Bidding for Reputation *

Jingyi Cui †

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Abstract

When product quality is difficult to assess ex ante, reputation is crucial. New sellers often invest in building reputation, such as by offering introductory discounts. These investments steal business from rivals but accelerate social learning about seller quality. I study the effects and efficiency of reputation investment in the context of a large online labor platform. I show that employers value worker reputation and experience, and that new workers initially bid low and raise their bids after receiving reviews. I develop and estimate a dynamic equilibrium model where forward-looking workers bid wages anticipating the impact of reputation and experience on future outcomes. Compared to a counterfactual with myopic workers, forward-looking bidding increases the equilibrium number of reviewed workers by 52% and quadruples the number of matches. Workers' investment generates large positive externalities for the employers and the platform. However, investment remains below the social optimum. Platform-funded subsidies for hiring new workers can raise total surplus by over 20%. Policy simulations highlight an exploration-exploitation trade-off in market design.

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†Yale Department of Economics; Contact information: jingyi.cui@yale.edu

1 Introduction

In markets of experience goods, sellers often offer early discounts or other incentives to invest in reputation (Bergemann and Välimäki, 1996; Villas-Boas, 2004). For example, in the early days of e-commerce, Amazon cut books' prices and operated at a loss to lure consumers from brick-and-mortar stores. Tesla provided early buyers free lifetime Supercharging to promote electric vehicles. In labor markets, students and recent graduates frequently accept low- or unpaid internships to build their resumes. Despite the prevalence of introductory pricing, its efficiency properties are less well understood. Introductory pricing is in part an investment in reputation. As with any investment, if the investor cannot fully appropriate the returns, the level of investment will be inefficiently low. Yet in most markets, buyers and sellers share the surplus from a transaction, and therefore also the value created by reputation. Sellers' reputation investment generates information that benefits future buyers. This positive externality suggests the potential for underinvestment. However, there is also a form of business stealing. Investment can displace other sellers, including reputable incumbents, leading to overinvestment.

I study the efficiency of reputation investment by workers in the context of Freelancer.com, an online labor platform. This context adds two additional layers of complexity. First, reputation is not the only way in which a worker-employer match today affects the future. Workers may accumulate human capital from experience, and have incentives to invest in human capital in addition to reputation. Second, workers and employers are not the only players in this market. The platform collects a commission on transactions. While the commission is just a transfer from workers and employers to the platform, it is important because it potentially gives the platform an incentive to adopt policies that increase total surplus. I develop an empirical framework incorporating the complex forces surrounding workers' reputation and human capital investment: the externalities on employers, the competition and business stealing among workers, and the incentives of the platform.

Several features of online labor platforms make them an ideal setting for studying the general issue of reputation investment. With the rise of digitization and remote work, these platforms are increasingly important: a recent World Bank report estimates that 4–13% of the global labor force engage in online gig work (Datta et al., 2023). On these platforms, after a worker completes a job, she may receive a public rating from the employer. These ratings are informative to future employers: the number of ratings signals experience, while the mix of good and bad ratings signals quality. The freelance nature of these markets means that employers, who typically hire for one-off jobs, do not internalize the information and human capital gains that their hiring creates. This makes workers' reputation investment particularly important.

Workers submit wage bids for jobs. These wage bids are a straightforward margin for workers to invest in reputation and experience. By contrast, offline reputation building behaviors such as new restaurants' pricing or unpaid internships are rarely recorded in data typically available to researchers. I use proprietary data covering three million wage bids submitted by over 100,000 international workers to 83,000 jobs, the universe of job auctions in a skill category in a seven-month period. The data allows me to follow workers over time as they build reputation, making this paper the first to study empirically the efficiency of workers' investment in reputation.

I first present evidence that employers value reputation and experience. Within a given worker, the probability of winning a job rises sharply with the number of good reviews and, to a smaller extent, with bad reviews.[1] Controlling for the worker's wage bid, the first good review increases the probability of winning by 50%, and the first ten good reviews raise it by 171%. The positive coefficient for bad reviews indicates that experience raises a worker's winning probability regardless of whether the information signal is good or bad, which I attribute to human capital accumulation. The larger coefficient on good reviews compared to that on bad reviews suggests that, in addition to human capital, good reviews increase employers' expectations of the worker's quality.

Using data on both successful and unsuccessful bids, I show next that new workers initially bid low and raise their bids after receiving good reviews—and, more modestly, after bad reviews. Within a given worker, the first good review is associated with a 5% increase in wage bid, and the first ten good reviews with a 17% increase. The first bad review is associated with a less than 1% increase in wage bid. Later, with the estimated model, I separate the investment incentives in the observed bid responses from the static incentives.

To evaluate the effects and efficiency of workers' investment in reputation and human capital, I develop a dynamic equilibrium auction model. The model features a discrete number of *public types* that capture permanent differences across workers. These public types are commonly known (e.g. from workers' profiles) irrespective of reviews or experience. Conditional on the public type, there is uncertainty about workers' *latent quality*, which the workers and employers learn symmetrically from reviews by past employers. In addition, workers accumulate human capital with job experience. Public types differ along four dimensions: (i) opportunity costs; (ii) baseline productivity; (iii) distribution of latent quality, which governs the mapping from reviews to expected quality; and (iv) the rate of human capital accumulation. Employers observe bidders' public types, bids, and past reviews, form expectations of workers'

[1] In my data, roughly 80% of employer ratings are five out of five; I classify these as good reviews and anything lower as bad reviews. My finding complements that of Pallais (2014), who provides experimental evidence that reputation improves employment prospects on a similar platform.

productivity, and choose a worker or the outside option. Anticipating the effects of reputation and experience on future outcomes, workers bid to maximize the value of lifetime payoffs.

I face two econometric endogeneity challenges. First, the observed correlation between reputation and outcomes may reflect unobserved worker heterogeneity rather than a causal effect (Heckman, 1981; Resnick et al., 2006; Cabral and Hortacsu, 2010). I address this with the modeling of public types who differ systematically in their propensity to accumulate reviews. Conditional on types, any remaining correlation between reviews and outcomes is attributable to information and human capital.

Second, even after conditioning on worker types and observables, match-specific productivity shocks can make bids endogenous. A worker may bid higher for a job because she is uniquely suited, and this may be known by the employer but not the econometrician. I address this using variation from exchange-rate fluctuations (Brinatti et al., 2021; Stanton and Thomas, 2025). In my context, workers are highly international and typically bid in USD; when a worker's home currency appreciates relative to the USD, her USD bid should rise. This exchange-rate–driven variation is unlikely to be correlated with changes in worker productivity and identifies the wage elasticity of labor demand.

To implement these solutions, I extend existing two-step estimation methods for dynamic games. In the first step, I estimate bid policy functions, winning probabilities, distribution of latent quality, and distribution of initial conditions, allowing each to vary with unobserved worker type. I adapt the expectation–maximization algorithm, first used by Arcidiacono and Miller (2011) in the estimation of dynamic games with unobservable heterogeneity, to incorporate exchange rates as an instrumental variable and to accommodate additional complexities that arise in my model. Specifically, (i) unobserved types affect multiple outcomes; (ii) some outcomes depend on the unobserved types of more than one worker. In the second step, I apply the Method of Simulated Moments to recover employers' preferences and workers' opportunity costs, matching moments from employers' choices and workers' bids. Continuation values in workers' bid first-order conditions are computed via forward simulation.

The estimates reveal meaningful permanent differences across workers. Without imposing a priori restrictions, I find that worker types with higher baseline productivity also have higher opportunity costs. This positive correlation is intuitive as more capable workers are more likely to have better off-platform options.

Within each worker type, employers place a high value on reputation and experience. Employers are willing to pay a 22-24% wage premium (different depending on worker type) for a worker with five good reviews compared to a worker with no reviews. Out of this 22-24%

wage premium, 8-12% is attributable to higher expected quality and 12-15% to human capital accumulation.

Using the estimated model, I quantify how a review and experience today affects the future payoffs of the reviewed worker, her competitors, and the employers. The value of a single review and experience is sizable. For a modal worker with no prior reviews it is $305; with five prior good reviews it is $169. Given the average job payment ($220) and the estimated average contemporaneous surplus of a job ($148), these estimates suggest that oftentimes the information and human capital value of a job exceeds the job's contemporaneous value. Notably, the value of a review and experience is *shared* between the reviewed worker and her potential employers. For a modal worker with no prior reviews, 35% of the value of the first review and experience accrues to the worker herself; 65% to her potential employers in the future; the worker's competitors take a minimal hit (-$2).

To investigate the equilibrium effects of workers' investments, I simulate a counterfactual where workers behave myopically, i.e. choose bids to maximize the payoffs from the current auction only and ignore the consequences of winning on their future payoffs. Compared to the case of myopic workers, workers' investments in reputation and experience increase the number of reviewed workers in equilibrium by 52%, significantly improving the choice sets for employers and leading to three times more matches. Workers benefit from the investments: annual worker surplus in the skill category I study goes up from $1.3 to $1.7 million, suggesting that the information and human capital gains of the investments outweigh business stealing. Even though each worker invests solely to maximize her own surplus, their behavior benefits the other side of the market and the platform. The annual employer surplus goes up from $0.7 to $4.0 million and the annual platform surplus goes up from $0.5 to $1.0 million.

Several forces make workers' investment in reputation essential to platform functioning. When workers are myopic, new workers bid similarly to well-reviewed incumbents, giving employers little reason to take a chance on them. As a result, new workers struggle to build reputation. Absent investment incentives, workers also bid higher wages. The shortage of well-reviewed workers, coupled with higher bids, pushes employers toward not hiring anyone. While a reputation system creates the potential for information flow, workers' (or sellers') costly investment in reputation—such as through introductory pricing—contributes significantly to realizing that potential. Absent investment to encourage employers (or buyers) to experiment, markets can stagnate in low information.

Given the large positive externalities that workers' reputation investment creates for employers and the platform, equilibrium investment is potentially below the social optimum. I therefore evaluate platform-funded subsidies for hiring unreviewed workers. I find that a range of subsidy levels raises total surplus, implying that workers' investment falls short of the social optimum. The subsidy that maximizes total surplus, which accounts for the surplus of workers, employers, and the platform, equals 30% of unreviewed workers' wage bids and raises total surplus by 22%. While the platform sees a revenue gain under the socially optimal subsidy, it prefers a lower subsidy of 20% (yielding a revenue increase of 8%). The wedge arises because the subsidy is an expenditure for the platform but a pure transfer from the social planner's perspective. Thus the platform internalizes the cost of the subsidy, whereas the social planner does not. Despite the misalignment, the platform's preferred subsidy level delivers 80% of the gains from the socially optimal subsidy. I compare the subsidies with a platform-wide new worker skill certification program, where the platform offers every registered new worker a quality signal equivalent to the information in one review. The platform's preferred subsidy achieves 58% of the gains from certification.

While the specific policies are tailored to this platform, the counterfactual simulations highlight an exploration–exploitation trade-off relevant to information design in many markets. Subsidizing hiring of new workers generates valuable information, but by shifting hiring away from well-reviewed incumbents it reduces employers' ability to exploit existing information. The optimal subsidy balances the gains from learning against the losses from reallocating hiring away from known high-quality matches.

Related Literature This paper contributes to a broad literature on incomplete information and reputation across economics. It is related to theoretical work studying information free-riding when experimental outcomes are publicly observed (Bolton and Harris, 1999; Keller et al., 2005), sellers' strategic responses to reputation incentives (Bergemann and Välimäki, 1996; Bergemann and Välimäki, 2000; Villas-Boas, 2004), and mechanism design to improve social learning (Kremer et al., 2014; Che and Hörner, 2018; Vellodi, 2018). I contribute by studying these questions empirically.

This paper is also related to the empirical literature on reputation mechanisms in online product markets, especially with regards to the cold-start problem and to sellers' responses (Bolton et al., 2004; Cabral and Hortacsu, 2010; Li et al., 2020). Closely related is Dendorfer and Seibel (2024), who estimate the cost of inefficient experimentation with new listings on Airbnb and design platform interventions. My paper provides the first empirical analysis of the effects and efficiency of introductory pricing in a labor context. It also incorporates human capital accumulation as a second channel through which a transaction today shapes future outcomes, a feature distinctive to labor markets.

In labor, this paper bridges two strands of literature that have previously been studied separately. The first is the literature on employer learning and general skills training (e.g. Altonji and Shakotko, 1987; Farber and Gibbons, 1996; Acemoglu and Pischke, 1998; Altonji and Pierret, 2001; Autor, 2001; Kahn and Lange, 2014; Pallais, 2014; Barlevy and Neal, 2019). The second concerns labor market power (e.g. Manning, 2003; Card et al., 2018; Dube et al., 2020; Azar et al., 2022; Lamadon et al., 2022; Berger et al., 2022; Rubens, 2023; Roussille and Scuderi, 2025). In closely related work, Pallais (2014) shows experimentally that reputation improves employment outcomes on a similar online labor platform and illustrates through a theoretical model that the hiring of new workers is lower than socially optimal. I innovate on this work both theoretically and empirically. Theoretically, her model assumes perfect competition, i.e. workers receive all the surplus from a match. Under this assumption, workers' investments would restore hiring to social optimum, and her inefficiency result relies on frictions from the minimum wage. In contrast, I show that the under-hiring of new workers arises naturally under imperfect competition, where employers share the surplus of a match. Empirically, I quantify how workers' underbidding for reputation helps mitigate the information problem and use the model to evaluate alternative platform designs, both within an equilibrium framework.

Methodologically, the paper contributes to the industrial organization literature on estimating dynamic games (Rust, 1987; Hotz and Miller, 1993; Hotz et al., 1994; Bajari et al., 2007). As mentioned previously, I extend the expectation-maximization approach of Arcidiacono and Miller (2011) (applied in Chung et al., 2014; Igami and Yang, 2016), who first used it to estimate dynamic games with serially correlated unobservable. My extension draws on insights from Arcidiacono and Jones (2003). Identification of the model relies on Kasahara and Shimotsu (2009). The equilibrium concept is similar to that in Weintraub et al. (2008). Computation of counterfactuals follows Sweeting (2012).

This paper is also related to work on online labor platforms (e.g. Horton et al., 2011; Agrawal et al., 2015; Stanton and Thomas, 2016; Filippas et al., 2018; Barach et al., 2020; Barach and Horton, 2021; Holtz et al., 2022; Krasnokutskaya et al., 2020; Galdin and Silbert, 2024). Following Brinatti et al. (2021) and Stanton and Thomas (2025), I exploit exchange-rate fluctuations for identification. The focus on workers' bid responses to reputation incentives is new in this literature.

Outline Section 2 introduces the setting and data. Section 3 presents descriptive evidence on employers' preferences for reputation and experience and on workers' bid responses. Section 4 presents a dynamic equilibrium model. Section 5 discusses estimation method and results. Section 6 studies the equilibrium effect of workers' investment. Section 7 evaluates alternative platform design. Section 8 concludes.

2 Online Labor Platforms: Setting and Data

2.1 Setting

The setting of my study is Freelancer.com, one of the world's largest online labor platforms that matches global employers and workers to collaborate on short-term, often remote, jobs. According to its 2024 Annual Report, the platform has over 80 million registered users.[2] The top countries for employers are the United States, India, Australia, the United Kingdom, and Canada. Workers are similarly international. In 2024, Freelancer facilitated $85 million worth of contracts, with the average job paying $334 in the last quarter. The most popular job categories were design, media, and architecture (33% of completed projects), followed by websites, IT, and software (29%), writing and content (9%), and sales and marketing (7%).

Online labor platforms such as Freelancer, Upwork, and Fiverr meet businesses' demand for skilled, project-based work, such as designing websites, writing sales materials, or converting code into different languages. These platforms also expand income opportunities for workers, especially those in less developed countries or those excluded from traditional labor markets due to gender, disability, or other barriers (WTO, 2019; ILO, 2021). Market research firm Modor Intelligence estimates that the freelance platform sector reached a market size of $7.6 billion in 2025.

The primary mode of matching on Freelancer is through job auctions. Employers post public project descriptions under a specific skill category and specify a minimum budget (most projects in my data are fixed-price rather than hourly). Workers then submit bids that include a proposed pay at or above the minimum budget, an expected completion time, and a short description explaining their fit for the job. Workers' prior reviews—including their average star rating (from 1 to 5) and total number of ratings—are prominently displayed alongside their bids. Appendix Figure A1 displays a screenshot of a posted job and selected bids.

Although it is possible that employers might set the minimum budget strategically, the platform provides a drop-down menu for the employer to choose from, with options including "Task $10-30" and "Micro $30-50." Appendix Figure A1 plots the distribution of the minimum budgets and shows that most of the minimum budgets are bunched at the platform's preset options, suggesting the lack of strategic behavior. Given this, for the rest of the paper, I use minimum budget to normalize workers' bids and costs.

Bids are immediately visible to all upon submission. Bidding remains open until the em-

[2] All of the information in this paragraph is based on Freelancer's 2024 Annual Report.

ployer awards the project or the bid closes. Appendix Figure A2 plots the distribution of auctions' duration. Although job auctions are by default open for seven days, most jobs in my sample, if awarded, are awarded within two hours of posting. The default order in which workers' bids are displayed on the employer's page is based on a proprietary algorithm that accounts for factors including ratings from previous employers, skills, profile, and past experience.[3] Employers can re-sort bids in various ways (e.g. by bid amount). Employers can click on workers' profiles to learn more about the workers and reach out to workers for a private conversation before deciding whom to hire. Employers are free to award the job to any or none of the bidders.

After project completion, both parties rate each other, but can only see the rating they receive after submitting their own.

2.2 Data and Summary Statistics

I use proprietary data from Freelancer.com obtained through a research collaboration agreement. The primary dataset consists of the universe of job auctions posted under the popular skill category PHP—a programming language—from June 1 to December 31, 2018. I restrict the sample to fixed-payment auctions, which account for 89% of jobs in this category, and further to those denominated in USD (59% of fixed-budget projects). The final dataset includes 2,738,310 bids submitted to 83,210 jobs, with an average of 33 bids per job.

For each job, I observe the minimum budget and posting timestamp. For each bid, I observe worker ID, bid amount, and whether the bid was selected. If the employer awarded the job to a worker, I observe whether the employer left a rating and the content of the rating. I also observe the workers' countries. Appendix Section A.1 contains a list of variables.

In addition, I obtained the full review history for all the workers in my sample. The review data include the timestamp and rating of each review received. Given the skew towards five-star ratings (shown in Appendix Figure A4), I treat reviews as binary signals: a five-star rating is classified as a good signal, and any lower rating as a bad signal. I merge the review history with the bid data to reconstruct each worker's number of good and bad reviews at the time of bidding.

I supplement the bid data with daily exchange rates. Theses are daily interbank exchange rates that Freelancer uses to process payments.

Table 1 presents summary statistics of the main data set. The median job in my data sample has a minimum budget of $30, while the mean is considerably higher at $230. A subset of

[3] https://www.freelancer.com/support/freelancer/profile/bid-ranking-factors

Table 1: Summary Statistics

(a) PHP Auction Panel

	Mean	p25	p50	p75
Project-Level ($N = 83{,}210$)				
Number of bidders	33	10	22	44
Minimum budget (usd)	230	10	30	250
Winning bid (usd)	213	25	61	194
Normalized winning bid	3.4	1.5	2.5	3.6
Paid amount (usd)	228	20	50	180
Auction duration (hour)	71	.4	2.0	31
Job duration (hour)	862	1.1	40	281
Bid-Level ($N = 2{,}738{,}310$)				
Normalized bid	3.3	1.5	2.2	5.0
Number of good reviews	81	4	23	93
Number of bad reviews	15	0	4	15
Number of reviews	96	5	28	110
Bidder-Level ($N = 109{,}919$)				
Number of bids in sample	25	1	2	4

(b) Worker Panel

	Mean	p25	p50	p75
Bidder-Level ($N = 8{,}973$)				
Number of lifetime bids	596	16	53	194
Active months	22	2	15	37

Notes: Tables present statistics from (i) the main dataset—all fixed-budget, USD-denominated job auctions in the popular PHP skill category (a web programming language) from June–December 2018—and (ii) an auxiliary dataset comprising the complete bid histories of a random sample of workers who registered in 2018 and won at least one job. Normalized winning bids and normalized bids are bids divided by the job's minimum budget. Auction duration is the time between job posting and award. Job duration is the time between job acceptance and completion. Active months is the number of months between the worker's first and last bids. For the summary statistics of normalized bids, bids above $\exp(3)$ times minimum budget are excluded. The high means for the job duration and for the number of bids per worker reflect the presence of extreme values. All of the statistics are calculated from my data samples and do not reflect the platform average.

jobs are awarded.[4] Among awarded jobs, the median winning bid is $61 or about 2.5 times the minimum budget. Employers tend to act quickly: the median time between posting and awarding is just 2 hours. Jobs are typically short-term, with a median completion time of 40 hours. Appendix Figure A3 presents a further breakdown of jobs' duration.

