Online Appendices for

When "Signals" Boomerang: Employers' Reactions to a Novel Signaling Mechanism

Appendix A: Major Literature in Countersignaling, Signaling in Labor Markets, and Features to Reduce Information Asymmetry in Online Labor Markets

Table A1. Major Literature about Countersignaling

Papers	Context	Methodology	Empirically Studies Signal-Receiver Responses	Empirically Tests Whether Receiver Responses Are Justified	Findings
Feltovich et al. (2002)	Labor market	Modeling the relationship between schooling and signaling abilities when sufficiently informative about the individual productivity of workers (i.e., recommendation from a formal boss) exists	No	No	Workers are less likely to use schooling to signal quality whenever they receive recommendation letters from their previous boss.
Orzach et al. (2002)	Advertising	Modeling the relationship between firm advertising spending and product quality	No	No	High-quality firms spend less on advertising than low-quality firms.
Horstmann and Moorthy (2003)	Advertising	Modeling the relationship between advertising spending and restaurant service quality	No	No	Medium-quality restaurants spend more on advertising than either high-quality or low-quality ones.
Hvide (2003)	Labor market	Modeling the relationship between education and the allocation of talent	No	No	Intermediate individuals appear to pursue more education than bright individuals for professions where individuals with a license are not denied work.
Araujo et al. (2007)	Labor market	Modeling the relationship between schooling and signaling ability when noise (two aspects of ability--school technology and firm technologies) exists.	No	No	Workers are less likely to show schooling whenever school technology differs from firm technologies.
Mayzlin and Shin (2011)	Advertising	Modeling the relationship between advertising content and firm product quality	No	No	High-quality firms choose to produce messages devoid of any attribute information more than low-quality firms.
Luca and Smith (2015)	MBA program ranking	Using secondary data to examine the disclosure of MBA program ranking	No	No	Top schools (well-known) are least likely to disclose their rankings, whereas mid-ranked schools are most likely to disclose.
Bederson et al. (2018)	Restaurant hygiene grade cards	Using secondary data to explore how restaurants disclose hygiene grades	No	No	Higher-quality A restaurants are less likely to disclose than lower-quality As because the better A restaurants use nondisclosure as a countersignal.
Caldieraro et al. (2018)	FinTech market	Modeling the relationship between providing a loan description and borrower quality and empirically testing it	Yes	No	High-quality borrowers are less likely to provide loan descriptions. Lenders correctly interpret signals.

Gervais and Strobl (2020)	Finance	Modeling the relationship between portfolio transparency and manager quality	No	No	Medium-skill managers reduce portfolio transparency more than high-skill managers when high-skill managers rely on their performance to separate from low-skill managers over time.
Harbaugh and To (2020)	Finance	Modeling the relationship between good news disclosure and firm quality types	No	No	Firms disclose good news when prior expectations, in the absence of the news, are sufficiently favorable.
Aghamolla et al. (2021)	Finance	Modeling the relationship between guidelines and firm performance	No	No	Highly successful firms withhold earnings guidance when managers' ability to affect the firm's earnings level, as well as the precision of their previous forecast/guidance, is well known.
Kaplan and Pérez-Cavazos (2022)	Finance	Using secondary data to explore how variation in investment opportunities affects the information conveyed by dividend changes	Yes	No	Firms with strong investment opportunities (better earnings) reduce dividend changes more than firms with worse investment opportunities. Investors well perceived such countersignals.
Shi and Viswanathan (2023)	Online dating platform	Using secondary data to study the relationship between user verification decisions and types of users	Yes	No	Medium-type females (high-type males) are the most likely to opt into verification as compared with high-type females (low-type males) when associating with existing dominant signals (beauty for females and income for males). Verified users do benefit as they receive more contacts from higher-type users.
Hannane (2024)	Online labor platform	Using secondary data to study the relationship between worker status and bid-sponsorship	Yes	No	On a platform with bid-sponsorship (i.e., paid priority placement), new or unrated workers leverage this feature, while established freelancers abstain.
Our study	***Online labor market***	***Using secondary data to understand the relationship between the worker-offered guarantee and employers' response***	***Yes***	***Yes***	***Medium-reputation workers are more likely to offer guarantees. Employers make rational decisions and are less likely to hire them. Furthermore, employers' decisions are justified.***

Table A2. Recent Major Literature about Signaling in Labor Markets

Labor Market Studies	Context	Empirical/ Theory	New Signal	Financial Cost as Signal Cost	Countersignaling/counter-screening	Signaling Works As Expected	Experimentally Testing Underlying Mechanisms	Contributions to Signaling Theory
Benson et al. (2020)	Online labor market	Both (formal model + 3 field experiments)	Yes	No	No/No	Yes	No	Yes. The authors extend signaling theory by modeling how public employer reputation acts as relational contract enforcement in the absence of formal contracting, especially for less-visible firms.
Bester et al. (2021)	Labor markets	Theory	No (extends education as a traditional signal by adding strategic auditing)	Partially – education cost modeled as effort/disutility; audit cost is an explicit monetary cost to firms	Yes (implied)/No	No (works only when auditing cost is high)	No	Yes. The paper contributes to signaling theory by incorporating endogenous, strategic auditing into a standard job market signaling model, showing how auditing changes equilibrium outcomes.
Blair and Chung (2025)	U.S. labor market	Both (empirical + screening model theory)	Yes	Partially modeled cost includes direct licensing burden and difficulty (e.g., due to a criminal record), but not pure monetary cost	No/No	Yes	No	Yes. The authors develop a screening model in the spirit of Spence (1973) and provide empirical evidence that occupational licenses function as costly signals of worker ability, particularly reducing statistical discrimination for historically disadvantaged groups.
Botelho and Chang (2023)	U.S. labor market	Empirical (field experiment + interviews)	No	No	Yes (implied)/No	No (works only when positive experience)	No	No. It does not explicitly claim a contribution to signaling theory.
Câmara et al. (2023)	Labor market	Theory	Yes	No	No/No	Yes	No	Yes. The authors contribute to signaling theory by developing a model of strategic communication under two-sided asymmetric information, extending canonical signaling games by allowing the receiver (firm) to have private information, and showing how the adviser's reputation dynamically affects signal credibility and hiring outcomes.

Casella and Hanaki (2006)	Labor market	Theory	Yes	Partially-certification cost	No/No	Yes	No	No. It does not claim to develop or contribute new theoretical insights to signaling theory.
Campbell and Hahl (2022)	Labor markets	Empirical	Yes	No	No/No	No (penalize men)	No	Yes. They extend signaling theory by incorporating gendered perception mechanisms into signal interpretation.
Chen (2024)	Chinese labor market	Empirical (field experiment + survey)	No	Partially-education cost	Yes (implied)/No	No	No	No. It does not explicitly contribute to signaling theory.
Choudhury et al. (2024)	Labor markets	Empirical	Yes	No	No/No	No (works at early career)	No	Yes. They explicitly claim a contribution to signaling theory by offering a temporal and mobility-based refinement of how signals (like time to promotion and tenure) are interpreted in external labor markets.
Coles et al. (2013)	Decentralized labor markets	Theory	Yes	No	No/No	Yes	No	Yes. The paper contributes to signaling theory by modeling how scarce, costless preference signals can credibly convey information and improve match outcomes in congested markets, and by formally characterizing equilibrium behavior and welfare effects.
Dineen and Allen (2016)	Labor markets	Empirical	No	No	No/No	Yes	No	Yes. The authors contribute to signaling theory by introducing third-party employment branding as a credible and comparable organizational signal that affects both job seeker attraction and employee retention.
Forderer and Burtch (2025)	Online community	Empirical	No	No	No/No	Yes	No	Yes. The authors contribute to signaling theory by providing causal evidence that formal community leadership roles (e.g., Stack Exchange moderatorship) serve as labor-market signals that yield immediate job-mobility benefits, consistent with employer learning and signal decay over time.
Galperin et al. (2020)	Labor markets	Empirical (4 experiments with hiring managers)	No	Partially-education cost	Yes (implied)/No	Yes	No	No. It does not claim a contribution to signaling theory.
Hann et al. (2013)	Open Source Software (OSS) labor market	Empirical (panel data + fixed effects + 2SLS)	No (evaluates rank as existing signal)	No	No/No	Yes	No	Yes. The authors contribute to signaling theory by empirically demonstrating that OSS merit-based ranks function as credible, differentiated signals of worker

								productivity, with varying returns depending on rank and job context.
Heller and Kessler (2024)	U.S. youth labor market	Empirical (field experiment)	Yes	No	No/No	Yes	Yes	Yes. The authors contribute to signaling theory by providing large-scale experimental evidence that credible skill signals (recommendation letters) improve labor market outcomes by reducing employer uncertainty about worker productivity.
Ho and Rai (2017)	Firm-participating Open-Source Software (OSS) projects	Empirical	No	No	No/No	Yes	No	Yes. They contribute to the OSS and signaling literatures by demonstrating that experienced volunteers rely less than new volunteers on the signals associated with input quality controls in making a decision to continue their participation.
Horton (2019)	Online labor market	Empirical	Yes	No	No/No	Yes	No	No. It does not claim a theoretical or empirical contribution to signaling theory.
Kässi and Lehdonvirta (2022)	Online labor market	Both (signaling model + empirical tests using platform data)	Yes	No	No/No	Yes	No	Yes. The authors extend signaling theory by formalizing how employer uncertainty, alongside worker ability, determines the value and incidence of voluntary microcredential signals in online labor markets.
Ke and Zhu (2021)	Online labor market	Theory (game-theoretic modeling)	Yes	Yes	No/No	Yes	No	Yes. The authors contribute to signaling theory by modeling buyer-side cheap talk and post-match costly signaling, demonstrating when market structure sustains truthful signaling or incentivizes distortion.
Kokkodis et al. (2023)	Online labor market	Empirical	Yes	No	No/No	Yes	No	No. It does not make an explicit or formal contribution to signaling theory.
Lin et al. (2018)	Online labor market	Empirical (field data, matched sample, panel data)	No (analyzes existing vendor reputation signals)	No	No/No	Yes	No	Yes. The authors contribute to signaling theory by identifying contract form as a boundary condition that moderates the effectiveness of reputation signals in online labor markets.
Liu et al. (2024)	Female labor force participation in South Korea	Empirical	Yes (technology-enabled behavioral signal)	No	No/No	Yes	No	No. It does not explicitly state a contribution to signaling theory.

Moreno and Terwiesch (2014)	Online labor market	Empirical (1.8 million bids; mixed econometrics and text mining)	No (studies two existing signals: numeric and text-based reputation)	No	No/No	Yes	No	Yes. The paper extends signaling theory by showing how structured and unstructured reputation interact with contextual factors like certification and familiarity to shape buyer choice in service marketplaces.
Ndofor and Levitas (2004)	Labor markets	Theory	Yes	No	No/No	Yes	No	Yes. The authors contribute to signaling theory by developing a framework that explains how firms can use observable actions to create separating equilibria and convey the value of knowledge assets to labor and capital markets under varying conditions of uncertainty.
Swinkels (1999)	Labor markets	Theory	No	Partially- education cost	Yes (implied)/No	No	No	Yes. The paper refines classic signaling theory by showing that when firms can make private, preemptive job offers, traditional separating equilibria with overeducation may break down, resulting in pooling or even undereducation in equilibrium.
Yoganarasimhan (2013)	Online labor market	Empirical	No	No	No/No	Yes	No	Yes. Provides dynamic structural estimation of reputation returns in online labor markets and identifies biases in static reputation models
Zheng et al. (2023)	Online labor market	Empirical	Yes	Yes, platform refund insurance involves a prepaid insurance premium, tied to past seller performance (quantified signaling cost)	No/No	Yes	No	Yes. The authors contribute to signaling theory by introducing and empirically validating platform refund insurance as a novel, high-credibility, platform-endorsed quality signal that is more effective than seller-guaranteed refunds, particularly in filtering out low-quality service providers.
Our Study	***Online labor market***	***Empirical***	***Yes***	***Yes***	***Yes/Yes***	***No***	***Yes***	***Yes. We extend signaling theory to account for two cost dimensions (production cost and false-signal penalty), factors overlooked in both the traditional labor market and online platform context.***

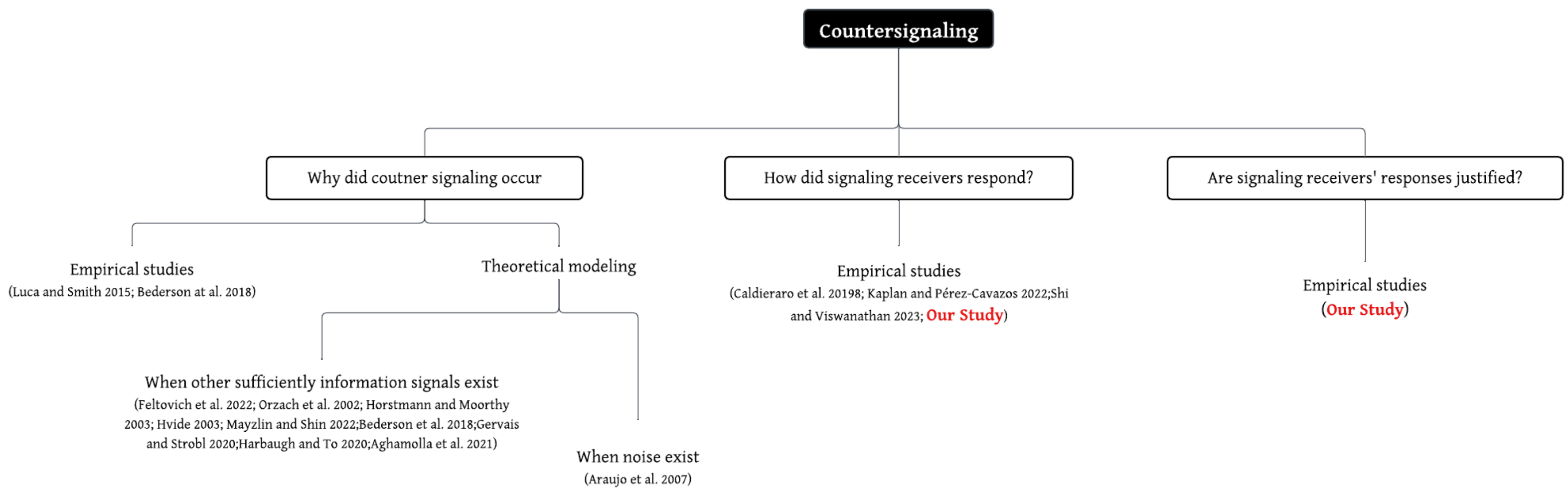
Table A3. Main Papers about Factors that Reduce Information Asymmetry in Online Labor Markets

