from the *Evaluation* experiments by profile gender and ethnicity

Evaluator:	Recruiters							
Object:	Profiles							
Dependent variable:	Hire		Accept likelihood		Hire		Accept likelihood	
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Daily wage (100s)	-0.151***	-0.198***	-0.127***	-0.168***	-0.153***	-0.159***	-0.137***	-0.145***
	(0.030)	(0.030)	(0.021)	(0.027)	(0.027)	(0.037)	(0.020)	(0.028)
At least one job	0.206**	0.179	0.115*	-0.026	0.166**	0.363***	0.070	0.106
	(0.085)	(0.127)	(0.067)	(0.102)	(0.082)	(0.138)	(0.061)	(0.108)
Number of jobs (10s)	0.197***	0.244***	0.065**	0.077*	0.228***	0.098	0.064**	0.046
	(0.036)	(0.068)	(0.029)	(0.041)	(0.037)	(0.063)	(0.026)	(0.047)
Share reviews	0.025	0.115	0.032	-0.035	0.048	0.009	0.027	-0.020
	(0.050)	(0.074)	(0.041)	(0.058)	(0.047)	(0.097)	(0.036)	(0.080)
Reputation badge	0.276***	0.099	0.101	-0.075	0.217***	0.320**	0.051	-0.013
	(0.084)	(0.112)	(0.064)	(0.087)	(0.073)	(0.127)	(0.054)	(0.100)
Years of experience (10s)	0.324***	0.305***	-0.036	0.104*	0.304***	0.370***	-0.005	0.030
	(0.055)	(0.068)	(0.041)	(0.054)	(0.048)	(0.090)	(0.038)	(0.074)
Master's degree	0.082	-0.000	-0.014	-0.116*	0.074	0.045	-0.038	-0.071
	(0.061)	(0.085)	(0.045)	(0.066)	(0.059)	(0.108)	(0.046)	(0.083)
Second experience	0.444***	0.527***	0.164***	0.162**	0.484***	0.507***	0.150***	0.266***
	(0.059)	(0.087)	(0.049)	(0.071)	(0.053)	(0.100)	(0.043)	(0.082)
Prestigious	0.072	0.092	-0.164***	-0.072	0.045	0.150	-0.160***	0.024
	(0.066)	(0.087)	(0.052)	(0.079)	(0.061)	(0.106)	(0.050)	(0.085)
Remote	0.062	0.031	0.085*	-0.047	0.066	-0.029	0.057	-0.073
	(0.062)	(0.095)	(0.044)	(0.063)	(0.061)	(0.099)	(0.042)	(0.074)
Full time	0.082	-0.056	0.107**	0.131*	0.014	0.118	0.124***	0.055
	(0.065)	(0.078)	(0.049)	(0.074)	(0.057)	(0.112)	(0.047)	(0.084)
MENA origin	0.024	-0.119	-0.069	-0.133*				
	(0.064)	(0.102)	(0.050)	(0.078)				
Female					0.042	-0.108	0.048	0.079
					(0.062)	(0.113)	(0.047)	(0.094)
Number of observations	5,565	2,975	5,565	2,975	6,613	1,922	6,613	1,922
Number of respondents	342	339	342	339	342	333	342	333
Outcome mean	6.088	5.888	6.911	6.774	6.027	5.991	6.893	6.760
Outcome standard deviation	1.955	1.997	1.506	1.546	1.979	1.938	1.521	1.516
Profile	Male	Female	Male	Female	European	MENA origin	European	MENA origin

Notes: This table reports results from estimating Equations (1) and (2) using OLS and participants from the *Evaluation* experiments. They correspond to those from the first 2 columns of Table 2, but splitting evaluations by the gender and ethnic origin of 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.7: 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)	-0.156***	-0.136***	0.910***	0.173***
	(0.025)	(0.018)	(0.030)	(0.018)
At least one job	0.207***	0.079	0.080	0.013
	(0.070)	(0.055)	(0.053)	(0.042)
Number of jobs (10s)	0.203***	0.065***	0.000	0.012
	(0.033)	(0.024)	(0.029)	(0.023)
Share reviews	0.040	0.011	0.008	-0.003
	(0.042)	(0.034)	(0.033)	(0.025)
Reputation badge	0.228***	0.047		
	(0.066)	(0.050)		
Years of experience (10s)	0.324***	0.007		
	(0.043)	(0.033)		
Master	0.056	-0.047		
	(0.051)	(0.039)		
Second experience	0.477***	0.172***		
	(0.048)	(0.040)		
Prestigious	0.075	-0.121***	-0.206***	-0.165***
	(0.053)	(0.045)	(0.041)	(0.032)
Remote	0.038	0.031	0.706***	0.156***
	(0.053)	(0.036)	(0.063)	(0.034)
Full time	0.023	0.109***	-0.053	0.006
	(0.051)	(0.041)	(0.042)	(0.029)
Duration (months)			0.018	0.018**
			(0.011)	(0.008)
Teamwork required			-0.037	-0.014
			(0.041)	(0.031)
Tight deadlines			-0.240***	-0.047
			(0.042)	(0.032)
MENA origin	-0.015	-0.082*	0.034	0.041
	(0.053)	(0.042)	(0.043)	(0.034)
Female	0.020	0.047	0.046	-0.005
	(0.053)	(0.042)	(0.035)	(0.029)
Number of observations	8,542	8,542	19,275	19,275
Number of respondents	342	342	771	771
Outcome mean	6.018	6.863	6.128	6.473
Outcome standard deviation	1.970	1.520	2.565	1.787

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

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

Evaluator:	Recruiters		Workers	
Object:	Profiles		Offers	
Dependent variable:	Hire	Accept likelihood	Accept	Offer likelihood
	(1)	(2)	(3)	(4)
Daily wage (100s)	-0.138***	-0.120***	0.905***	0.179***
	(0.026)	(0.020)	(0.030)	(0.021)
At least one job	0.232***	0.128*	0.026	-0.007
	(0.083)	(0.068)	(0.062)	(0.052)
Number of jobs (10s)	0.203***	0.050*	0.026	0.044
	(0.036)	(0.027)	(0.034)	(0.029)
Share reviews	0.021	-0.046	-0.019	0.011
	(0.051)	(0.047)	(0.039)	(0.033)
Reputation badge	0.262***	0.034		
	(0.075)	(0.063)		
Years of experience (10s)	0.327***	0.048		
	(0.048)	(0.041)		
Master	0.073	-0.013		
	(0.063)	(0.050)		
Second experience	0.452***	0.140***		
	(0.052)	(0.049)		
Prestigious	0.061	-0.132**	-0.176***	-0.148***
	(0.062)	(0.055)	(0.048)	(0.041)
Remote	0.034	0.027	0.646***	0.095**
	(0.061)	(0.047)	(0.070)	(0.043)
Full time	0.034	0.103*	-0.079	0.004
	(0.061)	(0.053)	(0.050)	(0.038)
Duration (months)			0.016	0.020*
			(0.012)	(0.010)
Teamwork required			-0.076	-0.070*
			(0.048)	(0.040)
Tight deadlines			-0.291***	-0.020
			(0.048)	(0.040)
MENA origin	-0.063	-0.131***	0.050	0.091**
	(0.059)	(0.050)	(0.052)	(0.044)
Female	-0.059	0.015	0.035	0.005
	(0.061)	(0.053)	(0.042)	(0.037)
Number of observations	8,542	8,542	19,275	19,275
Number of respondents	342	342	771	771
Outcome mean	6.018	6.863	6.128	6.473
Outcome standard deviation	2.434	2.063	3.102	2.464

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, 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.9: 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)	-0.153***	-0.129***	0.889***	0.173***
	(0.024)	(0.017)	(0.030)	(0.017)
At least one job	0.179***	0.057	0.085	0.011
	(0.069)	(0.054)	(0.052)	(0.042)
Number of jobs (10s)	0.203***	0.070***	-0.003	0.012
	(0.031)	(0.024)	(0.029)	(0.023)
Share reviews	0.031	0.007	0.010	-0.005
	(0.040)	(0.032)	(0.033)	(0.024)
Reputation badge	0.233***	0.063		
	(0.063)	(0.047)		
Years of experience (10s)	0.302***	0.024		
	(0.042)	(0.033)		
Master	0.036	-0.043		
	(0.049)	(0.038)		
Second experience	0.446***	0.161***		
	(0.045)	(0.038)		
Prestigious	0.068	-0.119***	-0.201***	-0.164***
	(0.050)	(0.042)	(0.040)	(0.032)
Remote	0.027	0.011	0.693***	0.152***
	(0.050)	(0.035)	(0.062)	(0.034)
Full time	0.017	0.086**	-0.052	0.003
	(0.048)	(0.039)	(0.042)	(0.029)
Duration (months)			0.016	0.018**
			(0.011)	(0.008)
Teamwork required			-0.052	-0.016
			(0.041)	(0.030)
Tight deadlines			-0.235***	-0.041
			(0.041)	(0.031)
MENA origin	-0.022	-0.080**	0.038	0.039
	(0.051)	(0.040)	(0.043)	(0.034)
Female	0.012	0.028	0.052	-0.004
	(0.050)	(0.040)	(0.035)	(0.029)
Number of observations	9,342	9,342	19,725	19,725
Number of respondents	374	374	789	789
Outcome mean	6.028	6.809	6.140	6.475
Outcome standard deviation	1.954	1.525	2.549	1.780

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, without restricting the participant sample to those who spent an average of at least 10 seconds per 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.10: Estimated preferences from the *Evaluation* experiments, including translation jobs

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

Notes: This table reports results from estimating Equations (1) and (2) using OLS and participants from the *Evaluation* experiments. They correspond to those from Table 2, including respondents who picked translation as a job category. 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, reweighting participants for market representativeness

Evaluator:	Recruiters		Workers	
Object:	Profiles		Offers	
Dependent variable:	Hire	Accept likelihood	Accept	Offer likelihood
	(1)	(2)	(3)	(4)
Daily wage (100s)	-0.155***	-0.131***	0.819***	0.141***
	(0.028)	(0.023)	(0.035)	(0.019)
At least one job	0.170*	0.075	0.106*	-0.001
	(0.087)	(0.075)	(0.059)	(0.048)
Number of jobs (10s)	0.218***	0.068**	-0.012	0.031
	(0.038)	(0.030)	(0.035)	(0.025)
Share reviews	0.022	0.004	-0.022	-0.033
	(0.051)	(0.040)	(0.042)	(0.032)
Reputation badge	0.251***	0.023		
	(0.079)	(0.061)		
Years of experience (10s)	0.363***	0.014		
	(0.047)	(0.043)		
Master	0.027	-0.035		
	(0.057)	(0.045)		
Second experience	0.517***	0.220***		
	(0.069)	(0.064)		
Prestigious	0.070	-0.061	-0.252***	-0.155***
	(0.057)	(0.051)	(0.051)	(0.036)
Remote	0.005	0.040	0.698***	0.118***
	(0.062)	(0.039)	(0.074)	(0.038)
Full time	0.049	0.117**	-0.120**	-0.004
	(0.066)	(0.051)	(0.054)	(0.032)
Duration (months)			0.024*	0.029***
			(0.013)	(0.010)
Teamwork required			-0.045	-0.034
			(0.048)	(0.033)
Tight deadlines			-0.198***	-0.039
			(0.048)	(0.036)
MENA origin	-0.033	-0.082	0.027	0.044
	(0.061)	(0.056)	(0.050)	(0.037)
Female	0.046	0.092*	0.063	0.010
	(0.067)	(0.048)	(0.044)	(0.032)
Number of observations	8,542	8,542	19,275	19,275
Number of respondents	342	342	771	771
Outcome mean	5.983	6.793	6.237	6.285
Outcome standard deviation	2.003	1.565	2.511	1.734

Notes: This table reports results from estimating Equations (1) and (2) using OLS and participants from the *Evaluation* experiments. They correspond to those from Table 2, but reweighting participants such that their characteristics match the average characteristics of platform users for the job categories included in the experiment. Reweighting for recruiters is based on: job category, number of completed jobs, and firm size. Reweighting for workers is based on: asked wage, number of completed jobs, job category, 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.12: Estimated preferences from the *Evaluation* experiments, by first versus second half of evaluations

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)	-0.141***	-0.159***	-0.154***	-0.117***	0.900***	0.926***	0.161***	0.187***
	(0.030)	(0.028)	(0.023)	(0.021)	(0.032)	(0.035)	(0.020)	(0.022)
At least one job	0.243**	0.230**	0.081	0.110	0.053	0.060	-0.013	0.014
	(0.102)	(0.097)	(0.076)	(0.078)	(0.080)	(0.072)	(0.064)	(0.052)
Number of jobs (10s)	0.178***	0.187***	0.041	0.066*	-0.021	0.025	0.006	0.020
	(0.041)	(0.047)	(0.030)	(0.035)	(0.042)	(0.042)	(0.034)	(0.029)
Share reviews	-0.006	0.076	0.027	-0.022	0.005	0.024	-0.011	0.012
	(0.059)	(0.059)	(0.047)	(0.046)	(0.046)	(0.047)	(0.037)	(0.034)
Reputation badge	0.279***	0.225***	0.012	0.060				
	(0.093)	(0.082)	(0.069)	(0.063)				
Years of experience (10s)	0.467***	0.194***	0.068	-0.034				
	(0.063)	(0.058)	(0.047)	(0.040)				
Master	0.044	0.069	-0.050	-0.027				
	(0.070)	(0.069)	(0.051)	(0.054)				
Second experience	0.353***	0.605***	0.081	0.261***				
	(0.064)	(0.068)	(0.051)	(0.054)				
Prestigious	0.057	0.088	-0.058	-0.178***	-0.284***	-0.144***	-0.254***	-0.086**
	(0.077)	(0.069)	(0.062)	(0.056)	(0.059)	(0.055)	(0.046)	(0.042)
Remote	0.044	0.042	0.018	0.087*	0.737***	0.704***	0.134***	0.194***
	(0.065)	(0.069)	(0.047)	(0.046)	(0.077)	(0.074)	(0.048)	(0.044)
Full time	-0.014	0.064	0.049	0.178***	-0.057	-0.058	0.042	-0.035
	(0.072)	(0.074)	(0.058)	(0.058)	(0.059)	(0.056)	(0.044)	(0.040)
Duration (months)					0.015	0.030**	0.025**	0.018
					(0.015)	(0.015)	(0.012)	(0.011)
Teamwork required					-0.108*	0.021	-0.075	0.046
					(0.063)	(0.054)	(0.046)	(0.041)
Tight deadlines					-0.323***	-0.171***	-0.036	-0.039
					(0.061)	(0.056)	(0.047)	(0.042)
MENA origin	-0.044	-0.009	-0.086	-0.098*	0.027	0.051	0.013	0.073
	(0.077)	(0.070)	(0.059)	(0.059)	(0.064)	(0.061)	(0.052)	(0.045)
Female	0.017	0.057	0.080	0.011	0.062	0.062	-0.026	0.037
	(0.074)	(0.069)	(0.055)	(0.056)	(0.052)	(0.052)	(0.041)	(0.040)
Number of observations	4,104	4,438	4,104	4,438	9,252	10,023	9,252	10,023
Number of respondents	342	342	342	342	771	771	771	771
Outcome mean	6.059	5.981	6.934	6.798	6.169	6.090	6.490	6.457
Outcome standard deviation	1.989	1.951	1.529	1.509	2.583	2.548	1.818	1.757
Part of experiment	First half	Second half	First half	Second half	First half	Second half	First half	Second half

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

Table B.13: Estimated preferences from the *Evaluation* experiments by respondent 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)	-0.159***	-0.151***	-0.129***	-0.157***	0.939***	0.815***	0.192***	0.109***
	(0.030)	(0.050)	(0.021)	(0.037)	(0.035)	(0.051)	(0.022)	(0.028)
At least one job	0.232***	0.170	0.093	0.066	0.119**	0.002	-0.018	0.077
	(0.086)	(0.124)	(0.067)	(0.099)	(0.060)	(0.104)	(0.048)	(0.085)
Number of jobs (10s)	0.208***	0.191***	0.078***	0.032	-0.007	0.008	0.012	0.009
	(0.038)	(0.067)	(0.029)	(0.042)	(0.035)	(0.054)	(0.027)	(0.043)
Share reviews	0.089*	-0.081	0.018	-0.018	0.052	-0.086	0.032	-0.091**
	(0.049)	(0.080)	(0.043)	(0.052)	(0.040)	(0.060)	(0.030)	(0.045)
Reputation badge	0.359***	-0.087	0.121**	-0.144				
	(0.083)	(0.098)	(0.059)	(0.089)				
Years of experience (10s)	0.322***	0.325***	-0.021	0.082				
	(0.051)	(0.082)	(0.039)	(0.062)				
Master	0.053	0.075	-0.081*	0.032				
	(0.062)	(0.088)	(0.048)	(0.061)				
Second experience	0.426***	0.592***	0.111**	0.302***				
	(0.056)	(0.090)	(0.046)	(0.077)				
Prestigious	0.045	0.141	-0.093*	-0.201**	-0.141***	-0.351***	-0.141***	-0.213***
	(0.065)	(0.090)	(0.052)	(0.087)	(0.048)	(0.076)	(0.037)	(0.065)
Remote	0.000	0.128	0.023	0.059	0.681***	0.754***	0.139***	0.193***
	(0.061)	(0.110)	(0.041)	(0.077)	(0.077)	(0.111)	(0.040)	(0.063)
Full time	0.004	0.075	0.057	0.220***	-0.075	0.003	-0.017	0.055
	(0.063)	(0.086)	(0.050)	(0.073)	(0.050)	(0.078)	(0.033)	(0.057)
Duration (months)					0.032**	-0.010	0.022**	0.014
					(0.013)	(0.021)	(0.009)	(0.017)
Teamwork required					0.028	-0.177**	0.021	-0.082
					(0.050)	(0.069)	(0.036)	(0.056)
Tight deadlines					-0.213***	-0.303***	-0.028	-0.085
					(0.052)	(0.072)	(0.037)	(0.059)
MENA origin	-0.087	0.146	-0.103**	-0.036	0.109**	-0.115	0.053	0.000
	(0.063)	(0.098)	(0.049)	(0.081)	(0.051)	(0.078)	(0.041)	(0.061)
Female	-0.003	0.062	0.046	0.068	0.035	0.076	-0.047	0.082
	(0.065)	(0.094)	(0.051)	(0.073)	(0.043)	(0.062)	(0.034)	(0.053)
Number of observations	5,971	2,571	5,971	2,571	13,150	6,125	13,150	6,125
Number of respondents	239	103	239	103	526	245	526	245
Outcome mean	6.035	5.980	6.948	6.666	6.071	6.250	6.536	6.337
Outcome standard deviation	1.975	1.957	1.515	1.531	2.596	2.499	1.757	1.850
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, splitting the sample by respondent gender. Gender of workers and recruiters is imputed from first names. See Table 2 for more details. All specifications include respondent fixed effects. Standard errors are clustered at the respondent level. $*p < 0.10, **p < 0.05, ***p < 0.01$.