Most bids come from experienced workers: the median bid is submitted by a worker with 23 good reviews and 4 bad reviews. Most workers in the sample submitted only one or two bids to USD-denominated PHP jobs during this seven-month period.

An auxiliary data set tracks a sample of workers who registered around the same time in 2018 and records all of the bids they ever submitted. I restrict to a subsample of workers who won at least one job on the platform, which contains about 9,000 workers. Among these workers, the mean number of bids submitted is 596 and the median is 53. The amount of time between the worker's first and last bids has a mean of 22 months and median of 15 months. These statistics suggest that successful workers are active for a long period of time on the platform, and it is reasonable to assume that they have dynamic incentives.

The vast majority, or 89%, of jobs done by workers in this sample involve employer–worker pairs that collaborated only once. This pattern is consistent with the freelance nature of the platform, where employers typically hire for one-off projects. Consequently, employers have limited incentives to invest in learning the worker's quality over time or training the worker, and instead rely on information from prior employers' reviews.

3 Descriptive Evidence

I provide evidence that employers value workers' reputation and experience and that workers change their wage bids as they accumulate reviews.

3.1 Employers Value Reputation and Experience

In this section, I show that a given worker's winning probability increases in her number of good reviews and to a smaller extent in her number of bad reviews. This suggests that employers are willing to pay for reputations and human capital.

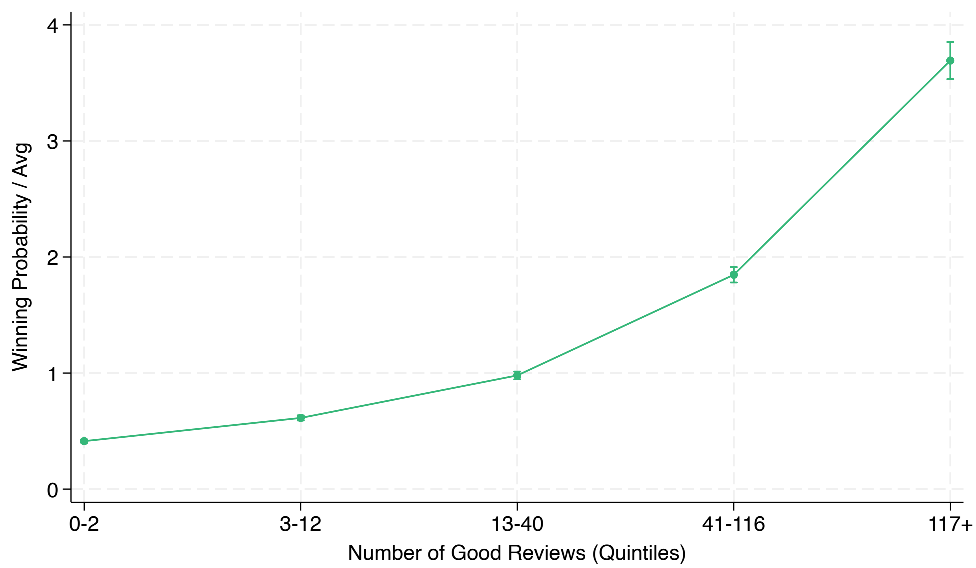
[4] According to the research collaboration agreement, I cannot disclose the project award rate.

As a start, I estimate the following logistic regression using the main data sample,

$$\Pr(y_{it}=1|b_{it},n_{it},x_t)=\Lambda(\beta_b \log b_{it}+\sum_{q=1}^{Q}\theta_q \mathbf{1}\{n_{it}^{\text{Good}}\in \mathcal{Q}_q\}+\beta_B \log n_{it}^{\text{Bad}}+\beta_x \log x_t), \tag{1}$$

where y_{it} equals 1 if the bid by worker i wins auction t, and 0 otherwise; b_{it} is the worker's normalized bid; $n_{it}=(n_{it}^{\text{Good}},n_{it}^{\text{Bad}})$ represents the number of good and bad reviews that worker i received prior to auction t; x_t is the job's minimum budget; and $\Lambda()$ is the standard logistic function.

Figure 1: Winning Probability and the Number of Good Reviews



Notes: Figure plots the model-predicted average probability of winning (normalized by the sample average) by quintiles of the number of good reviews, based on a logit regression. The prediction controls for the number of bad reviews, the worker's bid, and the minimum budget.

Figure 1 shows the average bid-level winning probability (normalized by the sample average) by quintiles of the number of good reviews, based on the estimated model in Equation 1. Controlling for a worker's wage bid, the winning probability rises sharply with the number of good reviews: workers in the fourth quintile are more than four times as likely to win as those in the first quintile, indicating that employers strongly favor workers with more positive reviews.

To test whether the reviews–winning probability relationship holds within workers, I estimate the following regression with worker fixed effects and instrument wage bids with demeaned exchange rates:

$$y_{it}=\alpha_i+\gamma_b \log b_{it}+\gamma_G \log n_{it}^{\text{Good}}+\gamma_B \log n_{it}^{\text{Bad}}+\gamma_x \log x_t+\epsilon_{it}, \tag{2}$$

and I use exchange rates to instrument for wage bids in

$$\log b_{it} = \delta_i + \pi_z z_{it} + \pi_G \log n_{it}^{\text{Good}} + \pi_B \log n_{it}^{\text{Bad}} + \pi_x \log x_t + \varepsilon_{it}. \tag{3}$$

Exchange rate z_{it} is the log of the price of one USD in the worker's local currency, demeaned at the country level.

I use an instrumental variable strategy to address match-specific unobservables that can bias the estimates. A worker may bid a high wage in a particular job because she is uniquely suited, and the employer knows, for example through the pre-award interview. Exchange rates should shift wage bids in USD. If a worker's home currency appreciates relative to USD, her wage bid in USD should increase. The exchange rate-induced variation should be independent from changes in match productivity.

Table 2: Determinants of Winning and Bid Amount

	(1) Winning: OLS	(2) Bid (log)	(3) Winning: IV
Bid (log)	-0.76***		-16.4***
	(0.013)		(1.9)
No. of good reviews (log)	-0.43***	0.0737***	0.66***
	(0.04)	(0.00187)	(0.14)
No. of bad reviews (log)	0.06	0.0153***	0.22***
	(0.05)	(0.00237)	(0.06)
Min. budget (log)	-0.57***	-0.351***	-6.04***
	(0.006)	(0.000243)	(0.68)
Exchange rate (log)		0.173***	
		(0.0133)	
Observations	2,684,310	2,684,310	2,684,310
Worker FE	Yes	Yes	Yes

Notes: The coefficient and standard error estimates in Columns (1) and (3) are normalized by the sample mean winning probability. The dependent variable in the second column is bids normalized by the job's minimum budget and then taken log. Exchange rate is the log of the price of one USD in the worker's local currency, demeaned at the country level. In Column (3), exchange rate is used to instrument for bid.

Table 2 presents estimation results. Column (1) presents OLS estimates: within a worker, the probability of winning declines with log bid and, somewhat counterintuitively, with the number of good reviews, while the coefficient on the number of bad reviews is imprecisely estimated. These estimates are likely biased due to the presence of match-specific unobservables.

Column (2) shows the first-stage regression of log bid on the exchange-rate instrument. I estimate an exchange rate pass-through to workers' wage bids of 0.17, which is close to the 0.20 estimate of Brinatti et al. (2021) and above the 0.08 estimate of Stanton and Thomas (2025), both from similar online labor platforms. Column (3) reports the 2SLS results using exchange rates as an instrument for log bids. Relative to the OLS results, the coefficient on log bid is significantly more negative, consistent with match-specific unobservables. The coefficient on the log number of good reviews is positive. Holding the worker's wage bid constant, the first good review increases the likelihood of winning by 50%, while the first ten good reviews raise it by 171%. The coefficient on good reviews exceeds that on bad reviews, indicating that good reviews raise winning probability more than bad reviews.

The results that employers value both reputation—given the stronger effect of good reviews—and experience, as even bad reviews are associated with higher winning probabilities.

Appendix Table A1 presents results from the above regressions where I control for worker country fixed effects instead of worker fixed effects.

3.2 Workers Increase Bids after Receiving Reviews

I show that workers increase their wage bids after accumulating reviews.

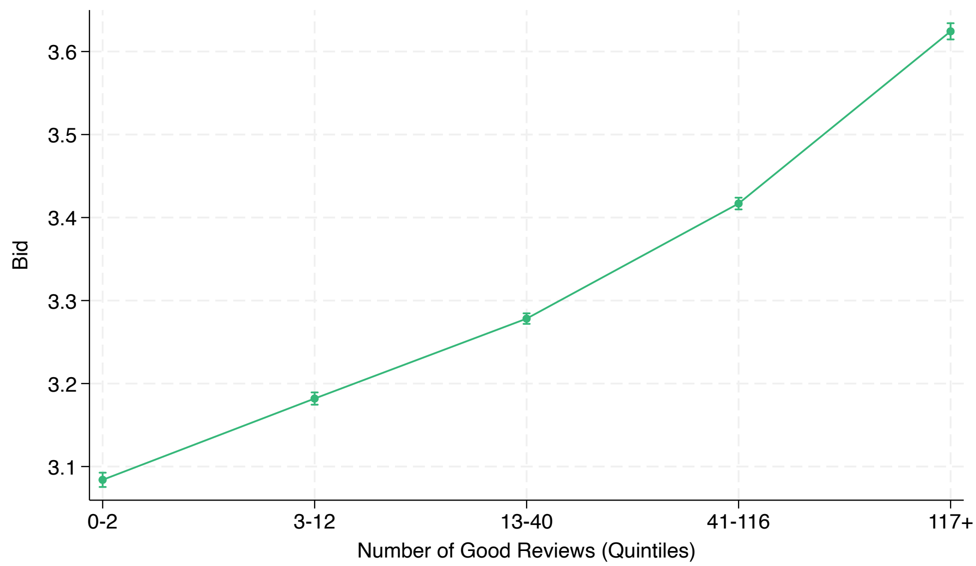
I begin by regressing normalized wage bids on quintiles of the number of good reviews, controlling for the number of bad reviews and the job's minimum budget. Figure 2 plots the coefficients on the quintile indicators. Bids rise with the number of good reviews: moving from the first to the fourth quintile increases bids by over 30% of the job's minimum budget, and moving to the fifth quintile raises bids by more than 50%.

To study within-worker bid changes, I regress the worker's log normalized bid on the number of good and bad reviews the worker received prior to the current job, as well as the job's minimum budget, controlling for worker fixed effects:

$$\log b_{it} = \alpha_i + \beta_G \log n_{it}^{\text{Good}} + \beta_B \log n_{it}^{\text{Bad}} + \beta_x \log x_t + \epsilon_{it}.$$

The results are presented in Table 3. In Column (1), I do not include worker fixed effects. Both across and within workers, bids increase after a worker receives a good review, and increase to a smaller extent following a bad review. For a given worker, the first good review is linked to a 5% increase in the wage bid, while the first ten good reviews correspond to a 17% increase. The first bad review is linked to a less than 1% increase.

Figure 2: Wage Bids and the Number of Good Reviews



Notes: Figure plots the average wage bid (as a multiple of the job's minimum budget) by quintiles of the number of good reviews, holding the number of bad reviews and the minimum budget at their mean values. Wage bids above 30 times the minimum budget are dropped from this calculation, as they are unlikely to reflect strategic bidding behavior.

The bid increase after receiving a bad review could be due to a couple of reasons: (i) the worker becomes more pessimistic about her own quality and decides to invest less in future jobs, because they anticipate receiving more negative reviews; (ii) the worker learns from the experience despite receiving a bad review and becomes more productive. The model will formalize these channels.

The higher response of wage bids to the number of good reviews when I control for worker fixed effects compared to when I do not is consistent with workers with more good reviews generally bidding lower. This suggests persistent worker heterogeneity and the endogeneity of reviews.

The changes in bids following reviews may reflect a worker's ability to charge a different statically optimal markup and/or changes in her dynamic incentives to invest in reputation and experience. In the coming sections, I use a structural model to separate the static and dynamic incentives in bidding and to examine the role of workers' strategic bidding behavior in shaping equilibrium outcomes.

Table 3: Wage Bids and Changes in Reputation and Experience

	(1) Bid (log)	(2) Bid (log)
No. of good reviews (log)	0.0429***	0.0699***
	(0.000454)	(0.00185)
No. of bad reviews (log)	0.0124***	0.0101***
	(0.000594)	(0.00234)
Min. budget (log)	-0.256***	-0.351***
	(0.000244)	(0.000243)
Observations	2,738,310	2,684,310
Worker FE	No	Yes

Notes: Bids are normalized by the job's minimum budget.

4 Model

I develop a dynamic equilibrium model that includes learning about worker quality, human capital accumulation, bidding for jobs, and hiring. Employers post one job and never return to the platform and therefore face no dynamic considerations. Workers are forward-looking. They stay on the platform for a length of time, and therefore have incentives to invest tin their reputation and experience. The model builds on the general class of dynamic game models introduced by Ericson and Pakes (1995), with innovations to accommodate a large number of market participants and to account for unobserved heterogeneity at both the worker and match levels.

Environment The high-frequency nature of the setting makes continuous-time models a natural fit. I develop a continuous-time model with infinite horizon (Arcidiacono et al., 2016; De Silva et al., 2023).

Workers, each denoted by i, are characterized by their country $o(i)$ and *public type* $k(i) \in \{1,...,K\}$. The public type is common knowledge and shapes the worker's expected productivity and opportunity cost in ways described below. The state variable is the number of good and bad reviews the worker has received by time t: $n_{it} = (n_{it}^{\text{Good}}, n_{it}^{\text{Bad}})$. The publicly visible number of job experiences is $(n_{it}^{\text{Good}} + n_{it}^{\text{Bad}})$.[5]

[5]Because employers do not always leave a review after a job, the worker's true number of jobs done on the platform may exceed the visible total. I assume that without a posted review, the worker cannot credibly signal that the job occurred. The human capital accumulation defined below should therefore be interpreted as reflecting human capital growth from both reviewed and unreviewed experiences. The model implies that the expected number of unreviewed jobs rises with the number of reviewed ones.

At each point in time, new workers enter the market exogenously at Poisson rate λ, each starting with zero reviews. Job auctions arrive at Poisson rate λ_a. Jobs are posted by different employers, so employers face no dynamic considerations—an assumption consistent with the platform's freelance nature. In what follows, t refers to time, the job auction posted at that time, and the employer posting the auction.

Worker i participates in an auction with exogenous probability $a(n_{it})$. The job's minimum budget x_t, exchange rates z_{ot}, and match-specific shocks ν_{it} realize. Observing these, participating workers submit total-payment bids. Let b_{it} represent the worker's bid divided by the job's minimum budget. The employer is free to award the job to one or none of the bidders. If the job is awarded, the employer leaves a review with exogenous probability r, updating the hired worker's reputation state. Finally, workers exit the market at Poisson rate $\delta(n_{it})$.

Review Workers have latent *quality* $\tilde{q}_i$. The latent quality is unknown to the worker or the employers. They learn the worker's quality symmetrically based on reviews by previous employers.

The priors over the latent quality follow a Beta distribution with parameters that depend on the worker's public type $\tilde{q}_i \sim \text{Beta}(a_{k(i)}, b_{k(i)})$. The worker's job performance gives the employer a binary signal of $\tilde{q}_i$. With exogenous probability r, the employer records this signal as a review. I assume that the employer reviews only the unknown part of the worker's productivity—the latent quality—and not the worker's overall productivity.[6] Based on Bayes's theorem, the expectation that the worker and the employers hold of the worker's latent quality, given her reviews and public type, is

$$\mathbb{E}[\tilde{q}_i | n_{it}, k(i)] = \frac{a_{k(i)} + n_{it}^{\text{Good}}}{a_{k(i)} + b_{k(i)} + n_{it}^{\text{Good}} + n_{it}^{\text{Bad}}}.$$

Employer's problem The employer receives workers' bids and chooses one of the bidders or the outside option to maximize her utility. The employer faces a tradeoff between wages and expected productivity. Her utility of hiring worker i for the job at time t is

$$u_{it} = \alpha_b \log b_{it} + q(k(i), o(i), n_{it}, \nu_{it}, x_t) + \epsilon_{it}, \tag{4}$$

[6] The assumption that the employer reviews a worker's latent quality rather than her total productivity aligns with the theory of expectation (dis)confirmation, which posits that consumers' evaluations reflect how experiences meet or fall short of prior expectations. Here the prior expectations are given by all the components of the worker's expected productivity in Equation 5 except the expected latent quality. Recent empirical evidence in support of the theory includes Li et al. (2025) on restaurant ratings, Bondi et al. (2025) on movie ratings, and Meister and Reinholtz (2025) on Airbnb.

where b_{it} is the normalized wage bid.

The expected worker productivity $q(k(i),o(i),n_{it},\nu_{it},x_t)$ equals

$$\underbrace{q_{o(i)}+q_{k(i)}+q_{k(i),x}\log x_t}_{\text{baseline productivity}}+\overbrace{\nu_{it}}^{\text{match-specific shock}}+\underbrace{\alpha_q\mathbb{E}[\tilde{q}_i|n_{it},k(i)]}_{\text{expected latent quality}}+\overbrace{h_{k(i)}\log(n_{it}^{\text{Good}}+n_{it}^{\text{Bad}}+1)}^{\text{human capital accumulation}}. \tag{5}$$

The first terms $q_{o(i)}+q_{k(i)}+q_{k(i),x}\log x_t$ represent the average expected productivity of a new type k worker from country o; the effect of the worker's type can differ depending on the job's minimum budget x_t. The match-specific shock ν_{it} is common knowledge and is i.i.d. over i,t. The influence of the expected latent quality is $\alpha_q\mathbb{E}[\tilde{q}_i|n_{it},k(i)]$. And $h_{k(i)}\log(n_{it}^{\text{Good}}+n_{it}^{\text{Good}}+1)$ captures the human capital accumulation. The speed of human capital accumulation can differ by worker's type. Finally, ϵ_{it} is the employer's private taste shock, distributed i.i.d. over i,t following T1EV distribution. The employer's outside option is normalized to have mean 0: $u_{0t}=\epsilon_{0t}$.

Worker i's winning probability given a set of bidders $B_t(i\in B_t)$ is, therefore,

$$\frac{\exp(\alpha_b\log b_{it}+q(k(i),o(i),n_{it},\nu_{it},x_t))}{1+\sum_{l\in B_t}\exp(\alpha_b\log b_{lt}+q(k(l),o(l),n_{lt},\nu_{lt},x_t))}. \tag{6}$$

Worker's problem Workers bid to maximize the sum of present and future payoffs. I first specify c_{it}, worker i's opportunity cost of working on job t, expressed in USD and normalized by the job's minimum budget. I assume that the cost follows

$$c_{it}=(c_{k(i)}+c_{o(i)}+c_x\log x_t+c_{k(i),\nu}\nu_{it})\times {z_{o(i)t}}^{c_z}. \tag{7}$$

where $c_{k(i)}+c_{o(i)}$ is the baseline opportunity cost for type-k workers from country o; x_t is the minimum budget; ν_{it} is the match-specific shock whose impact on opportunity costs can be type-specific; and $z_{o(i)t}$ is the worker's local currency per USD exchange rate divided by the mean exchange rate. I assume the exchange rates z_{ot} follow country-specific distributions F_Z^o, and are i.i.d. over time within the time window of my data. If $c_z=1$, that means complete pass-through from exchange rate shocks to workers' opportunity costs in USD, consistent with the case where workers' outside options are entirely domestic. If workers' outside options include working for foreign employers in other channels, the pass-through parameter c_z would be less than 1.

I summarize the four dimensions along which workers of different public types differ: (i) opportunity costs; (ii) baseline productivity; (iii) the latent quality distribution, which governs the mapping from reviews to expected quality; and (iv) the speed of human-capital accumulation.

When a worker decides how much to bid, she does not know the identities or the number of her competitors.[7] Workers hold beliefs over their chances of winning against the distribution of competitor sets. I denote a particular bidder set that includes worker i by B. The beliefs are given by

$$G_{o(i)}^{k(i)}(b_{it},n_{it},x_t,\nu_{it}) = \int \frac{\exp(\alpha_b \log b_{it} + q(k(i),o(i),n_{it},\nu_{it},x_t))}{1+\sum_{l\in B}\exp(\alpha_b \log b_{lt} + q(k(l),o(l),n_{lt},\nu_{lt},x_t))} f(B)dB. \tag{8}$$

The probability of a set of competitors $f(B)$ is determined by the workers' auction participation probabilities and is given by $\Pi_{l\neq i,l\in B}a(n_{lt})\Pi_{l\notin B}(1-a(n_{lt}))$. Equation 8 mimics the distribution of the highest rival bid, an object often used in the literature on seal-bid auctions to describe the bidder's problem. The difference is that in my context, employers care about non-wage worker characteristics, so the winning probability is not simply a function of the distribution of the highest rival bid.