Paper	Factors	Offered by	Employer-specific	Data	Employer/Workers Responses	Workers' Performance	Findings
Yoganarasimhan (2013)	Worker reputation (rating)	Worker	No	Secondary data	Employer	No	Employers positively respond to reputation.
Moreno and Terwiesch (2014)	Worker reputation (rating)	Worker	No	Secondary data	Employer	No	Same as above
Lin et al. (2018)	Worker reputation (rating)	Worker	No	Secondary data	Employer	No	Same as above
Gu and Zhu (2021)	Worker satisfaction (score)	Worker	No	Secondary data	Employer	No	Enhanced trust from workers' satisfaction scores increases the likelihood of high-quality freelancers being hired.
Hong et al. (2021)	Direct messages	Worker	Yes	Secondary data	Employer	No	Direct messaging has positive effects on employers' hiring. The beneficial effects are amplified for lower-status workers.
Stanton and Thomas (2015b)	Agency affiliation	Third-party (Agency)	No	Secondary data	Employer	No	Workers affiliated with an agency have substantially higher job-finding probabilities and wages.
Kässi and Lehdonvirta (2022)	Certification	Third-party (Certifier)	No	Secondary data	Employer	No	Certification increases workers' hiring probabilities. But the effect is lower for more experienced workers.
Leung (2018)	Learning from past experience	Employer	No	Secondary data	Employer	No	Prior positive/negative experiences with similar jobs (versus dissimilar jobs) lead employers to be more/less likely to subsequently hire from that country.
Ghani et al. (2014)	Worker's location	Employer	Yes	Secondary data	Employer	Yes	Ethnic Indians are substantially more likely to choose a worker in India, but there are no performance differences between diaspora-based contracts and their peers.
Chan and Wang (2017)	Gender	Workers	No	Secondary data	Employer	No	A positive hiring bias in favor of female workers
Horton (2019)	Worker capacities	Workers	No	Secondary data	Employer	No	Workers signaling to have high capacity were more likely to be hired.

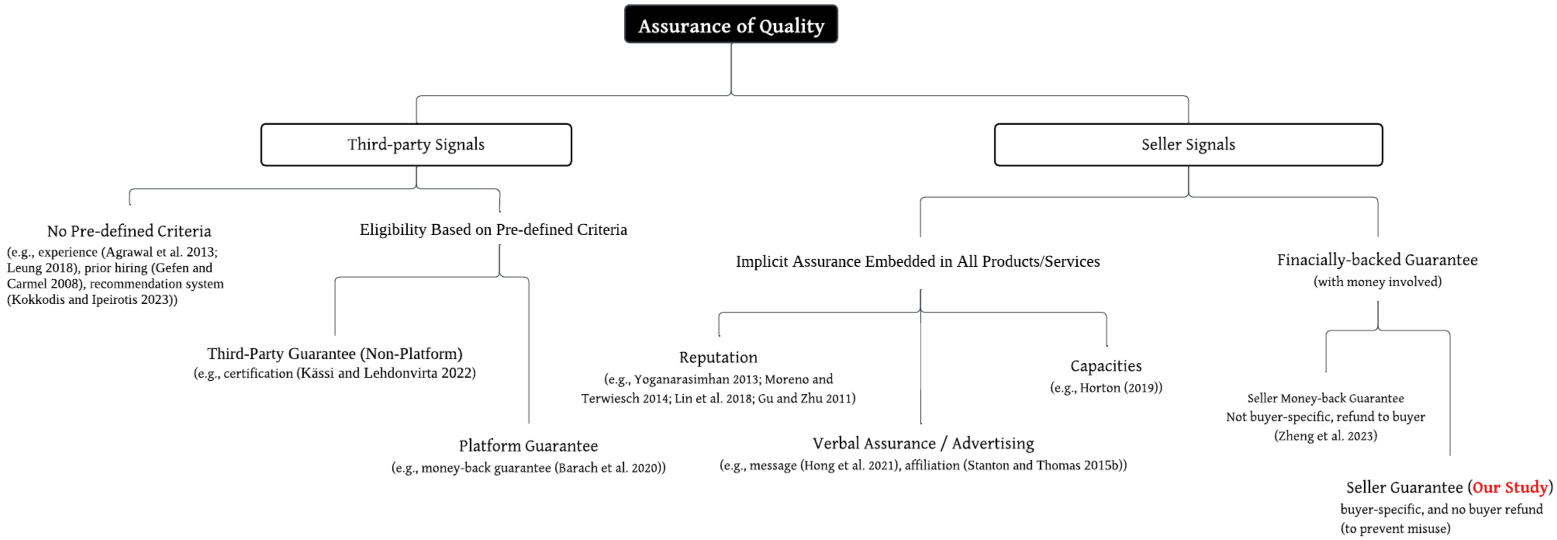
Kokkodis (2023)	Skillset exploration and exploitation	Workers	No	Secondary data	Employer	No	A worker's exploration of new skills similar to their previous skills increases contractor hireability.
Troncoso and Luo (2023)	Profile picture	Workers	No	Secondary data	Employer	Yes	Freelancers who "look the part" of a job are more likely to be hired, but there is no strong correlation between "looking the part" and job performance.
Barach et al. (2020)	Platform money-back guarantee	Third-party (platform)	No	Secondary data	Employer	No	The presence of a guarantee strongly steered buyers to these guaranteed sellers.
Zheng et al. (2023)	Money-back guarantee	Worker	No	Modeling and secondary data	Employer	No	Platform refund insurance on seller demand is stronger than that of the seller-guaranteed refund. Sellers with a better reputation or lower popularity might benefit less from refund options.
Hashim and Bockstedt (2021)	Intervention (reward, punishment)	Third-party (Platform)	No	Experiment	Worker	No	Punishing the group and rewarding or sanctioning an individual significantly increase workers' effort.
Benson et al. (2020)	Employer reputation	Third-party (Platform)	No	Experiment	Worker	No	Employers with good reputations can find it easier to receive bids from high-quality workers.
Liang et al. (2022)	Auction duration and project description length	Employer	No	Secondary data	Worker	No	Auctions with longer durations and item descriptions attract more bids (i.e., a higher quantity of bidders).
Liang et al. (2023)	Monitoring policy in three dimensions (intensity, transparency, and control)	Employer	No	Experiment on AMT and Prolific	Worker	No	While monitoring intensity decreases workers' willingness to accept monitoring, being transparent increases it.
Our study	***Workers offered guarantee (job and relational specific, without refund to employers)***	***Worker***	***Yes***	***Secondary data***	***Employer***	***Yes***	***Employers are less likely to hire workers who offer a guarantee. We also find that employers' decisions are justified, as workers who offer guarantees perform worse than those who do not.***

Fig. A1

(a) Major Studies of Countersignaling



(b) Major Studies of Quality Assurance Mechanisms in the Online Labor Market



Appendix B: Descriptive Statistics and Key Variable Correlation Matrix

Table B1. Variables Definitions, Measurements, and Descriptive Statistics

Variables	Definitions and Measurements	Mean	Std	Min	Max
	Bidding and Job Outcomes				
*JobRating**[1]	A number representing the rating a worker received from an employer who hired them for a job. It ranges from 0 to 10, with 0 being the worst and 10 the best.	4.861	3.414	0	10
Selected‡	An indicator that equals 1 if the bid is chosen as the winning bid for the focal job; 0 otherwise	0.074	0.262	0	1
	Guarantee Information‡				
Guarantee	An indicator that equals 1 if a worker deposited a guarantee; 0 otherwise	0.043	0.203	0	1
GuaranteeRatio[2]	The ratio of the guarantee deposit amount to the bid amount if the worker deposited a guarantee	0.370	0.396	0	1
GuaranteeAmount[2]	The amount of guarantee that a worker deposited with the bid	336.50	267.45	4	7500
	Worker Characteristics‡				
#OfRatings	The number of ratings a worker has received at the time of bidding	25.674	59.674	0	1291
AvgRating[3]	The average rating a worker has received from previous contracts at the time of bidding	6.020	4.523	0	10
Certified	An indicator that equals 1 if a worker has received certifications at the time of bidding; 0 otherwise	0.019	0.137	0	1
WorkerTenure	Number of months since a worker registered on the platform at the time of bidding	11.247	13.916	0	115.2
HavingPic	An indicator that equals 1 if a worker has a picture at the time of bidding; 0 otherwise	0.458	0.498	0	1
	Bid Characteristics‡				
BidAmount	The amount a worker bid for the current job	192.55	235.38	4	7500
BidOrder	Sequential number of the current bid from the first bid of the focal job	11.239	13.548	1	271
HavingSimiJob	An indicator that equals 1 if a worker has completed jobs in the same job categories as the focal job categories; 0 otherwise	0.758	0.429	0	1
SameCountry	An indicator that equals 1 if the worker comes from the same country as the employer; 0 otherwise	0.086	0.281	0	1
BidSameEmployer	An indicator that equals 1 if the worker bid on the same employer's previous jobs	0.091	0.288	0	1
	*Employer and Job Characteristics**				
EmployerTenure	Number of months since an employer registered on the platform at the time of posting the focal job	17.796	18.329	0	96.3
EmployerExperience	The number of jobs an employer has completed when posting the current job	21.772	56.503	0	1278
JobDesLen	Number of words in the job description provided by the employer who posted that job	107.507	77.543	0	395
JobValueType	A series of dummy variables that show the value range of the job as the employer designated when they created the request. It has the following values: $0.01 - $499.99; At least $500; or "not sure"				
Categories	A series of dummy variables that show the job category. It has the following main categories: 1 (Graphic Design and Writing & Content); 2 (Network, Website, & Software Development); 3 (Data Entry and Management); and 4 (Others).				

	Worker Messageǂ				
MsgLen(log)	Log value of total words in messages sent by a worker to the buyer who creates a job at the time when this worker placed a bid for the job.	3.795	1.410	0	9.596
MsgReadability(fog)	Readability of messages sent by a worker to the buyer who creates a job at the time when this worker placed a bid for the job. We use the Fog Index, a widely used readability formula, to assess the level of text difficulty or how easy a text is to read.	2.365	0.856	0	3.932
MsgConcreteness	Log value of the concreteness of messages sent by a worker to the buyer who created a job at the time when this worker placed a bid for the job. We use the concreteness rating of the words used in the pitches based on the list developed by Brysbaert et al. (2014).	0.340	0.240	0	1.700
MsgSentiment	Sentiment in messages sent by a worker to the buyer who creates a job at the time when this worker placed a bid for the job. We use the VADER (Valence Aware Dictionary and sEntiment Reasoner) package, written in Python and developed by Hutto and Gilbert (2014), to extract sentiment.	0.302	0.266	-0.96	0.999

Note. * means variables are at the job level. ǂ means variables are at the bid level. 1. *JobRating* is conditional on winning projects; 2. *GuaranteeRatio* and *GuaranteeAmount* are conditional on the offering of a guarantee; 3. *AvgRating* is conditional on having previous ratings.

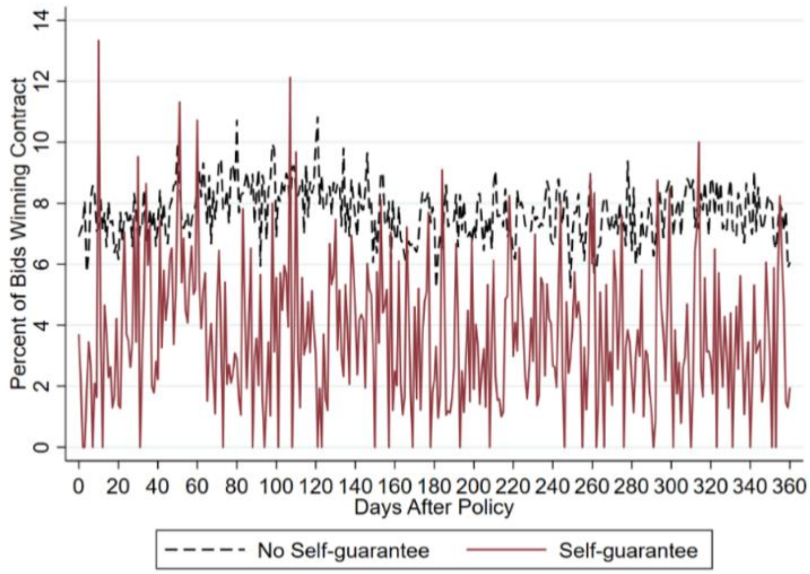
Table B2. Key Variable Correlation Matrix