Table B.14: Estimated preferences from the *Evaluation* experiments by respondent MENA origin

Evaluator:	Recruiters				Workers			
Object:	Profiles				Offers			
Dependent variable:	Hire		Accept likelihood		Accept		Offer likelihood	
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Daily wage (100s)	-0.160***	-0.086	-0.137***	-0.128**	0.911***	0.892***	0.169***	0.218**
	(0.027)	(0.073)	(0.019)	(0.049)	(0.031)	(0.130)	(0.018)	(0.090)
At least one job	0.215***	0.254	0.093	-0.060	0.073	0.156	-0.001	0.185
	(0.073)	(0.293)	(0.057)	(0.182)	(0.053)	(0.293)	(0.043)	(0.212)
Number of jobs (10s)	0.195***	0.284***	0.059**	0.136	0.007	-0.069	0.022	-0.126
	(0.035)	(0.063)	(0.025)	(0.107)	(0.030)	(0.138)	(0.023)	(0.112)
Share reviews	0.036	0.109	0.004	0.098	0.026	-0.261**	-0.011	0.078
	(0.042)	(0.260)	(0.035)	(0.107)	(0.034)	(0.123)	(0.025)	(0.135)
Reputation badge	0.210***	0.586	0.036	0.135				
	(0.068)	(0.345)	(0.051)	(0.217)				
Years of experience (10s)	0.307***	0.637***	0.016	-0.154				
	(0.045)	(0.187)	(0.034)	(0.141)				
Master	0.069	-0.052	-0.040	-0.119				
	(0.053)	(0.174)	(0.041)	(0.087)				
Second experience	0.484***	0.271**	0.176***	0.067				
	(0.050)	(0.113)	(0.042)	(0.093)				
Prestigious	0.071	0.238	-0.126***	-0.058	-0.239***	0.287*	-0.180***	0.071
	(0.054)	(0.239)	(0.046)	(0.202)	(0.042)	(0.169)	(0.032)	(0.183)
Remote	0.016	0.450*	0.024	0.182	0.716***	0.543**	0.158***	0.121
	(0.054)	(0.257)	(0.037)	(0.172)	(0.066)	(0.237)	(0.035)	(0.135)
Full time	0.021	0.199	0.123***	-0.257	-0.059	0.072	-0.005	0.145
	(0.051)	(0.286)	(0.042)	(0.163)	(0.044)	(0.167)	(0.030)	(0.125)
Duration (months)					0.017	0.018	0.021**	-0.010
					(0.012)	(0.040)	(0.009)	(0.035)
Teamwork required					-0.022	-0.311*	-0.001	-0.200
					(0.042)	(0.185)	(0.031)	(0.141)
Tight deadlines					-0.240***	-0.239	-0.031	-0.282*
					(0.044)	(0.166)	(0.032)	(0.149)
MENA origin	-0.020	0.060	-0.089**	-0.011	0.032	0.065	0.031	0.110
	(0.055)	(0.186)	(0.043)	(0.187)	(0.043)	(0.236)	(0.034)	(0.162)
Female	0.016	0.108	0.063	-0.173	0.064*	-0.200	0.005	-0.167
	(0.055)	(0.253)	(0.043)	(0.136)	(0.036)	(0.159)	(0.029)	(0.141)
Number of observations	8,067	475	8,067	475	18,075	1,200	18,075	1,200
Number of respondents	323	19	323	19	723	48	723	48
Outcome mean	6.022	5.956	6.846	7.156	6.113	6.353	6.433	7.077
Outcome standard deviation	1.974	1.888	1.523	1.471	2.555	2.717	1.774	1.966
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, splitting the sample by respondent MENA origin. Ethnicity of workers and recruiters is imputed from first names. See Table 2 for more details. All specifications include respondent fixed effects. Standard errors are clustered at the respondent level. $*p < 0.10, **p < 0.05, ***p < 0.01$.

Table B.15: 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)	-0.168***	-0.104*	-0.148***	-0.079*
	(0.029)	(0.055)	(0.020)	(0.047)
At least one job	0.250***	0.057	0.113*	-0.040
	(0.077)	(0.184)	(0.062)	(0.128)
Number of jobs (10s)	0.208***	0.173*	0.049*	0.116**
	(0.036)	(0.087)	(0.028)	(0.049)
Share reviews	0.045	0.045	0.019	-0.008
	(0.048)	(0.089)	(0.040)	(0.059)
Reputation badge	0.260***	0.165	0.063	-0.045
	(0.078)	(0.117)	(0.057)	(0.104)
Years of experience (10s)	0.293***	0.435***	0.036	-0.056
	(0.048)	(0.105)	(0.037)	(0.078)
Master's degree	0.102*	-0.012	-0.040	-0.012
	(0.056)	(0.109)	(0.044)	(0.075)
Second experience	0.444***	0.564***	0.125***	0.338***
	(0.053)	(0.118)	(0.044)	(0.104)
Prestigious	0.071	0.028	-0.135***	-0.102
	(0.059)	(0.125)	(0.051)	(0.093)
Remote	0.065	-0.109	0.038	-0.026
	(0.056)	(0.150)	(0.043)	(0.064)
Full time	0.046	-0.013	0.103**	0.096
	(0.058)	(0.123)	(0.049)	(0.081)
MENA origin	-0.063	0.122	-0.080*	-0.112
	(0.058)	(0.138)	(0.047)	(0.097)
Female	0.043	-0.087	0.061	-0.009
	(0.060)	(0.119)	(0.046)	(0.106)
Number of observations	6,742	1,600	6,742	1,600
Number of respondents	270	64	270	64
Outcome mean	6.088	5.766	6.848	6.974
Outcome standard deviation	1.961	2.007	1.521	1.536
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 1-2 of Table 2, splitting the sample by recruiter organization size. 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 respondent 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)	-0.166***	-0.146***	-0.143***	-0.129***	0.840***	0.990***	0.155***	0.196***
	(0.031)	(0.041)	(0.026)	(0.025)	(0.044)	(0.040)	(0.026)	(0.024)
At least one job	0.173*	0.269**	0.089	0.092	0.078	0.079	0.011	0.011
	(0.094)	(0.104)	(0.078)	(0.076)	(0.071)	(0.078)	(0.058)	(0.062)
Number of jobs (10s)	0.216***	0.182***	0.056	0.065**	-0.006	0.004	0.044	-0.015
	(0.049)	(0.045)	(0.035)	(0.033)	(0.040)	(0.043)	(0.031)	(0.034)
Share reviews	0.007	0.077	-0.005	0.027	-0.002	0.044	-0.033	0.029
	(0.060)	(0.059)	(0.046)	(0.048)	(0.047)	(0.046)	(0.036)	(0.034)
Reputation badge	0.312***	0.130	0.041	0.034				
	(0.087)	(0.103)	(0.069)	(0.071)				
Years of experience (10s)	0.331***	0.317***	-0.016	0.041				
	(0.057)	(0.066)	(0.045)	(0.048)				
Master	0.013	0.118	-0.007	-0.086				
	(0.070)	(0.074)	(0.055)	(0.055)				
Second experience	0.466***	0.484***	0.196***	0.136**				
	(0.067)	(0.068)	(0.058)	(0.054)				
Prestigious	0.135*	0.012	0.012	-0.277***	-0.241***	-0.164***	-0.142***	-0.171***
	(0.071)	(0.079)	(0.060)	(0.065)	(0.061)	(0.054)	(0.045)	(0.047)
Remote	0.028	0.047	0.079	-0.023	0.683***	0.707***	0.109**	0.191***
	(0.079)	(0.070)	(0.049)	(0.055)	(0.090)	(0.090)	(0.047)	(0.049)
Full time	0.012	0.051	0.128**	0.078	-0.134**	0.015	-0.014	0.017
	(0.068)	(0.077)	(0.057)	(0.059)	(0.064)	(0.057)	(0.040)	(0.042)
Duration (months)					0.028*	0.005	0.032**	0.006
					(0.016)	(0.015)	(0.012)	(0.011)
Teamwork required					-0.037	-0.041	-0.047	0.020
					(0.055)	(0.061)	(0.040)	(0.046)
Tight deadlines					-0.190***	-0.276***	-0.045	-0.042
					(0.059)	(0.061)	(0.044)	(0.046)
MENA origin	-0.092	0.070	-0.128**	-0.044	0.048	0.040	0.071	0.009
	(0.074)	(0.076)	(0.060)	(0.058)	(0.060)	(0.061)	(0.044)	(0.051)
Female	0.102	-0.076	0.134**	-0.042	0.056	0.044	-0.009	-0.004
	(0.075)	(0.074)	(0.058)	(0.060)	(0.054)	(0.048)	(0.040)	(0.042)
Number of observations	c	c	c	c	c	c	c	c
Outcome mean	5.944	6.106	6.683	7.076	6.241	6.032	6.212	6.722
Outcome standard deviation	1.973	1.966	1.551	1.483	2.506	2.614	1.713	1.839
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, splitting the sample by respondents with versus without at least one job completed on the platform. See Table 2 for more details. All specifications include respondent fixed effects. c denotes a suppressed sensitive observation count; see Table 1 for summary statistics on completed jobs. Standard errors are clustered at the respondent level. $*p < 0.10, **p < 0.05, ***p < 0.01$.

Table B.17: Estimated preferences from the *Evaluation* experiments, by respondent freelancing experience

Evaluator:	Workers			
Object:	Offers			
Dependent variable:	Accept		Offer likelihood	
	(1)	(2)	(3)	(4)
Daily wage (100s)	0.804***	0.998***	0.129***	0.209***
	(0.045)	(0.039)	(0.025)	(0.025)
At least one job	0.060	0.094	0.038	-0.016
	(0.080)	(0.070)	(0.063)	(0.058)
Number of jobs (10s)	-0.011	0.010	0.021	0.007
	(0.045)	(0.039)	(0.035)	(0.031)
Share reviews	-0.053	0.065	-0.013	0.003
	(0.048)	(0.046)	(0.036)	(0.034)
Prestigious	-0.216***	-0.200***	-0.172***	-0.158***
	(0.058)	(0.057)	(0.045)	(0.046)
Remote	0.581***	0.812***	0.118**	0.189***
	(0.089)	(0.089)	(0.050)	(0.047)
Full time	-0.087	-0.022	0.060	-0.045
	(0.062)	(0.058)	(0.043)	(0.040)
Duration (months)	-0.003	0.035**	-0.000	0.035***
	(0.015)	(0.016)	(0.011)	(0.012)
Teamwork required	0.025	-0.099*	0.027	-0.052
	(0.057)	(0.058)	(0.042)	(0.043)
Tight deadlines	-0.185***	-0.284***	-0.083*	-0.014
	(0.060)	(0.059)	(0.047)	(0.042)
Female	0.027	0.064	-0.025	0.007
	(0.052)	(0.049)	(0.040)	(0.041)
MENA origin	0.013	0.057	-0.012	0.079*
	(0.064)	(0.057)	(0.050)	(0.046)
Number of observations	8,750	10,525	8,750	10,525
Number of respondents	350	421	350	421
Outcome mean	6.311	5.976	6.219	6.684
Outcome standard deviation	2.482	2.633	1.734	1.829
Freelancer experience	$\leq$ 3 years	>3 years	$\leq$ 3 years	>3 years

Notes: This table reports results from estimating Equations (1) and (2) using OLS and participants from the *Evaluation* experiments. They correspond to those from columns 3-4 of Table 2, splitting the sample by whether the respondent's self-reported years of 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.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)	1.040***	0.220***
	(0.057)	(0.035)
At least one job	-0.018	-0.080
	(0.106)	(0.082)
Number of jobs (10s)	0.035	0.055
	(0.063)	(0.045)
Share reviews	-0.031	-0.017
	(0.065)	(0.046)
Prestigious	-0.079	-0.064
	(0.071)	(0.058)
Remote	0.728***	0.143*
	(0.138)	(0.073)
Full time	0.003	0.004
	(0.084)	(0.060)
Duration (months)	0.008	0.005
	(0.022)	(0.016)
Teamwork required	-0.087	0.020
	(0.085)	(0.063)
Tight deadlines	-0.283***	-0.003
	(0.085)	(0.060)
Female	0.115*	0.001
	(0.067)	(0.059)
MENA origin	0.069	0.061
	(0.086)	(0.073)
Number of observations	c	c
Outcome mean	5.938	6.858
Outcome standard deviation	2.633	1.801
Projects	≥ 5	$\geq$5

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

Table B.19: Estimated preferences from the *Evaluation* experiments, ordered probit

Evaluator:	Recruiters		Workers	
Object:	Profiles		Offers	
Dependent variable:	Hire	Accept likelihood	Accept	Offer likelihood
	(1)	(2)	(3)	(4)
Daily wage (100s)	-0.087***	-0.099***	0.415***	0.103***
	(0.014)	(0.012)	(0.015)	(0.010)
At least one job	0.097***	0.040	0.034	0.007
	(0.038)	(0.039)	(0.025)	(0.025)
Number of jobs (10s)	0.117***	0.049***	-0.001	0.005
	(0.018)	(0.018)	(0.014)	(0.013)
Share reviews	0.022	0.015	0.000	-0.004
	(0.023)	(0.023)	(0.016)	(0.015)
Reputation badge	0.135***	0.032		
	(0.036)	(0.036)		
Years of experience (10s)	0.168***	0.003		
	(0.024)	(0.023)		
Master	0.035	-0.039		
	(0.027)	(0.027)		
Second experience	0.249***	0.103***		
	(0.025)	(0.028)		
Prestigious	0.045	-0.085***	-0.092***	-0.093***
	(0.028)	(0.030)	(0.019)	(0.019)
Remote	0.018	0.026	0.324***	0.090***
	(0.029)	(0.025)	(0.029)	(0.020)
Full time	0.017	0.077***	-0.026	0.004
	(0.028)	(0.029)	(0.019)	(0.017)
Duration (months)			0.009*	0.012**
			(0.005)	(0.005)
Teamwork required			-0.017	-0.013
			(0.019)	(0.018)
Tight deadlines			-0.117***	-0.037**
			(0.020)	(0.019)
MENA origin	-0.015	-0.054*	0.016	0.019
	(0.028)	(0.029)	(0.020)	(0.020)
Female	0.010	0.034	0.023	-0.006
	(0.028)	(0.030)	(0.016)	(0.017)
Number of observations	8,542	8,542	19,275	19,275
Number of respondents	342	342	771	771
Outcome mean	6.018	6.863	6.128	6.473
Outcome standard deviation	1.970	1.520	2.565	1.787

Notes: This table reports results from estimating Equations (1) and (2) using an ordered probit and participants from the *Evaluation* experiments. They correspond to those from Table 2 estimated using an 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.20: Estimated preferences from the *Evaluation* experiments by tech and non-tech

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***	-0.175***	-0.117***	-0.157***	0.997***	0.752***	0.197***	0.128***
	(0.039)	(0.031)	(0.025)	(0.027)	(0.039)	(0.043)	(0.023)	(0.026)
At least one job	0.282***	0.141	0.018	0.146*	0.100	0.059	0.045	-0.030
	(0.089)	(0.109)	(0.076)	(0.080)	(0.068)	(0.082)	(0.052)	(0.070)
Number of jobs (10s)	0.141***	0.247***	0.095***	0.037	-0.003	-0.002	0.020	0.003
	(0.042)	(0.050)	(0.034)	(0.033)	(0.040)	(0.043)	(0.028)	(0.038)
Share reviews	0.032	0.052	-0.026	0.046	0.038	-0.024	0.017	-0.032
	(0.056)	(0.063)	(0.043)	(0.053)	(0.045)	(0.049)	(0.030)	(0.041)
Reputation badge	0.207**	0.259***	0.116*	-0.038				
	(0.092)	(0.094)	(0.068)	(0.072)				
Years of experience (10s)	0.368***	0.281***	0.050	-0.036				
	(0.060)	(0.063)	(0.045)	(0.049)				
Master	0.063	0.065	-0.049	-0.040				
	(0.074)	(0.069)	(0.056)	(0.055)				
Second experience	0.453***	0.500***	0.134***	0.205***				
	(0.064)	(0.071)	(0.051)	(0.062)				
Prestigious	0.118*	0.031	-0.056	-0.196***	-0.127**	-0.301***	-0.111***	-0.225***
	(0.071)	(0.078)	(0.059)	(0.066)	(0.053)	(0.063)	(0.038)	(0.055)
Remote	-0.055	0.129*	0.033	0.030	0.851***	0.532***	0.185***	0.122**
	(0.077)	(0.075)	(0.048)	(0.057)	(0.092)	(0.084)	(0.044)	(0.053)
Full time	0.153**	-0.104	0.161***	0.044	-0.097*	0.006	-0.004	0.016
	(0.075)	(0.068)	(0.058)	(0.058)	(0.057)	(0.063)	(0.034)	(0.049)
Duration (months)					0.037**	-0.002	0.021**	0.018
					(0.015)	(0.016)	(0.009)	(0.014)
Teamwork required					0.047	-0.125**	0.004	-0.030
					(0.054)	(0.062)	(0.036)	(0.051)
Tight deadlines					-0.258***	-0.227***	-0.041	-0.056
					(0.058)	(0.061)	(0.039)	(0.051)
MENA origin	0.026	-0.070	-0.079	-0.084	0.080	-0.013	0.030	0.042
	(0.071)	(0.081)	(0.054)	(0.066)	(0.056)	(0.067)	(0.042)	(0.055)
Female	-0.011	0.049	0.056	0.047	0.073	0.029	-0.035	0.026
	(0.079)	(0.072)	(0.060)	(0.058)	(0.048)	(0.051)	(0.037)	(0.045)
Number of observations	4,392	4,150	4,392	4,150	10,450	8,825	10,450	8,825
Number of respondents	176	166	176	166	418	353	418	353
Outcome mean	6.163	5.865	6.933	6.790	6.055	6.214	6.693	6.213
Outcome standard deviation	1.961	1.981	1.458	1.590	2.619	2.501	1.618	1.968
Job category	Tech	Non-tech	Tech	Non-tech	Tech	Non-tech	Tech	Non-tech

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, separating jobs between tech and non-tech. Tech includes development and integration jobs. Non-tech includes growth marketing, communication, and social media and community managers. See Table 2 for additional details. Standard errors are clustered at the respondent level. $^{*}p < 0.10$, $^{**}p < 0.05$, $^{***}p < 0.01$.