Given these beliefs, each worker selects a bid to maximize the sum of the present and future payoffs. Let $V_o^k(n)$ represent the value of being in the market for a worker of public type k from country o and with reputation state n. Because I assume that the job's minimum budget x_t, exchange rates z_{ot}, and match-specific shocks ν_{it} are distributed independently over time, the model implies that conditional on k and o, the reputation state n is the only state variable.

I assume no discounting of future payoffs.[8] The Hamilton-Jacobi-Bellman equation is

$$\delta(n)V_o^k(n) = \lambda_a a(n)\mathbb{E}_{z,x,\nu}\left[\max_b \overbrace{G_o^k(b,n,x,\nu)}^{\text{expected winning prob}} \Big(x(b-c)+r\mathbb{E}[V_o^k(n'|n)-V_o^k(n)]\Big)\right],$$

where $\delta(n)$ is the exit rate and the left-hand side is the instantaneous loss from exiting the market; on the right-hand side, λ_a is the auction's arrival rate, $a(n)$ the worker's participation probability, and the expression inside the expectation operator the worker's expected gain when bidding in an auction with minimum budget x and faced with exchange rate z and match-specific shock ν.

The first-order condition is

[7] In practice, workers can observe the identities and bids of earlier bidders. However, 50% of all bids arrive within 10 minutes of a project's posting and 75% within the first two hours, making it unlikely that workers carefully review prior bidders' profiles or tailor their bids accordingly. It is therefore reasonable to model workers as bidding against an average, expected set of competitors.

[8] This is driven by the observation that most workers in my sample are active in the market for less than a year. However, discounting can be easily incorporated into the model and estimation.

$$b = c - \underbrace{\frac{G_o^k(b,n,x,\nu)}{\partial G_o^k/\partial b}}_{\text{static markup}} - \underbrace{\frac{1}{x} r \mathbb{E}[V_o^k(n'|n) - V_o^k(n)]}_{\text{dynamic incentives}}. \tag{9}$$

The static markup comes from worker differentiation in expected productivity, which includes the worker's type, the information from the reviews, the human capital accumulation from experience, the match-specific idiosyncratic quality shocks, and the employer's private taste shocks. In addition, workers respond to dynamic incentives. If they expect that winning a job will increase their continuation value on the platform, they will shade their bids down in response.

Equilibrium I consider a large market equilibrium concept similar to an oblivious equilibrium, an approximation to Markov-perfect equilibria in dynamic games with many agents (Weintraub et al., 2008; Iyer et al., 2014).[9] This equilibrium concept fits my setting because the worker population exceeds 100,000, making it unrealistic for each worker to track every other worker's reputation state. Instead, workers condition on an aggregate statistic—the expected winning-probability function—similar to Backus and Lewis (2025). An equilibrium is a pair of bid strategies $b_o^k(n,z,\nu,x)$ and expected winning probabilities $G_o^k(b,n,x,\nu)$ such that

1. Workers' bids maximize the sum of present and future payoffs, given workers' expected winning probabilities;

2. Workers' expected winning probabilities are equal to the average winning probabilities in a stationary distribution where workers follow the bid strategies and employers choose the option that generates the highest utility.

5 Estimation

I estimate the auction arrival rate and worker participation rates directly from the data. Worker entry and exit rates are estimated to match the observed number and distribution of bidders in an average auction. Appendix Section B.1 contains more details.

[9] The equilibrium concept is similar to OE because workers do not track the particular realizations of competitors' characteristics at each t, including reputation states; rather, they bid against the stationary distribution of competitors' characteristics. It is not exactly OE because of aggregate shocks from exchange rate fluctuations. However, because exchange rate shocks are assumed i.i.d., the distribution of workers' states is still stationary conditional on exchange rate realizations.

This section covers estimation of the remaining parameters. I use a two-step method to estimate my model (Rust, 1987; Hotz and Miller, 1993; Hotz et al., 1994; Bajari et al., 2007). The key estimation challenge is the unobservability of workers' types k. This persistent unobserved heterogeneity renders the first-step estimation no longer straightforward. I address this by adapting the Expectation-Maximization (EM) algorithm, developed by Arcidiacono and Miller (2011) for estimation of dynamic games, to estimate the type-specific bid policy functions, win probability functions, prior distributions, and initial condition distributions. These objects will then be used in a second step, where I estimate parameters of employers' demand and workers' opportunity costs.

5.1 First-Step Estimation via the EM Algorithm

In the first step, I estimate the population distribution of types (π_k) and the type-specific bid policy functions, winning probability functions, prior over workers' latent quality, and distribution of initial conditions—collectively represented by the parameter vector θ—using maximum likelihood.[10]

Let $d_t^{-i_t^*}$ denote the vector of participation decisions in auction t for all workers other than the winner i_t^*. If the employer selects the outside option, then $d_t^{-i_t^*} = d_t$.

The log likelihood I maximize in the first step is:

$$LL(\theta) = \sum_{i=1}^{N} \ln \Bigg[\sum_k \pi_k \Bigg[\Big(\prod_t \underbrace{Pr(b_{it} \,|\, \theta, k, x_t, z_{it}, n_{it}, o_i)}_{\text{Bid}} \times \underbrace{\mathbb{E}_{d_t^{-i_t^*}} \left[Pr(i_t^* \,|\, \theta, x_t, k, b_{i_t^* t}, z_{i_t^* t}, n_{i_t^* t}, o_{i_t^* t}, d_t^{-i_t^*}) \right] \Big)^{\mathbb{I}\{i_t^* = i\}}}_{\text{Winning}}$$
$$\times \underbrace{Pr(r_{i_t^*} \,|\, \theta, k, n_{i_t^* t})^{\mathbb{I}\{i_t^* = i\}}}_{\text{Review content}} \Big) \times \underbrace{Pr(n_{i1} \,|\, \theta, k)}_{\text{Initial condition}} \Bigg] \Bigg] + \sum_t \underbrace{\ln \mathbb{E}_{d_t^{-i_t^*}} \left[Pr(i_t^* \,|\, \theta, x_t, d_t^{-i_t^*}) \right]^{\mathbb{I}\{i_t^* = 0\}}}_{\text{Employer chooses outside option}}. \tag{10}$$

In Appendix Section B.2, I show that Equation 10 represents the log likelihood of the observed data integrated over the participation decisions of non-winners in each auction. By integrating over the non-winners' participation decisions, I replace the probability that a worker wins the auction, which depends on her actual competitors' unobserved types, with its expected value before competitors are drawn. In other words, this is the log likelihood computed as if the auction identifiers for non-winning bids were unobserved.

[10] The parameters of the bid policy functions and the distribution of the initial conditions are not structural parameters, because the functional forms assumed in the first stage of the estimation are not necessarily consistent with the structural model. This is a common drawback of two-step estimators, as discussed in Bajari et al. (2007).

Although the integrated likelihood ignores available information, it offers a key advantage that facilitates the application of expectation-maximization algorithm: each term depends only on the realization of a single worker's unobserved type and, for a subset of terms, on the population distribution of types—but never on the realizations of multiple workers' unobserved types. Although maximizing this integrated likelihood is less efficient than maximizing the full data likelihood, the estimator remains consistent.

The need for the integrated likelihood arises from a feature of my model that is absent in the Monte Carlo examples in Arcidiacono and Miller (2011) and in other applications (Chung et al., 2014; Igami and Yang, 2016). In my setting, the transition probability of an individual's observed state—a worker's reputation—depends not only on her own unobserved type but also on the unobserved types of other workers, even after conditioning on current-period actions. This is because the employer's choice depends on the whole set of bidders' types (see Equation 6). This contrasts with the examples in Arcidiacono and Miller (2011), where, conditional on current-period exit and entry decisions, the transition probability of an individual's observed state—a firm's incumbency status—depend on neither its own unobserved state (demand shock), nor other firms' unobserved states.

Parametrization I specify the bid policy function to take the following form

$$\log b_{it} = \delta_{o(i)} + \beta_z \log z_{o(i)t} + \beta^k + \beta^k_x x_t + \beta^k_q \mathbb{E}[\tilde{q}_i | n_{it}, k(i)] + \beta^k_e \log(n^{Good}_{it} + n^{Bad}_{it} + 1) + \beta_\nu \nu_{it}, \tag{11}$$

where δ_o is the fixed effect for workers from country o; $z_{o(i)t}$ is the demeaned exchange rate of worker's local currency per USD; $\mathbb{E}[\tilde{q}_i | n_{it}, k(i)]$ is the posterior mean of the worker's latent quality given her reputation; $\log(n^{Good}_{it} + n^{Bad}_{it} + 1)$ is the human capital accumulation effect; and ν_{it} is the match-specific shock. I assume that $\{o(i), z_{o(i)t}\}$ are uncorrelated with the rest of the variables, which allows to me to first estimate $\delta_{o(i)}$ and β_z using an ordinary least squares regression outside of the EM algorithm.

The expected probability of winning against an average competitor set follows from the demand model. Let

$$f(b,x,k,o,n,z) = -\alpha_b \log b + q_o + q_k + q_{k,x} \log x + \nu + \alpha_q \mathbb{E}[\tilde{q}_i | n, k] + h_k \log(n^{\text{Good}} + n^{\text{Bad}} + 1),$$

where ν, according to the bid policy function, is equal to $\frac{1}{\beta^k_\nu}(\log b - \delta_o - \beta^z z - \beta^k_x x - \beta^k - \beta^k_q \mathbb{E}[\tilde{q} | n, k] - \beta^k_e \log(n^{Good} + n^{Bad} + 1))$. I denote the expected winning probability against an average competitor set as

$$Pr\left(i_t^*|\,\theta,x_t,k_{i_t^*},b_{i_t^*t},z_{i_t^*t},n_{i_t^*t},o_{i_t^*t}\right):=\mathbb{E}_{d_t^{-i_t^*}}\left[Pr(i_t^*\,|\,\theta,x_t,k_{i_t^*},b_{i_t^*t},z_{i_t^*t},n_{i_t^*t},o_{i_t^*t},d_t^{-i_t^*})\right]$$

According to the model, it is equal to

$$\mathbb{E}_{d_t^{-i_t^*}}\left[\frac{\exp(f(b_{i_t^*t},x_t,k_{i_t^*},o_{i_t^*},n_{i_t^*t},z_{i_t^*t}))}{1+\exp(f(b_{i_t^*t},x_t,k_{i_t^*},o_{i_t^*},n_{i_t^*t},z_{i_t^*t}))+\sum_{l\neq i_t^*}\left[\mathbb{I}\{d_{lt}=1|d_t^{-i_t^*}\}\times\exp(f(b_{lt},x_t,k_l,o_l,n_{lt},z_{lt}))\right]}\right]. \tag{12}$$

Based on the review model, the probability that the next review is good is equal to the latent quality expectation conditional on past reviews and on worker type

$$Pr(r_{i_t^*}|\theta,k_{i_t^*},n_{i_t^*t})=\frac{a_k+n_{i_t^*}^{\text{Good}}}{a_k+b_k+n_{i_t^*}^{\text{Good}}+n_{i_t^*}^{\text{Bad}}}.$$

I specify the worker's initial state—defined as the worker's reputation level at the time of her first bid in the sample period—to be one of three states and estimate the type-specific distribution:

$$Pr(n_{i1}|k)=\begin{cases}\rho_k^1 & \text{if } \max\{n_{i1}^{\text{Good}},n_{i1}^{\text{Bad}}\}=0\\ \rho_k^2 & \text{if } \max\{n_{i1}^{\text{Good}},n_{i1}^{\text{Bad}}\}>0,\ \frac{n_{i1}^{\text{Good}}}{n_{i1}^{\text{Good}}+n_{i1}^{\text{Bad}}}\leq\text{median}\\ 1-\rho_k^1-\rho_k^2 & \text{if } \max\{n_{i1}^{\text{Good}},n_{i1}^{\text{Bad}}\}>0,\ \frac{n_{i1}^{\text{Good}}}{n_{i1}^{\text{Good}}+n_{i1}^{\text{Bad}}}>\text{median},\end{cases}$$

where median refers to the median ratio of good reviews among workers.

EM algorithm I adapt the EM algorithm with a sequential maximization step (developed by Arcidiacono and Jones, 2003), an extension of the EM algorithm, to estimate the parameter vector θ. The algorithm alternates between an expectation step and a maximization step. My likelihood comprises four types of outcomes: bids, employers' worker choices, reviews received by workers, and workers' initial reputation states. Some parameters contribute to the likelihood of multiple outcomes. For example, the prior over workers' latent quality affects bids, reviews, and employers' choices. Arcidiacono and Jones (2003) show that these parameters can be estimated sequentially in the maximization step, substantially reducing computational burden.

For iteration $m+1$, the algorithm performs the following steps:

1. **Expectation step** Compute $\pi_{ik}^{(m+1)}$, the posterior probability that worker i belongs to type

k, given the current parameter estimates $\theta^{(m)}$ (include $\pi_k^{(m)}$):

$$\frac{\pi_k^{(m)} L_i(k;\theta^{(m)})}{\sum_{k'} \pi_{k'}^{(m)} L_i(k';\theta^{(m)})}$$

where $L_i(k;\theta^{(m)})$ is the likelihood of worker i's outcomes if she belongs to type k, given the current parameter estimates, and is equal to

$$L_i(k;\theta^{(m)}) = \left[\prod_t Pr(b_{it}\,|\,\theta^{(m)},k,...)\left[Pr(i_t^*\,|\,\theta^{(m)},k,...)\right]^{\mathbb{I}\{i_t^*=i\}} Pr(r_{i_t^*}\,|\,\theta^{(m)},k,...)^{\mathbb{I}\{i_t^*=i\}}\right] Pr(n_{i1}\,|\,\theta^{(m)},k).$$

2. **Maximization step** Given the vector of workers' posterior type probabilities $\pi_{ik}^{(m+1)}$, compute $\theta^{(m+1)}$ to maximizes an auxiliary function[11]

$$Q(\theta^{(m+1)};\,\theta^{(m)}) = \sum_i \sum_k \pi_{ik}^{(m+1)} \left[\log \pi_k^{(m=1)} + \sum_t \log Pr(b_{it}|\theta^{(m+1)},k,...) + \sum_t \log Pr(i_t^*|\theta^{(m+1)},x_t,k,...)^{\mathbb{I}\{i_t^*=i\}} \right.$$
$$\left. + \sum_t \log Pr\left(r_{i_t^*}|\theta^{(m+1)},k,...\right)^{\mathbb{I}\{i_t^*=i\}} + \log Pr(n_{i1}|\theta^{(m+1)},k)\right] + \sum_t \log Pr\left(i_t^*\middle|\,\theta^{(m+1)},x_t\right)^{\mathbb{I}\{i_t^*=0\}}.$$

As mentioned, this is done sequentially:

(a) Update the prior over types

$$\pi_k^{(m+1)} = \frac{\sum_i \pi_{ik}^{(m+1)}}{\sum_i \sum_{k'} \pi_{ik'}^{(m+1)}};$$

(b) Update the priors over workers' latent quality by maximizing with regards to ${a_k}^{(m+1)}$, ${b_k}^{(m+1)}$

$$\sum_i \sum_k \pi_{ik}^{(m+1)} \left[\sum_t \log Pr\left(r_{i_t^*}\middle| {a_k}^{(m+1)},\, {b_k}^{(m+1)},\, n_{i_t^* t}\right)^{\mathbb{I}\{i_t^*=i\}}\right];$$

(c) Update the bid policy functions by estimating a weighted OLS regression (Equation 11), using $\pi_{ik}^{(m+1)}$ as weights;

[11] The difference between the auxiliary function and the actual objective function is that the log operator is moved inside. The EM algorithm is based on the observation that any parameter $\theta^{(m+1)}$ that increases $Q(\theta^{(m+1)};\,\theta^{(m)})$ beyond $Q(\theta^{(m)};\,\theta^{(m)})$ must also increase $LL(\theta^{(m+1)})$ beyond $LL(\theta^{(m)})$ (see Martin Haugh's Machine Learning for OR&FE notes for more details).

(d) Update the demand parameters by maximizing

$$\sum_i \sum_k \pi_{ik}^{(m+1)} \left[\sum_t \log Pr\left(i_t^* \middle| \, \theta^{(m+1)}, x_t, k, \ldots \right)^{\mathbb{I}\{i_t^*=i\}} \right] + \sum_t \log Pr\left(i_t^* \middle| \, \theta^{(m+1)}, x_t \right)^{\mathbb{I}\{i_t^*=0\}},$$

where the probability inside the expectation (given in Equation 12) is simulated by drawing competitor sets from the data. Appendix Section B.3 provides further details on the simulated MLE;

(e) Update the initial condition distribution

$$\rho_k^{j\,(m+1)} = \frac{\sum_i \left(\pi_{ik}^{(m+1)} \times \mathbb{I}\{j(i)=j\} \right)}{\sum_i \pi_{ik}^{(m+1)}},$$

where $j(i)$ represents the category of i's initial reputation state.

The algorithm continues until the increase in log likelihood falls below a criterion. Appendix Section B.3 provides additional details of the EM implementation.

5.2 Second-Step Estimation: Employers' Demand

I use Method of Simulated Moments (McFadden, 1989; Pakes and Pollard, 1989) to estimate demand parameters to match employers' choices, drawing on results from the first-stage estimation.

Although as part of the E-M algorithm, I already obtained estimates of employers' demands (see step (d) of the maximization step). The moments I used there are the winning probabilities of a worker with a set of characteristics against the average, expected set of competitors.[12] Here, I re-estimate employers' demands taking advantage of data on the observed competitor characteristics. These finer moments provide more precise estimates.

The data moments are $\{d_{it}\}_{i,t}$, where d_{it} is equal to 1 if the bid by worker i for job t won and 0 otherwise. Let p_{it} represent the model-implied probability that worker i wins auction t. The model-implied probability is conditional on the observed characteristics and bids of worker i and her competitors, and is integrated over the unobserved types of the bidders. It is given by

$$\int \ldots \int \frac{\exp(f(k_i, x_t, b_{it}, o_i, n_{it}, \nu_{it}))}{1 + \sum_{l \in B_t} \exp(f(k_l, x_t, b_{lt}, o_l, n_{lt}, \nu_{lt}))} \prod_l Pr(k_l | \{b_{m\tau}, x_\tau, o_m, n_{m\tau}, z_{m\tau}\}_{m,\tau}) dk_l, \tag{13}$$

[12] As explained in Section 5.1, this ensures the applicability of the EM algorithm.

where

$$f(k_i,x_t,b_{it},o_i,n_{it},\nu_{it})=\alpha_b \log b_{it}+q_o+q_k+q_{k,x}\log x_t+\nu_{it}+\alpha_q\mathbb{E}[\tilde{q}_i|n_{it},k_i]+h_k\log(n_{it}^{\text{Good}}+n_{it}^{\text{Bad}}+1),$$

and, by Bayes's rule,

$$\begin{aligned}Pr(k_i|\{b_{lt},x_t,o_l,n_{lt},z_{lt}\}_{l,t}) &= Pr(k_i|\{b_{it},x_t,o_i,n_{it},z_{it}\}_t) \\ &= \frac{\pi_k \times Pr(\{b_{it},x_t,o_i,n_{it},z_{it}\}_t|k)}{\sum_{k'}\pi_k' \times Pr(\{b_{it},x_t,o_i,n_{it},z_{it}\}_t|k')}.\end{aligned}$$

The probability of each bidder's unobserved type can be computed in the same way as in the expectation step in the EM algorithm using the estimates from the first step.

The wage elasticity of employers' demand is estimated from exchange rate-induced variation in bids. This is because all the other factors driving variation in bids are controlled for in the utility function. Those include the worker's country, expected latent quality, learning-by-doing effects, the job's minimum budget, and the match-specific shocks.

The MSM estimator is

$$\underset{\theta}{\operatorname{argmin}}(d-P(\theta))'W'W(d-P(\theta)),$$

where $d-P(\theta)$ is a vector of size $M\times 1$, consisting of individual moments $d_{it}-p_{it}$ stacked together, and W is a $K\times M$ matrix of instruments. Appendix section B.4 contains the list of instruments and more information on the estimator.

5.3 Second-Step Estimation: Workers' Costs

I use MSM to estimate cost parameters matching observed bids, using the bid first-order conditions. The presence of the value functions in the bid first-order conditions reflects workers' dynamic considerations. I follow Hotz et al. (1994) and Bajari et al. (2007) and forward simulate for value functions using the previously estimated bid policy functions and employer preference parameters.