Variables	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)
(1) Selected	1.000										
(2) JobRating	0.779***	1.000									
(3) Guarantee	-0.031***	-0.027***	1.000								
(4) GuaranteeRatio	-0.030***	-0.024***	0.675***	1.000							
(5) GuaranteeAmount	-0.032***	-0.025***	0.898***	0.795***	1.000						
(6) #OfRatings	0.089***	0.097***	-0.057***	-0.081***	-0.063***	1.000					
(7) AvgRating	0.099***	0.109***	-0.064***	-0.095***	-0.071***	0.658***	1.000				
(8) Certified	0.024***	0.024***	0.037***	0.000	0.030***	0.144***	0.088***	1.000			
(9) WorkerTenure	0.052***	0.062***	-0.045***	-0.063***	-0.037***	0.656***	0.532***	0.115***	1.000		
(10) HavingPic	0.000	0.009***	-0.029***	-0.025***	-0.021***	0.199***	0.164***	0.066***	0.138***	1.000	
(11) BidAmount	-0.105***	-0.079***	0.132***	0.077***	0.183***	-0.003**	-0.047***	0.030***	0.089***	0.030***	1.000
(12) BidOrder	-0.207***	-0.155***	0.009***	0.011***	0.009***	-0.034***	-0.058***	-0.020***	0.003***	0.032***	-0.003**
(13) HavingSimiJobs	0.068***	0.067***	-0.070***	-0.088***	-0.067***	0.507***	0.702***	0.063***	0.422***	0.131***	0.013***
(14) SameCountry	0.035***	0.029***	0.004***	-0.004***	0.008***	-0.041***	-0.025***	0.037***	-0.025***	-0.038***	0.020***
(15) BidSameEmployer	0.054***	0.049***	-0.030***	-0.024***	-0.028***	0.189***	0.129***	0.022***	0.119***	0.038***	-0.036***
(16) EmployerTenure	0.037***	0.028***	-0.023***	-0.011***	-0.029***	0.011***	0.015***	0.001	-0.002	-0.002	-0.148***
(17) EmployerExperience	0.050***	0.039***	-0.031***	-0.016***	-0.040***	0.006***	0.018***	0.002	-0.010***	-0.011***	-0.202***
(18) JobDesLen	-0.021***	-0.023***	0.039***	0.022***	0.044***	-0.024***	-0.028***	0.004***	0.002	-0.021***	0.178***
(19) MsgLength(log)	0.011***	0.010***	0.002	-0.009***	0.013***	0.185***	0.156***	0.040***	0.180***	0.113***	0.239***
(20) MsgReadability(fog)	-0.021***	-0.018***	0.005***	0.000	0.015***	0.146***	0.118***	0.030***	0.140***	0.088***	0.184***
(21) MsgConcreteness	0.037***	0.034***	-0.003***	0.008***	-0.005***	-0.025***	-0.011***	-0.003***	-0.025***	-0.028***	-0.114***
(22) MsgSentiment	-0.030***	-0.025***	0.002*	0.002	0.010***	0.110***	0.081***	0.003**	0.079***	0.079***	0.076***
Variables	(12)	(13)	(14)	(15)	(16)	(17)	(18)	(19)	(20)	(21)	(22)
(12) BidOrder	1.000										
(13) HavingSimiJobs	-0.081***	1.000									
(14) SameCountry	-0.033***	-0.028***	1.000								
(15) BidSameEmployer	-0.049***	0.115***	-0.015***	1.000							
(16) EmployerTenure	-0.030***	0.002	-0.011***	0.133***	1.000						
(17) EmployerExperience	-0.045***	-0.001	-0.015***	0.215***	0.765***	1.000					
(18) JobDesLen	-0.022***	0.006***	0.016***	-0.053***	0.001	-0.048***	1.000				
(19) MsgLength(log)	0.019***	0.187***	0.018***	-0.002*	-0.047***	-0.073***	0.100***	1.000			
(20) MsgReadability(fog)	0.017***	0.157***	-0.023***	-0.008***	-0.036***	-0.059***	0.076***	0.791***	1.000		
(21) MsgConcreteness	-0.041***	-0.024***	-0.049***	0.030***	0.024***	0.035***	-0.081***	-0.115***	0.301***	1.000	
(22) MsgSentiment	0.031***	0.109***	-0.043***	0.009***	-0.022***	-0.036***	0.031***	0.368***	0.502***	0.280***	1.000

Note. *** $p<0.01$, ** $p<0.05$, * $p<0.1$

Appendix C: Employers' Response to Worker-Offered Guarantee

Figure C1. Contract Winning Percent with/without Guarantee Over Time



C-1: Addressing Endogeneity Using Instrumental Variables

Table C1. Main Instrumental Variables Used in Recent Online Labor Market Studies

Paper	Independent Variables	Data	DVs	Workers' Performance	instruments
Hong et al. (2016)	Open vs. closed auction	Secondary data	Hiring	No	GDP_PPP
Hong and Pavlou (2017)	Worker's country (language, time zone, cultural) differences and the country's IT development, workers' bids	Secondary data	Hiring	No	Normalized exchange rate
Hong et al. (2021)	Direct messages	Secondary data	Hiring	No	Whether the message initiated by the worker in their most recent prior job application, if any, was read by the relevant employer
Horton (2019)	Worker capacities	Secondary data	Hiring	No	relative time of day
Horton et al. (2017)	Worker's bids	Secondary data	Hiring	No	Exchange rate
Kokkodis (2023)	Skillset exploration and exploitation	Secondary data	Hiring	No	Heteroskedasticity -based
Laitenberger et al. (2023)	The supply of online labor for microtasking	Secondary data	Hiring	No	Bartik-style instrumental variables (IV)
Ludwig et al. (2022)	Communication	Secondary data	Hiring	No	Gaussian copulas to model the correlation between each
Stanton and Thomas (2015a)	Worker's bids	Secondary data	Hiring	No	Exchange rate

Table C2. Effects of *Guarantee* on Employer's Hiring Decision
(First and Second Stage Estimation Using *BidFailureRate* and *ForeignExchange* as Instrumental Variables)

DEP. VAR.	*Guarantee*		*Guarantee*		*Guarantee*	
MODEL	Probit (IV first-stage)	SE	IV-Pooled LPM (IV second-stage)	SE	IV-FE LPM (IV second-stage)	SE
BidFailureRate	0.061***	0.000				
ForeignExchange	0.023***	0.006				
Probability of Guarantee			1.198***	0.004	1.167***	0.004
#OfRatings	-0.025***	0.004	0.000*	0.000	0.000	0.000
AvgRating	0.004***	0.001	-0.000	0.000	-0.000	0.000
Certified	0.592***	0.021	-0.013***	0.002	-0.009***	0.002
WorkerTenure	-0.048***	0.004	0.001***	0.000	0.001***	0.000
HavingPic	-0.109***	0.008	0.002***	0.000	0.002***	0.000
MsgLength(log)	-0.025***	0.005	0.001**	0.000	0.000	0.000
MsgReadability(fog)	0.013	0.010	-0.000	0.000	-0.002***	0.001
MsgConcreteness	0.045**	0.021	-0.001	0.001	0.003**	0.001
MsgSentiment	0.039**	0.016	-0.000	0.001	-0.001	0.001
BidAmount	1.579***	0.025	-0.042***	0.002	-0.154***	0.004
BidOrder	0.017***	0.003	-0.000	0.000	-0.002***	0.000
HavingSimiJobs	-0.276***	0.011	0.006***	0.001	0.004***	0.001
SameCountry	-0.041***	0.013	0.001	0.001	0.001	0.001
BidSameEmployer	-0.163***	0.015	0.002***	0.001	0.003***	0.001
EmployerTenure(month)	-0.000	0.004	0.000	0.000		
EmployerExperience	-0.005	0.003	-0.000	0.000		
JobDesLen	0.060***	0.005	-0.001***	0.000		
Constant	-6.235***	0.059	-0.001	0.003	0.016***	0.003
# of Observations	669,728		669,728		669,728	
# of Jobs	87,236		87,236		87,236	
Job category fixed effects	YES		YES		NO	
Job value fixed effects	YES		YES		NO	
Job fixed effects	NO		NO		YES	
Year-quarter fixed effects	YES		YES		YES	

Note. *** p<0.01, ** p<0.05, * p<0.1. For first-stage Probit estimation, conventional standard errors are used; for second-stage estimation, robust standard errors are clustered at the job level.

Table C3. Effects of Guarantee on Employer's Hiring Decision
(Third Stage Estimation Using *BidFailureRate* and *ForeignExchange* as Instrumental Variables)

DEP. VAR.	*Selected*		*Selected*	
MODEL	IV-Pooled LPM (IV third-stage)	SE	IV-FE LPM (IV third-stage)	SE
Guarantee	-0.008***	0.002	-0.006***	0.002
#OfRatings	0.008***	0.000	0.012***	0.000
AvgRating	0.003***	0.000	0.003***	0.000
Certified	0.019***	0.003	0.015***	0.003
WorkerTenure	-0.000	0.000	-0.003***	0.000
HavingPic	-0.004***	0.001	-0.000	0.001
MsgLength(log)	0.027***	0.000	0.021***	0.000
MsgReadability(fog)	-0.036***	0.001	-0.019***	0.001
MsgConcreteness	0.071***	0.002	0.029***	0.002
MsgSentiment	-0.029***	0.001	-0.014***	0.001
BidAmount	-0.203***	0.002	-0.281***	0.004
BidOrder	-0.044***	0.000	0.017***	0.000
HavingSimiJobs	-0.002*	0.001	-0.005***	0.001
SameCountry	0.028***	0.001	0.032***	0.001
BidSameEmployer	0.006***	0.001	-0.014***	0.001
EmployerTenure(month)	-0.000	0.000		
EmployerExperience	0.003***	0.000		
JobDesLen	0.005***	0.000		
Constant	0.460***	0.011	0.020***	0.003
# of Observations	669,728		669,728	
# of Jobs	87,236		87,236	
Job category fixed effects	YES		NO	
Job value fixed effects	YES		NO	
Job fixed effects	NO		YES	
Year-quarter fixed effects	YES		YES	

Note. *** p<0.01, ** p<0.05, * p<0.1. Robust standard errors are clustered at the job level.

Appendix D: Employers' Response to Worker-Offered Guarantee (Heterogeneity Analyses and Robustness Checks)

D-1: Heterogeneities in Worker Reputation

We first explore the moderating effects of workers' reputation. Workers with higher reputations (i.e., more positive feedback) are generally seen as more reliable and lower risk by employers (Lin et al. 2018). As reputation acts as a strong quality signal, employers likely view additional signals, such as guarantees, through the lens of existing credibility. We conjecture that, for workers with higher reputation, a guarantee reinforces existing perceptions of quality and is interpreted as a commitment to deliver excellent work. In contrast, for workers with lower reputation, employers may interpret a guarantee with more skepticism, potentially viewing it as a weak substitute for a lack of proven ability. This aligns with prior studies indicating that reputation systems effectively reduce adverse selection by helping buyers distinguish between high- and low-quality workers, and that reputation moderates the value of additional signals (Moreno and Terwiesch 2014). Therefore, we expect that guarantees offered by workers with a high reputation will be perceived less negatively, or even positively, than the same guarantees offered by workers with a low reputation.

We leverage a three-level reputation model, using the medium level as the baseline, and include the interaction term between the guarantee offer and worker reputation levels in addition to the regression model.[1] This allows us to test whether counter-screening effects differ across low-, medium-, and high-reputation workers. In line with our conjecture, the coefficients of interaction terms in Table D1 indicate that the negative effect of offering a guarantee is moderated by worker reputation. Specifically, the negative effect of *Guarantee* is stronger for low-reputation workers (insignificant in Column 1 but significant in Column 2) and weaker for high-reputation workers (significant in Column 1). This suggests that employers perceive guarantees from reputable workers more favorably, likely viewing them as reinforcing existing credibility rather than as compensatory signals.

Table D1. Effects of *Guarantee* on Employer's Hiring Decision
(Worker's Reputation: Low vs. Medium vs. High)

DEP. VAR.	*Selected*		*Selected*	
MODEL	Clogit	SE	FE-LPM	SE
Guarantee	-0.885**	0.446	0.000	0.004
Reputation [Low]	1.101***	0.078	0.027***	0.002
Reputation [High]	1.462***	0.076	0.041***	0.001
Guarantee× Reputation [Low]	-0.311	0.457	-0.012***	0.004
Guarantee× Reputation [High]	0.885**	0.448	-0.004	0.005
#OfRatings	0.242***	0.006	0.013***	0.000
Certified	0.188***	0.039	0.014***	0.003
WorkerTenure	-0.039***	0.007	-0.002***	0.000

[1] We classify worker reputation into three levels: Low (no rating), Medium (0–6.02), and High [6.02–10], using the overall mean rating of 6.02 as the cutoff.

HavingPic	0.021*	0.013	-0.000	0.001
MsgLength(log)	0.484***	0.011	0.021***	0.000
MsgReadability(fog)	-0.404***	0.017	-0.020***	0.001
MsgConcreteness	0.737***	0.040	0.029***	0.002
MsgSentiment	-0.235***	0.028	-0.014***	0.001
BidAmount	-8.983***	0.154	-0.283***	0.004
BidOrder	0.412***	0.011	0.017***	0.000
HavingSimiJobs	0.213***	0.026	0.004***	0.001
SameCountry	0.615***	0.022	0.032***	0.001
BidSameEmployer	-0.249***	0.024	-0.015***	0.001
Constant			0.022***	0.003
# of Observations	372,531		669,728	
# of Jobs	37,353		87,236	
Job fixed effects	YES		YES	
Year-quarter fixed effects	YES		YES	

Note. *** p<0.01, ** p<0.05, * p<0.1. Robust standard errors are clustered at the job level.

D-2: Heterogeneities in Job Value (Expensive vs. Inexpensive)

We examine the heterogeneous effect of *Guarantee* in terms of job values on our findings. Higher project value implies greater project complexity, which is a major factor that affects the contractual relationship (Dey et al. 2010). A more complex job tends to have more requirements and scope, increasing the likelihood of failure. Bidders, therefore, face a steeper "cost" to offer a guarantee on these complex tasks, and employers recognize this, treating guarantees on high-complexity jobs as a relatively strong signal of confidence. As a result, the negative hiring penalty for guaranteed bids should be smaller for these complex projects. Conversely, on lower-complexity jobs—those with a narrower scope, routine requirements, and much higher completion rates—forfeiture risk is lower. Here, most workers could freely offer guarantees, but employers interpret them as a weaker signal, and the resulting drop in hiring probability is far larger. To test this, we split the subsample of jobs with (at least one) guarantee-backed bids at the median contract price (a proxy for complexity) and re-estimate the conditional logit from Table 2 separately within each subgroup.

Table D2 reports that the coefficient of guarantee is negative and statistically significant at a .01 level when using more expensive job data in Column 1, but has a larger effect when using less expensive job data in Column 2. The results show that the negative effects of guarantee on employers' selection become stronger as job values decrease, supporting our conjecture.