Table B.21: Estimated preferences from the *Evaluation* experiments for highly-rated profiles and offers

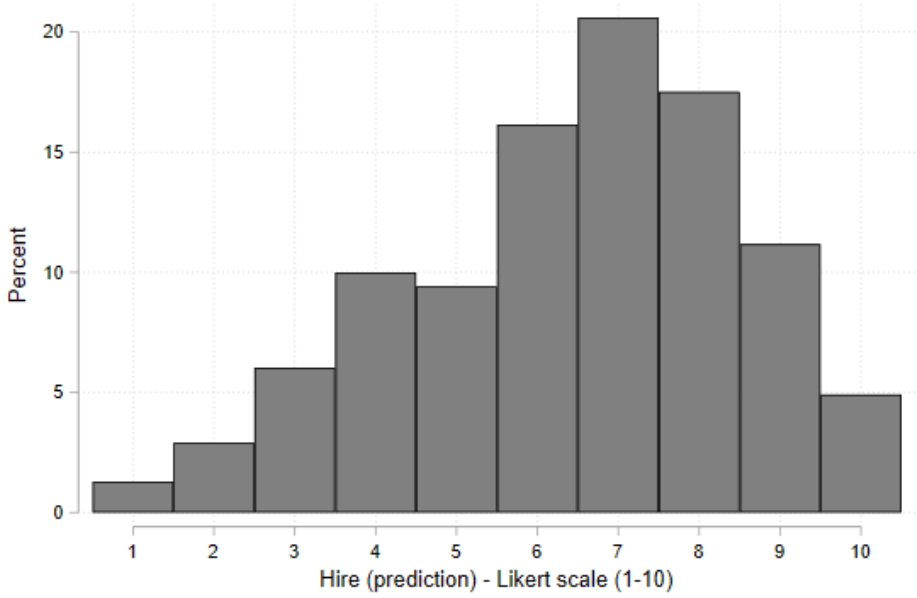
Evaluator:	Recruiters				Workers			
Object:	Profiles				Offers			
Dependent variable:	Hired	Hire>8	Accepted offer	Accept likelihood>8	Accepted	Accept>8	Offered	Offer>8
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Daily wage (100s)	-0.022***	-0.021***	-0.023***	-0.022***	0.082***	0.092***	0.022***	0.023***
	(0.003)	(0.003)	(0.003)	(0.003)	(0.003)	(0.004)	(0.003)	(0.003)
At least one job	-0.007	0.006	-0.008	0.003	0.008	0.001	0.002	0.002
	(0.011)	(0.011)	(0.012)	(0.012)	(0.008)	(0.009)	(0.008)	(0.008)
Number of jobs (10s)	0.029***	0.031***	0.010**	0.010*	-0.003	-0.003	0.000	-0.002
	(0.005)	(0.005)	(0.005)	(0.005)	(0.005)	(0.005)	(0.004)	(0.004)
Share reviews	0.004	0.005	0.011	0.016**	0.000	-0.004	-0.003	-0.002
	(0.007)	(0.007)	(0.007)	(0.006)	(0.005)	(0.006)	(0.005)	(0.005)
Reputation badge	0.047***	0.033***	0.019*	0.010				
	(0.012)	(0.011)	(0.011)	(0.011)				
Years of experience (10s)	0.025***	0.023***	0.004	-0.001				
	(0.006)	(0.007)	(0.008)	(0.007)				
Master	0.005	0.011	-0.010	-0.014*				
	(0.008)	(0.008)	(0.008)	(0.008)				
Second experience	0.039***	0.036***	0.007	0.006				
	(0.007)	(0.007)	(0.008)	(0.008)				
Prestigious	0.019**	0.014*	-0.012	-0.010	-0.020***	-0.020***	-0.019***	-0.011**
	(0.009)	(0.008)	(0.009)	(0.008)	(0.006)	(0.006)	(0.006)	(0.006)
Remote	-0.000	0.002	-0.002	0.009	0.055***	0.062***	0.019***	0.014**
	(0.008)	(0.007)	(0.009)	(0.007)	(0.007)	(0.008)	(0.006)	(0.006)
Full time	0.009	0.005	0.015*	0.019**	-0.001	-0.005	0.002	0.002
	(0.008)	(0.008)	(0.008)	(0.008)	(0.006)	(0.006)	(0.006)	(0.005)
Duration (months)					0.004**	0.003*	0.003*	0.003**
					(0.002)	(0.002)	(0.001)	(0.001)
Teamwork required					-0.001	-0.003	-0.012**	-0.013**
					(0.006)	(0.006)	(0.006)	(0.005)
Tight deadlines					-0.030***	-0.026***	-0.019***	-0.013**
					(0.006)	(0.007)	(0.006)	(0.006)
MENA origin	-0.009	-0.002	-0.015*	-0.006	0.010	0.010	0.007	0.004
	(0.009)	(0.008)	(0.009)	(0.009)	(0.007)	(0.007)	(0.007)	(0.006)
Female	0.007	0.005	0.004	0.006	0.006	0.003	-0.007	-0.002
	(0.008)	(0.008)	(0.010)	(0.009)	(0.005)	(0.006)	(0.005)	(0.005)
Number of observations	8,542	8,542	8,542	8,542	19,275	19,275	19,275	19,275
Number of respondents	342	342	342	342	771	771	771	771
Outcome mean	0.135	0.156	0.206	0.205	0.229	0.281	0.223	0.210

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, using different outcome variables. "Hired", "Accepted offer", "Accepted" and "Offered" are indicator variables equal to 1 for the profile(s) or offer(s) that received a participant's highest evaluation out of their 25 evaluations. ">8" is an indicator variable for a given profile or offer receiving an evaluation above 8 out of 10. See Table 2 for more details. All specifications include respondent fixed effects. Standard errors are clustered at the respondent level. $*p < 0.10, **p < 0.05, ***p < 0.01$.

B.2 *Prediction* experiments and perception gaps

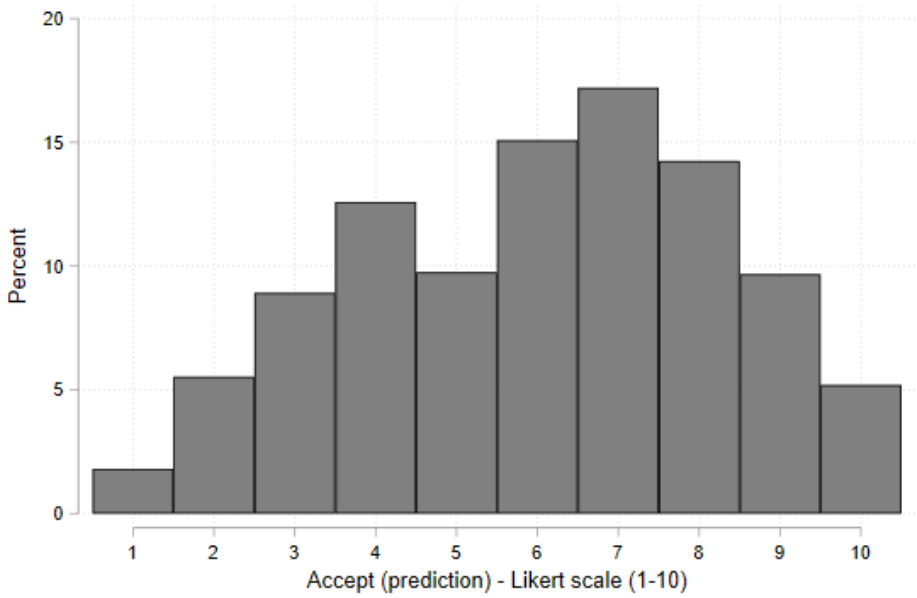
Figure B.4: Distribution of predictions

(a) Profiles



(b) Worker predictions

(c) Offers

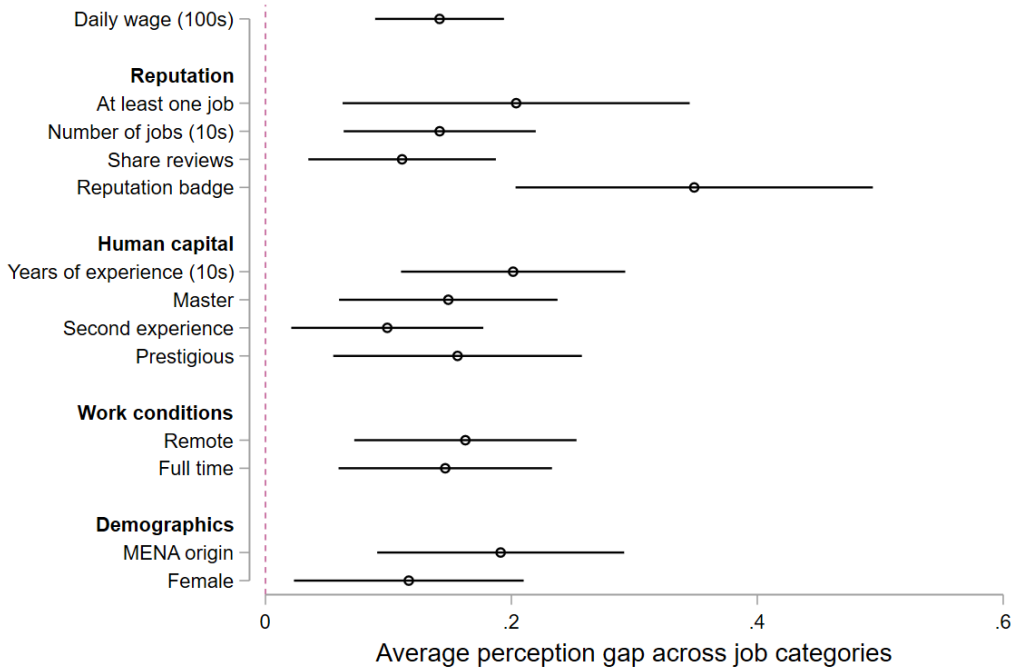


(d) Recruiter predictions

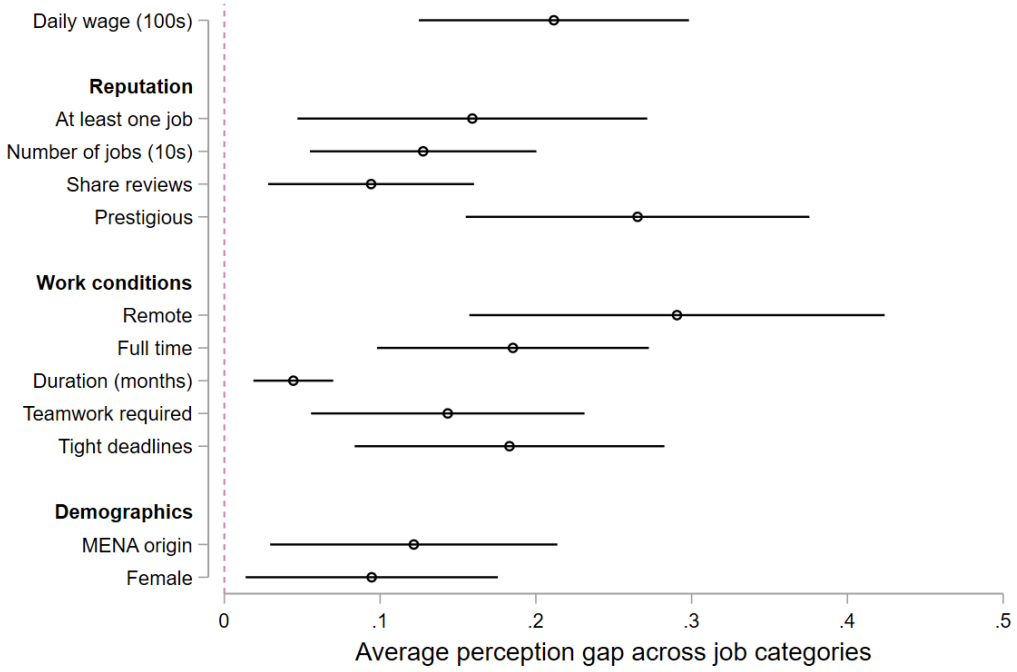
Notes: This figure shows histograms plotting the distribution of respondents' predictions in the *Prediction* experiments.

Figure B.5: Absolute value of perception gaps averaged across job categories

(a) Recruiter preferences (profile characteristics)



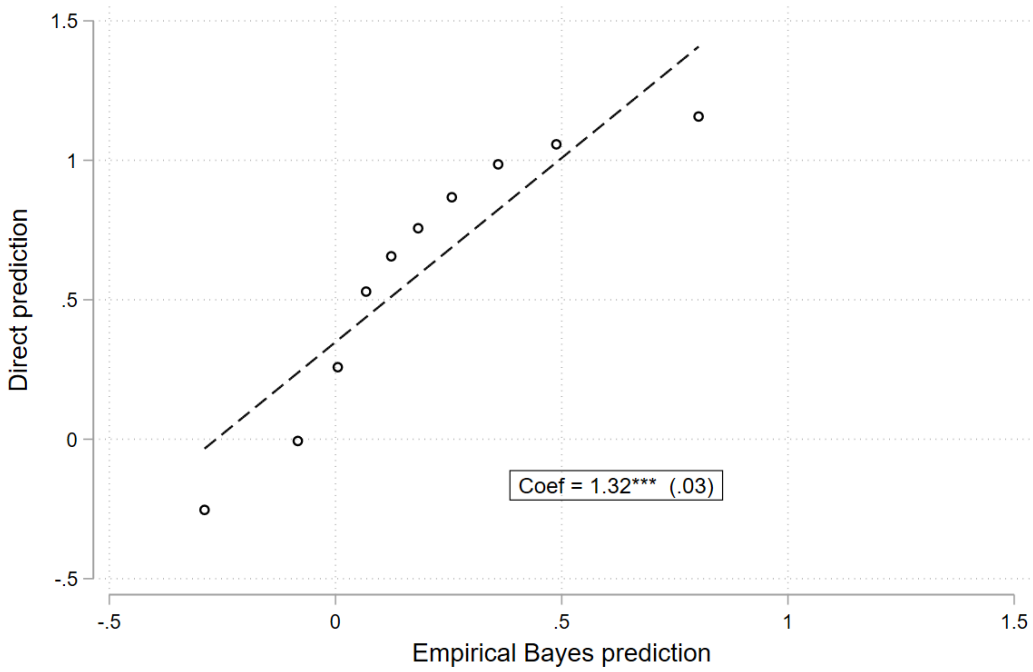
(b) Worker preferences (offer characteristics)



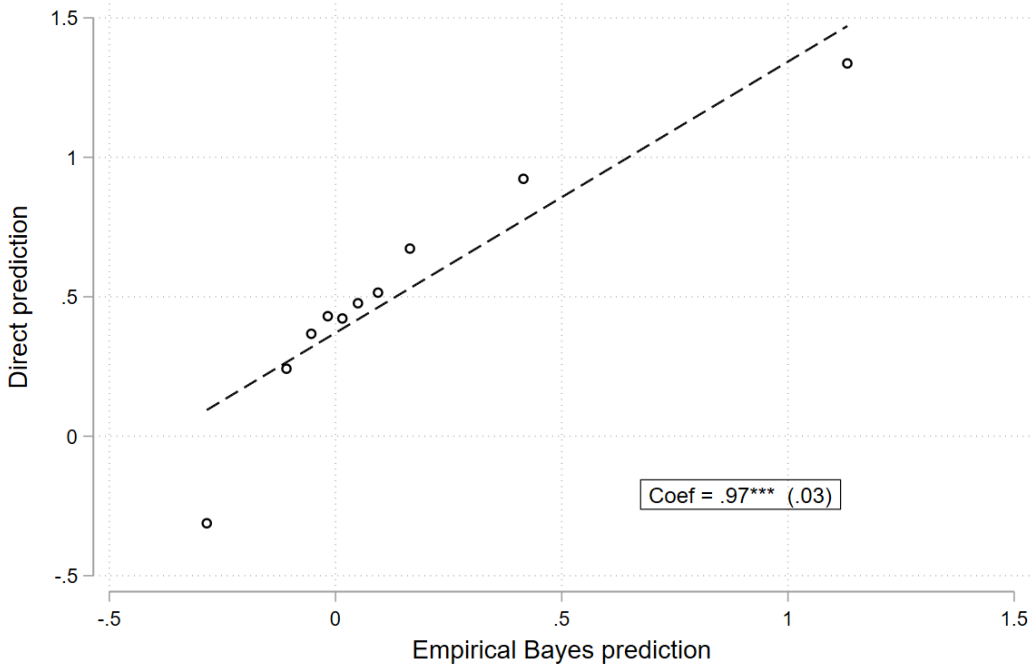
Notes: This figure plots perception gaps estimated at the job category level, transformed to their absolute value, and then averaged across categories. To recover the average perception gap with standard errors, we use a random effects meta-analysis, which weighs coefficients across different job categories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

Figure B.6: Correlation between direct and indirect predictions

(a) Profile characteristics



(b) Offer characteristics



Notes: This figure shows binned scatter plots of the predicted value of a characteristic as estimated through Equations 1 and 2 at the respondent level with values adjusted using the Empirical Bayes procedure described in Section 5 and the direct predicted effect of each characteristic elicited as part of the information treatment. All randomized characteristics are pooled. Dashed lines represent fitted slopes, with corresponding regression coefficients and standard errors included in the text boxes. $^{*}p < 0.10$, $^{**}p < 0.05$, $^{***}p < 0.01$.

Table B.22: Adjustment for multiple hypothesis testing

Object:	Profiles		Job offers	
Dependent variable:	Hire (evaluated and predicted)		Accept (evaluated and predicted)	
Test:	Unadjusted p-value	Sharpened q-value	Unadjusted p-value	Sharpened q-value
Panel (a): Evaluations				
Daily wage (100s)	<0.0001	0.0001***	<0.0001	0.0001***
At least one job	0.0026	0.0042***	0.1410	0.1964
Number of jobs (10s)	<0.0001	0.0001***	0.9701	0.5672
Share of projects reviewed	0.3427	0.3635	0.7969	0.5389
Reputation badge	0.0006	0.0013***	–	–
Years of experience (10s)	<0.0001	0.0001***	–	–
Master	0.2316	0.2774	–	–
Second experience	<0.0001	0.0001***	–	–
Prestigious	0.1422	0.1964	<0.0001	0.0001***
Remote	0.5076	0.4380	<0.0001	0.0001***
Full time	0.6022	0.4649	0.2101	0.2660
Duration (months)	–	–	0.1141	0.1842
Teamwork required	–	–	0.3239	0.3635
Tight deadlines	–	–	<0.0001	0.0001***
MENA origin	0.7845	0.5389	0.4177	0.3766
Female	0.7000	0.5386	0.1777	0.2352
Panel (b): Perception gaps				
Daily wage (100s) $\times$ P_i	<0.0001	0.0004***	0.0026	0.0144**
At least one job $\times$ P_i	0.0503	0.0897*	0.1540	0.1988
Number of jobs (10s) $\times$ P_i	0.5312	0.4538	0.6964	0.4735
Share reviews $\times$ P_i	0.2056	0.2195	0.8430	0.4735
Reputation badge $\times$ P_i	<0.0001	0.0004***	–	–
Years of experience (10s) $\times$ P_i	0.0036	0.0162**	–	–
Master's degree $\times$ P_i	0.1046	0.1390	–	–
Second experience $\times$ P_i	0.1748	0.2119	–	–
Prestigious $\times$ P_i	0.0108	0.0320**	<0.0001	0.0006***
Remote $\times$ P_i	0.0081	0.0277**	0.0500	0.0897*
Full time $\times$ P_i	0.0454	0.0897*	0.3837	0.3834
Duration (months) $\times$ P_i	–	–	0.0392	0.0897*
Teamwork required $\times$ P_i	–	–	0.4716	0.4243
Tight deadlines $\times$ P_i	–	–	0.9773	0.5428
MENA origin $\times$ P_i	0.2656	0.2786	0.1922	0.2187
Female $\times$ P_i	0.7079	0.4735	0.8241	0.4735

Notes: This table reports unadjusted p-values and sharpened q-values(Anderson, 2008) for estimated preferences shown in Columns 1 and 4 of Table 3 and estimated perception gaps shown in columns 3 and 6 of Table 3. Sharpened q-values control for the false discovery rate: the expected proportion of rejections that are type 1 errors, across Panels (a) and (b) separately. Based on sharpened q-values: $*q < 0.10, **q < 0.05, ***q < 0.01$.