The opportunity cost is specified in (7). I begin by estimating the non-linear parameter c_z, which governs the pass-through of exchange rate shocks to dollar-denominated opportunity costs. The bid first-order condition provides a link between the pass-through of exchange rate shocks to costs and the pass-through of exchange rate shocks to bids. I use this relationship to estimate c_z. Appendix Section B.4 provides more details. With the non-linear parameter estimated, the opportunity costs and the workers' payoffs are linear in the remaining unknown cost parameters c_k, c_o, and c_x.

I estimate the remaining opportunity cost parameters using MSM. The individual data moments are the observed bids. The model-implied moments are based on the bid first-order conditions:

$$b_{it} = c_{it} \underbrace{- \frac{G(b|k,o,x_t,n_{it},\nu_{it})}{\partial G/\partial b}}_{\text{Static Markup}} \underbrace{- \frac{1}{x_t} r\left[\mathbb{E}[V_o^k(n_{i,t+1})|n_{it}] - V_o^k(n_{it})\right]}_{\text{Dynamic Incentives}}.$$

I forward simulate for value functions $V_o^k(n)$ for each worker type k, country o, and on a grid of review states n. For each $\{k,o,n\}$, I simulate the trajectories of 5,000 workers starting with those characteristics. I simulate their bids, win outcomes, review transitions, and market exits for up to 10,000 auctions that they participate in (in almost all simulations, the worker exits the market before reaching the auction limit). I use the estimated bid policy functions to simulate the worker's bids. To simulate the workers' win outcomes, I draw an auction from the empirical distribution of auctions (with workers' type probabilities drawn based on EM estimates as described in Section 5.2), randomly drop one bidder, add the worker to the auction, and use the estimates of employers' preferences to determine the winner. If the worker wins the auction, I draw whether the employer leaves a review. If the employer does, I use the estimated Beta priors to draw whether the review is good. Finally, I draw an exit shock determining whether the worker continues onto the next auction.

To form the model-implied moments, I first draw the types of the workers associated with each bid (following the same procedure as above). I simulate for the static markup using the estimated demand parameters: it equals the change in a worker's average winning probability, averaged over 2,000 potential competitor sets drawn from the data, when she raises her bid by 1×10^{-4}. For the dynamic incentives, I combine results from the forward simulation with the guess cost parameters to compute continuation values at the reputation grid points. I apply linear interpolation for values between grid points and assign the value at the nearest grid point for observations outside the grid. These individual moments are then stacked and interacted with instruments to form the estimator. Appendix Section B.4 provides a list of the instruments and more details on the forward simulation.

5.4 Estimates

Table 4 presents estimates of type-specific bid policy functions, priors over workers' latent quality, and initial condition distributions from the EM algorithm in the first step of the estimation.

The three types differ in their bid levels: type 1, the most populous, submits lower baseline bids than type 2, which in turn bids less than type 3. These large, persistent gaps among different types of workers highlight the need to control for enduring worker heterogeneity. They may reflect persistent differences in opportunity costs (c_k), baseline quality ($q_k + q_{k,x} \log x$), or both—an issue addressed in the second-step estimation. Across all types, bids rise with the posterior mean of latent quality and with accumulated job experience, and log-normalized bids are higher when a job's minimum budget is lower.

The three types also differ in the distribution of the latent quality, with type 1 having a higher prior mean—and therefore a higher average probability of getting a good review—than type 2 and type 2 in turn than type 3.

Table 4: First-Stage Estimates from Expectation-Maximization Algorithm

	Type 1	Type 2	Type 3
Population Distribution			
	57%	36%	7%
Priors over Latent Quality			
Beta A	12.2	7.2	11.6
Beta B	2.2	1.7	4.9
Mean	0.85	0.81	0.71
Std dev	0.09	0.12	0.11
Bid Policies			
Constant	-0.60	-0.33	-0.22
Posterior mean	0.15	0.41	1.02
Experience (log)	0.02	0.02	0.02
Minimum budget (log)	-0.20	-0.34	-0.45
Initial Condition			
No review	85%	82%	73%
Reviewed (good-review ratio $<$ median)	7%	9%	15%
Reviewed (good-review ratio $>$ median)	8%	9%	12%

Notes: Table displays type-specific first-step estimates. Bids are first normalized by the auction's minimum budget, taken log, and then demeaned by worker country, with variation due to exchange rates also removed. The remaining variation is specified to be log-linear in the posterior mean of a worker's latent quality, the log number of reviews, and the log minimum budget, with the corresponding type-specific coefficients reported here. The initial condition distribution is over the worker's reputation state at the point of her her first bid submission in the sample. Demand is estimated as part of the EM algorithm; however, because demand is re-estimated in the second stage using an expanded set of moments—which yields more efficient estimates—I omit the demand estimates here.

Table 5 reports the demand estimates. Employers dislike higher wage bids. The estimated wage-bid coefficient is close to the -4.38 found for the largest employer type in Stanton and

Table 5: Estimates of Employers' Demand

	All	Type 1	Type 2	Type 3
Expected latent quality		7.47 (0.32)	5.65 (0.19)	7.03 (0.86)
Minimum budget (log)		-1.45 (0.24)	-1.80 (0.15)	-2.11 (0.32)
Experience (log)		0.33 (0.02)	0.27 (0.02)	0.27 (0.02)
Constant		-9.74 (0.46)	-6.61 (0.30)	-5.82 (0.57)
Bid (log)	-3.94 (0.72)			
China	0.22 (0.05)			
India	0.05 (0.07)			
Pakistan	0.21 (0.05)			
United States	0.94 (0.11)			
Other countries	0.75 (0.11)			
Avg. new worker productivity		-3.39	-2.03	-0.83

Notes: Table presents estimates from the second-step method of simulated moments estimator of employers' demand. Types refer to the types of workers recovered in the first-step estimation. The omitted country is Bangladesh. Bootstrapped standard errors in parentheses.

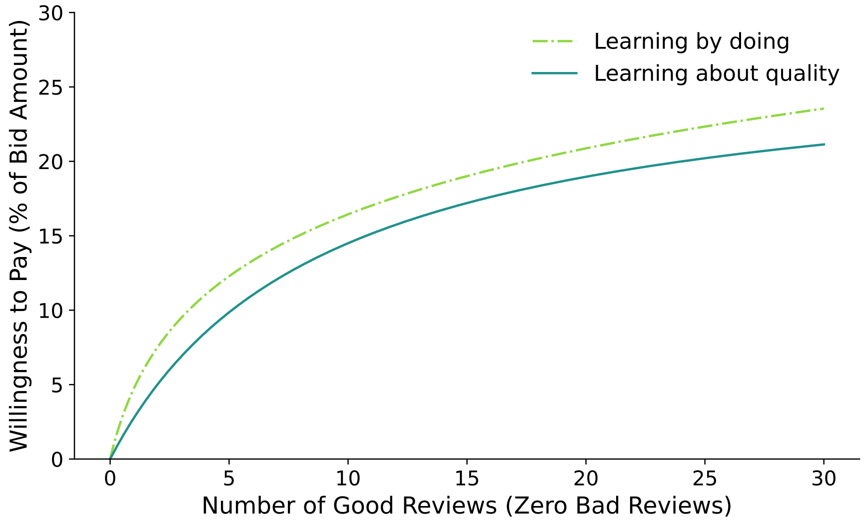
Thomas (2025), who study a similar online labor platform. The own-wage elasticity is about 4, implying a wage markup of roughly 33 percent. Despite facing many competitors in an auction, workers secure a sizable markup, consistent with productivity differentiation.

Employers place value on both improvements in a worker's expected latent quality and on accumulated experience. Figure 3 illustrates the estimated willingness to pay for additional good reviews, separating the contribution of information about latent quality from the learning-by-doing effect. Employers' willingness to pay for workers' reviews suggests that a review from today's match generates externalities for the worker's future matches, which I quantify in Section **??**.

The demand estimates reveal sizable productivity differences across worker types. Table 5 reports the estimated average expected productivity of an unreviewed worker by type. Type 1—the group that bids persistently lowest in the first-step estimates—also exhibits the lowest expected productivity. Employers are willing to pay about 35 percent more for a type-2 worker than for a type-1 worker, and about 30 percent more for a type-3 worker than for a type-2 worker. This suggests that the persistent bid hierarchy partly reflects underlying productivity differences. Finally, workers from different countries have different expected productivity. Workers from the U.S. have higher productivity than workers from other major countries.

Table 6 presents the estimates of normalized workers' costs in USD. The pass-through of

Figure 3: Employers' Willingness to Pay for Reviews



Notes: Figure shows estimated changes in employers' willingness to pay for type-2 workers as their number of good reviews increases. "Learning by doing" captures the increase in willingness to pay from greater experience, while "learning about quality" reflects the increase driven by changes in the worker's expected latent quality.

exchange rate shocks is less than 1, suggesting that workers' outside options are not entirely domestic but might include working for other foreign employers. Workers' costs are higher for jobs for which they have a higher match productivity shock with, potentially due to the higher effort they put in. Workers from different countries have different levels of opportunity costs, with workers from the U.S. having higher costs than workers from other major worker countries.

The cost estimates indicate that worker types who bid higher also face higher opportunity costs of work. Without imposing any restrictions on the correlation between quality and opportunity cost across types, I find a positive relationship between the two. This is intuitive, as higher-quality workers may have better outside options, leading to higher opportunity costs.

For the other parameters, I estimate auctions' arrival rate and workers' auction participation rates directly from the data, and workers' entry and exit rates are estimated to match the observed number and distribution of bidders in an average auction. Appendix Section B.1 contains more details.For the other parameters, I estimate auctions' arrival rate and workers' auction participation rates directly from the data, and workers' entry and exit rates are estimated to match the observed number and distribution of bidders in an average auction. Appendix Section B.1 contains more details.

Table 6: Estimates of Normalized Opportunity Costs

	All	Type 1	Type 2	Type 3
Constant		2.00 (.03)	3.18 (.06)	4.49 (.16)
Match productivity shock		0.57 (.15)	0.62 (.16)	0.47 (.12)
Minimum budget (log)	-1.16 (.01)			
China	-0.06 (.01)			
India	0.11 (.03)			
Pakistan	0.01 (.02)			
United States	0.52 (.01)			
Other countries	0.48 (.03)			

Notes: Table presents estimates of workers' opportunity cost parameters in Equation 7. The omitted country is Bangladesh. Bootstrapped standard errors in parentheses.

5.5 The Value of a Review

In this section, I use the estimated model to quantify the value of a review and experience. A review provides useful information to both the worker and her potential future employers, while experience raises the worker's human capital. The employer deciding whether and whom to hire today does not internalize these future benefits. Measuring the size of the value of a review and experience is therefore a first step toward assessing the scope of inefficiency in screening and hiring.

I estimate the value by simulating two scenarios: one in which a worker is hired today and receives a review, and one in which she is not hired. After today, the worker freely participates in auctions and may win additional jobs; the only difference across scenarios is the worker's initial reputation state. For a worker with a given reputation, I simulate auction participation, bids, employers' choices, and review dynamics for 5,000 worker draws until exit from the market. In each auction a worker enters, I record the payoffs of the worker, her competitors, and the employer.[13] I then compare these payoffs to a counterfactual scenario in which the worker receives one extra experience and one more review, which may be good or bad with probabilities given by the estimates. To ensure that the results are not influenced by the number of auctions a worker participates in before exiting the market, whenever one path exits earlier than the other I continue drawing auctions for the early-exiting path and compute the employer

[13]This approach abstracts from second-order effects, such as changes in the auctions that the worker's competitors enter, which may vary depending on whether those competitors win or lose the auctions they share with the worker in question. However, since the estimated first-order externalities on competitors are already small, I assume that any second-order effects are even smaller and unlikely to alter the qualitative conclusions.

and bidder utilities in those auctions. The difference in payoffs between the two scenarios is the value of a single review and experience.

Absent the model, this value is hard to quantify. First, we need to know how much information a marginal review contains and how much human capital a marginal experience produces. Second, employer surplus requires a model of employer demand, and worker surplus requires estimates of workers' costs.

Figure 4 reports the value of a review and experience for a type-2 worker from India (she can be considered the modal worker: type 2 is the median type and India is the most represented worker country) with 0 reviews, or 5, 10, or 50 good reviews.

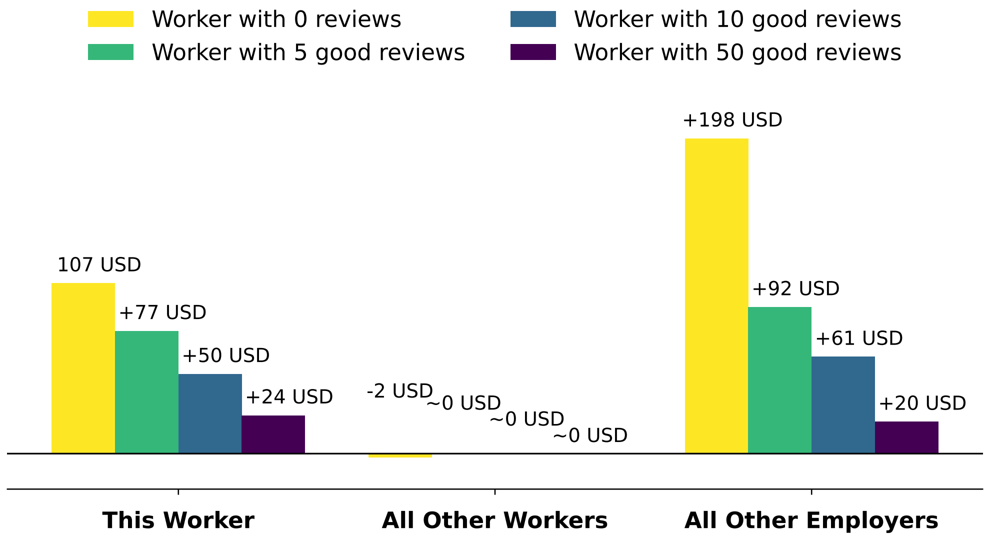
The value of a single review and experience is sizable. For a worker with no prior reviews it is \$305; with five prior good and zero bad reviews it is \$169. These magnitudes are comparable to the average job payment (\$220) and the estimated average contemporaneous surplus (\$148). A substantial share accrues to the worker herself (\$107 out of \$305 for a worker with no prior reviews), because an additional review and experience improve her prospects in future auctions. Future employers also take a significant share (\$198 out of \$305 for a worker with no prior reviews), because the review helps them make more informed hiring decisions and they benefit from the worker's higher human capital. The value for future competitors is minimal. The total change of competitors' welfare is at most \$2 spread across thousands of workers, which translates into a per-competitor effect that is effectively zero. This finding supports the model's large-market assumption, under which workers do not track the reputation updates of individual competitors.

A review and experience carry substantially more value for a new worker than for a well-reviewed worker: \$305 for a new worker, \$111 for a worker with 10 good reviews, and \$44 for a worker with 50 good reviews. This pattern holds for the total value and for the components accruing to the worker and to her future employers. The mechanism is twofold: (i) there is more uncertainty to resolve about a new worker's latent quality, and (ii) there is more human capital to accumulate. Consequently, hiring a new worker generates larger future benefits than hiring an experienced worker.

Beyond these examples, I compute the value for all potential matches observed in the data and plot the distribution in Appendix A5. For the median bidder, the value of a review and experience is \$55.

Because the employer making today's hiring decision does not internalize these future benefits, a wedge can arise between private and social incentives. However, since part of the value accrues to the reviewed worker, a forward-looking worker will respond by bidding a

Figure 4: The Value of a Review and Experience



Notes: Figure presents the value of a review and experience for the reviewed worker, the other workers, and for employers. These are calculated for a type-2 worker from India (the median worker type and most represented country). For reference, the average job payment is \$220 and the estimated job's average contemporaneous surplus is \$148.

lower wage today to invest in reputation and experience. In Section 6, I study the welfare effects of such bid responses.

5.6 Forward-Looking Incentives Shape Workers' Wage Bids

Workers choose wage bids to maximize the sum of the present and future payoffs. Equipped with the estimated model, I analyze how forward-looking incentives shape workers' optimal bids. I do so by comparing dynamically and statically optimal strategies.

The statically optimal bid maximizes the expected payoff from the current auction alone:

$$b_S = \underset{b}{\operatorname{argmax}} G_o^k(b,n,x,\nu)x(b-c),$$

where $G_o^k(b,n,x,\nu)$ is the worker's expected probability of winning given the worker's type k, country o, bid b, reputation state n, the job's minimum budget x, and the match-specific shock ν; and c is the worker's opportunity cost.

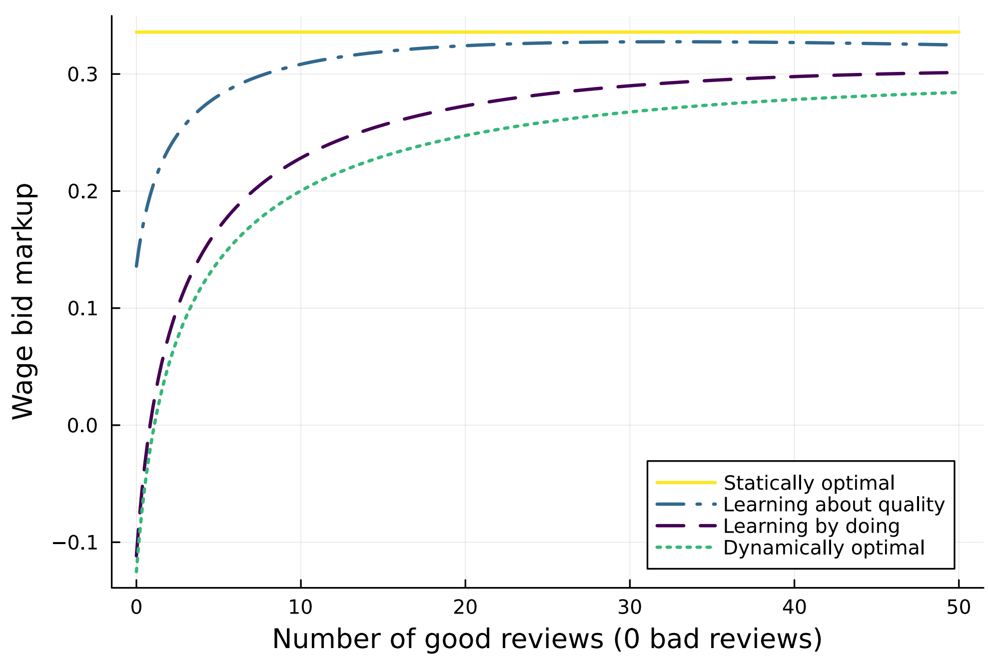
The dynamically optimal bid also accounts for how winning the job and receiving a review influences the worker's future payoffs:

$$b_D = \underset{b}{\operatorname{argmax}} G_o^k(b,n,x,\nu)\left(x(b-c)+r\left[\mathbb{E}[V_o^k(n')|n]-V_o^k(n)\right]\right)\Bigg],$$

where $V_o^k(n)$ denotes the continuation value and r is the probability that the worker receives a review upon winning.

To compute the optimal bids, I draw 2,000 auctions from the data, randomly remove one bidder from each, and assign types to the remaining bidders by sampling from the posterior type distribution implied by their observed actions and outcomes (the output of the EM algorithm). I then simulate their bids using the estimated bid policy functions and calculate continuation values through forward simulation. The statically and dynamically optimal bids are defined as the grid points that maximize their respective objective functions, averaged over the 2,000 auction draws.

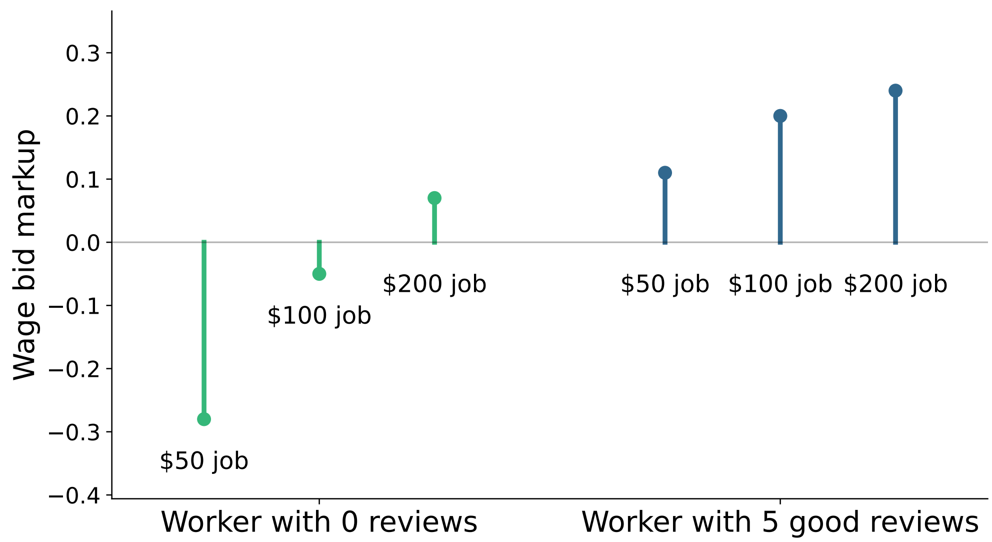
Figure 5: Dynamic Incentives in Bidding



Notes: Figure plots simulated statically and dynamically optimal bids for a type-2 worker from India (median type, most represented country) bidding in an auction with minimum budget \$100, facing an average exchange rate and average match-specific productivity shock. In addition, to isolate the two sources of workers' forward-looking incentives, figure plots dynamically optimal bids in counterfactuals where employers value reviews and experience only for information about latent quality—referred to as "learning about quality"—and where employers value reviews and experience only for "learning by doing" effects. To smooth the simulated bid values, I use the function $\alpha_1 \log(n^{\text{Good}}+1)+\alpha_2[\log(n^{\text{Good}}+1)]^2$.