Table D2. Effects of *Guarantee* on Employer's Hiring Decision
(Job Value: Expensive vs. Inexpensive)

DEP. VAR.	*Selected*		*Selected*	
SUBSAMPLE	Expensive Jobs		Inexpensive Jobs	
MODEL	Clogit	SE	Clogit	SE
Guarantee	-0.177***	0.045	-0.561***	0.122
#OfRatings	0.308***	0.014	0.317***	0.031
AvgRating	0.109***	0.007	0.085***	0.013
Certified	0.298***	0.079	0.254	0.188
WorkerTenure	-0.066***	0.018	-0.024	0.035
HavingPic	0.010	0.030	0.071	0.063
MsgLength(log)	0.643***	0.028	0.384***	0.053
MsgReadability(fog)	-0.613***	0.044	-0.206**	0.083
MsgConcreteness	1.157***	0.113	0.423**	0.181
MsgSentiment	-0.192***	0.068	-0.041	0.131
BidAmount	-5.942***	0.178	-87.545***	2.575
BidOrder	0.501***	0.027	0.162***	0.049
HavingSimiJobs	-0.128*	0.076	-0.112	0.131
SameCountry	0.878***	0.051	0.563***	0.117
BidSameEmployer	-0.142**	0.059	-0.261**	0.118
# of Observations	94,683		29,977	
# of Jobs	6,378		1,646	
Job fixed effects	YES		YES	
Year-quarter fixed effects	YES		YES	

Note. *** p<0.01, ** p<0.05, * p<0.1. Robust standard errors are clustered at the job level.

D-3: Heterogeneity in Employer Experience (Experienced vs. Inexperienced Employers)

We also explore the heterogeneity of employer experience. Employers who posted jobs and worked with workers previously are likely well-versed in providing clear information about their jobs and the approaches to evaluating workers. However, employers who have never used the platform are likely confused about many aspects of operational procedures, such as creating clear job descriptions, evaluating workers, and managing the auction process. That means experienced employers have less uncertainty in the auction process than inexperienced employers. Therefore, we expect that the more experienced an employer is, the more likely it is to hire workers with a guarantee (i.e., we should observe a weaker negative impact of guarantee among experienced employers). We test this conjecture in this section.

We first identify inexperienced and experienced employers who received guaranteed bids for their posted jobs. We consider employers whose number of completed jobs and registered days on the studied platform are more than three-quarters of the total number of employers when posting current jobs. This upper-quartile threshold allows us to distinguish employers with substantively greater platform familiarity in a setting where employer activity is highly skewed. It aligns with our objective of identifying employers most likely to have learned how platform signals function through repeated hiring interactions. They posted 1,354 jobs that received (at least one) bids with worker-offered guarantees during the first year after the guarantee was implemented. We define employers who have just registered and completed zero jobs when posting the current jobs as inexperienced employers. They posted 1,446 jobs that received (at least one) bids with worker-offered guarantees during the first year after the guarantee was implemented. Our results are robust to alternative experience cutoffs (e.g., top tercile).

We estimate the same model as the main model in Table 2 for jobs within each subgroup. From Table D3, the coefficient of guarantee is negative and statistically significant at the .01 level for inexperienced employers, but it becomes insignificant for experienced employers. The results support our conjecture, showing that experienced employers are less likely to penalize guarantee-backed bids than inexperienced employers.

Table D3. Effects of *Guarantee* on Employer's Hiring Decision
(Employer Experience: Experience vs. Inexperience)

DEP. VAR.	*Selected*		*Selected*	
SUBSAMPLE	Experienced Employers		Inexperienced Employers	
MODEL	Clogit	SE	Clogit	SE
Guarantee	-0.090	0.097	-0.484***	0.107
#OfRatings	0.264***	0.028	0.301***	0.029
AvgRating	0.095***	0.015	0.108***	0.015
Certified	0.263	0.183	0.644***	0.151
WorkerTenure	0.015	0.036	-0.098**	0.038
HavingPic	0.076	0.065	0.008	0.064
MsgLength(log)	0.402***	0.057	0.748***	0.062

MsgReadability(fog)	-0.367***	0.092	-0.693***	0.099
MsgConcreteness	0.852***	0.209	1.230***	0.256
MsgSentiment	-0.114	0.138	-0.183	0.149
BidAmount	-7.890***	0.563	-6.133***	0.366
BidOrder	0.418***	0.056	0.408***	0.054
HavingSimiJobs	-0.019	0.159	-0.284*	0.153
SameCountry	0.705***	0.110	0.788***	0.105
BidSameEmployer	-0.307***	0.096	0.998**	0.463
# of Observations	20,857		24,244	
# of Jobs	1,354		1,446	
Job fixed effects	YES		YES	
Year-quarter fixed effects	YES		YES	

Note. *** p<0.01, ** p<0.05, * p<0.1. Robust standard errors are clustered at the job level.

The heterogeneity analyses reported in Sections D-1, D-2, and D-3 should be interpreted as complementary rather than mutually exclusive explanations. Worker reputation, job value, and employer experience may be correlated, and separate sample splits could partially reflect overlapping sources of variation. Our goal is to illustrate how employer responses to guarantees vary across substantively meaningful platform contexts, rather than to isolate independent causal channels. As a robustness check, we estimated alternative specifications conditioning one moderator on another and using alternative split thresholds; the qualitative patterns remain unchanged. These additional checks indicate that the reported heterogeneity patterns are not driven solely by overlapping sample partitions.

D-4: Employers' First Interaction with Guarantees

We further explore whether employers' learning could explain our main results. Employers can learn from previous experience (particularly worse ones) working with workers who offered a guarantee in the online labor market (Mill 2011, Kokkodis and Ransbotham 2023). We have all the bidding information for all jobs of all employers during our study period. Over 10.99% of employers received bids from workers who offered guarantees in multiple job postings. Hence, employer learning may be an alternative explanation for all findings if workers who offer a guarantee do not perform satisfactorily, especially for employers who were present on the platform before the mechanism was introduced. To address this concern and as a robustness test, we focus on employers who registered on the studied platform after the guarantee implementation and include only all bids for their first jobs that received guaranteed bids. This ensures that employers have no prior experience with either the pre-guarantee period or guaranteed bids. We estimate the same conditional logit model and the fixed-effects linear probability model. The results in Table D4 show that employers' negative view of guarantee forms even during their first interaction with guarantees.

Table D4. Effects of *Guarantee* on Employer's Hiring Decision
(Using Employer's First Job Received Guaranteed Bids)

DEP. VAR.	*Selected*		*Selected*	
SUBSAMPLE	First Job with Guarantee		First Job with Guarantee	
MODEL	Clogit	SE	FE-LPM	SE
Guarantee	-0.479***	0.087	-0.014***	0.002
#OfRatings	0.294***	0.024	0.008***	0.001
AvgRating	0.114***	0.012	0.002***	0.000
Certified	0.586***	0.130	0.022***	0.006
WorkerTenure	-0.113***	0.031	-0.002***	0.001
HavingPic	0.001	0.054	-0.001	0.001
MsgLength(log)	0.705***	0.049	0.017***	0.001
MsgReadability(fog)	-0.656***	0.079	-0.018***	0.002
MsgConcreteness	1.038***	0.199	0.020***	0.004
MsgSentiment	-0.212*	0.123	-0.007***	0.003
BidAmount	-6.790***	0.324	-0.152***	0.007
BidOrder	0.418***	0.045	0.010***	0.001
HavingSimiJobs	-0.247**	0.126	-0.006***	0.001
SameCountry	0.738***	0.089	0.020***	0.003
BidSameEmployer	-0.003	0.208	0.001	0.007
Constant			0.011*	0.006
# of Observations	33,365		77,020	
# of Jobs	2,091		4,958	
Job fixed effects	YES		YES	
Year-quarter fixed effects	YES		YES	

Note. *** p<0.01, ** p<0.05, * p<0.1. Robust standard errors are clustered at the job level.

D-5: Worker Panel Data Analysis

The conditional logit model and the LPM with job fixed effects we analyzed so far are based on the natural grouping of bids by job. To ensure the robustness of our results, we adopt an alternative approach and focus on the worker panel data instead, since our dataset provides a unique identifier for each worker. Our goal is to rely on within-worker variations in guarantee offering and associate them with their winning probabilities. We trace the worker's bidding history over the year following guarantee implementation to construct a worker panel dataset. Workers who only placed one bid or whose bids all won or failed during our study period are excluded because they will not offer the within-worker variations that this analysis requires. This new dataset includes 283,046 bids from 4,797 workers (note: 254,728 bids from 2,631 workers have within-worker variations). We estimate a worker panel model on this dataset. The analysis data remains at the bid level but is now grouped at the worker level. The dependent and main independent variables are still *Selected* and *Guarantee*, respectively. We run a logit model and LPM, both with worker-specific fixed effects and include the same control variables. The coefficient of *Guarantee* is negative and statistically significant in both Logit and LPM models. These results indicate that workers are less likely to win contracts when they provide guarantees (compared to when they do not).

Table D5. Effects of *Guarantee* on Employer's Hiring Decision
(Using Worker Panel Data)

DEP. VAR.	*Selected*		*Selected*	
MODEL	FE-logit	SE	FE-LPM	SE
Guarantee	-0.274***	0.042	-0.018***	0.002
#OfRatings	-0.048	0.030	-0.002	0.002
AvgRating	0.008*	0.004	0.000	0.000
Certified	0.157	0.126	0.011	0.009
WorkerTenure	0.300***	0.055	0.017***	0.003
MsgLength(log)	0.430***	0.025	0.024***	0.002
MsgReadability(fog)	-0.628***	0.038	-0.042***	0.003
MsgConcreteness	1.022***	0.073	0.083***	0.006
MsgSentiment	-0.167***	0.057	-0.021***	0.004
BidAmount	-3.713***	0.121	-0.156***	0.005
BidOrder	-0.703***	0.011	-0.039***	0.001
HavingSimiJobs	-0.564***	0.050	-0.029***	0.003
SameCountry	0.149***	0.038	0.011***	0.003
BidSameEmployer	0.163***	0.029	0.015***	0.002
EmployerTenure(month)	0.018**	0.009	0.001	0.000
EmployerExperience	0.031***	0.008	0.002***	0.000
JobDesLen	0.092***	0.011	0.003***	0.001
Constant			0.446***	0.016
# of observations	254,728		283,046	
# of workers	2,631		4,797	
Worker fixed effects	YES		YES	
Job value fixed effects	YES		YES	
Job category fixed effects	YES		YES	
Year-quarter fixed effects	YES		YES	

Note. *** p<0.01, ** p<0.05, * p<0.1. Robust standard errors are clustered at the worker level.

D-6: Alternative Independent Variables

The main independent variable in our primary analysis is a binary indicator (*Guarantee*) capturing whether a worker offered a guarantee in a bid. As a robustness check, we further examine whether the magnitude of the guarantee influences employer decisions. Workers specify either the dollar amount of the guarantee deposit (*GuaranteeAmount*) or the guarantee amount as a percentage of the bid value (*GuaranteeRatio*). If employers view larger guarantees as stronger commitments or more credible signals, the monetary value of the guarantee should affect hiring decisions beyond the simple presence of a guarantee. Conversely, if employers primarily respond to the existence of a guarantee, neither *GuaranteeAmount* nor *GuaranteeRatio* should have additional explanatory power. We therefore re-estimate our models using *GuaranteeAmount* and *GuaranteeRatio* in place of the binary guarantee indicator.

We use the same dataset and run the exact model specification as we used for the main analysis, except that we replace *Guarantee* with either the proportion or the dollar amount of guarantee deposits and estimate two separate models. We use the log-transformed guarantee amount (plus one for bids that are not placed with guarantees), as this amount is highly skewed (Lin et al., 2018); however, the results are not sensitive to this transformation. Table D6 reports the results. The coefficients of both *GuaranteeRatio* and *GuaranteeAmount* are negative and statistically significant at .01 level. These results are consistent with the findings we previously reported: Employers are less likely to select workers who offer larger guarantee amounts and who guarantee a higher ratio of the bid price.

Table D6. Effects of *Guarantee Ratio* and *Guarantee Amount* on Employer's Hiring Decision (Using Alternative Independent Variables)

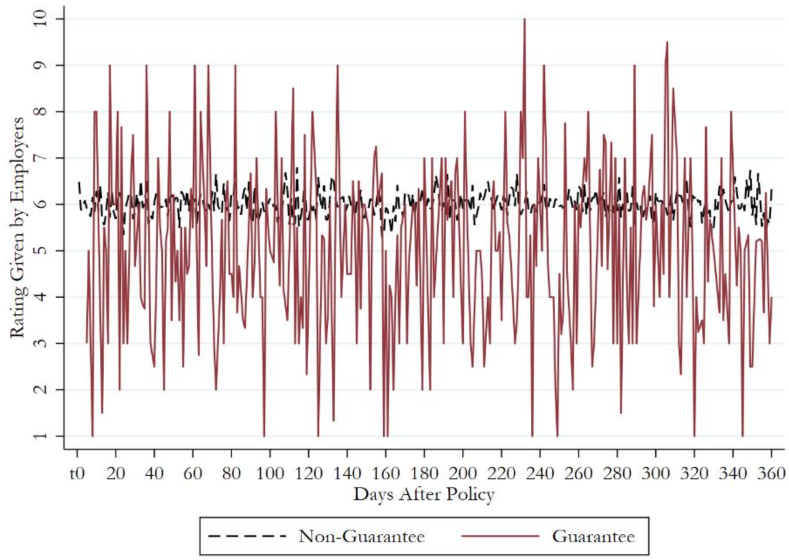
DEP. VAR.	*Selected*		*Selected*		*Selected*		*Selected*	
INDEP. VAR.	Guarantee Ratio		Guarantee Ratio		Guarantee Amount		Guarantee Amount	
MODEL	Clogit	SE	LPM	SE	Clogit	SE	LPM	SE
GuaranteeRatio	-1.064***	0.103	-0.014***	0.002				
GuaranteeAmount					-0.075***	0.012	-0.001***	0.000
#OfRatings	0.232***	0.006	0.012***	0.000	0.232***	0.006	0.012***	0.000
AvgRating	0.074***	0.003	0.003***	0.000	0.075***	0.003	0.003***	0.000
Certified	0.193***	0.039	0.014***	0.003	0.196***	0.039	0.014***	0.003
WorkerTenure	-0.054***	0.007	-0.003***	0.000	-0.054***	0.007	-0.003***	0.000
HavingPic	0.023*	0.013	-0.000	0.001	0.022*	0.013	-0.000	0.001
MsgLength(log)	0.483***	0.011	0.021***	0.000	0.483***	0.011	0.021***	0.000
MsgReadability(fog)	-0.401***	0.017	-0.019***	0.001	-0.401***	0.017	-0.019***	0.001
MsgConcreteness	0.739***	0.040	0.029***	0.002	0.739***	0.040	0.029***	0.002
MsgSentiment	-0.224***	0.028	-0.014***	0.001	-0.226***	0.028	-0.014***	0.001
BidAmount	-8.982***	0.154	-0.282***	0.004	-8.933***	0.153	-0.281***	0.004
BidOrder	0.413***	0.011	0.017***	0.000	0.413***	0.011	0.017***	0.000
HavingSimiJobs	-0.012	0.027	-0.005***	0.001	-0.008	0.027	-0.004***	0.001
SameCountry	0.619***	0.022	0.032***	0.001	0.621***	0.022	0.032***	0.001
BidSameEmployer	-0.244***	0.024	-0.014***	0.001	-0.244***	0.024	-0.014***	0.001
Constant			0.020***	0.003			0.020***	0.003
# of Observations	372,531		669,728		372,531		669,728	

# of jobs	37,353	87,236	37,353	87,236
Job fixed effects	YES	YES	YES	YES
Year-quarter fixed effects	YES	YES	YES	YES

Note. *** p<0.01, ** p<0.05, * p<0.1. Robust standard errors are clustered at the job level.