Table B.23: Perception gaps by predictor gender and MENA origin

Evaluator:	Recruiters				Workers			
Predictor:	Workers				Recruiters			
Object:	Profiles				Offers			
Dependent variable:	Hire				Accept			
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Daily wage (100s) × P_i	0.136***	0.102***	0.122***	0.161***	0.129***	0.138**	0.147***	-0.057
	(0.030)	(0.036)	(0.029)	(0.047)	(0.047)	(0.070)	(0.045)	(0.073)
At least one job × P_i	0.149*	0.179	0.175**	0.057	0.134	0.045	0.082	0.495***
	(0.087)	(0.111)	(0.085)	(0.138)	(0.088)	(0.127)	(0.082)	(0.172)
Number of jobs (10s) × P_i	0.049	-0.014	0.017	0.087	-0.009	-0.033	0.004	-0.264*
	(0.042)	(0.047)	(0.039)	(0.067)	(0.048)	(0.066)	(0.044)	(0.153)
Share reviews × P_i	0.089*	0.004	0.070	0.002	-0.000	-0.036	-0.002	-0.084
	(0.050)	(0.065)	(0.050)	(0.089)	(0.053)	(0.069)	(0.049)	(0.119)
Reputation badge × P_i	0.290***	0.394***	0.370***	-0.064				
	(0.079)	(0.100)	(0.078)	(0.127)				
Years of experience (10s) × P_i	0.191***	0.062	0.132**	0.288***				
	(0.055)	(0.064)	(0.052)	(0.096)				
Master × P_i	0.108*	0.063	0.066	0.331***				
	(0.062)	(0.068)	(0.059)	(0.104)				
Second experience × P_i	-0.097*	-0.034	-0.077	-0.039				
	(0.058)	(0.074)	(0.056)	(0.099)				
Prestigious × P_i	0.146**	0.189**	0.167***	0.096	0.237***	0.220**	0.240***	0.184
	(0.065)	(0.083)	(0.063)	(0.127)	(0.065)	(0.086)	(0.060)	(0.152)
Remote × P_i	-0.170***	-0.137*	-0.151**	-0.224**	-0.163*	-0.161	-0.164*	-0.156
	(0.062)	(0.074)	(0.060)	(0.107)	(0.091)	(0.117)	(0.085)	(0.168)
Full time × P_i	0.126**	0.104	0.115*	0.125	0.056	0.035	0.040	0.172
	(0.062)	(0.073)	(0.060)	(0.097)	(0.062)	(0.091)	(0.058)	(0.164)
Duration (months) × P_i					0.033*	0.032	0.028*	0.088**
					(0.018)	(0.020)	(0.016)	(0.040)
Teamwork required × P_i					0.002	0.141*	0.021	0.282**
					(0.062)	(0.085)	(0.058)	(0.137)
Tight deadlines × P_i					0.014	-0.030	0.009	-0.010
					(0.068)	(0.096)	(0.063)	(0.171)
MENA origin × P_i	-0.117*	0.045	-0.043	-0.281**	-0.103	-0.003	-0.075	-0.149
	(0.064)	(0.082)	(0.062)	(0.122)	(0.065)	(0.090)	(0.060)	(0.201)
Female × P_i	0.047	-0.025	0.025	-0.005	0.042	-0.077	0.032	-0.252**
	(0.063)	(0.073)	(0.061)	(0.102)	(0.055)	(0.073)	(0.051)	(0.126)
Observations	23,517	13,617	26,217	10,917	25,525	21,650	27,325	19,850
Number of predictors	599	203	707	95	250	95	322	23
Number of evaluators	342	342	342	342	771	771	771	771
Evaluator outcome standard deviation	1.970	1.970	1.970	1.970	2.565	2.565	2.565	2.565
Origin/gender of respondent name	Male	Female	Non MENA	MENA	Male	Female	Non MENA	MENA

Notes: This table reports estimates of columns 3 and 6 from Table 3, splitting predictors by their gender and ethnic origin. Gender and ethnicity of workers and recruiters are imputed from first names. See Table 3 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 by tech and non-tech

Evaluator:	Recruiters		Workers	
Predictor:	Workers		Recruiters	
Object:	Profiles		Offers	
Dependent variable:	Hire		Accept	
	(1)	(2)	(3)	(4)
Daily wage (100s) × P_i	0.138***	0.109***	0.016	0.341***
	(0.043)	(0.038)	(0.056)	(0.068)
At least one job × P_i	0.106	0.156	0.031	0.204
	(0.106)	(0.129)	(0.102)	(0.127)
Number of jobs (10s) × P_i	0.180***	-0.057	-0.023	-0.001
	(0.052)	(0.056)	(0.061)	(0.062)
Share reviews × P_i	0.069	0.051	-0.056	0.041
	(0.064)	(0.074)	(0.066)	(0.069)
Reputation badge × P_i	0.390***	0.243**		
	(0.103)	(0.111)		
Years of experience (10s) × P_i	0.210***	0.077		
	(0.070)	(0.075)		
Master × P_i	0.111	0.072		
	(0.083)	(0.081)		
Second experience × P_i	-0.092	-0.065		
	(0.073)	(0.084)		
Prestigious × P_i	0.115	0.203**	0.145*	0.334***
	(0.081)	(0.095)	(0.079)	(0.087)
Remote × P_i	-0.107	-0.208**	-0.384***	0.089
	(0.084)	(0.084)	(0.118)	(0.116)
Full time × P_i	0.009	0.232***	0.171**	-0.107
	(0.084)	(0.081)	(0.077)	(0.086)
Duration (months) × P_i			0.039*	0.026
			(0.023)	(0.021)
Teamwork required × P_i			-0.045	0.129
			(0.077)	(0.084)
Tight deadlines × P_i			0.002	0.002
			(0.089)	(0.086)
MENA origin × P_i	-0.171**	0.065	-0.121	-0.038
	(0.081)	(0.095)	(0.081)	(0.088)
Female × P_i	0.041	-0.003	-0.031	0.050
	(0.089)	(0.082)	(0.069)	(0.072)
Observations	17,367	11,225	14,725	13,175
Number of predictors	519	283	171	174
Number of evaluators	176	166	418	353
Evaluator outcome standard deviation	1.970	1.970	2.565	2.565
Job category	Tech	Non-tech	Tech	Non-tech

Notes: This table reports estimates of columns 3 and 6 from Table 3 split by tech and non-tech jobs. See Tables 3 and B.20 for additional details. Standard errors are clustered at the respondent level. $^{*}p < 0.10$, $^{**}p < 0.05$, $^{***}p < 0.01$.

Table B.25: Perception gaps by predictor experience

Evaluator:	Recruiters		Workers	
Predictor:	Workers		Recruiters	
Object:	Profiles		Offers	
Dependent variable:	Hire		Accept	
	(1)	(2)	(3)	(4)
Daily wage (100s) × P_i	0.121***	0.131***	0.138**	0.127**
	(0.031)	(0.035)	(0.055)	(0.052)
At least one job × P_i	0.134	0.225**	0.045	0.181*
	(0.092)	(0.096)	(0.102)	(0.097)
Number of jobs (10s) × P_i	0.011	0.035	0.042	-0.079
	(0.043)	(0.045)	(0.053)	(0.055)
Share reviews × P_i	0.079	0.041	0.015	-0.030
	(0.052)	(0.060)	(0.057)	(0.061)
Reputation badge × P_i	0.319***	0.318***		
	(0.082)	(0.091)		
Years of experience (10s) × P_i	0.149***	0.161***		
	(0.057)	(0.060)		
Master × P_i	0.101	0.092		
	(0.064)	(0.065)		
Second experience × P_i	-0.074	-0.077		
	(0.060)	(0.065)		
Prestigious × P_i	0.164**	0.145*	0.222***	0.243***
	(0.067)	(0.076)	(0.067)	(0.077)
Remote × P_i	-0.137**	-0.173**	-0.093	-0.242**
	(0.063)	(0.068)	(0.101)	(0.097)
Full time × P_i	0.087	0.160**	-0.001	0.100
	(0.064)	(0.068)	(0.070)	(0.069)
Duration (months) × P_i			0.013	0.054***
			(0.019)	(0.019)
Teamwork required × P_i			0.136**	-0.054
			(0.069)	(0.068)
Tight deadlines × P_i			0.013	-0.012
			(0.075)	(0.079)
MENA origin × P_i	-0.065	-0.082	-0.020	-0.140**
	(0.068)	(0.072)	(0.075)	(0.069)
Female × P_i	0.032	0.015	0.053	-0.028
	(0.066)	(0.068)	(0.059)	(0.062)
Observations	c	c	c	c
Number of evaluators	342	342	771	771
Evaluator outcome standard deviation	1.970	1.970	2.565	2.565
Experience	No jobs	At least one job	No jobs	At least one job

Notes: This table reports estimates from columns 3 and 6 of Table 3, splitting predictors by whether they completed at least one job. See Table 3 for more details. All specifications include respondent fixed effects. c denotes a suppressed sensitive observation count, see Table 1 for summary statistics on completed jobs. Standard errors are clustered at the respondent level.
$*p < 0.10, **p < 0.05, ***p < 0.01$.

Table B.26: Perception gaps, by experience of workers making predictions

Evaluator:	Recruiters		
Predictor :	Workers		
Object:	Profiles		
Dependent variable:	Hire		
	(1)	(2)	(3)
Daily wage (100s) × P_i	0.168***	0.124***	0.129***
	(0.042)	(0.031)	(0.033)
At least one job × P_i	0.282**	0.131	0.203**
	(0.127)	(0.093)	(0.096)
Number of jobs (10s) × P_i	0.011	0.011	0.037
	(0.058)	(0.044)	(0.044)
Share reviews × P_i	0.001	0.053	0.071
	(0.080)	(0.054)	(0.056)
Reputation badge × P_i	0.373***	0.348***	0.294***
	(0.112)	(0.084)	(0.087)
Years of experience (10s) × P_i	0.074	0.189***	0.105*
	(0.077)	(0.058)	(0.059)
Master's degree × P_i	0.076	0.094	0.096
	(0.080)	(0.064)	(0.065)
Second experience × P_i	-0.052	-0.058	-0.096
	(0.083)	(0.061)	(0.064)
Prestigious × P_i	0.139	0.134*	0.185***
	(0.108)	(0.069)	(0.072)
Remote × P_i	-0.177**	-0.155**	-0.162**
	(0.082)	(0.065)	(0.065)
Full time × P_i	0.221***	0.149**	0.081
	(0.084)	(0.065)	(0.067)
MENA origin × P_i	-0.082	-0.039	-0.104
	(0.087)	(0.068)	(0.070)
Female × P_i	0.113	0.025	0.022
	(0.083)	(0.067)	(0.067)
Observations	c	19,217	17,917
Number of predictors	c	427	375
Number of evaluators	342	342	342
Evaluator outcome standard deviation	1.970	1.970	1.970
Experience	$\geq$ 5 jobs	$\leq$ 3 years exp	$>$ 3 years exp

Notes: This table reports estimates from column 3 of Table 3, restricting to predictions of workers with at least 5 completed jobs (column 1) and splitting by whether workers making predictions have below versus above median years of freelancing experience (columns 2-3). See Table 3 for 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 including fast respondents

Evaluator:	Recruiters	Workers
Predictor:	Workers	Recruiters
Object:	Profiles	Offers
Dependent variable:	Hire	Accept
	(1)	(2)
Daily wage (100s)	0.129***	0.113**
	(0.029)	(0.044)
At least one job	0.167**	0.104
	(0.083)	(0.079)
Number of jobs (10s)	0.032	-0.010
	(0.039)	(0.043)
Share reviews	0.059	-0.014
	(0.049)	(0.048)
Reputation badge	0.331***	
	(0.077)	
Years of experience (10s)	0.153***	
	(0.052)	
Master	0.091	
	(0.058)	
Second experience	-0.081	
	(0.055)	
Prestigious	0.146**	0.243***
	(0.062)	(0.058)
Remote	-0.149**	-0.175**
	(0.060)	(0.083)
Full time	0.114*	0.037
	(0.059)	(0.057)
Duration (months)		0.032**
		(0.016)
Teamwork required		0.034
		(0.056)
Tight deadlines		0.027
		(0.063)
MENA origin	-0.067	-0.077
	(0.061)	(0.060)
Female	0.026	0.020
	(0.060)	(0.049)
Observations	29,692	28,650
Number of evaluators	342	771
Number of predictors	846	375
Outcome mean	6.286	6.081
Evaluator outcome standard deviation	1.970	2.565

Notes: This table reports estimates of columns 3 and 6 from Table 3, including respondents who spent an average of less than 6 seconds per prediction. See Table 3 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 estimated with an ordered probit

Evaluator:	Recruiters	Workers
Predictor:	Workers	Recruiters
Object:	Profiles	Offers
Dependent variable:	Hire	Accept
	(1)	(2)
Daily wage (100s) × P_i	0.072***	-0.023
	(0.017)	(0.021)
At least one job × P_i	0.091*	0.047
	(0.049)	(0.038)
Number of jobs (10s) × P_i	0.012	-0.007
	(0.024)	(0.021)
Share reviews × P_i	0.044	-0.004
	(0.029)	(0.023)
Reputation badge × P_i	0.204***	
	(0.047)	
Years of experience (10s) × P_i	0.097***	
	(0.031)	
Master × P_i	0.058*	
	(0.034)	
Second experience × P_i	-0.043	
	(0.033)	
Prestigious × P_i	0.094**	0.119***
	(0.037)	(0.028)
Remote × P_i	-0.094***	-0.131***
	(0.035)	(0.040)
Full time × P_i	0.070**	0.034
	(0.035)	(0.028)
Duration (months) × P_i		0.013*
		(0.008)
Teamwork required × P_i		0.018
		(0.028)
Tight deadlines × P_i		0.023
		(0.030)
MENA origin × P_i	-0.029	-0.036
	(0.036)	(0.029)
Female × P_i	0.013	0.000
	(0.036)	(0.024)
Observations	28,592	27,900
Number of predictors	802	345
Number of evaluators	342	771
Evaluator outcome standard deviation	1.970	2.565

Notes: This table reports estimates of columns 3 and 6 from Table 3 estimated by ordered probit instead of OLS. See Table 3 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: Estimated perception gaps, with participants in the *Evaluation* and *Prediction* experiments reweighted to match platform workers and recruiters

Reweighted	Evaluators		Predictors	
Evaluator:	Recruiters	Workers	Recruiters	Workers
Predictor:	Workers	Recruiters	Workers	Recruiters
Object:	Profiles	Offers	Profiles	Offers
Dependent variable:	Hire	Accept	Hire	Accept
	(1)	(2)	(3)	(4)
Daily wage (100s)	0.124***	0.224***	0.123***	0.129***
	(0.031)	(0.048)	(0.030)	(0.047)
At least one job	0.205**	0.088	0.147*	0.091
	(0.098)	(0.085)	(0.085)	(0.085)
Number of jobs (10s)	0.005	-0.003	0.014	-0.005
	(0.043)	(0.047)	(0.040)	(0.044)
Share reviews	0.080	0.022	0.061	-0.040
	(0.057)	(0.055)	(0.049)	(0.050)
Reputation badge	0.300***		0.315***	
	(0.087)		(0.077)	
Years of experience (10s)	0.107*		0.159***	
	(0.055)		(0.053)	
Master	0.128**		0.103*	
	(0.063)		(0.059)	
Second experience	-0.117		-0.111**	
	(0.075)		(0.057)	
Prestigious	0.167**	0.276***	0.166***	0.203***
	(0.066)	(0.066)	(0.063)	(0.061)
Remote	-0.127*	-0.153*	-0.159***	-0.151*
	(0.067)	(0.092)	(0.060)	(0.089)
Full time	0.095	0.114*	0.124**	0.065
	(0.072)	(0.066)	(0.061)	(0.061)
Duration (months)		0.026		0.018
		(0.017)		(0.016)
Teamwork required		0.046		0.018
		(0.062)		(0.060)
Tight deadlines		-0.040		-0.009
		(0.066)		(0.064)
MENA origin	-0.048	-0.069	-0.062	-0.076
	(0.069)	(0.065)	(0.063)	(0.063)
Female	-0.003	-0.003	0.018	0.006
	(0.073)	(0.056)	(0.062)	(0.053)
Observations	28,592	27,900	28,592	27,900
Number of predictors	802	345	802	345
Number of evaluators	342	771	342	771
Evaluator outcome standard deviation	1.970	2.565	1.970	2.565

Notes: This table reports estimates from columns 3 and 6 of Table 3, with recruiters (column 1) and workers (column 2) in the *Evaluation* experiments reweighted to match platform distributions or with workers (column 3) and recruiters (column 4) in the *Prediction* experiments reweighted to match platform distributions. See Table 3 for details. Reweighting for recruiters is based on: job category, number of completed jobs, and firm size. Reweighting for workers is based on: asked wage, number of completed jobs, job category, and experience level. All specifications include respondent fixed effects. Standard errors are clustered at the respondent level. $*p < 0.10, **p < 0.05, ***p < 0.01$.