Figure 5 plots the estimated statically optimal and dynamically optimal bid markups—defined as (bid-cost)/cost—at different reputation levels for a type-2 worker from India bidding on a job with average characteristics: average minimum budget, average match productivity, and average exchange rate.

Figure 6: Dynamic Incentives in Bidding By Job's Minimum Budget



Notes: Figure plots the dynamically optimal bid markups for a type-2 worker from India (median type and most represented country) facing an average exchange rate and average match-specific productivity shock. The statically optimal bid markups for all combinations are around 0.36.

I find that forward-looking incentives—instead of static incentives—are the main drivers behind the wage bid responses to changes in reviews. While a worker's probability of winning rises substantially with more good reviews—at the dynamically optimal bid, the winning probability for a worker with ten good reviews is three times that of a worker with no reviews—the statically optimal bid increases only minimally with reputation.[14] In contrast, dynamic considerations lead workers with fewer reviews to shade their bids more aggressively, producing a steep profile of wage bids.

To illustrate the roles played by the two sources of dynamic incentives—learning about latent quality through the reviews and learning by doing—I simulate the dynamically optimal bids when only one source is present. For example, to isolate learning about quality, I assume that employers do not factor in workers' productivity gains from experience when making

[14]The inelasticity of statically optimal bids with respect to the number of good reviews stems from the cross second-order derivative of the utility function being close to zero: $\frac{\partial^2 G}{\partial b \partial n^{\text{Good}}} = \frac{1}{\alpha_b} \times \frac{du}{dn^{\text{Good}}} \times \frac{G}{1-G}$, which is close to zero because the winning probability G is small. Under a more flexible utility specification—for example, one that directly interacts bid with the number of good reviews—statically optimal bids could be more elastic in the number of reviews.

hiring decisions. Each source on its own pushes workers to bid below what they would if they were myopic. Taken together, the results in Figure 5 underscore the importance of dynamic incentives in explaining the positive relationship between bids and reviews observed in the estimated bid policy functions.

I also examine how a job's minimum budget affects the interaction between the static and the forward-looking considerations. In Figure 6, I plot the dynamically optimal bid markups across jobs with different minimum budgets. Workers bid higher markups for jobs with larger minimum budgets. The intuition is straightforward: the dynamic incentives from receiving a review are constant across jobs, but the static payoff is larger for higher-budget jobs. As a result, static considerations weigh more heavily when the job is larger, leading workers to bid higher to capture the greater immediate earnings.

5.7 Counterfactual Computation and Model Fit

To evaluate model fit, I compute the status quo equilibrium and compare its features to the data. I adapt existing methods to accommodate the large state space.

Solving the model involves an outer loop and an inner loop. In the outer loop, I simulate 5,000 market days—enough for the system to reach a steady state. Each day, new workers enter; a fixed number of auctions are posted; workers decide whether to participate and submit bids according to the current bid policy functions; employers' taste shocks are realized and an employer either hires a bidder or selects the outside option; the chosen worker receives a review with some probability, with the realized rating drawn as a function of the worker's latent quality; reputation states are updated at day's end; and some workers exit. I take the last five days of simulated bidder sets—after randomly dropping one bidder from each set—as the steady-state distribution of competitors.

Table 7: Model Fit

	Data	**Simulation**
Avg No. Bidders	33	33
Median Bid	2.2	2.5

Notes: Table compares the status quo equilibrium of the estimated model with the data.

In the inner loop, following Sweeting (2012), I use policy iteration (Judd, 1998; Rust, 2000) to solve for optimal bid policies given the current competitor distribution. The algorithm alternates between (i) policy evaluation—computing value functions given bid policies—and (ii) policy improvement—updating bid policies given value functions. Because the state space—especially the reputation state (counts of good and bad reviews)—is large, I approximate both value and policy functions. I draw 1,000 (good, bad) review-count pairs from the data to form a grid, evaluate the value and bid-policy functions on these grid points, and interpolate elsewhere. For value functions, I use restricted cubic splines (cubic polynomials with four knots). For bid policies, I first regress bids on exchange rates, country fixed effects, and worker-type effects; I then regress the residuals on $\log n^{\text{Good}}$, $(\log n^{\text{Good}})^2$, $\log n^{\text{Bad}}$, $(\log n^{\text{Bad}})^2$, and $\log$ minimum budgets, allowing all coefficients to be worker-type specific. I iterate these two steps until bid policies converge, then advance the outer loop by simulating another 5,000 days using the updated policies. A solution is attained when bid policies change negligibly across successive outer loops—i.e., when they are optimal in the steady state induced by those policies.

Table 7 shows that the model fits the data well in terms of the average number of bidders per job and the median bid.[15]

I use the model to quantify the effects of workers' bids for reputation on employers' decisions and total surplus, first in partial equilibrium and then in full equilibrium.

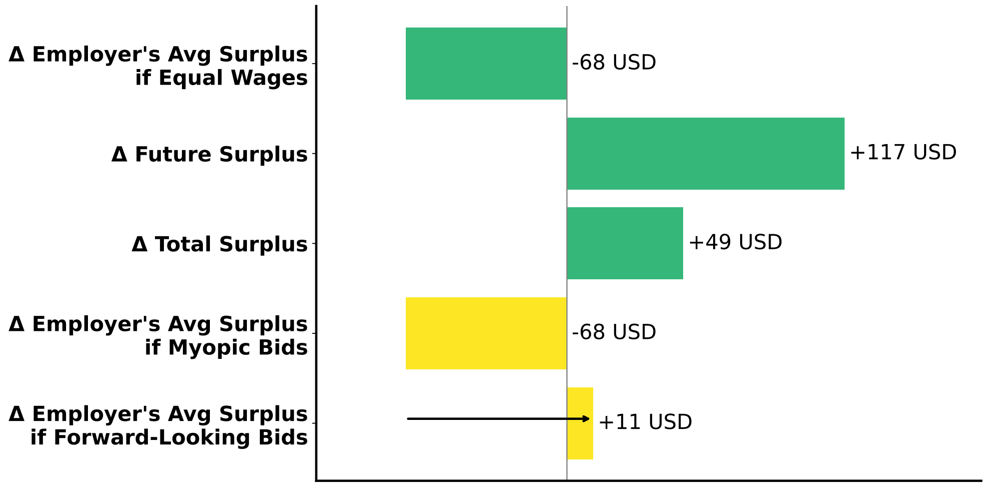
6 The Effect of Workers' Reputation and Human Capital Investment

I use the model to quantify the effects of workers' forward-looking bidding on market efficiency, first in an illustrative example and then in full equilibrium.

An Example I illustrate through an example that workers' forward-looking bidding can move employers' choices toward the social optimum. Consider an employer choosing between a worker with no reviews and one with ten good reviews, holding all else equal. As shown in Figure 7, if the two workers bid the same amount, the employer would, on average, prefer the worker with ten good reviews because of higher expected latent quality and human capital accumulation. With logit taste shocks, the choice is probabilistic; the expected utility advantage of the worker with ten good reviews is \$68, which is sizable relative to the average job payment of \$220. Because wages are transfers and the two workers have the same costs, this \$68 equals the difference in contemporaneous surplus. A social planner, however, would also account for future benefits—the informational and human capital gains from today's match—which are \$117 higher for hiring the new worker. Absent workers' wage responses, this \$117 wedge

[15] I also evaluate fit by comparing the average probability that a job is filled (as opposed to the employer choosing the outside option). Under my agreement with Freelancer, I cannot disclose the underlying empirical moment, but the model-generated value lies within 20% of that moment.

Figure 7: Hiring a Worker with 0 Reviews vs. a Worker with 10 Good Reviews



Notes: Figure presents (i) the difference in the present employer surplus, averaged over logit task shocks, between hiring a worker with 0 reviews versus one with 10 good reviews, ceteris paribus. Because the two workers have the same opportunity costs, this equals the difference in present total surplus (of the workers and employer); (ii) the difference in future surplus for all workers and employers generated by the employer's choice, due to the review and experience created by the job; (iii) the difference in total surplus, i.e. (i) + (ii); (iv) the difference in the present employer surplus under myopic bidding and; and (v) under forward-looking bidding Calculations are done for a type-2 worker from India (modal worker), a job with minimum budget \$100, and employer's utility is converted to USD assuming \$220 payment to winner.

separates the employer's private incentives from the social planner's.

How do workers' wage responses change the employers' decisions? I use the model to simulate the statically and dynamically optimal bids. The statically optimal bids are very similar across the two workers and thus do not change the employer's decision. Under forward-looking bidding, the new worker bids significantly lower, by \$79, which shifts the employer's choice toward hiring the new worker despite the lower expected productivity. Bid responses therefore push the decision toward the social optimum, though they do not fully eliminate the wedge.

Full Equilibrium While the partial-equilibrium analysis shows that forward-looking bids raise welfare within a given auction, this potentially understates the effect of workers' investments as it holds key market outcomes the same, including the number and composition of bidders. Motivated by this, I turn to full-equilibrium counterfactual analyses.

I conduct three counterfactual simulations and compare them to the status quo.

1. No reputation system: A counterfactual equilibrium without a public reputation and feedback mechanism. Employers do not observe reviews left by previous employers

or the number of jobs a worker has completed on the platform, and workers cannot credibly signal such information. Without a public reputation system, workers are no longer forward-looking.

2. Myopic workers: A counterfactual equilibrium with the same public reputation and feedback system as in the status quo, but where workers are myopic. They choose bids to maximize their immediate payoffs from current auctions only, ignoring the effects of reviews and accumulated experience on future outcomes.

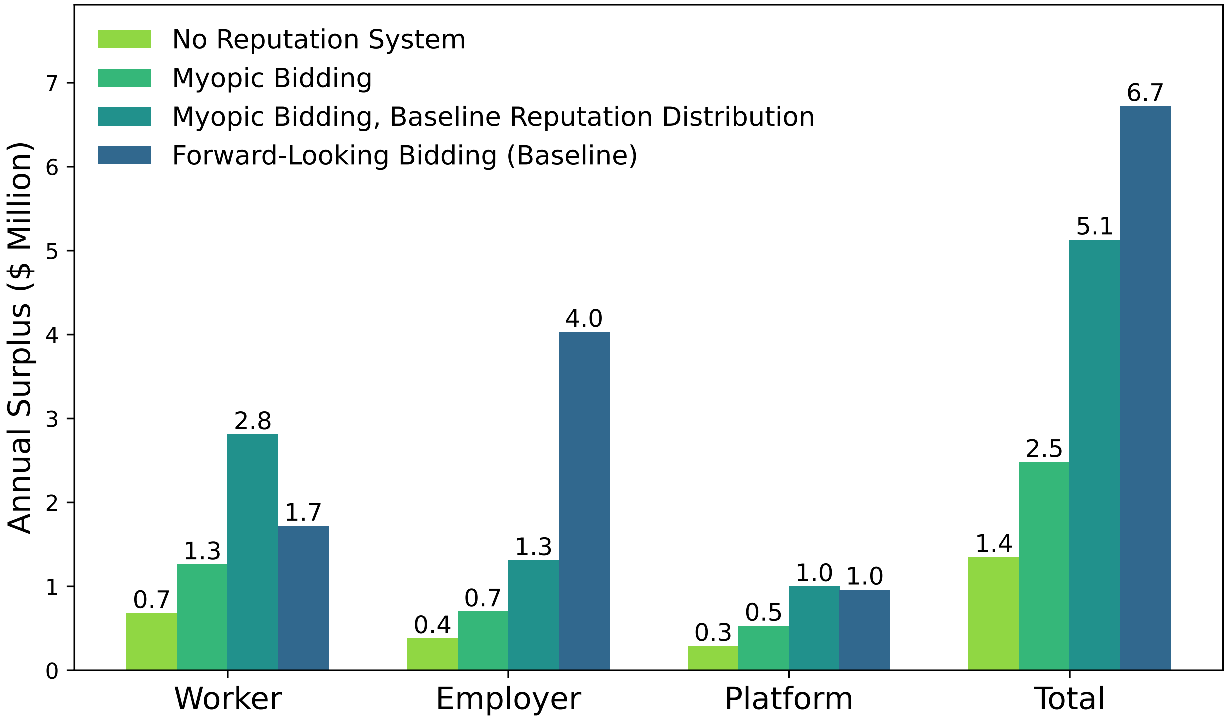
3. Myopic bids under status quo distribution: A counterfactual case where workers bid myopically, but the distribution of workers—including their reputation states—is held fixed at the status quo equilibrium, where workers are forward-looking.

Table 8: Counterfactual Results: Effects of Workers' Reputation Investment

	No Reviews	**Public Reviews**		
		Myopic	Myopic+Baseline Dist.	Baseline
Job Fill Rate / Baseline	12%	22%	38%	1
No. New Workers	1,079	1,099	414	414
No. Experienced Workers	1,347	1,327	2,012	2,012
No. New Worker Hired / Baseline	58%	56%	12%	1
Wage Bill ($m)	2.21	4.06	7.73	7.39
Employer Surplus ($m)	0.38	0.70	1.31	4.03
Worker Surplus ($m)	0.68	1.26	2.81	1.72
Platform Surplus ($m)	0.29	0.53	1.00	0.96
Total Surplus ($m)	1.35	2.48	5.13	6.72
Surplus Per Match / Baseline	1.7	1.7	2.0	1

Notes: Table reports results of simulations under four scenarios: (i) *No Reviews*: employers do not rate workers after matches, and workers cannot credibly signal their job history on the platform. Without the reputation system, workers also do not have dynamic incentives; (ii) *Myopic*: employers rate workers and ratings and experience are publicly observable, but when bidding workers ignore the impact of receiving a review and experience; (iii) *Myopic+Baseline Rep*: combine bid strategy in myopic equilibrium (ii) but the distribution of workers' reputation and experience in baseline equilibrium (iv); (iv) *Baseline*: workers bid to maximize lifetime payoffs, which is the status quo. Across all simulations, the daily number of posted jobs is fixed, and workers' market entry, exit, and auction-participation behavior is fixed. Job fill rate is the share of job posts for which an employer selects a bidder rather than the outside option. No. new workers and No. experienced workers denote, respectively, the average numbers of active workers who have never been hired and those who have been hired at least once. No. new worker hired is the daily average number of new workers hired. Wage bill and surplus are calculated at the annual level. All of the numbers are limited to the PHP skill category.

Figure 8: Effects of Workers' Reputation Investment

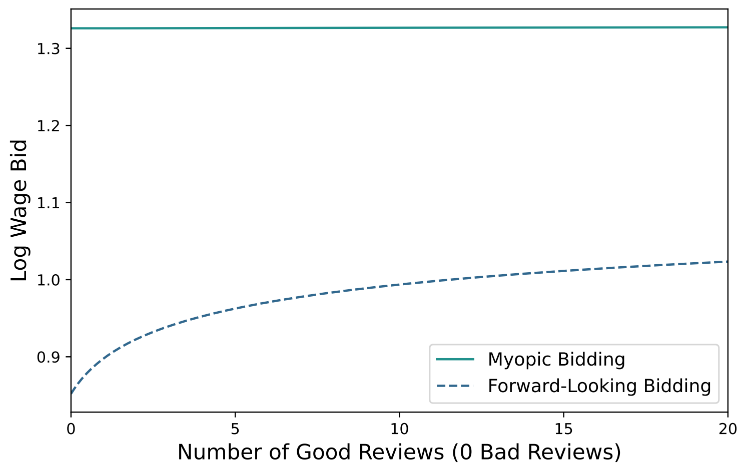


Notes: Figure displays results of simulations under four scenarios: (i) Employers do not rate workers after matches, and workers cannot credibly signal their job history on the platform. Without the reputation system, workers also do not have dynamic incentives; (ii) Employers rate workers and ratings and experience are publicly observable, but when bidding workers ignore the impact of receiving a review and experience; (iii) Combine bid strategy in myopic equilibrium (ii) but the distribution of workers' reputation and experience in baseline equilibrium (iv); (iv) Workers bid to maximize lifetime payoffs, which is the status quo.

The focus for these exercises is on changes in workers' bids. Therefore, for these simulations, I hold workers' market entry, market exit, and auction participation behavior the same as under status quo, as well as employers' job postings. Table 8 and Figure 8 summarize the results of these simulations.

Comparing equilibria in which workers set wage bids myopically (ii) versus dynamically (iv) shows that workers' investment generates large social gains. If workers did not invest, far fewer workers would accumulate reviews and experience. At a given point in time, the number of workers with at least one review would fall by 34%, limiting employers' options and increasing the likelihood that vacancies remain unfilled. This is further illustrated in Figure 10, which plots the distribution of expected latent quality for a given type of workers (type 1, the most common type) in these two equilibria. Because more workers are reviewed, the distribution is significantly wider in the baseline equilibrium compared to the myopic equilibrium. The information from reviews helps employers differentiate higher-quality workers from lower-quality ones.

Figure 9: Bid Policy in Myopic vs. Baseline Equilibrium



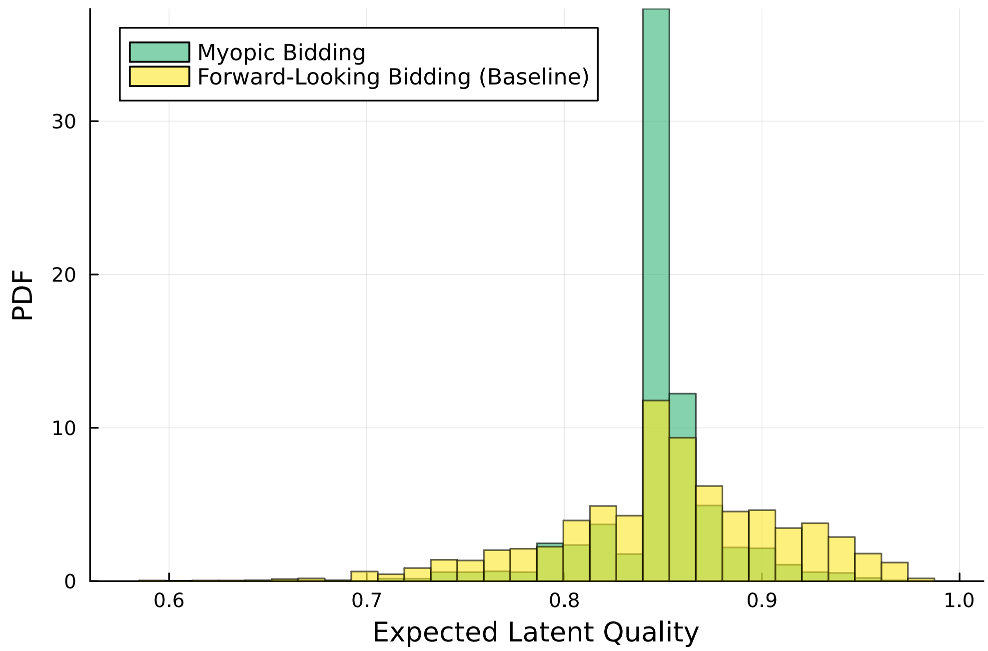
Notes: Figure displays the equilibrium bid policy for type 2 Indian workers in the equilibrium where workers bid to maximize current payoffs vs. in the equilibrium where workers bid accounting for the effect of reviews and experience on their future payoffs.

Although there are more new workers in the equilibrium without worker investments, these new workers bid similarly to the experienced workers (Figure 9), giving employers little incentive to take a risk on new workers. The flat wage bids weaken the market's ability to screen and promote new talent.

Absent investment, the market's job fill rate—the probability that employers choose one of the bidders instead of the outside option—falls to 22% of the status-quo level, and total annual surplus in the PHP skill category for the workers, employers, and the platform combined declines by 63% (from $6.7 to $2.5 million). While workers' investment creates surplus gains for workers, the largest gain notably accrues to the employers and a significant share to the platform.