Appendix E: Workers' Guarantee and Workers' Job Performance

Figure E1. Rating Given by Employers for Winning Bids with/without Guarantee Over Time



E-1: Addressing Workers' Self-selection into Adoption of Guarantee

We have two empirical concerns about the estimation of the effect of guarantee on worker performance. One is workers' self-selection into the adoption of the guarantee, which causes endogeneity concerns, like the estimation of the effect of the guarantee on employers' hiring decisions. The other concern is the sample selection issue, given that the rating for a job can only be observed for the contracted worker. Therefore, our estimates may be biased if we only use a sample of contracted workers while excluding information from non-contracted workers. These concerns, if not addressed properly, may bias our estimation. Following Wooldridge (2010, Section 19.6.2), we implement the instrumental variables estimation with Heckman selection correction (Heckman 1976) to address these concerns. This approach has been widely implemented in many fields (e.g., Mroz 1987, Shaver 1998, He and Chittoor 2023).

We employ the same three-stage procedure with the same instrumental variables approach used in the main analysis (Wooldridge 2010), as *Guarantee* is a binary variable (Angrist and Pischke 2008). We also confirm instrument validity before estimating our model specification. We, in addition, implement the Heckman selection correction during the estimation process. Specifically, in the first step, which is the selection stage, we ran a random-effects probit model to regress whether a bid for a job is selected by the employer who creates the job (*Selected*) on all control variables in Table B1.[2] We calculated the inverse Mills ratio (IMR) based on the estimated probit model. In the second step, we run an IV first-stage probit model to regress guarantee (as a binary dependent variable) on the same instruments and control variables used in Appendix C-1, deriving the *probability of Guarantee*. Finally, we estimate the IV second- and third-stage models for *JobRating* in the selected sample, instrumenting *Guarantee* with the predicted probability of *Guarantee* obtained from the first-stage probit model. Notably, IMR is included in the IV second and third stages to address sample selection bias. Due to the inclusion of IMR, bootstrapped standard errors are used for the IV second and third stages. For the model to be identified, we need to satisfy the exclusion restriction, which requires that at least one variable appears with a non-zero coefficient in the selection-stage and IV first-stage equations but not in the IV second- and third-stage equations. In our context, those variables that measure *worker message* fit this criterion, as they appear only in the selection-stage and IV first-stage equations, since worker message information will affect employers' selection decisions. We estimated both an IV-pooled-Heckman and an IV-FE-Heckman model and conducted the same instrument validity tests (for under-identification test, Anderson LM-statistic = 10,000, $p<0.001$; for weak IV test, Cragg-Donald Wald F-statistic

[2] In our case, the employer only selects a worker from all workers bidding on her or his job. Thus, the selection of worker analysis should include job fixed effects. However, the probit model is required for the first stage of the Heckman selection model, but probit regression with fixed effects will cause an incidental parameters problem (Greene 2002). Therefore, we implemented a random-effects probit model at the first stage.

= 14,000, p-value <0.001). We report selection stage and IV first-stage estimations in Table E1a and report IV second- and third-stage estimations in Table E1b, which further confirms our findings.

Table E1a. Effects of *Guarantee* on Job Rating Given by Employers: Heckman-IV Models (Workers' Self-selection and IV First Stage Estimation)

DEP. VAR.	*Selected*		*Guarantee*	
MODEL	Probit (selection-stage)	SE	Probit (IV first-stage)	SE
BidFailureRate			0.061***	0.000
ForeignExchange			0.023***	0.006
#OfRatings	0.061***	0.002	-0.025***	0.004
AvgRating	0.027***	0.001	0.004***	0.001
Certified	0.105***	0.016	0.592***	0.021
WorkerTenure	-0.003	0.003	-0.048***	0.004
HavingPic	-0.030***	0.005	-0.109***	0.008
MsgLength(log)	0.236***	0.004	-0.025***	0.005
MsgReadability(fog)	-0.273***	0.007	0.013	0.010
MsgConcreteness	0.520***	0.015	0.045**	0.021
MsgSentiment	-0.199***	0.011	0.039**	0.016
BidAmount	-2.030***	0.026	1.579***	0.025
BidOrder	-0.362***	0.002	0.017***	0.003
HavingSimiJobs	0.020**	0.010	-0.276***	0.011
SameCountry	0.194***	0.008	-0.041***	0.013
BidSameEmployer	0.000	0.008	-0.163***	0.015
EmployerTenure(month)	0.001	0.003	-0.000	0.004
EmployerExperience	0.024***	0.002	-0.005	0.003
JobDesLen	0.056***	0.003	0.060***	0.005
Constant	-0.338***	0.029	-6.235***	0.059
# of Observations	669,728		669,728	
# of Jobs	87,236		87,236	
Job category fixed effects	YES		YES	
Job value fixed effects	YES		YES	
Employer fixed effects	NO		NO	
Year-quarter fixed effects	YES		YES	

Note. *** p<0.01, ** p<0.05, * p<0.1. Conventional standard errors are used. All observations (both selected and unselected) are used.

Table E1b. Effects of *Guarantee* on Job Rating Given by Employers: Heckman-IV Models (Second and Third Stages)

DEP. VAR.	*Guarantee*		*JobRating*		*Guarantee*		*JobRating*	
MODEL	IV-pooled-Heckman (IV second-stage)	SE	IV-pooled-Heckman (IV third-stage)	SE	IV-FE-Heckman (IV second-stage)	SE	IV-FE-Heckman (IV third-stage)	SE
Guarantee			-0.990***	0.183			-1.075***	0.269
#OfRatings	0.000	0.001	0.072***	0.014	0.001	0.001	0.045***	0.016
AvgRating	0.001***	0.000	0.198***	0.007	0.001**	0.000	0.181***	0.008
Certified	-0.027***	0.005	0.046	0.069	-0.030***	0.005	-0.021	0.113
WorkerTenure	0.001**	0.001	0.039**	0.017	0.001*	0.001	0.049***	0.019
HavingPic	0.003***	0.001	0.169***	0.025	0.003*	0.001	0.158***	0.038
BidAmount	0.032***	0.010	-0.901***	0.227	0.035**	0.015	-1.326***	0.334
BidOrder	0.005***	0.001	0.347***	0.037	0.002	0.002	0.275***	0.046
HavingSimiJobs	0.016***	0.001	-0.594***	0.067	0.016***	0.002	-0.434***	0.068
SameCountry	0.002	0.002	0.097*	0.050	0.001	0.002	0.044	0.068
BidSameEmployer	0.002	0.001	-0.148***	0.044	0.002	0.002	-0.024	0.052
EmployerTenure	-0.000	0.000	-0.015	0.018	0.002	0.003	0.463***	0.079
EmployerExperience	0.001	0.000	-0.003	0.013	-0.000	0.002	-0.457***	0.050
JobDesLen	-0.000	0.001	-0.067***	0.019	0.000	0.001	-0.120***	0.028
Probability of Guarantee	1.186***	0.022			1.210***	0.030		
Inverse mills ratio	-0.007	0.005	-0.605***	0.116	-0.001	0.005	-0.474***	0.157
Constant	-0.056***	0.008	5.019***	0.162	-0.066***	0.013	4.872***	0.278
# of observations	49,949		49,949		49,949		49,949	
# of employers	14,986		14,986		14,986		14,986	
Job value fixed effects	YES		YES		YES		YES	
Job category fixed effects	YES		YES		YES		YES	
Employer fixed effects	NO		NO		YES		YES	
Year-quarter fixed effects	YES		YES		YES		YES	

Note. *** p<0.01, ** p<0.05, * p<0.1. Bootstrapped standard errors are used. Only selected observations are used.

E-2: Addressing Selection Bias with Consideration of Data Structure

Our data have a hierarchical structure among employers, jobs, and bids. The effect of *Guarantee* can be modeled as the employer-level random slopes. Therefore, we could build a mixed-effects, hierarchical linear model to capture this data structure. Since job ratings are only observable after workers complete the job, we also address sample selection issues using the Heckman correction. We conducted a Heckman mixed linear model for *JobRating*. However, with random slopes, the Heckman correction approach using inverse Mills ratio (IMR) does not work since the bias is not homogeneous across observations, and the standard IMR term cannot capture this heterogeneity. Alternatively, we estimate the selection and outcome equations simultaneously in a full likelihood Heckman-Mixed-Linear model, incorporating random intercepts and slopes of the impact of *Guarantee* (only for the outcome equation).

Specifically, we use *i* to index a job, j to index a bid, and *k* to index an employer. We specify the selection equation as a latent variable model and specify the outcome equation as a hierarchical linear model (HLM) with random effects (for the intercept) and random slopes (for *Guarantee*).

Selection equation:

Level 1: Bid level

$$Selected_{ijk}^{*} = \theta_{0k} + \theta_1 Guarantee_{ijk} + Z_{ijk}\theta + \varepsilon_{1,ijk}$$

$$Selected_{ijk} = 1\{Selected_{ijk}^{*} > 0\}$$

Level 2: Employer Level

$$\theta_{0k} = \gamma_0 + \epsilon_{0k}$$

Outcome equation:

Level 1: Bid level

$$JobRating_{ijk} = \beta_{0k} + \beta_{1k} Guarantee_{ijk} + X_{ijk}\beta + \varepsilon_{2,ijk}$$

Level 2: Employer Level

$$\beta_{0k} = \gamma_1 + \epsilon_{1k},$$

$$\beta_{1k} = \gamma_2 + \epsilon_{2k}$$

According to the selection equation, *Job Rating* is only observed when $Selected_{ijk}^{*} > 0$. The random effect (θ_{0k}) is modeled at the employer level as the sum of a constant (γ_0) and an error term (ϵ_{0k}). In the outcome equation, the random effects (β_{0k}) is modeled at the employer level as the sum of a constant (γ_1) and an error term (ϵ_{1k}); the slope of *Guarantee* (β_{1k}) is modeled at the employer level as the sum of a constant (γ_2) and an error term (ϵ_{2k}). The error terms in the Level 2 equations ($\epsilon_{0k}, \epsilon_{1k}, \epsilon_{2k}$) jointly follow a multivariate normal distribution. Importantly, we allow a non-zero correlation between the error term of the outcome equation's random effects and the slopes of *Guarantee* (i.e., Cor ($\epsilon_{1k}, \epsilon_{2k}$)). Since the likelihood function of the Heckman-Mixed-Linear model is very complex, we estimate the model parameters using the Bayesian MCMC algorithm. The MCMC algorithm starts with 1,000 burn-in draws to adapt the sampler, followed by another 1,000 draws to form the posterior distribution of the parameters. To run the MCMC algorithm, we apply the *R* package "brms," which implements Bayesian models using *Stan* (Bürkner 2017).

We report the result in Table E2. The result indicates that the posterior mean of the mean parameter of the random slope of *Guarantee* (γ_2) is -1.05, with a 95% credible interval of [-1.22, -0.88]. The estimated effect of *Guarantee* on *Job Rating* is very close to the estimated effects from the FE model (β = -1.191, p-value < 0.01, from Table G2) or IV-FE Heckman model (β = -1.075, p-value < 0.01, from Table E1b).

Table E2. Effects of *Guarantee* on Job Rating Given by Employers: Heckman Mixed Effects Models

DEP. VAR.	*Selected**		*Job Rating*	
EQUATION	Selection Equation		Outcome Equation	
	Posterior Mean	Posterior SD	Posterior Mean	Posterior SD
Intercept (γ_0 for selection equation)	-4.13	3.91		
Intercept (γ_1 for outcome equation)			2.54	7.86
Guarantee (θ_1 for selection equation)	-0.32*	0.03		
Guarantee (γ_2 for outcome equation)			**-1.05***	**0.09**
Controls				
#OfRatings	0.12*	0.00	0.10*	0.01
AvgRating	0.06*	0.00	0.21*	0.01
Certified	0.21*	0.02	0.12	0.09
WorkerTenure	-0.01	0.01	0.03*	0.01
HavingPic	-0.06*	0.01	0.14*	0.03
BidAmount	-4.45*	0.05	-1.83*	0.15
BidOrder	-0.69*	0.01	0.17*	0.02
HavingSimiJobs	0.02	0.02	-0.59*	0.05
SameCountry	0.38*	0.01	0.19*	0.04
BidSameEmployer	0.04*	0.01	-0.13*	0.04
EmployerTenure	0.03*	0.01	-0.02*	0.01
EmployerExperience	0.04*	0.01	0.03*	0.01
JobDesLen	0.10*	0.01	-0.04*	0.01
Excluded Variables				
MsgLength(log)	0.47*	0.01		
MsgReadability(fog)	-0.53*	0.01		
MsgConcreteness	1.02*	0.02		
MsgSentiment	-0.38*	0.02		

Error Parameters	Posterior Mean		Posterior SD
Standard Deviation (ϵ_{0k})	0.36		0.01
Standard Deviation (ϵ_{1k})	0.57		0.02
Standard Deviation (ϵ_{2k})	0.14		0.11
Correlation (ϵ_{1k}, ϵ_{2k})	0.05		0.01
Standard Deviation ($\varepsilon_{(1\ or\ 2)ijk}$)	3.23		0.01
# of Observations		669,728	
# of Employers		24,558	
Job value fixed effects	YES		YES
Job category fixed effects	YES		YES
Employer fixed effects	NO		NO
Year-quarter fixed effects	YES		YES

Note. * means the posterior 95% credible interval does not contain 0 (i.e., significant at 5% level).