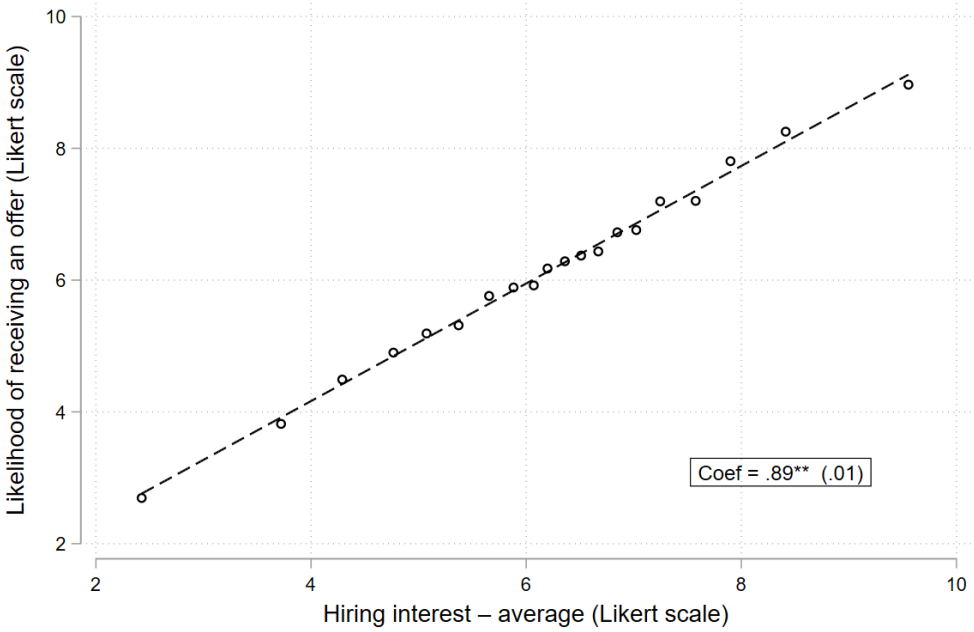
B.3 Experiment on segmentation and market returns

Figure B.7: Recruiter preferences, segmentation, and market returns

(a) Predicted hiring interest: average versus targeted segment

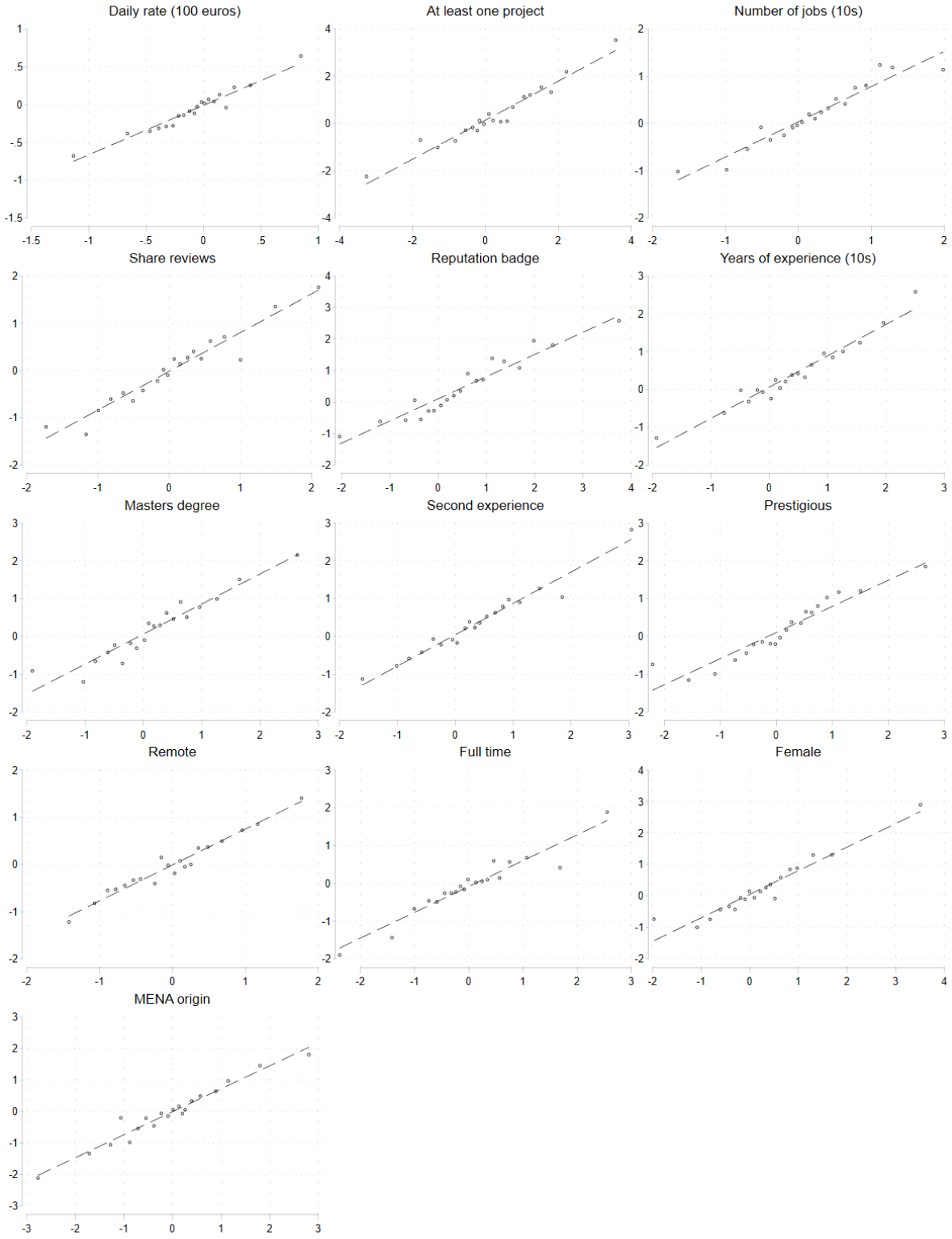


(b) Predicted average hiring interest versus predicted likelihood of receiving an offer



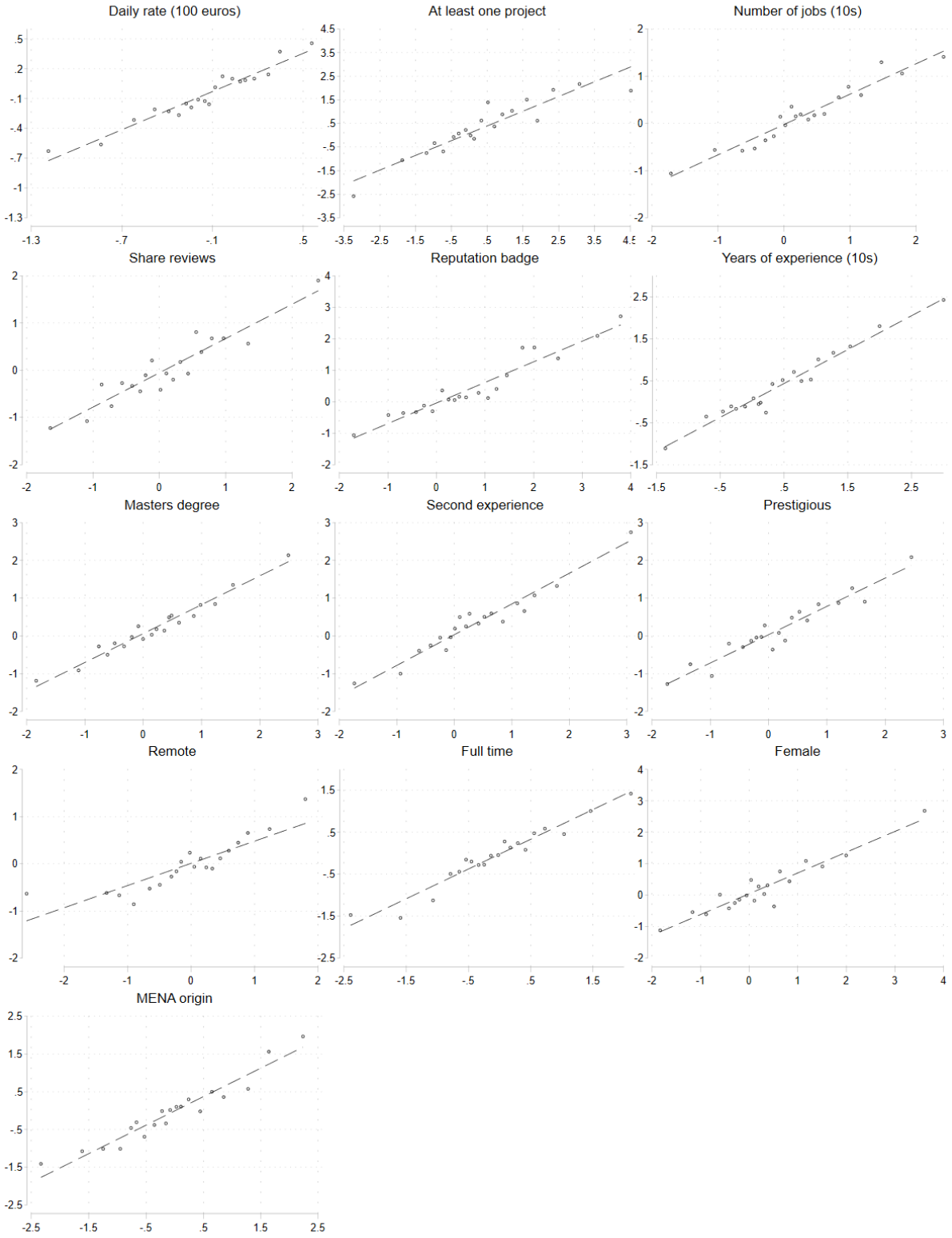
Notes: This figure shows binned scatter plots of individual workers' predictions of average recruiter hiring interest (the quantity elicited in our baseline experiment) against a) workers' predictions of recruiter hiring interest within each worker's own self-reported relevant segment of recruiters and b) workers' predictions of the likelihood that the profile would receive at least one job offer within the next three months. Dashed lines represent fitted slopes, with corresponding regression coefficients and standard errors included in the text boxes. See Section B.3 for more details and Section E.6 for experimental instructions. $^{*}p < 0.10$, $^{**}p < 0.05$, $^{***}p < 0.01$.

Figure B.8: Predicted impact of characteristics on average interest versus interest of recruiters in market segment



Notes: This figure shows binned scatter plots of the relationship shown in Panel (a) of Figure B.7, separately for each randomized profile characteristic. See Figure B.7 for more details.

Figure B.9: Predicted impact of characteristics on average interest versus the likelihood of receiving an offer

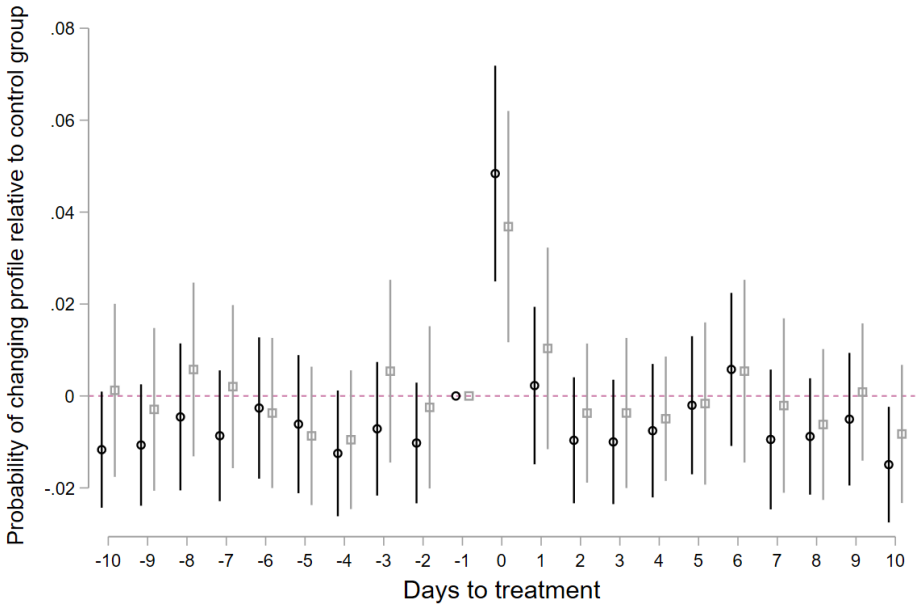


Notes: This figure shows binned scatter plots of the relationship shown in Panel (b) of Figure B.7, separately for each randomized profile characteristic. See Figure B.7 for more details.

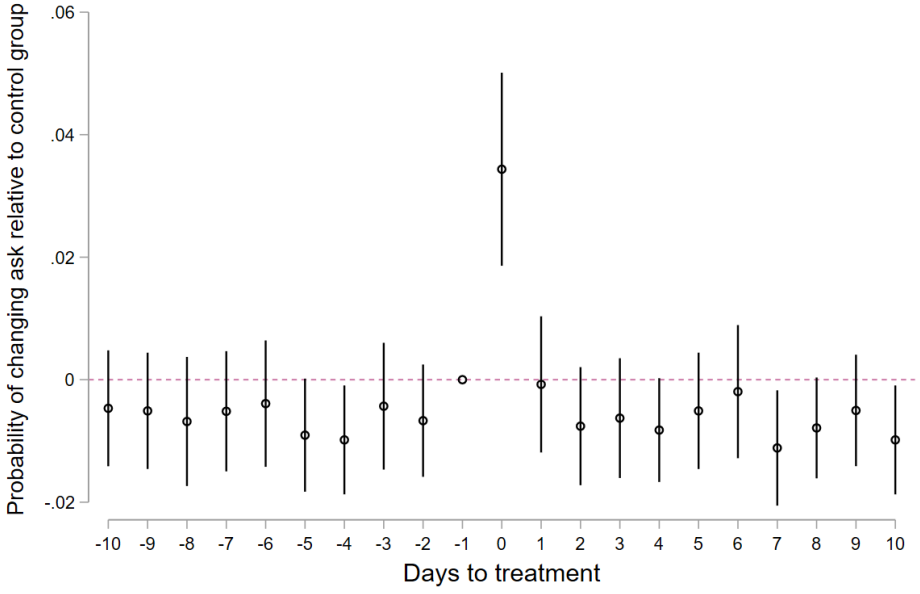
B.4 Information treatment

Figure B.10: Differences-in-Differences estimates of the information treatment on worker profile changes by intention to change profiles during the experiment and on changes in asked wages

(a) Probability of profile change, by stated likelihood in the experiment



(b) Probability of changing asked wage on profile



Notes: Panel (a) shows estimates from Figure 4a, splitting respondents by their self-reported likelihood of updating their profile at the time of taking the survey, after being provided with information. We define high likelihood as reporting being likely or very likely to change their profile. Panel (b) shows estimates from Figure 4a, restricting to changes in the asked wage rather than any profile characteristic. Baseline rate of updating asked wages for workers before the experiment is 0.5%. See Figure 4 for details. Bars represent 95 % confidence intervals.

Table B.30: Do workers change their asked wages in the direction indicated by the information?

Dependent variable:	Decreases asked wage		
	(1)	(2)	(3)
Underestimates wage sensitivity	0.032**		
	(0.014)		
Overestimates own market value		0.022*	
		(0.013)	
Underestimates wage sensitivity and overestimates own market value			0.033**
			(0.015)
Original asked wage (100s)	0.009**		0.010**
	(0.004)		(0.004)
Own market value		-0.001	-0.012
		(0.015)	(0.017)
Observations	799	799	799
Outcome mean	0.035	0.035	0.035

Notes: This table reports the probability of a worker decreasing their asked wage (rather than leaving it unchanged or increasing it) on the day of or the day following the information treatment. Column 1 tests the differential probability for workers who were informed that they underestimate recruiter wage sensitivity (rather than overestimate or have fairly accurate beliefs about it), implying that they should decrease their asked wage. Column 2 tests the differential probability for workers who were informed that they overestimate the market value of their own profile characteristics, again implying that they should decrease their asked wage. We follow the procedure outlined in Table 4 to measure a profile's market value and predicted market value, but we use direct predictions about the marginal effect of each characteristic elicited as part of the information treatment to calculate the predicted value since these predictions determine the information shown to each participant. Column 3 tests the differential probability for workers who satisfy the condition in both columns 1 and 2. $^{*}p < 0.10$, $^{**}p < 0.05$, $^{***}p < 0.01$.

C Theoretical framework details

C.1 Proposition 1

C.1.1 Assumptions

Throughout this section, perception gaps are considered separately, as in the main text. For the recruiter-side exercise, the worker's ask is held fixed at its correct-beliefs value. For the worker-side exercise, workers form beliefs about recruiter behavior using their perceived value $\hat{v}$, while realized recruiter decisions depend on the true value v.

Assumption 1 (Recruiter pricing regularity). For all values of $(\tilde{v}, \tilde{u}, w)$ in the relevant support, the objective

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

has a unique interior maximizer.

Under correct beliefs, we denote this maximizer by

$$p^*(w; v, u) \in \arg\max_{p \geq 0} \sigma(u + p - w)(v - p),$$

with associated maximized surplus

$$\Pi^*(w; v, u) = \max_{p \geq 0} \sigma(u + p - w)(v - p).$$

Under a recruiter perception gap, the corresponding objects are $p^{\Gamma}(w; v, \hat{u})$ and $\Pi^{\Gamma}(w; v, \hat{u})$.

For a worker who perceives their value to recruiters as $\hat{v}$, define perceived expected payoff from posting ask w as

$$\widehat{W}(w; \hat{v}) = \mathbb{E}_u \left[\mathbf{1}\{\Pi^*(w; \hat{v}, u) \geq c\} \, A(p^*(w; \hat{v}, u); u, w) \, (u + p^*(w; \hat{v}, u)) \right].$$

Assumption 2 (Worker pricing regularity). For every $\hat{v}$ in the relevant support, $\widehat{W}(w; \hat{v})$ is twice continuously differentiable and has a unique interior maximizer $w(\hat{v})$. At

this maximizer,

$$\frac{\partial^2 \widehat{W}(w;\hat{v})}{\partial w^2} < 0 \qquad \text{and} \qquad \frac{\partial^2 \widehat{W}(w;\hat{v})}{\partial w\, \partial \hat{v}} > 0.$$

Assumption 3 (Recruiter-type regularity). The distribution of recruiter types u is continuous and has strictly positive density in neighborhoods of the relevant offer cutoffs. Relevant correct-beliefs and distorted-belief offer cutoffs are interior to the support. In particular, there is no positive probability mass at a type satisfying $\Pi^*(w; v, u) = c$.

C.1.2 Proof

1. Pricing. *Recruiter wages.* Fix (v, w) and consider a recruiter with perceived worker utility $\hat{u} = u + \Gamma$. The recruiter chooses

$$p^\Gamma(w; v, \hat{u}) \in \arg\max_{p \geq 0} \sigma(\hat{u} + p - w)(v - p).$$

Let

$$z \equiv \hat{u} + p^\Gamma - w.$$

By Assumption 1, the optimum is interior and satisfies

$$\sigma'(z)(v - p^\Gamma) - \sigma(z) = 0.$$

Using $\sigma'(z) = \sigma(z)[1 - \sigma(z)]$, this can be written

$$(v - p^\Gamma)[1 - \sigma(z)] = 1. \tag{C.1}$$

Differentiating (C.1) with respect to $\hat{u}$ gives

$$\frac{\partial p^\Gamma}{\partial \hat{u}} = -\sigma(z) < 0.$$

Hence the optimal offered wage is strictly decreasing in the recruiter's perceived value of the job to the worker. Since $\hat{u} = u + \Gamma$,

$$\Gamma > 0 \quad \Longrightarrow \quad p^\Gamma(w; v, \hat{u}) < p^*(w; v, u),$$

while

$$\Gamma < 0 \quad \Longrightarrow \quad p^{\Gamma}(w; v, \hat{u}) > p^{*}(w; v, u).$$

Worker asks. A worker with perceived value $\hat{v} = v + \Delta$ chooses

$$w(\hat{v}) \in \arg\max_{w \geq 0} \widehat{W}(w; \hat{v}).$$

By Assumption 2, the solution is unique and interior and therefore satisfies

$$\widehat{W}_w(w(\hat{v}); \hat{v}) = 0.$$

Applying the implicit function theorem,

$$\frac{dw(\hat{v})}{d\hat{v}} = -\frac{\widehat{W}_{w\hat{v}}(w(\hat{v}); \hat{v})}{\widehat{W}_{ww}(w(\hat{v}); \hat{v})} > 0,$$

where the inequality follows from Assumption 2.