To decompose the equilibrium impact of workers' investment, I consider the counterfactual case where the distribution of workers is the same as in status quo, but workers bid myopically (iii). This intermediate case can help separate the two channels through which workers' forward-looking incentives matter: (a) the investment changes the equilibrium distribution of worker reputation and experience; (b) investment incentives lower wages, which can result in increased hiring. Figure 8 shows that both channels matter. Keeping workers' bids at the myopically optimal levels and improving the distribution of worker reputation and experience to the status quo level (moving from (ii) to (iii)) achieves 62% of total surplus gains from forward-looking bidding. Holding the worker distribution at the status quo level, going from

Figure 10: Reputation Investment Increases Revealed Information



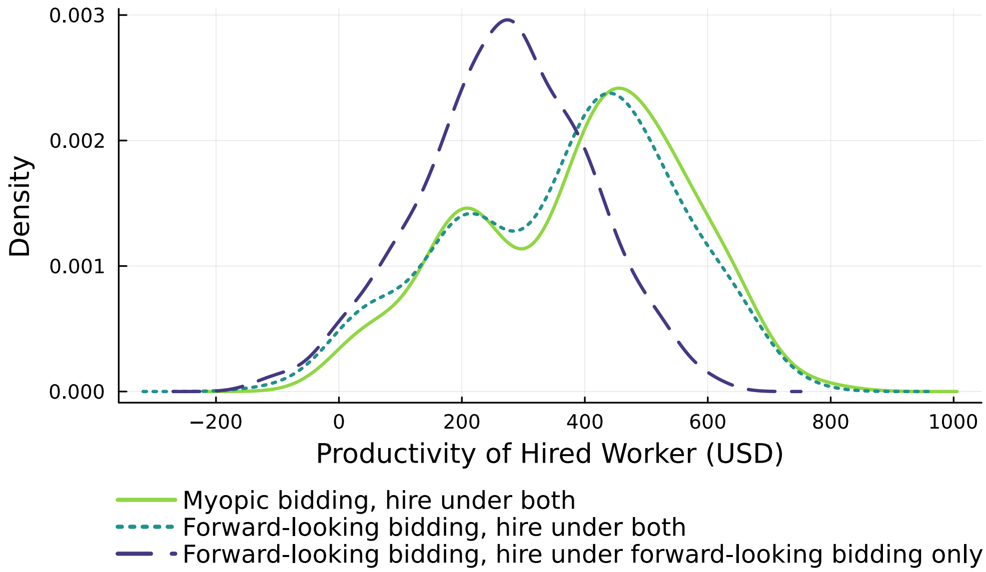
Notes: Figure displays the distribution of expected latent quality for active type 1 workers in the equilibrium where workers bid to maximize current payoffs vs. in the equilibrium where workers bid accounting for the effect of reviews and experience on their future payoffs.

myopic to forward-looking bidding further increases total surplus.

Given a fixed distribution of workers, moving from myopic to forward-looking bidding changes not only how many jobs are filled but also which workers are hired. Figure 11 plots the distribution of hired workers' productivity in USD, measured as the non-bid component of employers' utility normalized by the outside option. Among auctions in which the employer hires under both myopic and forward-looking bidding, the productivity distribution shifts to the right under myopic bidding. This illustrates one channel through which workers' reputation investment can lower total surplus: it reallocates hiring from high- to lower-quality matches—a manifestation of business stealing. However, forward-looking bidding also increases the number of matches, as lower wage bids induce employers to choose the inside option more often. The productivity distribution of hired workers in these new matches enabled by workers' investment is even lower on average.

While the reputation and feedback system have been viewed as instrumental for fostering trust in online marketplaces such as eBay (see Tadelis (2016) for a review and Reimers and Waldfogel (2021) for quantification), I further show that much of their effectiveness hinges on sellers' and workers' investments in reputation. Comparing the counterfactual equilibrium

Figure 11: Workers' Investment and Match Productivity



Notes: Figure displays the distribution of hired workers' match productivity—measured as the non-bid component of employers' utility normalized by the outside option—in simulations where the distribution of worker reputation and experience is held fixed at the status quo level. Workers are either myopic, maximizing payoffs from current auctions only, or forward-looking, accounting for the effects of reputation and experience on future payoffs. The figure distinguishes between (i) auctions in which employers hire a worker under both bidding schemes, and (ii) auctions in which employers hire only under forward-looking bidding.

without a reputation system (i), I show that 79% of the surplus gains attributable to the reputation system vanish in the absence of workers' investments. The intuition is straightforward: although the system enables employers to learn from each other, without workers' investments employers have weak incentives to take a chance on new workers, so little information or human capital is produced (as a result of little hiring). A reputation system is necessary but not sufficient; it must be complemented by workers' investment in reputation and, potentially, platform-provided incentives that I study next.

7 Platform Design to Improve Worker Screening and Training

In this section, I simulate counterfactual equilibria to evaluate the effect of alternative market design, including platform-funded subsidies for hiring new workers and a market-wide certification program.

The platform is a natural candidate to implement policies that could raise total surplus, but its incentives are not perfectly aligned with the social planner's. Workers' forward-looking wage bids partially internalize the information and human-capital gains generated by matches, but a gap remains: benefits that accrue to the worker's future employers are not internalized by either party to today's match. Because the platform earns a 13% commission on each transaction, it internalizes some of the dynamic effects through changes in future transaction volume and may therefore have incentives to implement policies that increase total surplus. However, the platform's objective (commission revenue net of any subsidy costs) generally differs from social surplus (the sum of worker, employer, and platform surplus), so its preferred policy need not be socially optimal.

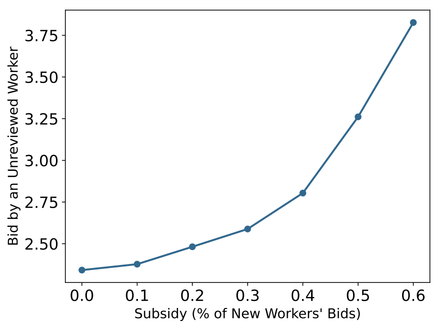
I begin by studying the design of a platform-subsidized employer discount for hiring workers with no reviews. The subsidy is a discount off the worker's posted bid: under a 20% subsidy, the employer pays 80% of the bid and the platform covers the remainder. The policy compensates employers for the risk of hiring an unreviewed worker while generating information and human-capital that benefit future matches.[16] While such a subsidy can be welfare-improving, choosing its magnitude is ultimately a quantitative question. I simulate counterfactual equilibria across subsidy rates and report effects on match rates; employer, worker, and platform surplus (commission revenue net of subsidy outlays); and total surplus. Table 9 summarizes the results, and Figure 12 visualizes the key patterns.

Workers adjust their wage bids in response to the subsidy, so optimal policy design must account for these equilibrium responses. Figure 12a plots new workers' equilibrium bids—specifically, type-2 workers from India in an average auction—across alternative subsidy rates. Higher subsidies induce higher bids, partially offsetting the intended reduction in new workers' wage bids. Ignoring these bid adjustments would bias estimated subsidy effects on wages, match rates, and surplus.

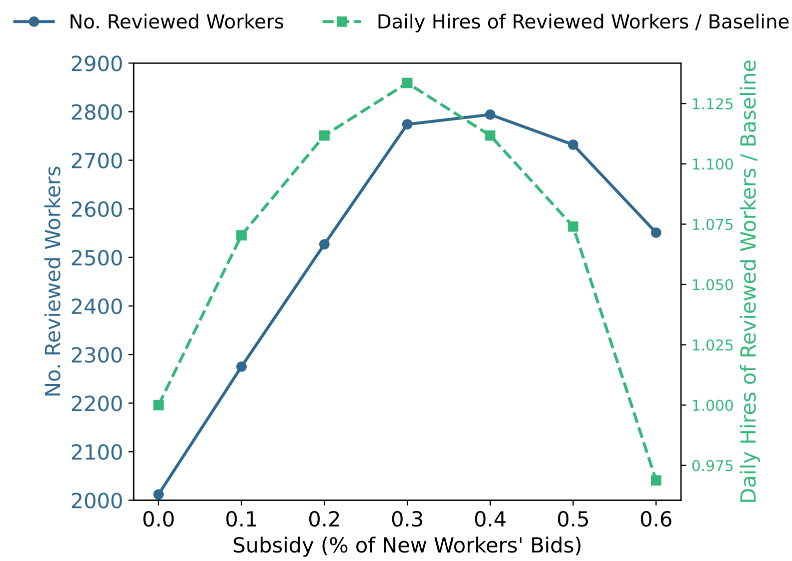
As Table 9 shows, the platform benefits—via higher commission revenue—across a range of subsidy levels. Subsidies between 10% and 30% yield a net positive return. Under these subsidy levels, the induced increase in transaction volume raises commission revenue by more than the platform's out-of-pocket subsidy expenditures. From the platform's perspective, the optimal new-worker discount is 20% off new workers' bids, which raises net platform surplus (commission revenue minus subsidy expenditures) by about $79,000 in the PHP skill category—an increase of 8%. Appendix Table A2 reports, for each subsidy expenditure, the subsidy outlay, the

[16] The platform subsidy mirrors government hiring/training subsidies for young workers. In the U.S., the Workforce Innovation and Opportunity Act reimburses employers up to 50% of the trainee's wage "for the extraordinary costs of providing the training and supervision related to the training." France provides up to €6,000 to employers for taking on apprentices and young workers.

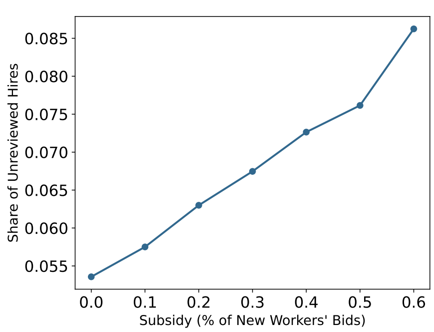
Figure 12: Equilibrium Effects of Platform-Funded Subsidy for Hiring Unreviewed Workers



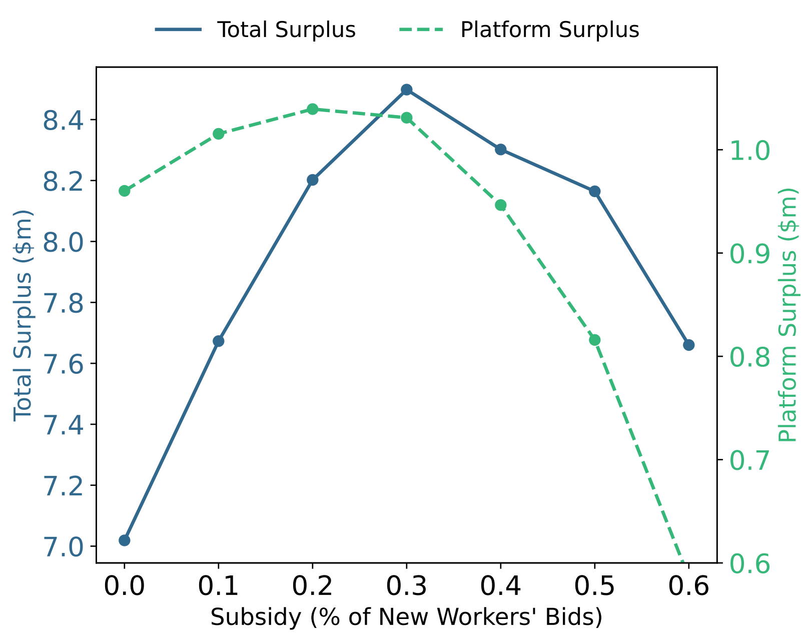
(a) Unreviewed Workers' Bids



(b) Number and Hires of Reviewed Workers



(c) Share of Unreviewed Hires



(d) Surplus: Platform vs. Total

Notes: Figures plot estimated employers' and workers' annual surplus, total annual surplus (workers, employers, and the platform), number of reviewed workers (on a given day), and the bid by type-2 Indian workers with no reviews on an average auction—under different levels of subsidies for hiring new workers.

Table 9: Market Design Counterfactual Summary

	Δ **Surplus** (1,000$)			
Counterfactual	Worker	Employer	Platform	Total
Subsidy: 10%	199	400	55	654 (+9.7%)
Subsidy: 20%	409	695	79	1,183 (+17.6%)
Subsidy: 30%	562	847	71	1,479 (+22.0%)
Subsidy: 40%	553	744	-14	1,283 (+19.1%)
Subsidy: 50%	754	536	-144	1,146 (+17.1%)
Subsidy: 60%	1,076	-61	-374	641 (+9.5%)
Verification	1,222	514	309	2,044 (30.4%)

Notes: Table reports estimated annual changes in surplus for employers, workers, the platform, and all three parties combined under alternative policies, for the PHP skill category. "Subsidy: 10%" denotes a 10 percent discount on unreviewed workers' wage bids. Verification refers to granting every new entrant a first review and experience without requiring an employer hire. The platform's surplus change equals the sum of (i) subsidy expenditures—zero under the verification policy—and (ii) the change in platform 10% commissions from the wage bill.

resulting change in commission revenue, and the net effect (commission change minus subsidy).

The socially optimal platform-subsidized discount is 30% off new workers' bids. At this rate, annual total surplus in the PHP category rises by roughly $1,479,000—an 22.0% increase relative to the status quo. Approximately 57% of the gain accrues to employers, 38% to workers, and 5% to the platform.

The socially optimal subsidy exceeds the platform's preferred level. Figure 12d shows that platform surplus peaks at a lower subsidy. The misalignment is because the platform internalizes subsidy costs, whereas the social planner treats the subsidy as a transfer. Moreover, the platform internalizes only a portion of the benefits from the subsidy. Even so, the platform-preferred subsidy raises total surplus by 17.6%, capturing about 80% of the welfare gains under the socially optimal subsidy.

Figures 12b and 12c illustrate the exploration–exploitation trade-off in subsidy design. As the subsidy rate rises, employers become more likely to hire unreviewed workers, conditional on hiring at all. This shift indicates that the subsidy encourages employers to explore new workers. At moderate levels, such exploration increases the number of matches and raises total surplus.

At higher subsidy levels, however, excessive exploration can reduce overall efficiency as the market over-allocates hiring toward uncertain workers. The number of reviewed workers hired per day, as well as the total stock of reviewed workers active in the market, both exhibit a hump-shaped pattern. The initial increase reflects greater inflows—more new workers obtain their first reviews. The subsequent decline arises from reduced exploitation of existing information and human capital. This reduction operates along two margins. At the intensive margin, conditional on hiring, employers hire reviewed workers less often. At the extensive margin, reviewed workers exit more frequently, as they are less likely to win jobs.

Together, these forces generate an internal optimum in welfare, where the benefits of exploration are balanced against the costs of diminished exploitation.

I also study the effect of a skill certification program. The certification applies to all new workers, and reveals information that is equivalent to one review from an employer. In other words, the skill certification program grants all new workers a first review without having to win a job. The certification program brings large benefits to the platform, increasing total surplus by 2,044,000, or 30.4% of the status quo surplus. The platform experiences a $309,000 increase in revenue. Given the estimated entry rate of 9 new workers per day, this is a revenue increase of $94 per new worker. Although it is difficult to directly evaluate the costs of such certification, if we imagine that it will take a software engineer half an hour to review a worker, the benefit $94 exceeds the average half-hourly pay of software engineers in Australia of $23 according to Indeed.com, indicating that the certification will be profitable for the platform.

I compare the effect of the platform's preferred new worker subsidy to that of the skill certification. The platform's preferred subsidy achieves 58% of the surplus gains from a platform-wide skill certification program. Interestingly, the two design choices have different incidence implications. The subsidy benefits the employers more while the certification benefits the workers more. This is consistent with the subsidy being a direct discount of the employers' out-of-pocket pay, while the certification creates more differentiation among workers, allowing workers to bid a higher wage.

8 Conclusion

When an employer takes a chance on a new worker, she learns about the worker's quality and shares that information through a public review. The experience also raises the worker's human capital. In this way, the employer's choice today shapes the future of the market. The freelancing nature of the market means that these effects by and large accrue to the workers and the other employers, and are therefore externalities to the employer making the hiring decision today. This could lead to socially inefficient experimentation with new workers.

Workers partially counteract this by investing in reputation. Forward-looking workers bid lower when they have little reputation or experience, generating systematic bid differences by reputation. Relative to a counterfactual with myopic workers, these investments raise the equilibrium number of reviewed workers by 50%, improving employers' choice sets and increasing total surplus. The resulting spillovers benefit both employers and the platform.

Yet because workers do not capture the full informational and human capital gains they create, investment likely remains below the social optimum. A simple platform policy—subsidizing hires of unreviewed workers—can help close the gap: a 20% subsidy is profitable for the platform and raises total surplus by 17.6%, delivering 58% of the surplus gains achieved by platform-wide skill certification.

Although the evidence comes from one online labor platform, the mechanisms are broader. Introductory pricing and other reputation-building investments—new restaurants pricing below cost, startups operating at a loss, students taking unpaid internships—generate surplus for future buyers and employers as well as for the investors themselves. Because these investments create market-wide benefits, institutions can play a productive role: governments can subsidize early on-the-job training, and marketplaces can spotlight new products to accelerate discovery.[17]

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[17] One such government policy in place is On-the-Job Training, a U.S. federal program funded by the Workforce Innovation and Opportunity Act (WIOA) that reimburses employers for training skilled workers). In the realm of marketplaces, an example is Steam, a distributor of video games, lets users play new games for free.

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A Data and Descriptive Evidence

Table A1: Determinants of Winning and Bid Amount

	(1) Winning: OLS	(2) Bid (log)	(3) Winning: IV
Bid (log)	-0.87***		-5.48***
	(0.01)		(0.91)
No. of good reviews (log)	0.53***	0.0509***	0.77***
	(0.008)	(0.000467)	(0.05)
No. of bad reviews (log)	-0.42***	0.00576***	-0.40***
	(0.01)	(0.000604)	(0.01)
Min. budget (log)	-0.65***	-0.260***	-1.84***
	(0.005)	(0.000244)	(0.24)
Exchange rate (log)		0.242***	
		(0.0126)	
Observations	2,738,310	2,738,310	2,738,310
Worker FE	No	No	No
Worker Country FE	Yes	Yes	Yes

Notes: The coefficients and standard error estimates in Columns (1) and (3) are normalized by the sample mean winning probability. The dependent variable in Column (2) is bids in USD normalized by the job's minimum budget and then taken log. Exchange rate is the log of the price of one USD in the worker's local currency, demeaned at the country level. In Column (3), exchange rate is used to instrument for bid.