E-3: Heterogeneity in Worker Reputation, Job Values, and Employer Experience

We now examine whether their decisions are justified by exploring the moderating effects of worker reputation, job values, and employer experience on the relationship between guarantee and employer satisfaction (as measured by *JobRating*).

We estimate three different model specifications and use the same dataset as the main analysis. In the first specification, we estimate the same model as the main analysis but replace average rating variables (i.e., *AvgRating*) with *Reputation* and its interaction with *Guarantee*. In the second specification, we added *Expensive,* a binary variable indicating whether a job is more expensive (please see section D-2 for definition), and the interaction of *Guarantee* with *Expensive* into the model. In the last specification, we added *Experienced,* a binary variable indicating whether the employer who creates the job is an experienced employer (please see section D-3 for definition), and the interaction of *Guarantee* with *Experienced* into the model. For the last specification, we use employer random effects instead of fixed effects, due to the lack of within-employer variations.

Table E3 extends our performance analysis by allowing the guarantee–rating relationship to vary with worker reputation, job complexity, and employer experience. In Column 1, the main effect of a guarantee among medium-reputation workers is significantly negative ($\beta = -1.752$, p-value < 0.01), but the interactions with low-reputation and high-reputation tiers are significantly positive ($\beta = 1.651$, p-value < 0.01) and positive but statistically insignificant ($\beta = 0.433$, p-value $= 0.13$), respectively, indicating that when even well-rated workers offer guarantees their end-of-job ratings fall sharply relative to low-rated peers. These results are likely due to employers' higher performance expectations when they "put more trust in" well-rated workers. Column 2 shows that the coefficient of *Guarantee*×*Expensive* is positive but statistically insignificant. Finally, Column 3 reveals that for highly experienced employers, the coefficient of *Guarantee*×*Experienced* is (weakly) significantly negative ($\beta = –0.646$, $p = 0.08$), mirroring our hiring-decision findings: Experienced employers tend to hold a more negative view on the performance of workers who offered guarantees, despite having a less negative view about the guarantees than inexperienced employers. Together, these heterogeneity tests show that employers are more likely to make correct decisions to counter-screen based on guarantees when the workers are more reputable and when the employers themselves are more experienced.

Table E3. Effects of *Guarantee* on Job Rating Given by Employers
(Heterogeneity in Worker Reputation, Job Values, and Employer Experience)

DEP. VAR.	*Job Rating*		*Job Rating*		*Job Rating*	
MODERATOR	Worker Reputation		Job Value		Employer Experience	
MODEL	Fixed Effects	SE	Fixed Effects	SE	Random Effects	SE
Guarantee	-1.752***	0.268	-1.342***	0.383	-0.625**	0.263
Reputation [Low]	1.077***	0.154				
Reputation [High]	2.648***	0.148				
Guarantee× Reputation [Low]	1.651***	0.462				
Guarantee× Reputation [High]	0.433	0.289				
Expensive			-0.272	0.185		
Guarantee×Expensive			0.182	0.415		
Experienced					0.472	0.821
Guarantee×Experienced					-0.646*	0.368
#OfRatings	0.074***	0.016	0.080	0.057	0.138**	0.057
AvgRating			0.176***	0.028	0.221***	0.028
Certified	0.033	0.104	-0.402	0.306	0.030	0.322
WorkerTenure	0.061***	0.019	0.141**	0.072	0.082	0.071
HavingPic	0.144***	0.036	0.277**	0.116	0.348***	0.124
BidAmount	-2.018***	0.245	-0.634	0.700	-0.946	0.582
BidOrder	0.141***	0.020	0.140**	0.065	0.093	0.060
HavingSimiJobs	-0.230***	0.070	-0.323	0.309	-0.606**	0.296
SameCountry	0.118*	0.061	0.149	0.198	-0.007	0.180
BidSameEmployer	-0.040	0.053	-0.412**	0.163	-0.110	0.213
EmployerTenure	0.470***	0.083	0.549**	0.248	-0.162	0.178
EmployerExperience	-0.452***	0.054	-0.394**	0.160	0.041	0.133
JobDesLen	-0.100***	0.030	-0.105	0.105	-0.172*	0.089
Constant	3.537***	0.271	1.990	1.256	2.610**	1.047
# of Observations	49,949		8,024		2,802	
# of Employers	14,986		5,089		2,061	
Job value fixed effects	YES		YES		YES	
Job category fixed effects	YES		YES		YES	
Employer fixed effects	YES		YES		NO	
Year-quarter fixed effects	YES		YES		YES	

Note. *** p<0.01, ** p<0.05, * p<0.1. Robust standard errors are clustered at the employer level.

E-4: Robustness Tests: Alternative Dependent and Independent Variables

We conduct a series of robustness tests. In the first test, we use an alternative metric to measure the quality of work. We track whether the employer hired the same worker again in the future (*Rehiring*) and obtain the logged work duration of the current job (*WorkDuration*). Rehiring a worker indicates that the employer and worker are beginning to establish a long-term work relationship following their initial encounter. It suggests that the employer is truly satisfied with the worker's performance (Banerjee and Duflo 2000). A shorter work duration means a reduced waiting time for the employer to obtain the completed project, indicating a high level of satisfaction with the (timely) delivered work. Furthermore, we use two alternative measures to replace *Guarantee* in the main analysis, similar to our robustness check on hiring decisions. One is the proportion of guarantee amount a worker offered in a bid to the total amount of the bid (*GuaranteeRatio)*. The other is the absolute guarantee amount a worker offered in the bid (*GuaranteeAmount)*.

Table E4 reports all test results. Column 1 shows the results of tests using *Rehiring* as the dependent variable. The coefficient of the *Guarantee* variables is negative and statistically significant at the .01 level. Thus, a worker who offers a guarantee is less likely to be rehired by the same employer in the future. Column 2 reports that the coefficient of *Guarantee* is significantly positive at .01 level, indicating that the project awarded to the worker who places a bid with a guarantee takes a longer time to complete. Columns 3 and 4 report the results of the two tests with alternative *Guarantee* measures, showing both coefficients of *GuaranteeRatio* and *GuaranteeAmount* are also negative and statistically significant at .01 level. These results show that workers who offered a larger guarantee amount or a higher ratio of guarantee amount to bid price are less likely to receive higher ratings from employers. These results are consistent with our main finding that employers' reluctance to hire workers who offer guarantees is associated with lower subsequent performance.

Table E4. Effects of *Guarantee* on Employer Satisfaction
(Alternative Dependent and Independent Variables)

DEP. Var.	*Rehiring*		*Work Duration*		*Job Rating*		*Job Rating*	
INDEP. Var	*Guarantee*		*Guarantee*		*Guarantee Ratio*		*Guarantee Amount*	
MODEL	FE-logit	SE	FE-linear	SE	Ordered Logit	SE	Ordered Logit	SE
Guarantee	-0.769***	0.106	0.107**	0.050				
GuaranteeRatio					-1.294***	0.182		
GuaranteeAmount							-0.165***	0.017
#OfRatings	0.047***	0.012	-0.071***	0.007	0.048***	0.007	0.048***	0.007
AvgRating	0.026***	0.005	0.016***	0.003	0.117***	0.003	0.118***	0.003
Certified	0.071	0.076	-0.078*	0.041	0.041	0.045	0.047	0.045
WorkerTenure	0.030**	0.014	0.143***	0.009	0.026***	0.009	0.025***	0.009
HavingPic	0.046*	0.027	0.096***	0.016	0.085***	0.016	0.083***	0.016
BidAmount	0.294	0.182	1.535***	0.099	-1.044***	0.088	-0.951***	0.089
BidOrder	0.076***	0.014	0.174***	0.009	0.093***	0.008	0.093***	0.008
HavingSimiJobs	0.005	0.052	0.025	0.032	-0.309***	0.032	-0.309***	0.032
SameCountry	-0.115**	0.045	-0.290***	0.026	0.110***	0.024	0.112***	0.024
BidSameEmployer	0.130***	0.040	-0.029	0.024	-0.086***	0.025	-0.087***	0.025
EmployerTenure(month)	0.354***	0.065	0.047	0.035	-0.008	0.009	-0.008	0.009
EmployerExperience	-0.458***	0.048	-0.102***	0.023	0.004	0.007	0.004	0.007
JobDesLen	0.083***	0.020	0.026*	0.014	-0.020**	0.010	-0.019*	0.010
Constant			2.449***	0.095				
# of observations	49,949		49,949		49,949		49,949	
# of employers	14,986		14,986		14,986		14,986	
Job value fixed effects	YES		YES		YES		YES	
Job category fixed effects	YES		YES		YES		YES	
Employer fixed effects	YES		YES		NO		NO	
Year-quarter fixed effects	YES		YES		YES		YES	

Note. *** p<0.01, ** p<0.05, * p<0.1. For Columns 1 and 2, robust standard errors are clustered at employer level; for Columns 3 and 4, conventional standard errors are used

Appendix F: Online Experiment: Effects of Guarantee Signaling Cost on Employers' Hiring Decisions

Our results support H1b: employers tend to view guarantees negatively. This hypothesis is based on theoretical reasoning that the signaling cost of guarantee is low and cannot distinguish between high- and low-quality workers. We therefore expect that increasing the signaling cost of a guarantee would boost employer acceptance. To test this conjecture, we ran an online experiment in which the primary treatment raised guarantee costs; we also included a secondary reputation manipulation to reflect its role as the key alternative signal. If the experimental outcomes align with our expectations, raising guarantee costs may help counteract the unintended negative effects of worker-offered guarantees.

1) Sampling and Experimental Procedure

We recruited U.S.-based participants through the U.K.-based survey platform Prolific, offering compensation for their participation. The target sample size was determined a priori using G*Power software (Erdfelder et al. 1996) based on a two-way between-subjects ANOVA (2×3 design), aiming for 95% power to detect a small-to-medium effect size ($f = 0.25$). Power analysis indicated a minimum of 251 participants (approximately 42 per condition). To ensure data quality, we restricted participation to individuals who had (1) a Prolific approval rate of at least 95%, (2) completed at least 100 tasks, (3) English as their primary language, (4) a minimum of a college-level education, and (5) used a desktop or laptop computer. A total of 310 eligible participants completed the study. We excluded participants who spent less than the required three minutes (indicating likely failure to understand the task) or more than 18 minutes (three times the estimated 6 minutes completion time, suggesting possible distraction). The final sample included 276 participants. Among them, 53.3% identified as female; racially, 68.1% identified as Caucasian, 22.1% as Black or African American, 4% as Asian, 2.9% as Hispanic or Latino, and 2.2% as another race. The age distribution was as follows: 7.6% (18–24 years), 35.5% (25–34), 27.2% (35–44), 17% (45–54), 6.5% (55–64), and 6.5% (65 or older).

Upon entering the experiment, participants were randomly assigned to one of the six experimental conditions (condition details are provided in the next paragraph) in a between-subjects design with equal assignment probabilities. Randomization was implemented automatically at the survey level and was independent of participant characteristics. Because all participants were drawn from the same pre-screened Prolific population and recruited within a short time window, participants across conditions are comparable. We additionally conducted balance checks on observable characteristics and found no systematic differences across conditions, confirming that randomization was successful. Participants were compensated at a fixed rate corresponding to approximately $8 per hour, based on an average completion time of about seven minutes, which meets Prolific's recommended minimum hourly pay guidelines at the time of the study. Compensation was not contingent on participants' decisions.

The goal of our experiment is to examine whether employers' responses to guarantees would change if the platform requires that workers who wish to offer guarantees must do so at a high ratio. On the platform we studied, there was no minimum but a "suggested" ratio of 10%. We examine whether employers' reactions to guarantees would change when the platform imposes a threshold for using guarantee. We also wanted to study whether employer reactions to guarantee would change based on different worker ratings. Thus, this study employed a 2 × 3 factorial design to manipulate job applicants' attributes, specifically varying the cost associated with offering a guarantee (*HighCost* vs. *LowCost*) and the job applicant's reputation (*Low, Medium, High*). In the *HighCost* condition, only freelancers who deposited at least $50 or 30% of their bid amount (whichever was greater) were permitted to offer a guarantee (e.g., if a worker bids $100 for a project and wishes to use a guarantee, they must deposit at least $50). This threshold was chosen to reflect a meaningfully costly guarantee grounded in the platform's observed data rather than an arbitrary cutoff: in the field data, guarantees average approximately 30% of the bid value, with typical bid amounts around $180, implying a guarantee magnitude close to $50. In contrast, the *LowCost* condition allowed any workers—regardless of experience, rating, or reputation—to include a guarantee with their bid, mirroring the platform's permissive baseline practice.

Reputation was manipulated through the visibility of applicant ratings. In the *LowReputation* condition, the applicant's profile displayed zero out of five stars; in the *MediumReputation* condition, three out of five stars were shown; and in the *HighReputation* condition, the profile displayed a full five-star rating. This design resulted in six experimental conditions, representing all combinations of signaling cost and reputation level.

Participants were randomly assigned to one of these six conditions and presented with information about two job applicants—one who offered a guarantee and one who did not. The two applicants were designed to have the same average rating and comparable numbers of completed jobs within each reputation condition. To maintain internal validity and ensure that the experimental manipulations remained salient, all participants viewed the same applicant profiles at each reputation level. At the same time, to create a realistic trade-off and encourage participants to weigh the value of the guarantee, the applicant who did not offer a guarantee was intentionally presented as slightly more attractive overall, with marginally greater experience and a slightly lower bid price.

All participants were first instructed to imagine that (1) they are the owners of a business and are trying to hire a freelancer from an online labor platform (e.g., Freelancer.com or Upwork.com) to design a website for their business; (2) freelancers will specify how much they need to complete the job (i.e., bid amount); (3) they can see these freelancers' backgrounds (i.e., average ratings received from previous employers, and number of completed jobs). After reading these initial instructions, participants were presented with additional background information about the platform's features and the worker-offered guarantee policy.