Under correct beliefs the worker chooses $w^{*}(v) = w(v)$, whereas a worker with perception gap Δ chooses

$$w^{\Delta}(v) = w(v + \Delta).$$

Hence

$$\Delta > 0 \quad \Longrightarrow \quad w^{\Delta}(v) > w^{*}(v),$$

while

$$\Delta < 0 \quad \Longrightarrow \quad w^{\Delta}(v) < w^{*}(v).$$

This establishes the worker-side pricing claim.

2. Matching and expected payoff. We consider worker and recruiter perception gaps separately.

Worker perception gaps.

Realized recruiter behavior following ask w is determined by the true worker value v.

From (C.1), now evaluated under correct beliefs, differentiating with respect to w gives

$$\frac{\partial p^*(w;v,u)}{\partial w} = \sigma(u + p^*(w;v,u) - w) \in (0,1). \tag{C.2}$$

The recruiter's maximized surplus is

$$\Pi^*(w;v,u) = \max_{p \geq 0} \sigma(u + p - w)(v - p).$$

By the envelope theorem,

$$\frac{\partial \Pi^*(w;v,u)}{\partial w} = -\sigma'(u + p^*(w;v,u) - w)\,(v - p^*(w;v,u)) < 0. \tag{C.3}$$

Thus a higher worker ask strictly lowers recruiter profitability and weakly shrinks the set of recruiter types willing to make an offer. By Assumption 3, the probability of receiving an offer strictly falls when the ask rises and strictly increases when the ask falls.

Conditional on an offer from a given recruiter type, acceptance depends on

$$u + p^*(w;v,u) - w.$$

Using (C.2),

$$\frac{d}{dw}\left[u + p^*(w;v,u) - w\right] = \sigma(u + p^*(w;v,u) - w) - 1 < 0. \tag{C.4}$$

Hence, for any recruiter type that makes an offer under both asks, a higher ask strictly reduces the probability that the offer is accepted.

Define the match probability with recruiter type u as

$$M(w;v,u) = \mathbf{1}\left\{\Pi^*(w;v,u) \geq c\right\} A(p^*(w;v,u);u,w)\,.$$

Equations (C.3)–(C.4) imply that $M(w;v,u)$ is weakly decreasing in w for every u, and strictly decreasing for a positive-measure set of recruiter types under Assumption 3. Therefore aggregate matching is strictly decreasing in the worker's ask.

From Part 1,

$$\Delta > 0 \quad \Longrightarrow \quad w^{\Delta}(v) > w^{*}(v),$$

so the probability of receiving an offer falls, acceptance from recruiter types offering in both regimes falls, and overall matching falls. The reverse holds for $\Delta < 0$.

Now consider the worker's true expected payoff from posting ask w:

$$W(w; v) = \mathbb{E}_u \left[\mathbf{1}\{\Pi^*(w; v, u) \geq c\} \, A(p^*(w; v, u); u, w) \, (u + p^*(w; v, u)) \right].$$

This is exactly the perceived objective $\widehat{W}(w; \hat{v})$ evaluated at $\hat{v} = v$. Hence, by Assumption 2, $w^*(v)$ is the unique maximizer of true expected payoff.

For any $\Delta \neq 0$, Part 1 implies

$$w^{\Delta}(v) \neq w^{*}(v).$$

Therefore, by uniqueness of the correct-beliefs optimum,

$$W(w^{\Delta}(v); v) < W(w^{*}(v); v).$$

Thus whenever the worker perception gap distorts the ask, it strictly lowers the worker's true expected payoff.

Recruiter perception gaps.

Hold the worker's ask fixed at its correct-beliefs value $w^*(v)$. The recruiter's perceived maximized surplus is

$$\Pi^{\Gamma}(w^*; v, \hat{u}) = \max_{p \geq 0} \sigma(\hat{u} + p - w^*)(v - p).$$

By the envelope theorem,

$$\frac{\partial \Pi^{\Gamma}(w^*; v, \hat{u})}{\partial \hat{u}} = \sigma'\big(\hat{u} + p^{\Gamma} - w^*\big) \, (v - p^{\Gamma}) > 0. \tag{C.5}$$

Therefore $\Gamma > 0$ raises perceived profitability and weakly expands the set of recruiter types making offers, while $\Gamma < 0$ shrinks it. By Assumption 3, aggregate offer probability

changes strictly in the corresponding direction.

From Part 1,

$$\Gamma > 0 \quad \Longrightarrow \quad p^{\Gamma} < p^{*}.$$

Actual acceptance depends on the true u, so for any recruiter type making an offer under both regimes,

$$A(p^{\Gamma}; u, w^{*}) < A(p^{*}; u, w^{*}).$$

Thus $\Gamma > 0$ increases offer probability but lowers the probability of acceptance for recruiter types offering in both regimes. When $\Gamma < 0$, offer probability falls and acceptance for recruiter types offering in both regimes rises.

Finally, define the recruiter's true expected surplus from wage p by

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

Under correct beliefs, the recruiter chooses between making no offer and choosing the wage p^{*} that maximizes T:

$$R^{*}(v, u, w) = \max\left\{0,\, T(p^{*}; v, u, w) - c\right\}.$$

Under distorted beliefs, the recruiter's realized true payoff is

$$R^{\Gamma}(v, u, w) = \mathbf{1}\left\{\Pi^{\Gamma}(w; v, \hat{u}) \geq c\right\}\left[T(p^{\Gamma}; v, u, w) - c\right].$$

The correct-beliefs decision maximizes true expected payoff over the same feasible choices: making no offer or making an offer at some $p \geq 0$. Therefore

$$R^{\Gamma}(v, u, w) \leq R^{*}(v, u, w).$$

By Assumption 1, the optimal offered wage is unique, and by Assumption 3 there is no positive mass of recruiters exactly indifferent at the offer cutoff. Whenever the distorted choice differs from the unique correct-beliefs optimum, the inequality is strict except possibly for a recruiter exactly indifferent between making and not making an offer under

correct beliefs. By Assumption 3, such recruiter types have measure zero.

Thus aggregate expected recruiter payoff is strictly lower whenever the perception gap changes behavior for a positive-measure set of recruiter types.

This establishes Part 2 and completes the proof of Proposition 1. □

C.2 Investment distortions

We now allow workers and recruiters to choose a binary characteristic prior to entering the market in a given period. Timing 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 value to recruiters:

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

Each recruiter j chooses $y_j \in \{0, 1\}$ at cost κ_{yj}, where κ_{yj} is independently drawn from a continuous distribution G_y with support on $\mathbb{R}_+$. Recruiters differ in their baseline job utility u_{0j}, which follows a continuous distribution and is independent of investment costs. The characteristic affects workers' utility from the job:

$$u_j(y_j) = u_{0j} + u_1 y_j, \qquad u_1 > 0.$$

Workers may misperceive how the characteristic x affects their value to recruiters:

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

where $\Delta \in \mathbb{R}$ can be positive or negative.

Recruiters may misperceive how the characteristic y affects workers' utility from their job:

$$\hat{u}_j(y_j) = u_{0j} + (u_1 + \Gamma)y_j,$$

where $\Gamma \in \mathbb{R}$ can be positive or negative.

To isolate investment distortions, we again consider each perception gap separately.

Workers may misperceive the return to investing in x, while abstracting from recruiter perception gaps, and recruiters may misperceive the return to investing in y, while abstracting from worker perception gaps. Conditional on realized (x, y), wage posting, offer decisions, and acceptance follow the correct-beliefs baseline model. Thus, subjective beliefs affect outcomes here only through the choice of x or y, not through subsequent pricing or acceptance. In practice, perception gaps may affect both pricing and investment, but we keep these channels separate for simplicity.

Let $J(v)$ denote the worker's optimized expected payoff in the baseline model when their value to recruiters is v, holding the distribution of recruiter characteristics at its correct-beliefs benchmark. Thus, conditional on investment choice x,

$$J(x) \equiv J(v(x)), \qquad \widehat{J}(x) \equiv J(\widehat{v}(x)).$$

Similarly, let $\Pi(u)$ denote the recruiter's optimized expected payoff in the baseline model when the job provides utility u to workers, holding the distribution of worker characteristics at its correct-beliefs benchmark. Thus, for recruiter j, conditional on investment choice y_j,

$$\Pi_j(y_j) \equiv \Pi(u_j(y_j)), \qquad \hat{\Pi}_j(y_j) \equiv \Pi(\hat{u}_j(y_j)).$$

Workers choose $x = 1$ if and only if

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

Recruiter j chooses $y_j = 1$ if and only if

$$\hat{\Pi}_j(1) - \hat{\Pi}_j(0) \geq \kappa_{yj}.$$

Proposition 2. *Consider each perception gap separately in the investment extension, and suppose that pricing, offer, and acceptance decisions follow the correct-beliefs baseline conditional on investment choices.*

1. ***Investment distortions.*** *For workers, $\Delta > 0$ leads them to invest more in the*

characteristic than under correct beliefs; $\Delta < 0$ *leads them to invest less. For recruiters,* $\Gamma > 0$ *leads them to provide more of the characteristic;* $\Gamma < 0$ *leads them to provide less.*

2. ***Matching and expected payoff.***

   For workers, $\Delta > 0$ *increases the prevalence of high-productivity workers and weakly increases matching;* $\Delta < 0$ *reduces their prevalence and reduces matching relative to the correct-beliefs benchmark.*

   For recruiters, $\Gamma > 0$ *increases the prevalence of high-utility jobs and weakly increases matching;* $\Gamma < 0$ *reduces their prevalence and reduces matching relative to the correct-beliefs benchmark.*

   Whenever perception gaps alter investment decisions, they reduce the agent's own expected payoff net of investment costs relative to the correct-beliefs optimum.

C.3 Proposition 2

C.3.1 Assumptions

We maintain Assumptions 1–3 from Section C.1 and impose the following additional conditions for the investment extension. In particular, recruiters' baseline job utility u_{0j} follows a continuous distribution with strictly positive density in neighborhoods of the relevant offer cutoffs and is independent of investment costs. Realized utility $u_j = u_{0j} + u_1 y_j$ is assumed to satisfy the recruiter-type regularity conditions in Assumption 3, including interior offer cutoffs.

Assumption 4 (Cost distributions). Worker investment costs κ_x are independently drawn from a continuous distribution G_x with support on $\mathbb{R}_+$, and recruiter investment costs κ_y are independently drawn from a continuous distribution G_y with support on $\mathbb{R}_+$. Both distributions are strictly increasing on their supports and have no atoms.

Assumption 5 (Investment nondegeneracy). For every worker value v relevant to the investment exercise, there is positive probability over recruiter types that the worker receives an offer under correct beliefs. For any two recruiter job values $u' < u''$ compared in the investment exercise, including perceived values, there is positive probability over

worker types that the recruiter makes an offer at the higher value u'' under correct beliefs. All perceived values $\hat{v}(x)$ and $\hat{u}(y)$ remain in the relevant support.

C.3.2 Proof

We first establish how worker value v and recruiter job value u affect continuation payoffs and matching under correct beliefs.

Worker value. For a worker with value v, define

$$d \equiv v - w, \qquad s \equiv p - w.$$

Since the recruiter optimum is interior by Assumption 1, the constraint $p \geq 0$ is slack. Writing $s \equiv p - w$ and $d \equiv v - w$, the interior pricing problem is therefore characterized by

$$\max_s \sigma(u + s)(d - s).$$

Let $s^*(d, u)$ denote the solution. Its first-order condition is

$$(d - s^*(d, u))\left[1 - \sigma(u + s^*(d, u))\right] = 1.$$

Differentiating with respect to d gives

$$\frac{\partial s^*(d, u)}{\partial d} = 1 - \sigma(u + s^*(d, u)) > 0. \tag{C.6}$$

Define the recruiter's maximized gross return from making an offer as

$$\pi(d, u) = \sigma(u + s^*(d, u))\left(d - s^*(d, u)\right).$$

By the envelope theorem,

$$\frac{\partial \pi(d, u)}{\partial d} = \sigma(u + s^*(d, u)) > 0. \tag{C.7}$$

Thus a higher d raises recruiter profitability and expands the set of recruiter types making offers. Moreover, by (C.6), it raises $s^*(d, u)$ and therefore acceptance among recruiter

types making offers under both values of d.

Let

$$M(d) = \mathbb{E}_u \left[\mathbf{1}\{\pi(d,u) \geq c\} \sigma(u + s^*(d,u)) \right]$$

denote the worker's probability of matching. By the envelope theorem and the recruiter's first-order condition,

$$\frac{\partial \pi(d,u)}{\partial u} = \sigma'(u + s^*(d,u))(d - s^*(d,u)) = \sigma(u + s^*(d,u)) > 0.$$

Thus the offer decision is characterized by a cutoff $\bar{u}(d)$ satisfying $\pi(d, \bar{u}(d)) = c$. From (C.7),

$$\bar{u}'(d) = -\frac{\pi_d(d, \bar{u}(d))}{\pi_u(d, \bar{u}(d))} = -1.$$

A higher d therefore expands the set of recruiter types making offers. Moreover, by (C.6), acceptance strictly increases for every recruiter type making an offer under both values of d. Together with Assumption 3, these two effects imply

$$M'(d) > 0. \tag{C.8}$$

Using $w = v - d$ and $p = w + s^*(d,u)$, the worker's payoff conditional on acceptance can be written

$$u + p = u + s^*(d,u) + v - d.$$

Hence the worker's expected payoff as a function of (d, v) is

$$F(d,v) = vM(d) + K(d), \tag{C.9}$$

where

$$K(d) = \mathbb{E}_u \left[\mathbf{1}\{\pi(d,u) \geq c\} \sigma(u + s^*(d,u)) \left(u + s^*(d,u) - d\right) \right].$$

Let

$$d^*(v) \equiv v - w^*(v)$$

denote the correct-beliefs optimum. Since the optimal ask is interior by Assumption 2,

choosing w is locally equivalent to choosing d, and

$$F_d(d^*(v), v) = 0, \qquad F_{dd}(d^*(v), v) < 0.$$

From (C.9),

$$F_{dv}(d, v) = M'(d) > 0.$$

Applying the implicit function theorem,

$$\frac{dd^*(v)}{dv} = -\frac{M'(d^*(v))}{F_{dd}(d^*(v), v)} > 0. \tag{C.10}$$

Since matching equals $M(d^*(v))$, (C.8)–(C.10) imply that a worker's correct-beliefs probability of matching is strictly increasing in v.

Let $J(v)$ denote the worker's optimized continuation payoff, as defined in Section C.2. By the envelope theorem,

$$J'(v) = F_v(d^*(v), v) = M(d^*(v)) > 0, \tag{C.11}$$

where the final inequality follows from Assumption 5. Thus higher value to recruiters raises both the worker's optimized expected payoff and their probability of matching.

Recruiter job value. Now fix a worker with value v and correct-beliefs ask $w^*(v)$. From the recruiter's first-order condition, evaluated under correct beliefs,

$$\frac{\partial p^*(w^*(v); v, u)}{\partial u} = -\sigma(u + p^*(w^*(v); v, u) - w^*(v)) < 0. \tag{C.12}$$

Therefore

$$\frac{d}{du}\left[u + p^*(w^*(v); v, u) - w^*(v)\right] = 1 - \sigma(u + p^*(w^*(v); v, u) - w^*(v)) > 0. \tag{C.13}$$

Thus a higher u raises acceptance among recruiter types making offers under both values of u.

The recruiter's maximized gross return satisfies, by the envelope theorem,

$$\frac{\partial \Pi^*(w^*(v); v, u)}{\partial u} = \sigma'(u + p^*(w^*(v); v, u) - w^*(v))\,(v - p^*(w^*(v); v, u)) > 0. \qquad \text{(C.14)}$$

Hence a higher u also expands the set of worker types to whom the recruiter makes an offer.

Let $m_R(u)$ denote a recruiter's probability of matching, integrating over the correct-beliefs distribution of worker types and their optimal asks. Equations (C.13)–(C.14) imply that a higher u weakly raises matching for every worker type: acceptance rises whenever an offer is made under both values of u, and the set of worker types receiving an offer weakly expands. By Assumption 5, at the higher value of u, offers are made to a positive-probability set of worker types. For these types, matching either becomes possible or acceptance increases. Hence $m_R(u)$ is strictly increasing over the relevant comparisons.

Similarly, let $\Pi(u)$ denote the recruiter's optimized expected continuation payoff, as defined in Section C.2. For a given worker type, the recruiter's true expected payoff is

$$\max\{0, \Pi^*(w^*(v); v, u) - c\}.$$

Equation (C.14) implies that this payoff is weakly increasing in u for every worker type. By Assumption 5, it increases strictly for a positive-probability set of worker types when comparing the relevant values of u. Therefore, $\Pi(u)$ is strictly increasing over these comparisons.

1. Investment distortions.

Workers. Under correct beliefs, the worker's true incremental benefit from investing in $x = 1$ is

$$B_x \equiv J(v_0 + v_1) - J(v_0) > 0,$$

where the inequality follows from (C.11).

A worker with perception gap Δ instead perceives the incremental benefit to be

$$\widehat{B}_x(\Delta) \equiv J(v_0 + v_1 + \Delta) - J(v_0).$$

From (C.11),

$$\frac{d\widehat{B}_x(\Delta)}{d\Delta} = J'(v_0 + v_1 + \Delta) > 0.$$

The worker therefore invests if and only if

$$\kappa_x \leq \widehat{B}_x(\Delta),$$

so the prevalence of $x = 1$ is

$$\Pr(x = 1) = G_x\Big(\widehat{B}_x(\Delta)\Big).$$

By Assumption 4, this prevalence is increasing in Δ. Relative to correct beliefs, $\Delta > 0$ therefore leads workers to invest more in x, while $\Delta < 0$ leads them to invest less.

Recruiters. Under correct beliefs, the true incremental benefit from choosing $y_j = 1$ for a recruiter with baseline utility u_{0j} is

$$B_y(u_{0j}) \equiv \Pi(u_{0j} + u_1) - \Pi(u_{0j}) > 0,$$

where the inequality follows from the strict monotonicity of $\Pi(u)$ and $u_1 > 0$.

A recruiter with perception gap Γ instead perceives

$$\hat{B}_y(u_{0j}, \Gamma) \equiv \Pi(u_{0j} + u_1 + \Gamma) - \Pi(u_{0j}).$$

By the strict monotonicity of $\Pi(u)$ over the relevant comparisons established above, $\widehat{B}_y(u_{0j}, \Gamma)$ is strictly increasing in Γ for every baseline recruiter type u_{0j}.

Recruiter j chooses $y_j = 1$ if and only if

$$\kappa_{yj} \leq \hat{B}_y(u_{0j}, \Gamma),$$

so

$$\Pr(y_j = 1 \mid u_{0j}) = G_y\left(\hat{B}_y(u_{0j}, \Gamma)\right)$$

is increasing in Γ.