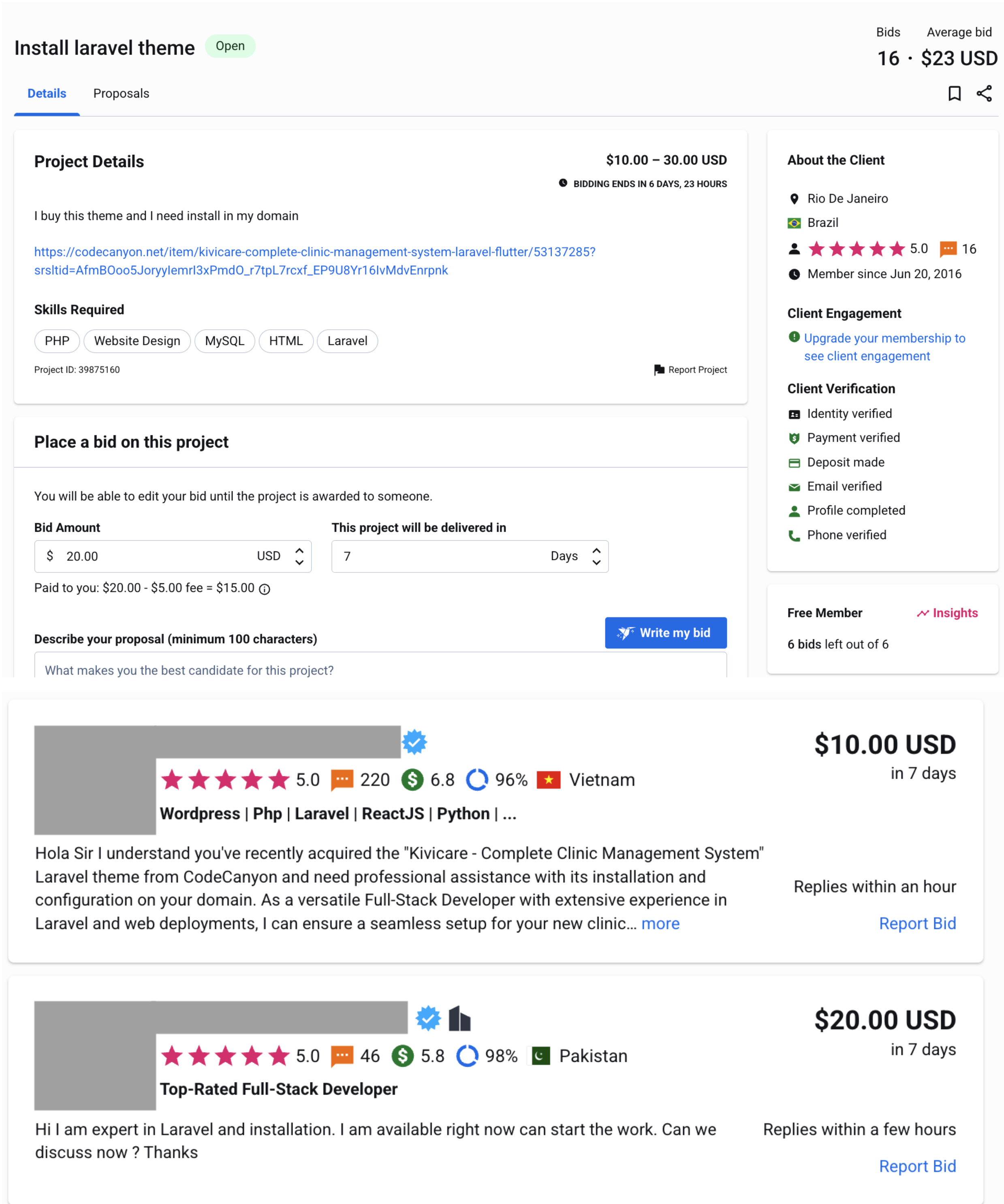
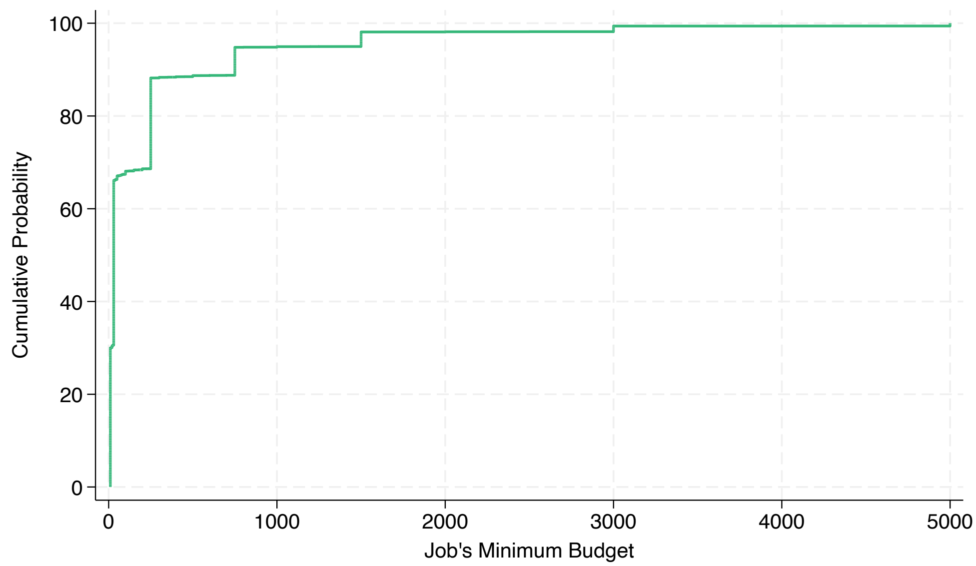


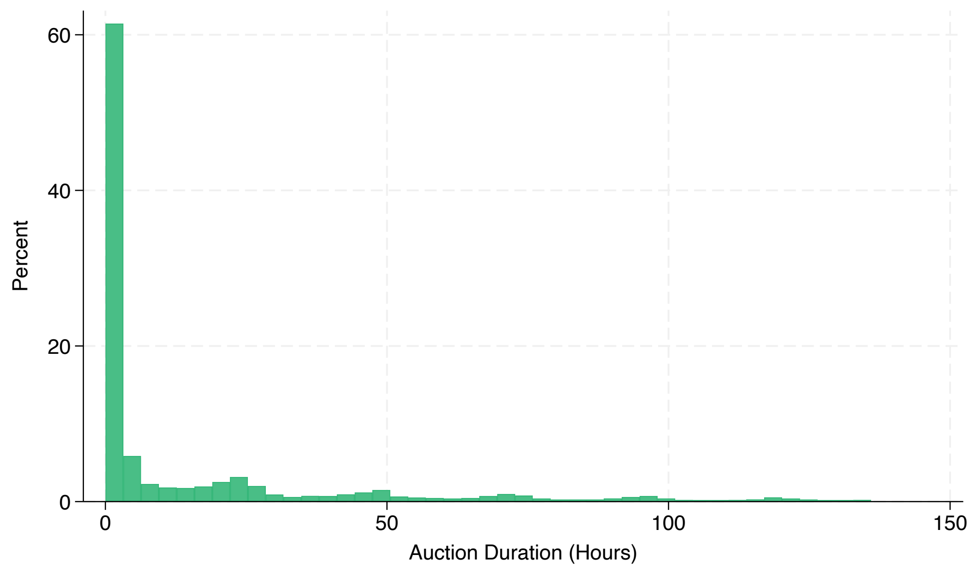
Figure A1: Screenshot of a Job Auction and Selected Bids on Freelancer.com

Figure A1: Cumulative Density Function of Minimum Budget



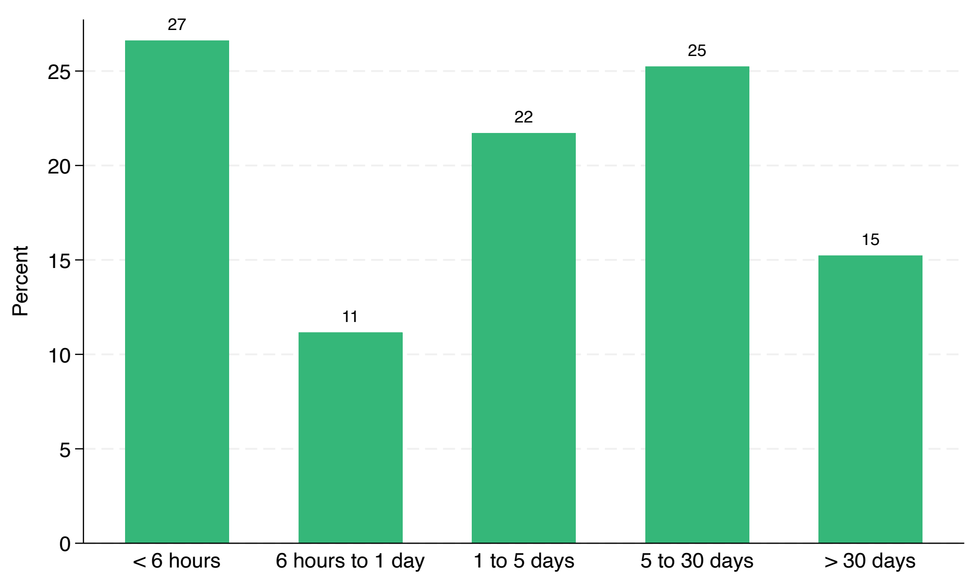
Notes: Employers are required to set a minimum budget, which is the lowest amount that workers may bid. Minimum budgets are denominated in U.S. dollars. Bunching occurs at values corresponding to the platform's drop-down menu options, although employers are free to customize the minimum budget so long as it is at least $10.

Figure A2: Distribution of Auction's Duration



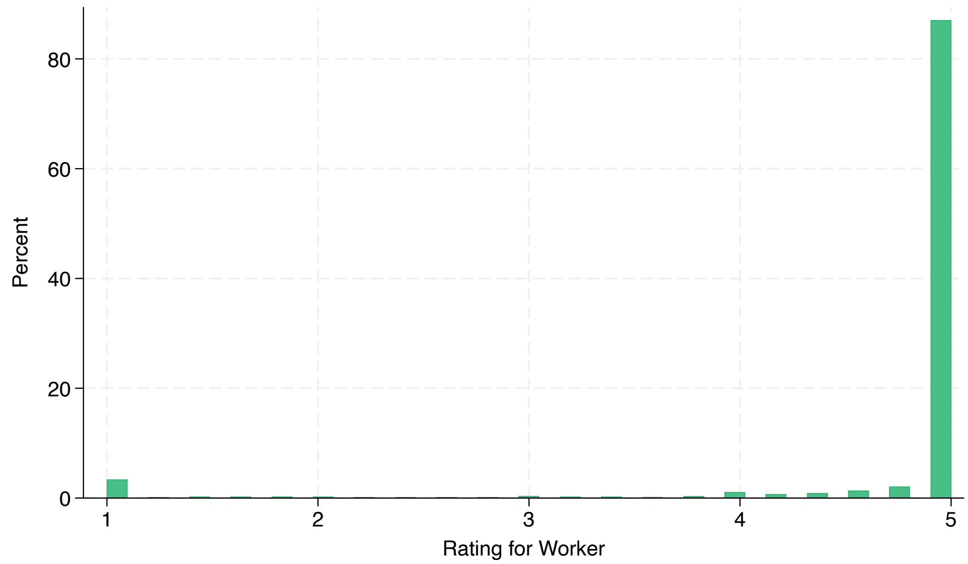
Notes: Auction duration is defined as the time between when the job is posted and when the job is awarded, and is therefore only defined for job auctions that are awarded. Auctions that lasted for over 136 hours (90th percentile) or less than 0 hour (3 observations) are excluded.

Figure A3: Distribution of Jobs' Duration



Notes: A job's duration is computed as the time between when the worker accepts the job and when the employer marks the project as complete.

Figure A4: Distribution of Workers' Ratings



Notes: Employers are asked to give workers one to five stars on five dimensions: work quality, communication, expertise, professionalism, and whether they would hire the worker again. The rating presented here, and displayed on the worker's profile, is the average across these five dimensions.

A.1 Data

I provide a list of variables.

- x_t: the job's minimum budget. Employers are required to specify a minimum budget when posting a job. Workers have to bid at or above the minimum budget.
- b_{it}: normalized bid. Workers' bids divided by the minimum budget, so they fall in $[1,\infty)$.
- $n_{it} = (n_{it}^{\text{Good}}, n_{it}^{\text{Bad}})$: worker's reputation state, which includes the number of good (five-star) reviews and the number of bad (less than five-star) reviews.

B Estimation

B.1 Estimation of Other Parameters

In this section, I discuss the estimation of daily auction arrival rates, workers' auction participation probabilities, daily platform entry and exit rates, and the probability of receiving a review conditional on being awarded a job.

Auction arrival rate The daily auction arrival rate is estimated to be 390, equal to the average number of auctions posted per day in the sample.

Auction participation probabilities I use an auxiliary data set to estimate a worker's average daily auction participation, allowing this measure to vary with the worker's total number of reviews. The auxiliary data set contains all bids submitted by a random sample of workers—across all skill areas, not limited to PHP—who registered in the second half of 2018 up till data extraction in 2024. In total, the data set covers over 5 million bids submitted by 8,973 workers. I discretize workers' review counts at the time of bid submission into five bins of approximately equal size (0–2, 3–8, 9–21, 22–62, and 63 or more reviews) and estimate average auction participation rate separately for each experience level. I then estimate parameters of an auction participation function $a(n) = a_1 + a_2 \times \log(n^{\text{Good}} + n^{\text{Bad}} + 1)$ based on the data moments. The estimated auction participation probability function is $a(n) = \min(9.1, 1.27 + 1.84 \times \log(n^{\text{Good}} + n^{\text{Bad}} + 1))/390$.

Market entry and exit rates The market entry rate is defined as the mean of a Poisson distribution governing the number of new entrants each day. Market exit rates are defined as the probability that a worker exits the market on a given day, which I allow to vary with the worker's number of reviews. I parameterize the exit rate as $\delta(n) = (e_1 + e_2 \times \log(n^{\text{Good}} + n^{\text{Bad}} + 1))^{-1}$. Given the auction participation probabilities, I estimate the market entry and exit rates by matching two sets of moments: (i) the average number of bids submitted by workers in each of the five experience levels at a typical auction (estimated from the main data set as 10.10, 2.14, 3.49, 5.71, and 11.52) and (ii) the average total number of lifetime bids submitted by workers (estimated from the auxiliary data set as 596).

Probability of review upon winning Because reviews are not mandatory, workers who are awarded a job are not always reviewed by employers. Using the main data set, I estimate the probability of receiving a review to be 61%.

B.2 First Stage Likelihood

Each worker belongs to one of K types: $k_i \in \{1, \ldots, K\}$. Let π_k denote the probability that a worker is of type k. Let $\vec{k}$ denote the vector of type assignments for all N workers. The parameter vector θ comprises the parameters of type distribution and the parameters governing the endogenous outcomes—workers' bids, employers' choices, and employers' reviews of workers.

The observed data is

$$\left\{\left(d_t,\, x_t,\, \{b_{lt},\, z_{lt},\, n_{lt},\, o_l\}_{l\in B_t},\, i_t^*,\, r_{i_t^*}\right)\right\}_t.$$

Here, t denotes an auction. d_t is the vector of participation indicators $d_{lt}\in\{0,1\}$ for all N workers in auction t. B_t is the set of IDs of workers who participated in auction t; b_{lt} is the bid, z_{lt} the exchange rate, n_{lt} the reputation state, and o_l the country of worker l in the bidder set B_t. Finally, the outcomes of the auction are the winner $i_t^*\in B_t\cup\{0\}$, where $\{0\}$ denotes the outside option, and $r_{i_t^*}$, indicating whether the winner received a good or bad review from this auction.

The observed data likelihood integrates over $\vec{k}$:

$$\begin{aligned}
L=&\sum_{\vec{k}}\left[f(\vec{k})P\left(\left\{\left(d_t,\, x_t,\, \{b_{lt},\, z_{lt},\, n_{lt},\, o_l\}_{l\in B_t},\, i_t^*,\, r_{i_t^*}\right)\right\}_t\middle|\,\theta,\, \vec{k}\right)\right]\\
=&\sum_{\vec{k}}\left[f(\vec{k})\prod_t\left[P\left(d_t,\, x_t,\, \{b_{lt},\, z_{lt},\, n_{lt},\, o_l\}_{l\in B_t},\, i_t^*,\, r_{i_t^*}\middle|\,\theta,\, \vec{k},\, \left\{\left(d_\tau,\, x_\tau,\, \{b_{l\tau},\, z_{l\tau},\, n_{l\tau},\, o_l\}_{l\in B_\tau},\, i_\tau^*,\, r_{i_\tau^*}\right)\right\}_{\tau<t}\right)\right]\right]
\end{aligned}$$

The second equality follows from the chain rule. I now focus on the contribution to the likelihood from period t, given the type assignment $\vec{k}$

$$\begin{aligned}
L_1:=&\, P\left(d_t,\, x_t,\, \{b_{lt},\, z_{lt},\, n_{lt},\, o_l\}_{l\in B_t},\, i_t^*,\, r_{i_t^*}\middle|\,\theta,\, \vec{k},\, \left\{\left(d_\tau,\, x_\tau,\, \{b_{l\tau},\, z_{l\tau},\, n_{l\tau},\, o_l\}_{l\in B_\tau},\, i_\tau^*,\, r_{i_\tau^*}\right)\right\}_{\tau<t}\right)\\
=&\, P\left(\{b_{lt}\}_{l\in B_t},\, i_t^*,\, r_{i_t^*}\middle|\,\theta,\, \vec{k},\, \left\{\left(d_\tau,\, x_\tau,\, \{b_{l\tau},\, z_{l\tau},\, n_{l\tau},\, o_l\}_{l\in B_\tau},\, i_\tau^*,\, r_{i_\tau^*}\right)\right\}_{\tau<t},\, d_t,\, x_t,\, \{z_{lt},\, n_{lt},\, o_l\}_{l\in B_t}\right)\\
&\times P\left(d_t,\, x_t,\, \{z_{lt},\, n_{lt},\, o_l\}_{l\in B_t}\middle|\,\theta,\, \vec{k},\, \left\{\left(d_\tau,\, x_\tau,\, \{b_{l\tau},\, z_{l\tau},\, n_{l\tau},\, o_l\}_{l\in B_\tau},\, i_\tau^*,\, r_{i_\tau^*}\right)\right\}_{\tau<t}\right)\\
=&\, P\left(\{b_{lt}\}_{l\in B_t},\, i_t^*,\, r_{i_t^*}\middle|\,\theta,\, \vec{k},\, d_t,\, x_t,\, \{z_{lt},\, n_{lt},\, o_l\}_{l\in B_t}\right)\times P\left(\{n_{lt}\}_{l\in B_t}\middle|\,\theta,\, \vec{k},\, \left\{\left(\{n_{l\tau}\}_{l\in B_\tau},\, i_\tau^*,\, r_{i_\tau^*}\right)\right\}_{\tau<t}\right)\times C\\
=&\, P\left(\{b_{lt}\}_{l\in B_t}\middle|\,\theta,\, \vec{k},\, d_t,\, x_t,\, \{z_{lt},\, n_{lt},\, o_l\}_{l\in B_t}\right)\times P\left(i_t^*\middle|\,\theta,\, \vec{k},\, d_t,\, x_t,\, \{b_{lt},\, z_{lt},\, n_{lt},\, o_l\}_{l\in B_t}\right)\\
&\times P\left(r_{i_t^*}\middle|\,\theta,\, \vec{k},\, d_t,\, x_t,\, \{b_{lt},\, z_{lt},\, n_{lt},\, o_l\}_{l\in B_t},\, i_t^*\right)\times\prod_i P\left(n_{it}\middle|\,\theta,\, k_i,\, \left\{\left(n_{i\tau},\, i_\tau^*,\, r_{i_\tau^*}\right)\right\}_{\tau<t}\right)\times C\\
=&\left[\prod_{l\in B_t}P\left(b_{lt}\middle|\,\theta,\, k_l,\, x_t,\, z_{lt},\, n_{lt},\, o_l\right)\right]\times P\left(i_t^*\middle|\,\theta,\, x_t,\, d_t,\, \{k_l,\, b_{lt},\, z_{lt},\, n_{lt},\, o_l\}_{l\in B_t}\right)\\
&\times P\left(r_{i_t^*}\middle|\,\theta,\, k_{i_t^*},\, n_{i_t^*t}\right)\times\prod_i P\left(n_{it}\middle|\,\theta,\, k_i,\, \left\{\left(n_{i\tau},\, i_\tau^*,\, r_{i_\tau^*}\right)\right\}_{\tau<t}\right)\times C
\end{aligned}$$

The first equality follows from the chain rule. In the second equality, the first component follows from the model's Markov assumption: conditional on type assignments, workers' reputation states are sufficient statistics for how the present depends on the past. The second component follows from the model's assumption that minimum budget x_t, exchange rates

z_{lt}, workers' auction participation decisions d_t, and workers' countries o_l are exogenously determined and thus absorbed into the constant C at the end.

In the third equality, the first three components follow from the chain rule, while the fourth component follows from the assumption that workers' states are conditionally independent across workers and depend only on (i) their own unobserved type, (ii) their own past reputation states, and (iii) wins and reviews from past auctions in which they participated. The current reputation state n_{lt} is not a deterministic function of $\{(n_{i\tau}, i^*_\tau, r_{i^*_\tau})\}_{\tau<t}$ because the data covers auctions for PHP jobs, and workers may have gained reputation from auctions in other skill categories. The key assumption is that the probability of obtaining reputation from other skill areas is independent of workers' unobserved types. Therefore, the only part of this likelihood that depends on workers' unobserved types is workers' initial reputation states during their first bid submission. Formally,

$$P\left(n_{it}\middle|\, \theta, k_i, \left\{\left(n_{i\tau}, i^*_\tau, r_{i^*_\tau}\right)\right\}_{\tau<t}\right) = \begin{cases} C & \text{if } \exists \tau < t \text{ s.t. } i \in B_\tau \\ P(n_{it}|\theta, k_i) & \text{otherwise.} \end{cases} \tag{14}$$

To simplify notation, in what follows I define a worker's reputation state during the first auction of the sample as her reputation during the first bid I observe her submit $n_{i1} := n_{it}, \nexists\, \tau < t$ s.t. $i \in B_\tau$. Therefore the contribution of the terms in Equation 14 to the total likelihood is $C \prod_i P(n_{i1}|\theta, k_i)$.

In the fourth equality, the first term follows from the model's assumption that a worker's bid is independent of other workers' types or states and that bids are uncorrelated conditional on the auction's minimum budget and the worker's country exchange rate. The second term reflects that the probability of the winner winning depends only on the characteristics of other auction participants, not on non-participants. The third term follows from the model's specification that the probability a review is good equals the posterior mean of the worker's latent quality, which depends only on the worker's own type and past reviews. The other terms remain unchanged.