Most importantly, participants were randomly assigned to read one of two descriptions of the worker-offered guarantee, depending on their assigned signaling cost condition. In the *LowCost* condition, participants read the following:

A Worker-Offered Guarantee is an optional feature that freelancers can voluntarily use by putting down a deposit as a sign of their commitment. If a freelancer who offers the guarantee fails to deliver satisfactory work, you do not receive the money — the deposit is forfeited to a third-party charity. On this platform, any worker — regardless of experience, ratings, or reputation — can include a guarantee with their bid in any small amount, at no personal cost until the job fails.

In contrast, participants assigned to the *HighCost* condition read:

A Worker-Offered Guarantee is an optional feature that freelancers can voluntarily use by putting down a deposit as a sign of their commitment. If a freelancer who offers the guarantee fails to deliver satisfactory work, you do not receive the money — the deposit is forfeited to a third-party charity. Recently, the platform introduced a new rule: Not every freelancer is allowed to use a guarantee. Only freelancers who deposit at least $50 or 30% of their bid amount (whichever is greater) are allowed to offer a guarantee. Freelancers can still bid without offering a guarantee.

These condition-specific instructions were designed to manipulate the perceived signaling cost associated with offering a guarantee, while keeping all other elements of the scenario constant across participants.

Before proceeding to the next screen, participants were required to answer comprehension questions to ensure they understood the guarantee policy. These questions included who is eligible to offer a guarantee and what happens to the deposit if a freelancer offers a guarantee but fails to deliver satisfactory work after being hired.

On the following screen, participants were shown a job description along with two job applicants' bids presented side by side in random order. Each bid displayed the bidder's number of jobs completed, average rating, guarantee deposit (if applicable), and bid amount. After reviewing the bids, participants were asked to choose which job applicant they would hire—they could hire one, the other, or neither. They were also instructed to rate the importance of several factors in shaping their decision: Whether the applicant offered a guarantee, the freelancer's average rating, the number of completed jobs, and the bid amount. Additionally, participants were asked to write a brief explanation of the most important reason behind their hiring choice.

On the next page, participants answered two manipulation check questions: One regarding the reputation ratings of the two bidders and another assessing whether they noticed any constraint associated with the ability to offer a guarantee. Finally, participants provided demographic information.

Figure F1 presents representative screenshots of the experimental interface and instructions shown to participants. Specifically, the figure includes the introductory instructions and comprehension checks, the Low-Cost and High-Cost guarantee policy descriptions, the six hiring scenarios corresponding to the 2×3 experimental conditions, the manipulation check questions, and the final demographic questionnaire. These screenshots illustrate exactly what information was communicated to participants at each stage of the experiment and demonstrate that all non-manipulated elements of the interface were held constant across conditions.

2) Measures and Variables

HiringGuarantee. It is an indicator that equals one if a participant hired a worker who offered a guarantee. Otherwise, 0. This variable has a mean of 0.431 and a standard deviation of 0.496.

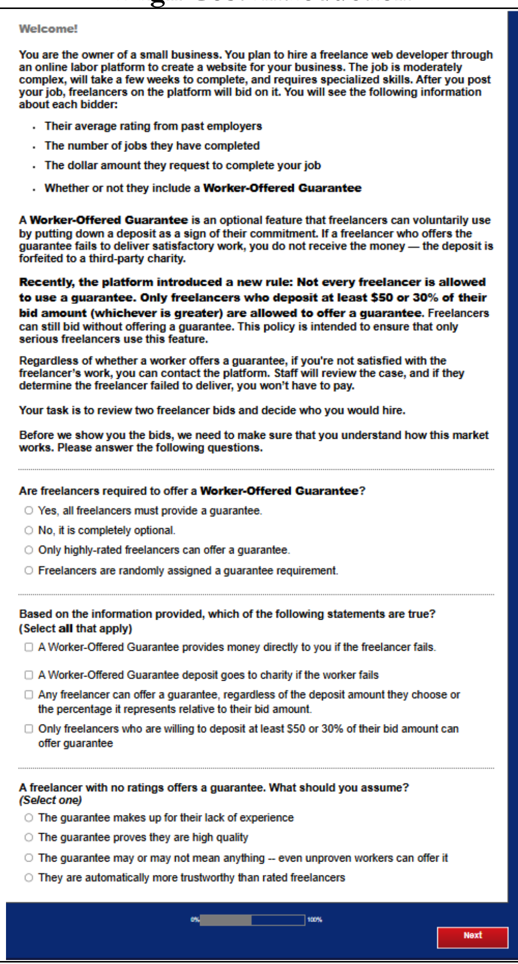
HiringOutcome. It is a categorical variable coded as 0, 1, or 2, indicating whether a participant hired a worker who did not offer a guarantee (0), offered a guarantee (1), or hired neither worker (2), respectively.

HighSignalingCost. It is an indicator that equals one if, in the randomly assigned condition, only freelancers who deposit at least \$50 or 30% of their bid amount (whichever is greater) are allowed to offer a guarantee. Otherwise, the value is 0.

Reputation. It is a categorical variable that indicates a job applicant's reputation level. It has three levels: Low, Medium, or High.

Fig. F1 Experiment Screenshots

High Cost Introduction	Low Cost Introduction



Welcome!

You are the owner of a small business. You plan to hire a freelance web developer through an online labor platform to create a website for your business. The job is moderately complex, will take a few weeks to complete, and requires specialized skills. After you post your job, freelancers on the platform will bid on it. You will see the following information about each bidder:

- Their average rating from past employers
- The number of jobs they have completed
- The dollar amount they request to complete your job
- Whether or not they include a **Worker-Offered Guarantee**

A **Worker-Offered Guarantee** is an optional feature that freelancers can voluntarily use by putting down a deposit as a sign of their commitment. If a freelancer who offers the guarantee fails to deliver satisfactory work, you do not receive the money — the deposit is forfeited to a third-party charity.

Recently, the platform introduced a new rule: Not every freelancer is allowed to use a guarantee. Only freelancers who deposit at least \$50 or 30% of their bid amount (whichever is greater) are allowed to offer a guarantee. Freelancers can still bid without offering a guarantee. This policy is intended to ensure that only serious freelancers use this feature.

Regardless of whether a worker offers a guarantee, if you're not satisfied with the freelancer's work, you can contact the platform. Staff will review the case, and if they determine the freelancer failed to deliver, you won't have to pay.

Your task is to review two freelancer bids and decide who you would hire.

Before we show you the bids, we need to make sure that you understand how this market works. Please answer the following questions.

Are freelancers required to offer a **Worker-Offered Guarantee**?

- ○ Yes, all freelancers must provide a guarantee.
- ○ No, it is completely optional.
- ○ Only highly-rated freelancers can offer a guarantee.
- ○ Freelancers are randomly assigned a guarantee requirement.

Based on the information provided, which of the following statements are true? (Select **all** that apply)

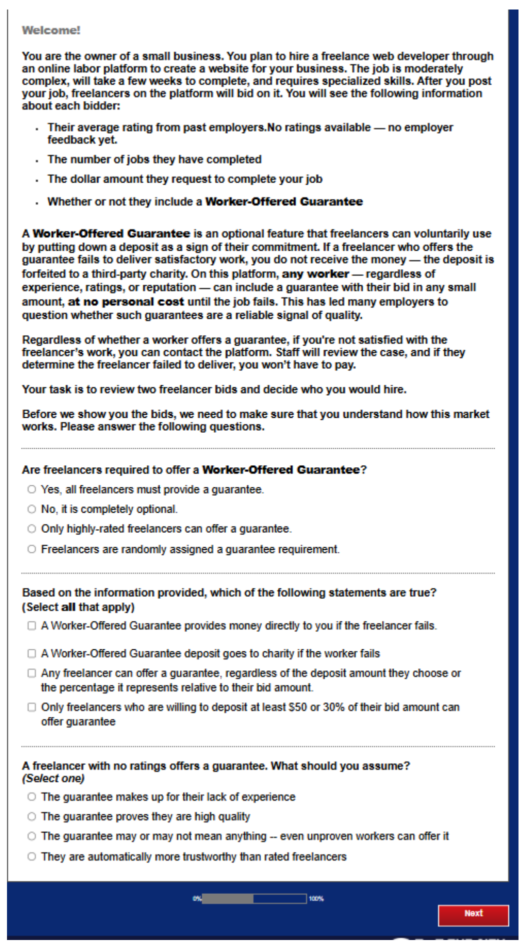
- ☐ A Worker-Offered Guarantee provides money directly to you if the freelancer fails.
- ☐ A Worker-Offered Guarantee deposit goes to charity if the worker fails
- ☐ Any freelancer can offer a guarantee, regardless of the deposit amount they choose or the percentage it represents relative to their bid amount.
- ☐ Only freelancers who are willing to deposit at least \$50 or 30% of their bid amount can offer guarantee

A freelancer with no ratings offers a guarantee. What should you assume? *(Select one)*

- ○ The guarantee makes up for their lack of experience
- ○ The guarantee proves they are high quality
- ○ The guarantee may or may not mean anything -- even unproven workers can offer it
- ○ They are automatically more trustworthy than rated freelancers

0% 100%

Next



Welcome!

You are the owner of a small business. You plan to hire a freelance web developer through an online labor platform to create a website for your business. The job is moderately complex, will take a few weeks to complete, and requires specialized skills. After you post your job, freelancers on the platform will bid on it. You will see the following information about each bidder:

- Their average rating from past employers.No ratings available — no employer feedback yet.
- The number of jobs they have completed
- The dollar amount they request to complete your job
- Whether or not they include a **Worker-Offered Guarantee**

A **Worker-Offered Guarantee** is an optional feature that freelancers can voluntarily use by putting down a deposit as a sign of their commitment. If a freelancer who offers the guarantee fails to deliver satisfactory work, you do not receive the money — the deposit is forfeited to a third-party charity. On this platform, **any worker** — regardless of experience, ratings, or reputation — can include a guarantee with their bid in any small amount, **at no personal cost** until the job fails. This has led many employers to question whether such guarantees are a reliable signal of quality.

Regardless of whether a worker offers a guarantee, if you're not satisfied with the freelancer's work, you can contact the platform. Staff will review the case, and if they determine the freelancer failed to deliver, you won't have to pay.

Your task is to review two freelancer bids and decide who you would hire.

Before we show you the bids, we need to make sure that you understand how this market works. Please answer the following questions.

Are freelancers required to offer a **Worker-Offered Guarantee**?

- ○ Yes, all freelancers must provide a guarantee.
- ○ No, it is completely optional.
- ○ Only highly-rated freelancers can offer a guarantee.
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Based on the information provided, which of the following statements are true? (Select **all** that apply)

- ☐ A Worker-Offered Guarantee provides money directly to you if the freelancer fails.
- ☐ A Worker-Offered Guarantee deposit goes to charity if the worker fails
- ☐ Any freelancer can offer a guarantee, regardless of the deposit amount they choose or the percentage it represents relative to their bid amount.
- ☐ Only freelancers who are willing to deposit at least \$50 or 30% of their bid amount can offer guarantee

A freelancer with no ratings offers a guarantee. What should you assume? *(Select one)*

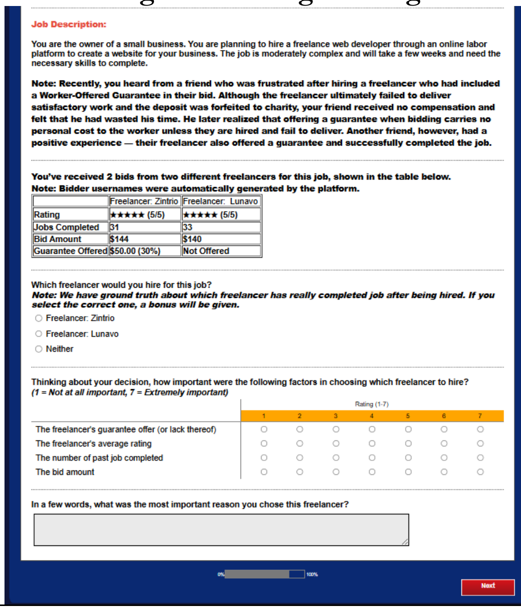
- ○ The guarantee makes up for their lack of experience
- ○ The guarantee proves they are high quality
- ○ The guarantee may or may not mean anything -- even unproven workers can offer it
- ○ They are automatically more trustworthy than rated freelancers

0% 100%

Next

Six Scenarios

High Cost x High Rating



Job Description:

You are the owner of a small business. You are planning to hire a freelance web developer through an online labor platform to create a website for your business. The job is moderately complex and will take a few weeks and need the necessary skills to complete.

Note: Recently, you heard from a friend who was frustrated after hiring a freelancer who had included a Worker-Offered Guarantee in their bid. Although the freelancer ultimately failed to deliver satisfactory work and the deposit was forfeited to charity, your friend received no compensation and felt that he had wasted his time. He later realized that offering a guarantee when bidding carries no personal cost to the worker unless they are hired and fail to deliver. Another friend, however, had a positive experience — their freelancer also offered a guarantee and successfully completed the job.

You've received 2 bids from two different freelancers for this job, shown in the table below.
Note: Bidder usernames were automatically generated by the platform.

	Freelancer: Zintrio	Freelancer: Lunavo
Rating	★★★★★ (5/5)	★★★★★ (5/5)
Jobs Completed	31	33
Bid Amount	$144	$140
Guarantee Offered	$50.00 (30%)	Not Offered

Which freelancer would you hire for this job?
Note: We have ground truth about which freelancer has really completed job after being hired. If you select the correct one, a bonus will be given.