By Assumption 4, $\Gamma > 0$ therefore increases investment for every baseline recruiter type, while $\Gamma < 0$ reduces it. Integrating over the distribution of u_{0j} establishes the same directional result for the overall prevalence of investment.

This establishes Part 1.

2. Matching and expected payoff.

Workers. Let $m_W(v)$ denote a worker's correct-beliefs probability of matching when their value to recruiters is v. From (C.8)–(C.10),

$$m_W(v_0 + v_1) > m_W(v_0).$$

Holding the distribution of recruiter characteristics fixed at its correct-beliefs benchmark, aggregate matching can therefore be written

$$\mathcal{M}_W(\Delta) = G_x\Big(\widehat{B}_x(\Delta)\Big)\, m_W(v_0 + v_1) + \Big[1 - G_x\Big(\widehat{B}_x(\Delta)\Big)\Big]\, m_W(v_0).$$

Since the prevalence of $x = 1$ is increasing in Δ and $m_W(v_0 + v_1) > m_W(v_0)$, $\Delta > 0$ increases matching while $\Delta < 0$ reduces matching relative to correct beliefs.

Recruiters. Since $m_R(u)$ is strictly increasing in u,

$$m_R(u_0 + u_1) > m_R(u_0)$$

for every baseline recruiter type u_0.

Holding the distribution of worker characteristics fixed at its correct-beliefs benchmark, aggregate matching can therefore be written

$$\begin{aligned} M_R(\Gamma) = \mathbb{E}_{u_0}\Big[& G_y\left(\hat{B}_y(u_0, \Gamma)\right) m_R(u_0 + u_1) \\ & + \left(1 - G_y\left(\hat{B}_y(u_0, \Gamma)\right)\right) m_R(u_0)\Big]. \end{aligned}$$

Since the probability of investing increases with Γ for every u_0, and $m_R(u_0 + u_1) > m_R(u_0)$, it follows that $\Gamma > 0$ increases aggregate matching while $\Gamma < 0$ reduces matching relative to correct beliefs.

Finally, consider the effect of distorted investment on the agent's own expected payoff

net of investment costs.

Under correct beliefs, a worker invests if and only if

$$\kappa_x \leq B_x,$$

whereas under distorted beliefs they invest if and only if

$$\kappa_x \leq \widehat{B}_x(\Delta).$$

Whenever the perception gap changes the worker's investment decision, one of two cases occurs. If the worker invests under distorted beliefs but not under correct beliefs, then

$$\kappa_x > B_x,$$

so the investment has negative true net return. If the worker does not invest under distorted beliefs but would invest under correct beliefs, then

$$\kappa_x < B_x,$$

so a positive true net return is forgone. In either case, the distorted investment choice strictly lowers the worker's true expected payoff net of investment costs.

The recruiter argument is analogous. Conditional on baseline utility u_{0j}, the correct-beliefs investment cutoff is $B_y(u_{0j})$, whereas distorted beliefs use $\hat{B}_y(u_{0j}, \Gamma)$.

Whenever these choices differ, the recruiter either undertakes an investment with negative true net return or forgoes one with positive true net return. Thus, distorted investment decisions lower the recruiter's true expected payoff net of investment costs.

This establishes Part 2 and completes the proof of Proposition 2.

D Quantification exercise

This appendix describes the counterfactual exercise used to quantify how correcting perception gaps would affect wages, matching, and match quality on the platform. The exercise operationalizes the pricing mechanisms of the model: inaccurate beliefs about market preferences influence the wages workers ask and recruiters offer, which in turn affect whom recruiters contact and whether those contacts result in matches.

The exercise proceeds in three steps. First, we estimate how workers' and recruiters' perception gaps are associated with their observed asking and offered wages. We use these relationships to construct counterfactual wages under different degrees of belief correction. Second, we use the preferences identified in the *Evaluation* experiments, together with observed platform behavior, to estimate how these wage changes affect recruiters' contact decisions and workers' acceptance decisions. Finally, we combine these estimates to calculate changes in expected matches and the average quality of those matches.

We consider five correction rates, $\rho \in \{0, 0.25, 0.50, 0.75, 1\}$. A correction rate of $\rho = 0$ represents the observed market, while $\rho = 1$ removes the entire component of wages associated with measured perception gaps. Throughout, we hold fixed the number of contacts sent by each recruiter, allowing the allocation of contacts and their likelihood of success to change. The exercise therefore captures the effects of corrected pricing on matching, but not any changes in recruiters' overall offer making or investments in worker and job characteristics.

Because perception gaps are observed only for participants in the *Prediction experiments*, we construct a synthetic market consisting of those workers and the job offers posted by those recruiters. We then reweight observations to reproduce the platform-wide distribution of contacts across job categories.

D.1 Workers: perception gaps and asking wages

We begin by estimating how workers' perceptions of recruiter preferences relate to their asking wages. This requires three components: a measure of how recruiters actually value worker characteristics, a corresponding measure of each worker's beliefs about those valuations, and an estimate of how the resulting perception gaps are associated with

asking wages.

Worker data. We construct a monthly panel of workers using administrative data from January 2025 to February 2026. For each worker and month, we observe monthly variation in asking wages, remote and full-time availability, reputation badges, years of experience, the number of completed jobs, and an indicator for having completed at least one job. All other characteristics for which we estimate perception gaps are held fixed over the monthly panel. We use these time-varying and fixed characteristics to construct workers' predicted and actual market values in each month. These characteristics are updated monthly, with experience measured on the first day of each month. We also observe the number of job offers received and the number of days the worker was visible and available to recruiters. We exclude worker-months in which the worker was never visible and available.

Recruiter preferences. We construct a measure of how recruiters value each worker's profile using the recruiter *Evaluation* experiments. An important feature of these preferences is that recruiters respond nonlinearly to asking wages based on their budget. We therefore allow the effect of asked wages to differ above and below a category-specific budget threshold.

For each job category k, we estimate

$$R_{lr} = \alpha_r + X'_{lr}\beta_k^R + g_k(w_{lr}) + \varepsilon_{lr},$$

where

$$g_k(w) = \gamma_{1k} w + \gamma_{2k} \max(w - B_k, 0). \tag{6}$$

Here, R_{lr} is recruiter r's evaluation of profile l, X_{lr} contains its randomized non-wage characteristics, and α_r is a recruiter fixed effect. The threshold B_k is the average stated recruiting budget in category k, ranging from €353 to €590 per day. Standard errors are clustered at the recruiter level. Below B_k, the slope is γ_{1k}; above it, the slope is $\gamma_{1k} + \gamma_{2k}$.

We estimate two versions of this preference function. The first captures the total response to asking wages, including their role as signals of competence. The second

additionally controls for recruiters' competence ratings, isolating the price response net of this signaling effect. We denote the corresponding wage function by g_k^P. We use the total response when predicting recruiters' contact decisions, but the competence-controlled response when expressing worker quality in wage-equivalent terms.

Perception gaps. We next compare these experimentally estimated recruiter preferences with each worker's beliefs about them.

For worker i in month t, the actual non-wage value of the worker's profile to recruiters is

$$v_{it} = X'_{it}\beta^R_{k(i)}.$$

We construct the worker's perceived value using the Empirical Bayes coefficients estimated from their 25 predictions in the *Prediction* experiment:

$$\hat{v}_{it} = X'_{it}\hat{\beta}^{eb}_i.$$

The difference between perceived and actual value is the non-wage perception gap,

$$\Delta_{it} = \hat{v}_{it} - v_{it}.$$

A positive gap indicates that the worker overestimates how much recruiters value the non-wage characteristics of their profile, while a negative gap indicates underestimation.

We also measure misperceptions about recruiters' sensitivity to asking wages. To do so, we re-estimate the hierarchical model using the same piecewise-linear wage specification as in Equation (5). Each worker's beliefs about the wage response are summarized by two Empirical Bayes coefficients, $\hat{\gamma}_{1i}$ and $\hat{\gamma}_{2i}$. We define

$$\Delta_{w1,i} = \hat{\gamma}_{1i} - \gamma_{1k(i)}$$

and

$$\Delta_{w2,i} = \hat{\gamma}_{2i} - \gamma_{2k(i)}.$$

The first captures misperceptions about the wage slope below the budget threshold; the second captures misperceptions about the change in that slope above the threshold.

Asking-wage responses. We estimate how these perception gaps relate to workers' actual asking wages following the approach in Table 4:

$$\ln w_{it} = \alpha_{k(i)} + \delta_t + \theta_v v_{it} + \theta_\Delta \Delta_{it} + \theta_1 \Delta_{w1,i} + \theta_2 \Delta_{w2,i} + e_{it}. \tag{7}$$

The specification includes job-category and month-year fixed effects. It separates the relationship between asking wages and actual recruiter valuations from the additional relationships associated with workers' misperceptions.

To construct counterfactual asking wages, we remove a fraction ρ of the wage component associated with perception gaps:

$$\ln w_{it}^{\rho} = \ln w_{it} - \rho \left(\theta_\Delta \Delta_{it} + \theta_1 \Delta_{w1,i} + \theta_2 \Delta_{w2,i} \right). \tag{8}$$

All other determinants of asking wages, including the regression residual, remain unchanged.

D.2 How asking wages affect recruiter contacts

We next estimate how the counterfactual asking wages change recruiters' interest in contacting workers. For each worker-month, we construct an index of recruiter interest combining the worker's non-wage profile value and asking wage:

$$H_{it} = v_{it} + g_{k(i)}(w_{it}).$$

The index is measured in units of the experimental hiring-interest Likert scale. We use the total wage response g_k, rather than the competence-controlled response g_k^P, because actual contact decisions may reflect both the price and the information about competence conveyed by their asking wage.

Using all workers in the administrative panel, we estimate the relationship between this index and the number of job offers received each month. Specifically, we use Poisson

pseudo-maximum likelihood:

$$E[C_{it}] = E_{it} \exp\left(\alpha_{k(i)} + \delta_t + \lambda_R H_{it}\right), \tag{9}$$

where C_{it} is the number of offers received and E_{it} is the number of days the worker was visible and available to recruiters. The parameter λ_R maps a one-point increase in experimentally predicted recruiter interest into the rate at which workers receive contacts.

Under each counterfactual, we recompute recruiter interest using the corrected asking wage:

$$H_{it}^{\rho} = v_{it} + g_{k(i)}(w_{it}^{\rho}).$$

Expressing worker quality in monetary terms. We also convert the non-wage value of worker profiles into wage-equivalent units, which will be used to measure match quality. We first subtract the average non-wage profile value within the worker's job category. We then divide this difference by the absolute value of the wage slope above the budget threshold in the competence-controlled preference function:

$$v_{it}^{eur} = \frac{v_{it} - \bar{v}_{k(i)}}{\left|\gamma_{1k(i)}^{P} + \gamma_{2k(i)}^{P}\right|}.$$

This measure represents the increase in asking wages that would offset the worker's non-wage quality advantage, evaluated where recruiters are sensitive to wages and excluding the competence-signaling effect of asking wages.

D.3 Recruiters: perception gaps and offered wages

We follow a parallel procedure for recruiters. We first measure how workers value the non-wage characteristics of job offers, compare these valuations with recruiters' beliefs, and estimate how the resulting gaps relate to offered wages.

Job-offer data. We use all contacts made by recruiters in 2025 in our targeted set of job categories. We retain an indicator for contacts originating from the platform's search engine. We calculate the offered daily wage from each job's budget and duration and

match each contact to the worker's asking wage at the beginning of the month in which the contact occurred.

Worker preferences and recruiter perception gaps. Using the worker *Evaluation* experiment, we estimate the coefficients β^W on non-wage job characteristics and β_p^W on offered wages, separately by job category. Unlike recruiters' response to asking wages, workers' response to offered wages is approximately linear.

For job offer j, we define its actual non-wage value to workers as

$$u_j = Y_j' \beta^W,$$

where Y_j contains the offer's non-wage characteristics.

We construct the corresponding perceived value using the Empirical Bayes coefficients of the recruiter $r(j)$ who posted the offer:

$$\hat{u}_j = Y_j' \hat{\beta}_{r(j)}^{eb}.$$

The recruiter's perception gap is then

$$\Gamma_j = \hat{u}_j - u_j.$$

A positive value indicates that the recruiter overestimates the attractiveness of the non-wage characteristics of their offer. We separately measure the gap in the recruiter's beliefs about workers' responsiveness to offered wages:

$$\Gamma_j^w = \hat{\beta}_{p,r(j)}^{eb} - \beta_p^W.$$

Offered-wage responses. We estimate

$$\ln p_j = \alpha_{k(j)} + \delta_t + \theta_u u_j + \theta_\Gamma \Gamma_j + \theta_{\Gamma w} \Gamma_j^w + e_j. \tag{10}$$

As with asking wages, this specification separates the relationship between observed compensation and actual market preferences from the additional relationships associated

with recruiters' perception gaps.

We then construct counterfactual offered wages by removing the fraction ρ of the offered-wage component associated with those gaps:[54]

$$\ln p_j^{\rho} = \ln p_j - \rho \left(\theta_{\Gamma} \Gamma_j + \theta_{\Gamma w} \Gamma_j^{w} \right).$$

The counterfactual changes offered wages while holding fixed other characteristics of the job and the residual determinants of compensation.

D.4 How wages affect workers' acceptance decisions

To predict whether contacts result in successful matches, we estimate how workers respond to the characteristics of job offers and to the difference between offered and asking wages.

The theoretical framework models acceptance as $A(p; u, w) = \sigma(u + p - w)$. We estimate an empirical counterpart using a logit model at the contact level:

$$\Pr(A_{ij} = 1) = \sigma \left(a_{k(j)} + \delta_t + b \, search_j + \lambda_A S_{ij} \right), \tag{11}$$

where

$$S_{ij} = u_j + \beta_p^W (p_j - w_{it}).$$

Here, $A_{ij} = 1$ if the contact results in an accepted quote, $search_j$ indicates whether the contact originated from the search engine, and $\sigma(\cdot)$ is the logistic function.

The index S_{ij} combines the non-wage attractiveness of the job with the difference between its offered wage and the worker's asking wage. This formulation reflects the role of asking wages in the theoretical framework.[55]

The relative importance of wages and non-wage characteristics is determined by the worker *Evaluation* experiment. The administrative data are used to estimate the scale parameter λ_A, the category and month effects, and the effect of the search channel. This

[54] We abstract from the possibility that recruiters adjust their offered wages in response to changes in workers' asking wages, holding offered wages fixed with respect to these changes.

[55] This specification assumes that workers evaluate offered wages relative to their asking wages, so a decrease in the asking wage has the same effect on acceptance as an equivalent increase in the offered wage, consistent with the theoretical framework.

preserves the experimentally identified trade-offs while allowing us to predict acceptance probabilities in the actual market.

Under each counterfactual, acceptance probabilities are recomputed using both the corrected offered wage and the corrected asking wage:

$$S_{ij}^{\rho} = u_j + \beta_p^W (p_j^{\rho} - w_{it}^{\rho}).$$

Consequently, belief correction can affect whether a contact succeeds through changes in prices on either side of the market.

Expressing job amenities in monetary terms. As for worker profiles, we convert the non-wage value of job offers into wage-equivalent units:

$$u_j^{eur} = \frac{u_j - \bar{u}_k}{\beta_p^W},$$

where $\bar{u}_k$ is the category-year average non-wage value of job offers. This measures the wage-equivalent value of a job's amenities relative to the category-year average.

D.5 Constructing the counterfactual market

Having estimated counterfactual asking and offered wages, as well as the contact and acceptance functions, we now combine them to predict matching outcomes.

Market composition and reweighting. The counterfactual market includes workers and recruiters for whom we observe perception gaps through the *Prediction* experiments, reweighting offers to match the platform's distribution of contacts across job categories.

For category k, the weight is

$$\omega_k = \frac{s_k^{platform}}{s_k^{sample}},$$

where the numerator is the category's share of all contacts on the platform and the denominator is its share of contacts in the *Prediction* sample.

Eligible worker–job pairs. For each job j posted by a recruiter in month t, we construct a set of eligible workers, denoted $\mathcal{E}_j$. This set consists of workers in the same job category who were visible and available during that month.

We impose one additional restriction to improve the feasibility of potential matches. When a job lists mandatory expertise requirements (up to three), a worker must possess at least one of them. We deliberately do not exclude workers based on their asking wages, since wages are what changes in the counterfactual exercise.

Allocation of contacts. We hold fixed the observed number of contacts N_j sent by the recruiter for each job, but allow the identities of the workers contacted to change.

The expected share of contacts for job j allocated to eligible worker i is

$$\pi_{ij}^{\rho} = \frac{\exp(\lambda_R H_{it}^{\rho})}{\sum_{\ell \in \mathcal{E}_j} \exp(\lambda_R H_{\ell t}^{\rho})}. \tag{12}$$

Workers with higher predicted recruiter interest receive larger expected shares of contacts. Correcting perception gaps changes those shares through its effect on asking wages and, consequently, on the recruiter-interest index H_{it}^{ρ}. This specification assumes that the relationship between predicted recruiter interest and observed contact rates, estimated at the worker-month level, also governs the allocation of contacts across eligible workers within each job.

The allocation is calculated separately for each job among its eligible workers. Thus, while recruiters send the same number of contacts as in the observed market, corrected wages can redirect those contacts toward different workers.

Acceptance and expected matches. For each feasible worker–job pair, we calculate the probability of acceptance using Equation (10) evaluated at the counterfactual asking and offered wages. Denote this probability by A_{ij}^{ρ}.

The expected probability that a contact sent for job j results in a match is

$$m_j^{\rho} = \sum_{i \in \mathcal{E}_j} \pi_{ij}^{\rho} A_{ij}^{\rho}.$$

Multiplying this probability by the fixed number of contacts yields the expected num-

ber of matches for that job:

$$M_j^\rho = N_j m_j^\rho.$$

We aggregate across jobs using the category weights. The resulting expected match rate per contact is

$$\frac{\sum_j \omega_{k(j)} M_j^\rho}{\sum_j \omega_{k(j)} N_j}.$$

Because the number of contacts remains fixed, the percentage change in this rate is also the percentage change in expected matches. Improvements can arise because contacts are redirected toward workers who are more attractive at their corrected asking wages, because corrected wage offers are more likely to be accepted, or both.

D.6 Counterfactual outcomes

We report changes in three types of outcomes: wages, the number of matches, and the quality of successful matches.

Asked and offered wages. For asking wages, we calculate the percentage change in the average ask, weighting each worker-month by its baseline expected number of contacts:

$$\sum_j \omega_{k(j)} N_j \pi_{ij}^0.$$

These weights remain fixed at their baseline values for every correction rate. This ensures that changes in the average asking wage reflect changes in prices rather than changes in the composition of workers receiving contacts. For offered wages, we calculate the percentage change in the average offer across jobs, weighted by $\omega_{k(j)}$.

Matches. We report the percentage change in expected matches relative to the observed market, calculated from the aggregate match rate in Section D.5.