Let $d_t^{-i^*_t}$ denote the vector of participation decisions in auction t for all workers other than the winner i^*_t. If the employer selects the outside option, then $d_t^{-i^*_t} = d_t$. I take expectation of L_1 with respect to $d_t^{-i^*_t}$. This expectation affects only one component of L_1, the probability that the winner wins.

$$\mathbb{E}_{d_t^{-i_t^*}}[L_1|d_t^{-i_t^*}] = \left[\prod_{l\in B_t} P\Big(b_{lt}\Big|\,\theta,k_l,x_t,z_{lt},n_{lt},o_l\Big)\right] \times P\Big(r_{i_t^*}\Big|\,\theta,k_{i_t^*}\Big) \times \prod_i P\Big(n_{i1}\Big|\,\theta,\,k_i,\,\big\{\big(n_{i\tau},\,i_\tau^*,\,r_{i_\tau^*}\big)\big\}_{\tau<t}\Big)$$
$$\times \mathbb{E}_{d_t^{-i_t^*}}\left[P\Big(i_t^*\Big|\,\theta,\,x_t,\,\{k_l,\,b_{lt},\,z_{lt},\,n_{lt},\,o_l\}_{l\in B_t}\Big)\right] \times C$$
$$= \left[\prod_{l\in B_t} P\Big(b_{lt}\Big|\,\theta,\,k_l,\,x_t,\,z_{lt},\,n_{lt},\,o_l\Big)\right] \times P\Big(r_{i_t^*}\Big|\,\theta,k_{i_t^*}\Big) \times \prod_i P\Big(n_{it}\Big|\,\theta,\,k_i,\,\big\{\big(n_{i\tau},\,i_\tau^*,\,r_{i_\tau^*}\big)\big\}_{\tau<t}\Big)$$
$$\times \mathbb{E}_{d_t^{-i_t^*}}\left[P\Big(i_t^*\Big|\,\theta,x_t,k_{i_t^*},b_{i_t^*t},z_{i_t^*t},n_{i_t^*t},o_{i_t^*t},\{k_l,b_{lt},z_{lt},n_{lt},o_l\}_{d_{lt}=1,\;l\neq i_t^*}\Big)\right] \times C \tag{15}$$

To simplify notation, let

$$\mathbb{E}_{d_t^{-i_t^*}}\left[P\Big(i_t^*\Big|\,\theta,x_t,k_{i_t^*},b_{i_t^*t},z_{i_t^*t},n_{i_t^*t},o_{i_t^*t},d_t^{-i_t^*}\Big)\right] := \mathbb{E}_{d_t^{-i_t^*}}\left[P\Big(i_t^*\Big|\,\theta,x_t,k_{i_t^*},b_{i_t^*t},z_{i_t^*t},n_{i_t^*t},o_{i_t^*t},\{k_l,b_{lt},z_{lt},n_{lt},o_l\}_{d_{lt}=1,\;l\neq i_t^*}\Big)\right]$$

Given equations 14 and 15, and because $f(\vec{k}) = \prod_{i=1}^N \pi_{k_i}$, I take expectation of the total observed data likelihood with respect to $\{d_t^{-i_t^*}\}_t$

$$\mathbb{E}_{\{d_t^{-i_t^*}\}_t}\left[L|\{d_t^{-i_t^*}\}_t\right] = \prod_{i=1}^N \Bigg[\sum_k \pi_k \Bigg[\Big(\prod_t P(b_{it}|\theta,k_i,x_t,z_{it},n_{it},o_i) \times \mathbb{E}_{d_t^{-i_t^*}}\left[P\Big(i_t^*\Big|\,\theta,x_t,k_{i_t^*},b_{i_t^*t},z_{i_t^*t},n_{i_t^*t},o_{i_t^*t},d_t^{-i_t^*}\Big)\right]^{\mathbb{I}\{i_t^*=i\}}$$
$$\times P\Big(r_{i_t^*}\Big|\,\theta,k_{i_t^*}\Big)^{\mathbb{I}\{i_t^*=i\}}\Big) \times P(n_{i1}|\theta,k_i)\Bigg]\Bigg] \times \prod_t \mathbb{E}_{d_t^{-i_t^*}}\left[P\Big(i_t^*\Big|\,\theta,x_t,d_t^{-i_t^*}\Big)\right]^{\mathbb{I}\{i_t^*=0\}}$$

Taking log of the above, I have

$$\log \mathbb{E}_{\{d_t^{-i_t^*}\}_t}\left[L|\{d_t^{-i_t^*}\}_t\right] = \sum_{i=1}^N \log \Bigg[\sum_k \pi_k \Bigg[\Big(\prod_t P(b_{it}|\theta,k_i,x_t,z_{it},n_{it},o_i) \times \mathbb{E}_{d_t^{-i_t^*}}\left[P\Big(i_t^*\Big|\,\theta,\ldots,d_t^{-i_t^*}\Big)\right]^{\mathbb{I}\{i_t^*=i\}}$$
$$\times P\Big(r_{i_t^*}\Big|\,\theta,k_{i_t^*}\Big)^{\mathbb{I}\{i_t^*=i\}}\Big) \times P(n_{i1}|\theta,k_i)\Bigg]\Bigg] + \sum_t \log \mathbb{E}_{d_t^{-i_t^*}}\left[P\Big(i_t^*\Big|\,\theta,x_t,d_t^{-i_t^*}\Big)\right]^{\mathbb{I}\{i_t^*=0\}}. \tag{16}$$

Equation 16 is the likelihood I maximize in Section 5.1 using the expectation-maximization algorithm.

B.3 Expectation-Maximization Algorithm

I provide further details on the implementation of the expectation–maximization algorithm.

The convergence criterion is that the proportional change in the log likelihood (defined by Equation 10) falls below 10^{-5}. Because the simulated MLE in step (d) of the maximization step can be time-consuming, I first use EM to maximize a similar but misspecified likelihood that does not require simulated MLE, and then use its estimates as starting values for maximizing the correct likelihood.

I start by performing EM to maximize a log likelihood function similar to the one in Equation 10:

$$\tilde{LL}=\sum_{i=1}^{N}\log\left[\sum_{k}\left[\pi_k\left[\prod_{t}P\left(b_{it}|\theta,k_i,x_t,z_{it},n_{it},o_i\right)\times\left(P\left(i_t^*|\theta,x_t,k_{i_t^*},b_{i_t^*t},z_{i_t^*t},n_{i_t^*t},o_{i_t^*t}\right)^{\mathbb{I}\{i_t^*=i\}}\right)\right.\right.\right.$$
$$\left.\left.\left.\times\left(\left[1-P\left(i_t^*|\theta,x_t,k_{i_t^*},\ldots\right)\right]^{\mathbb{I}\{i_t^*\neq i\}}\right)\times P\left(r_{i_t^*}|\theta,k_{i_t^*},n_{i_t^*,t}\right)^{\mathbb{I}\{i_t^*=i\}}\right]P\left(n_{i1}|k_i\right)\right]\right]. \quad (17)$$

The differences between $\tilde{LL}$ and the correct log likelihood LL are twofold: the addition of the likelihood of losers losing, and the omission of the likelihood of the outside option being selected. In addition, rather than using the model-implied functional form for the expected winning probability—which requires integration over all possible competitor sets—I approximate the expected probability function with a logistic function:

$$P\left(i_t^*\middle|\,\theta,x_t,k_{i_t^*},b_{i_t^*t},z_{i_t^*t},n_{i_t^*t},o_{i_t^*t}\right)=\frac{1}{1+\exp(-f(b_{i_t^*t},x_t,k_{i_t^*},o_{i_t^*},z_{i_t^*t},n_{i_t^*t}))},$$

where the function $f(.)$ is the average employer utility from working with i_t^* in a job with minimum budget x_t.

To maximize $\tilde{LL}$, the algorithm is largely the same as that described in Section 5.1, with one key modification. In step (d) of the maximization step, rather than running a simulated MLE to update the demand parameters, I estimate a weighted logistic regression of each bid's win/loss outcome on the bidder's own characteristics, using the current posterior over the worker's type, $\pi_{ik}^{(m+1)}$, as the weights.

I use a range of start values to initialize the EM algorithm to maximize $\tilde{LL}$. The start values consist of a prior over types and parameters of bid policy functions, logit win probability functions, distribution of initial conditions, and the priors over workers' latent quality. I set the initial values for the prior over types to be $(\pi_1^{(0)},\,\pi_2^{(0)},\,\pi_3^{(0)}=0.3,\,0.3,\,0.4)$, the initial Beta parameters to be $(Beta_a^k,\,Beta_b^k=7.8,\,1.4,\,\forall k)$, and the initial values for the distribution of the initial condition to be $p_k^I=0.5,\,\forall k$. To initialize the bid policy parameters, I begin by regressing bid residuals on worker fixed effects and a set of variables:

$$\tilde{b}_{lt} = \beta_l + \beta_x x_t + \beta_G \log(n_{lt}^{Good}) + \beta_B \log(n_{lt}^{Bad}) + \beta_\nu \nu_{lt}, \tag{18}$$

Workers are then ranked by their estimated individual fixed effects, and the observations are divided into three equally sized groups. For each group, I estimate the bid policy function (Equation 11) and the logit winning probability function to obtain type-specific parameter estimates. Using these estimates, I generate five sets of initial values for both functions by adding normally distributed noise with mean 0 and standard deviation 0.3. The parameter σ_ν, the standard deviation of the match-specific shock ν_{it}, is constrained to be positive.

For all five sets of initial values, the algorithm converged in fewer than 50 iterations. The resulting estimates are similar across runs, both in magnitude and in likelihood. The estimates yielding the highest likelihood serve as the base initial values (E1) for maximizing the correct log likelihood LL. Using estimates E1, I draw worker types according to the estimated posterior probabilities and estimate the logistic regression described below. The coefficients from the logistic regression, together with the remaining EM estimates E1, form the initial values for maximizing the correct log likelihood LL.

From these initial values, the algorithm converged in two iterations. This initialization reduced the number of simulated MLE runs required in the maximization step.

I provide more details on the simulated MLE. I set the initial values for the simulated MLE algorithm to be results from a logit regression

$$win_{it} = \Bigg(1 + \exp\Big(\gamma_2 \mathbb{I}\{k_i = 2\} + \gamma_3 \mathbb{I}\{k_i = 3\} + \gamma_b \log(b_{it}) + \gamma_x^k x_t + \sum_o \gamma_o$$
$$+ \sum_k \big(\gamma_q^k \mathbb{E}[\tilde{q} \mid n_{it}, Beta^{(m+1)}, k] + \gamma_h^k \log(n_{it}^{Good} + n_{it}^{Bad} + 1) + \gamma_\nu \nu_{it}\big)\Big)\Bigg)^{-1})$$

after first drawing worker types according to their current type posterior probabilities, $\pi_{ik}^{(m+1)}$. This approach ensures that the simulated MLE starts from a point close to the global maximum, reducing the risk of convergence to a local maximum. To simulate the set of competitors and competitor characteristics in the denominator of Equation 12, I do the below for each iteration of the simulated MLE:

1. Randomly select 1,000 auctions and the bids submitted to them. In the simulations, I use the observed country, exchange rate, worker reputation, and match shock $o_l, z_{lt}, n_{lt}, \nu_{lt}$, holding these fixed across iterations. For each bid, I draw a type based on the worker's

posterior type probability, comparing this probability with a fixed random number so that small changes in posterior probabilities do not produce large changes in the drawn types.

2. Because competitors' bids depend on the auction's minimum budget, I predict competitors' bids using the current bid policy parameters. To reduce computation, I coarsen minimum budgets into five bins and perform bid prediction for each bin.

3. With the simulated competitor set and bids in hand, I compute the expected winning probability for a winner or the outside option, conditional on the auction's minimum budget and the demand parameters.

B.4 Second-Stage Estimation

Demand I provide more detail on the second-stage estimation, beginning with the estimation of employer demand. The instruments W I use in the simulated method of moments estimator is a $K \times N$ matrix where K is the number of parameters and N is the number of prediction residuals. The K instruments include a constant, the worker's log normalized bid, the job's log minimum budget, indicators for the worker's type draw and country, the match component of the bid $\beta_k^{\nu}\nu_{it}$, and the number of good and bad reviews—each normalized by the mean of the respective variable.

Cost: exchange rate pass-through I estimate the pass-through of exchange rate shocks to dollar-denominated opportunity costs by rearranging the bid first-order condition to have cost on one side of the equation by itself, taking logs, and then differentiating with respect to the exchange rate:

$$\begin{aligned}\frac{\partial \log c}{\partial \log z} &= \frac{\partial}{\partial z}\log\Big(b+\frac{G(b)}{G'(b)}+X\Big)\\ &= \Big(b+\frac{G(b)}{G'(b)}+X\Big)^{-1}\left(2-\frac{G(b)G''(b)}{(G'(b))^2}\right)\frac{b}{z}\frac{\partial \log b}{\partial \log z},\end{aligned}$$

where $X = -\frac{1}{x_t} r\left[\mathbb{E}[V_o^k(n_{i,t+1})|n_{it}] - V_o^k(n_{it})\right]$.

I evaluate the right-hand side at the median bid. The median bid corresponds to a log normalized wage of 0.8, submitted by a type-2 worker from India whose posterior mean latent quality is 0.83. This worker has 28 reviews, so I assume the continuation value from an additional review is approximately zero. Under these values, the estimated pass-through of the exchange rate to opportunity costs, $\frac{\partial \log c}{\partial \log z}$, is approximately equal to the pass-through of the exchange rate to the bid, 0.31.

Cost: forward simulation The estimation of workers' costs involves forward simulation of value functions. I begin by constructing a grid over reputation states, defined by a 17×5 grid over $\{n^{\text{Good}}, n^{\text{Bad}}\}$, with denser representation at the lower end. This reflects the fact that the marginal impact of an additional review on total payoffs is greater when a worker has few reviews. Specifically, the grid for n^{Good} and n^{Bad} is $[0,1,2,3,4,5,6,7,8,12,18,30,50,120]$.

For each worker type k, country o, and grid point $(n^{\text{Good}}, n^{\text{Bad}})$, I simulate the lifetime payoffs for 5,000 workers starting from that reputation state. Each simulated worker proceeds through the following steps:

1. Draw an auction from the empirical distribution of auctions;
2. Use the auction date and the worker's country to determine the exchange rate. Draw a match-specific term $N(\sigma^k, 0)$. Use the estimated bid policy function to compute the worker's predicted bid;
3. Randomly drop one participant from the auction and compute the simulated worker's win probability. Simulate whether the worker wins by comparing this probability with a draw from Unif$(0,1)$;
4. If the worker wins, record the worker's earning and the cost covariates $x_t \times {z_{it}}^{c_z}$ and $x_t \times \log x_t \times {z_{it}}^{c_z}$;
5. If the worker wins, draw from Unif$(0,1)$ to determine whether the employer leaves a review. If the employer leaves a review, compute the probability that the review is good based on their current review state. Simulate whether the next review is good using a draw from Unif$(0,1)$, and update the worker's reputation state;
6. Draw an exit shock from Unif$(0,1)$ and compare it with the estimated per-auction exit; probability to determine whether the worker continues.
7. If the worker continues, I repeat the above. If the worker continues, repeat the process. Each worker is allowed to participate in up to 10,000 auctions, which far exceeds the average number observed in the data.

Importantly, the random number draws for auctions, wins, reviews, and exits are held constant across $\{k, o, n\}$ to ensure that simulated value functions are comparable.

Cost: instruments For the SMM estimation of workers' cost parameters, the instruments include a constant, the job's log minimum budget, and indicators for the worker's type draw and country.

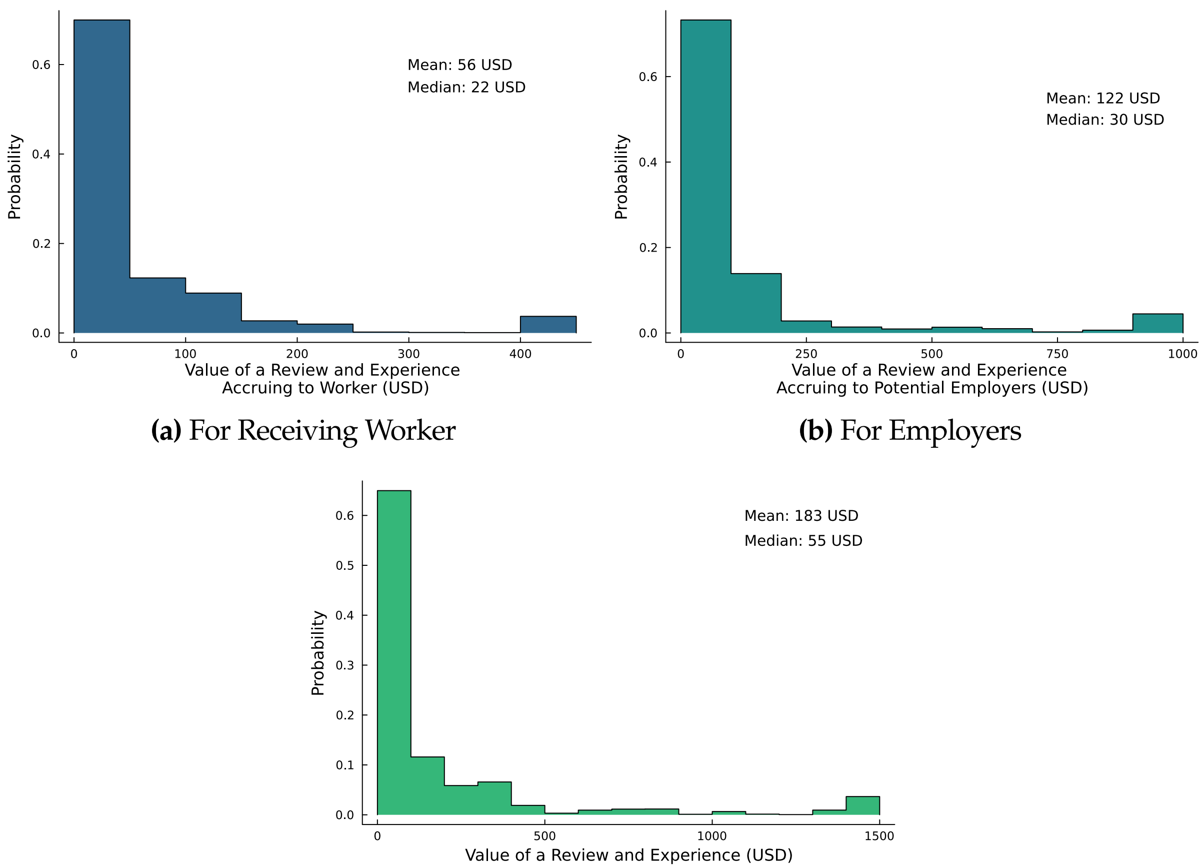
Match-specific shocks I provide additional details on how the estimation incorporates the match-specific shocks ν_{it}. In the model, ν_{it} enters linearly in the employer's utility function and also influences the worker's opportunity cost of work, with effects that vary by worker type. For estimation, I assume a specific functional form for the bid policy function: after removing country fixed effects and exchange–rate–induced variation, the log bid is linear in ν_{it}. Under this assumption, I obtain $\beta_\nu \nu_{it}$ from the estimated bid policy. In the second-step demand estimation, I include $\beta_\nu \nu_{it}$ and estimate the coefficient of the employer's utility on $\beta_\nu \nu_{it}$, which equals $1/\beta_\nu$. This coefficient allows me to recover ν_{it}. In the second-step cost estimation, I then estimate type-specific cost coefficients on ν_{it}, reported in Table 6.

C Results

Table A2: Cost and Benefit Analysis for the Platform

	Change in Platform's Payoffs ($1,000)		
New Worker Discount	Subsidy	Commissions	Total
10%	-31	87	55
20%	-76	155	79
30%	-134	205	71
40%	-215	202	-14
50%	-329	185	-144
60%	-518	143	-374

Notes: Table reports counterfactual equilibrium outcomes under alternative discounts for hiring new workers, focusing on changes in the platform's annual payoffs in the PHP skill category relative to the status quo. Subsidy lists the platform's subsidy expenditure; Commissions reports the change in commission revenue due to changes in total transaction volume (the platform charges a 13% fee); Total is the sum of the subsidy expenditure and the commission change.



(a) For Receiving Worker

(b) For Employers

(c) All

Figure A5: Value of a Review and Experience

Notes: Figures plot the distributions, across all bids (potential matches) in the sample, of the estimated value of a review and of experience, reported as (i) the total value, (ii) the component accruing to the reviewed worker, and (iii) the component accruing to employers. Values are computed on a grid of reputation states for all country–type combinations and interpolated between grid points. For reference, the average job payment is $220 and the estimated average contemporaneous surplus is $148.