Match quality. Beyond the number of matches, we examine whether corrected perceptions improve the average quality of realized matches. We define match quality as the

sum of the wage-equivalent non-wage values that each side receives from the match:

$$Q_{ij} = u_j^{eur} + v_{it}^{eur}.$$

The first component captures the value of the job's non-wage characteristics to the worker, while the second captures the value of the worker's non-wage characteristics to the recruiter. Match quality is measured relative to the average worker and job characteristics within each category. Percentage changes therefore capture improvements in the average quality premium of matches relative to this benchmark. Wages do not enter this measure directly because they represent transfers between workers and recruiters. Nevertheless, wages influence which matches occur through their effects on contact allocation and acceptance.

For each job category k, average quality among expected successful matches is

$$\bar{Q}_k^\rho = \frac{\sum_{j \in k} \omega_k N_j \sum_{i \in \mathcal{E}_j} \pi_{ij}^\rho A_{ij}^\rho Q_{ij}}{\sum_{j \in k} \omega_k N_j m_j^\rho}. \tag{13}$$

This expression weights each feasible match by its probability of occurring under the counterfactual. We calculate the percentage change in average match quality relative to $\rho = 0$ within each category and aggregate these changes using the categories' baseline shares of expected successful matches.

The measure captures changes in the average experimentally inferred quality of successful matches, relative to the observed allocation.

D.7 Results

Table D.1 summarizes the counterfactual outcomes for each correction rate. All percentage changes are measured relative to the observed market ($\rho = 0$).

Table D.1: Counterfactual effects of correcting perception gaps

ρ:	Asked wage	Offered wage	Aggregate matches	Match quality
0%	0.00	0.00	0.00	0.00
25%	-1.93	-0.32	0.68	1.05
50%	-3.78	-0.62	1.38	2.15
75%	-5.56	-0.89	2.11	3.10
100%	-7.25	-1.12	2.86	3.61

Notes: Asked and offered wages are reported as percentage changes relative to baseline (0%). Match quality reports the percent change relative to baseline, weighted by baseline predicted successful-match shares across job categories.

The results suggest that correcting perception gaps would lead to lower asking and offered wages on average, with a larger effect on asking wages. Under complete correction, average asking wages decline by 7.3%, while offered wages decline by 1.1%. These pricing changes alter the allocation of recruiter contacts and the probability that contacts result in accepted offers, increasing the expected number of matches by 2.9%.

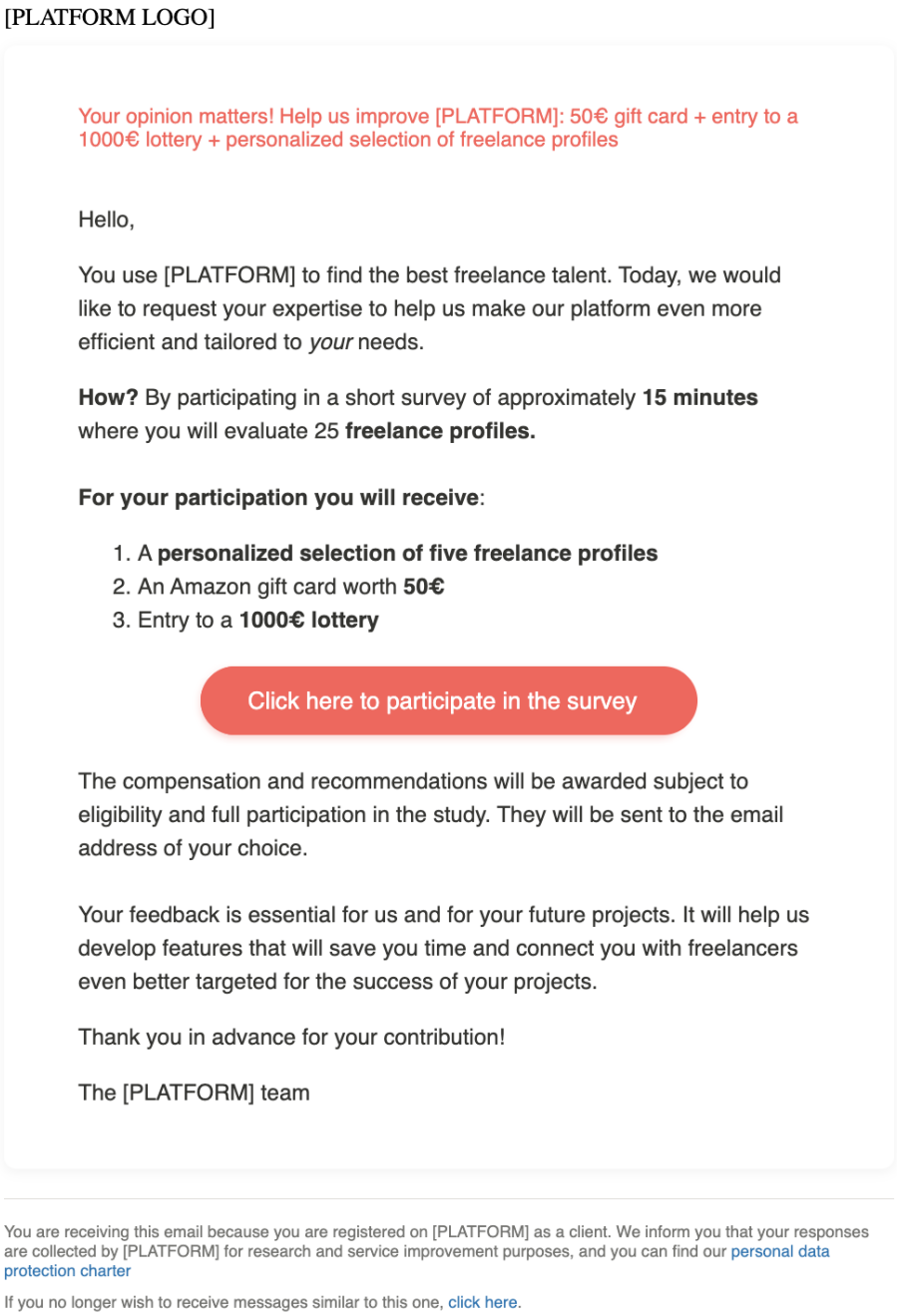
The exercise also predicts improvements in the quality of successful matches. Under complete correction, average match quality increases by 3.6%, indicating that the corrected pricing decisions lead not only to more matches but also to matches involving worker and job characteristics that are more highly valued by their respective counterparties.

These results quantify the potential importance of pricing distortions associated with the measured perception gaps. They should be interpreted as partial-equilibrium counterfactuals, conditional on the estimated relationships between perceptions and wages, experimentally measured preferences, the observed number of contacts, and the construction of the synthetic market. They do not incorporate changes in investment decisions, the total volume of recruiter search, or broader equilibrium adjustments.

E Experimental material

E.1 Recruitment

Figure E.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.

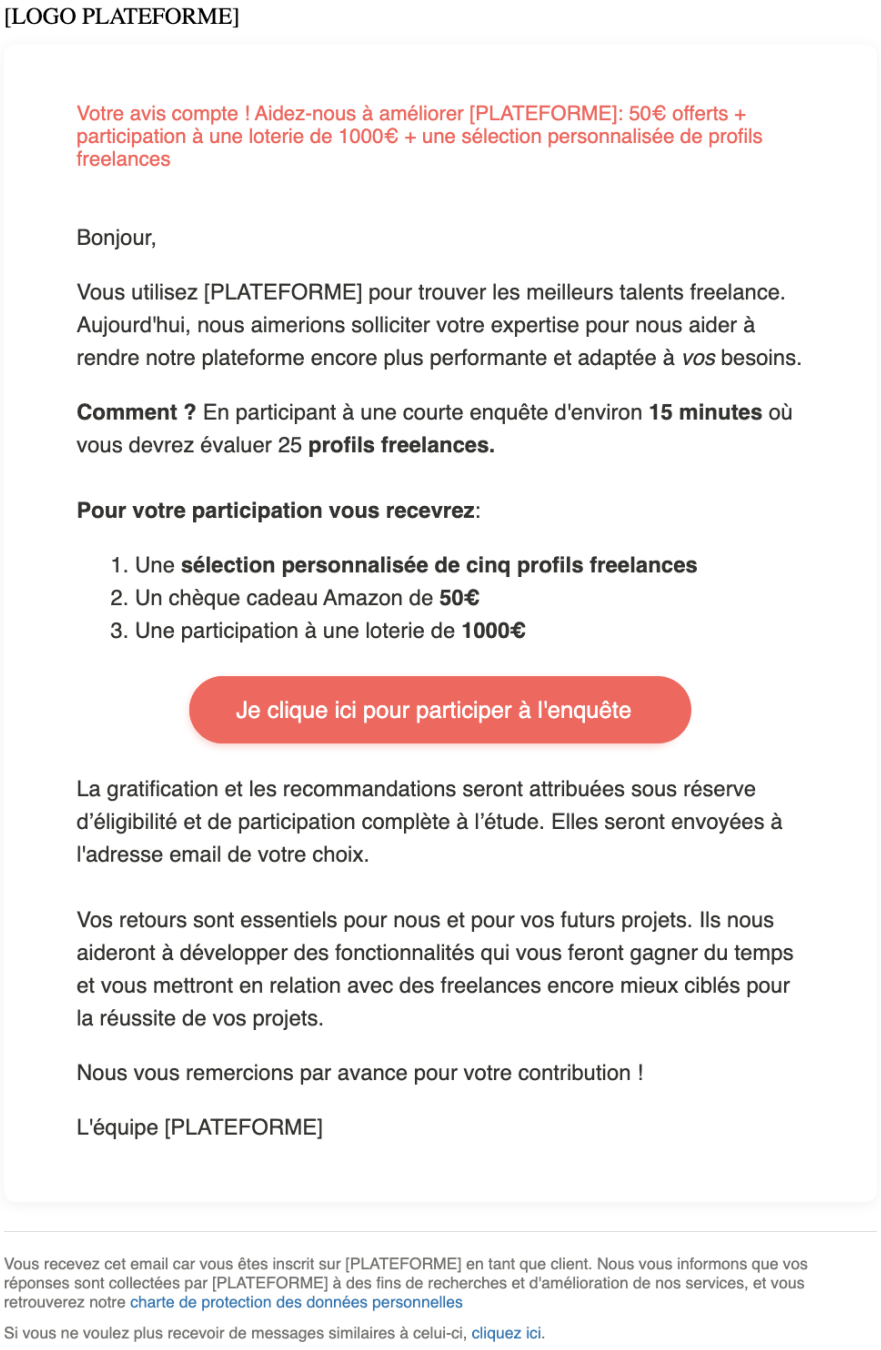
Thank you in advance for your contribution!

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 E.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 E.3: Recruitment email, workers - 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 E.4: Recruitment email, workers

[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.

E.2 *Evaluation* experiments – recruiter questionnaire

E.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.

E.2.2 Screening Questions

Q1. Which of the following job families 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

E.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):

E.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):

E.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):

E.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

E.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

E.3 *Evaluation* experiments – worker questionnaire

E.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.

E.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

E.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

E.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

E.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

E.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

E.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

E.4 *Prediction* experiments – predicting recruiter preferences

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.

E.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 [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.

E.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)
- 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.

E.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:

$$1 - \left(\frac{p-x}{3}\right)^2.$$

E.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

E.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).[56]

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

[56]Note: For ease of interpretation, some direct prediction questions were expressed using simple contrasts that differed from the units used in the regression specifications. We rescale these predictions to the corresponding regression units before comparing them with experimentally estimated effects or constructing perception gaps.

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)

E.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):

E.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

E.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

E.5 *Prediction* experiments – predicting worker preferences

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.

E.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.

E.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)
- 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.

E.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:

$$1 - \left(\frac{p-x}{3}\right)^2.$$

E.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

E.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)

E.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):

E.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

E.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

E.6 Experiment on segmentation and market returns

Note: This additional experiment was conducted with workers and was designed to assess whether beliefs about average recruiter preferences are representative of the market relevant to individual workers and of the returns they expect from different profile characteristics.

E.6.1 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. In addition, we will use the responses of 10% of respondents to recommend them for a job on [the platform] corresponding to their preferences.

Survey description.

- Give your opinion on the collaboration preferences of clients on the platform.
- Estimated time: approximately 15–20 minutes.

Thank you for your participation.

- An Amazon voucher worth 10–15 €, depending on your responses.
- Entry into a lottery to win 500 €.

- Voucher sent within 10 business days following completion of the survey.
- A potential recommendation for a job corresponding to your preferences.

*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.

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 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.

E.6.2 Preliminary Questions

Q1. End survey if None is selected. Which of the following job categories do you particularly target on [the platform]?

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

Q2. *(Asked only if "Marketing & Communication" is selected in Q1 and end survey if None is selected.)* Which occupation do you particularly target on [the platform]?

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

Q3. *(Asked only if "Tech" is selected in Q1 and end survey if None is selected.)* Which occupation do you particularly target on [the platform]?

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

E.6.3 Target jobs and clients

We will now ask you questions about the types of jobs and clients that you primarily target on [the platform]—those that you particularly seek to attract in order to generate your income on [the platform]. Your responses may be used to recommend you to a client after the study. Please therefore answer these questions carefully. The more closely your responses reflect your objectives, the more relevant your recommendation will be.

Q4. *(Occupation-specific.)* Among the following skills, select all those that you possess and that correspond to the skills you particularly target in your jobs.

Front-end developer.

- 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

Back-end developer.

- 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

Full-stack developer.

- 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

Web integration, CMS development, Webmaster.

- Web Integration & Development
- CMS & E-Commerce
- SEO
- HTML & CSS
- JavaScript
- PHP
- WordPress
- Drupal
- Elementor
- Shopify
- PrestaShop
- WooCommerce
- Magento
- Webflow
- None of the listed skills

Mobile developer.

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

Growth Marketing.

- Digital Acquisition Strategy
- Performance Analysis & 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

Content Writing.

- Copywriting
- Web & SEO Writing
- Other Writing (e.g., reports)
- Proofreading & Editing
- None of the listed skills

Social Media Strategy and Community Engagement.

- Social Media
- Community Management
- Communication Strategy
- Content Marketing
- None of the listed skills

Q5. What daily rate do you particularly target?

- Minimum target daily rate: [slider]
- Maximum target daily rate: [slider]

Q6. Do you particularly target full-time or part-time jobs?

- I target both
- Full-time
- Part-time

Q7. Do you particularly target remote or on-site jobs?

- I target both
- Remote
- On-site

Q8. Do you particularly target jobs that require working independently or as part of a team?

- I target both
- Independently
- As part of a team

Q9. Do you particularly target jobs with specific constraints regarding the starting date or deadlines? Select all that apply.

- Starting date as soon as possible
- Some advance notice before the starting date
- No tight or urgent deadlines
- I target jobs with any of these constraints

Q10. Do you particularly target jobs of a certain duration? Select all that apply.

- No, I target jobs of any duration
- Less than one week
- Approximately one week
- Approximately two weeks
- Approximately three weeks
- Approximately four weeks

- Approximately two months
- Approximately three months
- Approximately six months

Q11. Do you particularly target clients who have already completed a certain number of jobs on [the platform]?

- No, I do not particularly target clients based on the number of jobs they have already completed on [the platform]
- Yes, 1–2 jobs
- Yes, 3–5 jobs
- Yes, 6 jobs or more

Q12. Do you particularly target clients who have received a certain number of reviews on [the platform]?

- No, I do not particularly target clients based on the number of reviews they have received
- Yes, 1–2 reviews
- Yes, 3–5 reviews
- Yes, 6 reviews or more

Q13. Do you particularly target jobs with individual clients or with firms of a certain size? Select all that apply.

- No, I do not target clients of a particular size
- Yes, individuals rather than firms
- Yes, firms with 1–10 employees
- Yes, firms with 11–50 employees

- Yes, firms with 51–250 employees
- Yes, firms with 251–1,000 employees
- Yes, firms with more than 1,000 employees

Q14. Do you particularly target jobs in specific industries? Select all that apply.

- No, I target any industry
- Architecture, construction, and real estate
- Automotive, transportation, and aerospace
- Banking, insurance, and finance
- Biotechnology, health, and medical
- Consulting and professional services
- Cosmetics and consumer goods
- Culture, media, press, and publishing
- Education and research
- Energy and primary industries
- Retail, e-commerce, and distribution
- Food and restaurants
- Video games, leisure, sports, and tourism
- IT, software, and technology
- Telecommunications and Internet of Things
- Human resources
- Nonprofit and social sector
- Public sector and defense

E.6.4 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 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 different types of clients for the occupation: `the job category selected by the participant`.

When relevant, we ask you to distinguish between:

- **Your target clients:** the clients you indicated that you particularly seek to attract.
- **All clients in your occupation:** all clients who recruit freelancers in your occupation.

Your compensation.

- Fixed amount: 10 €
- Bonus for your predictions: up to 5 €
- The 10% of participants whose predictions are closest to the evaluations of their target clients will be recommended for a job with a client of this type.

We have put in place an incentive procedure: the closer you are to the true evaluations of the surveyed clients, the greater your bonus and your chances of receiving a recommendation.

Details on the bonus calculation. We will randomly choose 5 of the profiles for which you made predictions. For each selected profile, your prediction concerning **all clients in your occupation** will be compared with the evaluation of a client randomly drawn from the previous survey. The closer your prediction (p_1) is to this evaluation (x), the greater your probability of receiving a bonus of 1 €.

For each of the 5 selected profiles, you will receive 1 € with probability:

$$1 - \left(\frac{p_1 - x}{3}\right)^2.$$

For these same 5 profiles, your prediction concerning **your target clients** (p_2) will be used separately to determine recommendations.

For this purpose, we will randomly select one of the characteristics about which we asked you concerning the clients you target. We will then randomly draw a client from the previous survey who matches what you indicated that you target on this characteristic.

For example, if the randomly selected characteristic is whether a job is remote or on-site and you indicated that you target only remote jobs, the client will be randomly drawn from clients offering remote jobs.

If you indicated that you do not target a particular type on the randomly selected characteristic, the client will be randomly drawn from all clients in your occupation.

For each profile, we will compare your prediction (p_2) with the evaluation of this client (x). The error associated with each prediction is calculated as:

$$\left(\frac{p_2 - x}{3}\right)^2.$$

We will then calculate your average error across the 5 selected profiles. The 10% of participants with the lowest average error will be recommended for a job corresponding to the type of clients they indicated targeting.

E.6.5 Predictions

For each of the 25 profiles, respondents answered the following questions.

Q15. According to you, what level of interest (from 1 to 10) did clients express for this profile?

The clients answered the following 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."

Your target clients.

	Not at all							Completely	
1	2	3	4	5	6	7	8	9	10

All clients in your occupation.

	Not at all							Completely	
1	2	3	4	5	6	7	8	9	10

Q16. Taking into account clients' needs and competition from other freelancers, what are the chances that this profile receives at least one job offer over the next three months?

	No chance							Absolutely certain	
1	2	3	4	5	6	7	8	9	10

E.6.6 Additional Questions

Q17. How many years of work experience do you have?

- On [the platform]:
- As a freelancer:
- In total, including all your work experience:

Q18. Is freelancing your main source of income?

- Yes
- No

Q19. Is [the platform] your main source of income?

- Yes
- No