- Freelancer: Zintrio
- Freelancer: Lunavo
- Neither

Thinking about your decision, how important were the following factors in choosing which freelancer to hire?
(1 = Not at all important, 7 = Extremely important)

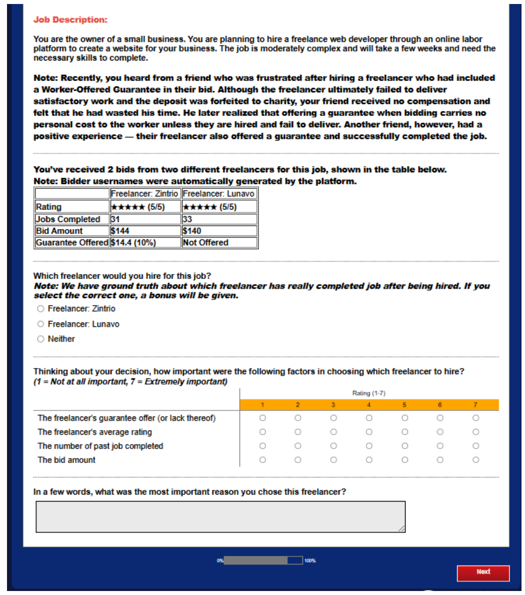
	Rating (1-7)						
	1	2	3	4	5	6	7
The freelancer's guarantee offer (or lack thereof)	○	○	○	○	○	○	○
The freelancer's average rating	○	○	○	○	○	○	○
The number of past job completed	○	○	○	○	○	○	○
The bid amount	○	○	○	○	○	○	○

In a few words, what was the most important reason you chose this freelancer?

0% 100%

Next

Low Cost x High Rating



Job Description:

You are the owner of a small business. You are planning to hire a freelance web developer through an online labor platform to create a website for your business. The job is moderately complex and will take a few weeks and need the necessary skills to complete.

Note: Recently, you heard from a friend who was frustrated after hiring a freelancer who had included a Worker-Offered Guarantee in their bid. Although the freelancer ultimately failed to deliver satisfactory work and the deposit was forfeited to charity, your friend received no compensation and felt that he had wasted his time. He later realized that offering a guarantee when bidding carries no personal cost to the worker unless they are hired and fail to deliver. Another friend, however, had a positive experience — their freelancer also offered a guarantee and successfully completed the job.

You've received 2 bids from two different freelancers for this job, shown in the table below.
Note: Bidder usernames were automatically generated by the platform.

	Freelancer: Zintrio	Freelancer: Lunavo
Rating	★★★★★ (5/5)	★★★★★ (5/5)
Jobs Completed	31	33
Bid Amount	$144	$140
Guarantee Offered	$14.4 (10%)	Not Offered

Which freelancer would you hire for this job?
Note: We have ground truth about which freelancer has really completed job after being hired. If you select the correct one, a bonus will be given.

- Freelancer: Zintrio
- Freelancer: Lunavo
- Neither

Thinking about your decision, how important were the following factors in choosing which freelancer to hire?
(1 = Not at all important, 7 = Extremely important)

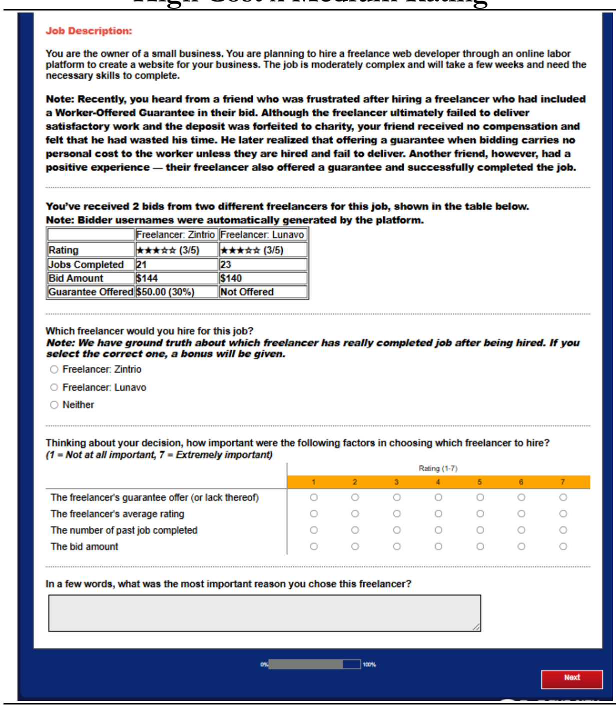
	Rating (1-7)						
	1	2	3	4	5	6	7
The freelancer's guarantee offer (or lack thereof)	○	○	○	○	○	○	○
The freelancer's average rating	○	○	○	○	○	○	○
The number of past job completed	○	○	○	○	○	○	○
The bid amount	○	○	○	○	○	○	○

In a few words, what was the most important reason you chose this freelancer?

0% 100%

Next

High Cost x Medium Rating



Job Description:

You are the owner of a small business. You are planning to hire a freelance web developer through an online labor platform to create a website for your business. The job is moderately complex and will take a few weeks and need the necessary skills to complete.

Note: Recently, you heard from a friend who was frustrated after hiring a freelancer who had included a Worker-Offered Guarantee in their bid. Although the freelancer ultimately failed to deliver satisfactory work and the deposit was forfeited to charity, your friend received no compensation and felt that he had wasted his time. He later realized that offering a guarantee when bidding carries no personal cost to the worker unless they are hired and fail to deliver. Another friend, however, had a positive experience — their freelancer also offered a guarantee and successfully completed the job.

You've received 2 bids from two different freelancers for this job, shown in the table below.
Note: Bidder usernames were automatically generated by the platform.

	Freelancer: Zintrio	Freelancer: Lunavo
Rating	★★★☆☆ (3/5)	★★★☆☆ (3/5)
Jobs Completed	21	23
Bid Amount	$144	$140
Guarantee Offered	$50.00 (30%)	Not Offered

Which freelancer would you hire for this job?
Note: We have ground truth about which freelancer has really completed job after being hired. If you select the correct one, a bonus will be given.

- Freelancer: Zintrio
- Freelancer: Lunavo
- Neither

Thinking about your decision, how important were the following factors in choosing which freelancer to hire?
(1 = Not at all important, 7 = Extremely important)

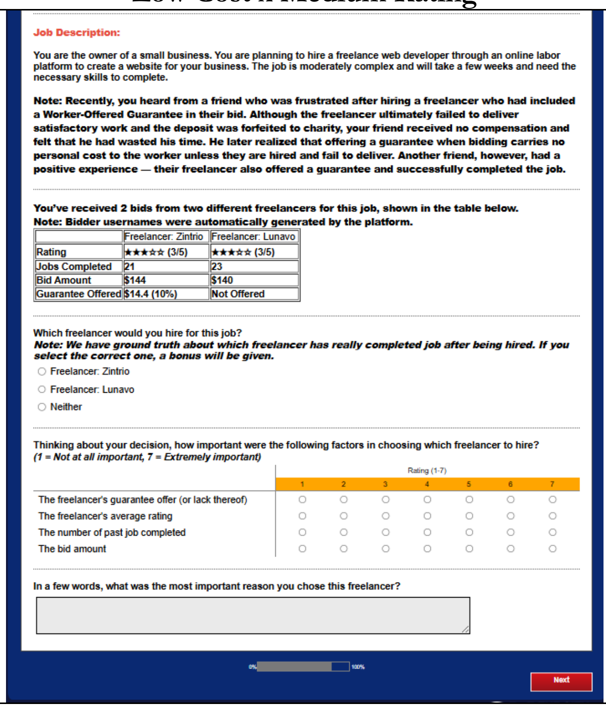
	Rating (1-7)						
	1	2	3	4	5	6	7
The freelancer's guarantee offer (or lack thereof)	○	○	○	○	○	○	○
The freelancer's average rating	○	○	○	○	○	○	○
The number of past job completed	○	○	○	○	○	○	○
The bid amount	○	○	○	○	○	○	○

In a few words, what was the most important reason you chose this freelancer?

0% 100%

Next

Low Cost x Medium Rating



Job Description:

You are the owner of a small business. You are planning to hire a freelance web developer through an online labor platform to create a website for your business. The job is moderately complex and will take a few weeks and need the necessary skills to complete.

Note: Recently, you heard from a friend who was frustrated after hiring a freelancer who had included a Worker-Offered Guarantee in their bid. Although the freelancer ultimately failed to deliver satisfactory work and the deposit was forfeited to charity, your friend received no compensation and felt that he had wasted his time. He later realized that offering a guarantee when bidding carries no personal cost to the worker unless they are hired and fail to deliver. Another friend, however, had a positive experience — their freelancer also offered a guarantee and successfully completed the job.

You've received 2 bids from two different freelancers for this job, shown in the table below.
Note: Bidder usernames were automatically generated by the platform.

	Freelancer: Zintrio	Freelancer: Lunavo
Rating	★★★☆☆ (3/5)	★★★☆☆ (3/5)
Jobs Completed	21	23
Bid Amount	$144	$140
Guarantee Offered	$14.4 (10%)	Not Offered

Which freelancer would you hire for this job?
Note: We have ground truth about which freelancer has really completed job after being hired. If you select the correct one, a bonus will be given.

- Freelancer: Zintrio
- Freelancer: Lunavo
- Neither

Thinking about your decision, how important were the following factors in choosing which freelancer to hire?
(1 = Not at all important, 7 = Extremely important)

	Rating (1-7)						
	1	2	3	4	5	6	7
The freelancer's guarantee offer (or lack thereof)	○	○	○	○	○	○	○
The freelancer's average rating	○	○	○	○	○	○	○
The number of past job completed	○	○	○	○	○	○	○
The bid amount	○	○	○	○	○	○	○

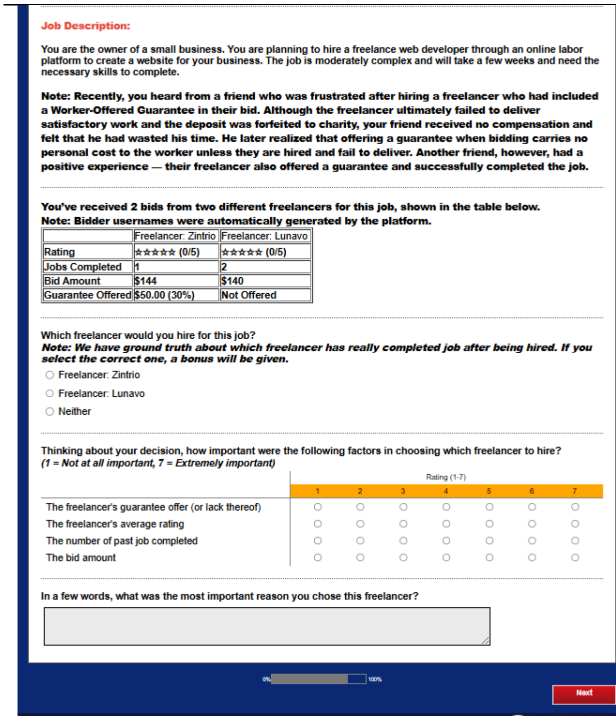
In a few words, what was the most important reason you chose this freelancer?

0% 100%

Next

High Cost x Low Rating

Low Cost x Low Rating



Job Description:

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Note: Recently, you heard from a friend who was frustrated after hiring a freelancer who had included a Worker-Offered Guarantee in their bid. Although the freelancer ultimately failed to deliver satisfactory work and the deposit was forfeited to charity, your friend received no compensation and felt that he had wasted his time. He later realized that offering a guarantee when bidding carries no personal cost to the worker unless they are hired and fail to deliver. Another friend, however, had a positive experience — their freelancer also offered a guarantee and successfully completed the job.

You've received 2 bids from two different freelancers for this job, shown in the table below.
Note: Bidder usernames were automatically generated by the platform.

	Freelancer: Zintrio	Freelancer: Lunavo
Rating	☆☆☆☆☆ (0/5)	☆☆☆☆☆ (0/5)
Jobs Completed	1	2
Bid Amount	$144	$140
Guarantee Offered	$50.00 (30%)	Not Offered

Which freelancer would you hire for this job?
Note: We have ground truth about which freelancer has really completed job after being hired. If you select the correct one, a bonus will be given.

- Freelancer: Zintrio
- Freelancer: Lunavo
- Neither

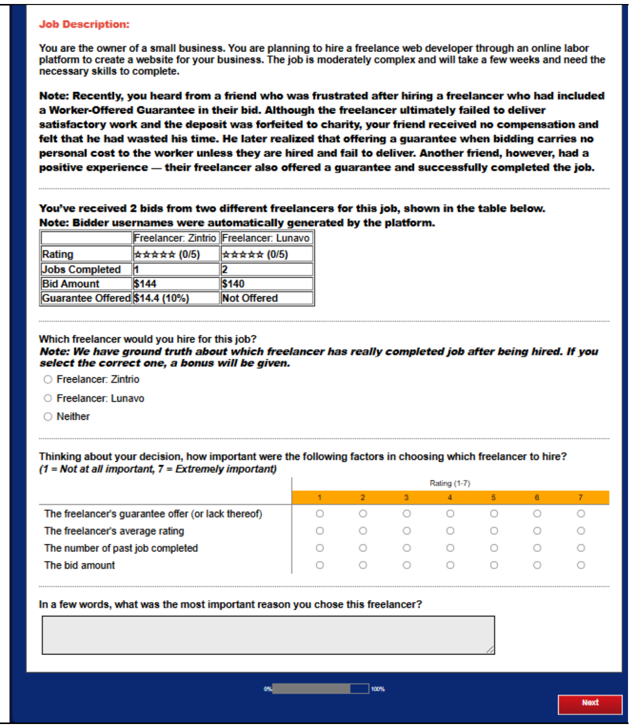
Thinking about your decision, how important were the following factors in choosing which freelancer to hire?
(1 = Not at all important, 7 = Extremely important)

	Rating (1-7) 1	2	3	4	5	6	7
The freelancer's guarantee offer (or lack thereof)	○	○	○	○	○	○	○
The freelancer's average rating	○	○	○	○	○	○	○
The number of past job completed	○	○	○	○	○	○	○
The bid amount	○	○	○	○	○	○	○

In a few words, what was the most important reason you chose this freelancer?

0% 100%

Next



Job Description:

You are the owner of a small business. You are planning to hire a freelance web developer through an online labor platform to create a website for your business. The job is moderately complex and will take a few weeks and need the necessary skills to complete.

Note: Recently, you heard from a friend who was frustrated after hiring a freelancer who had included a Worker-Offered Guarantee in their bid. Although the freelancer ultimately failed to deliver satisfactory work and the deposit was forfeited to charity, your friend received no compensation and felt that he had wasted his time. He later realized that offering a guarantee when bidding carries no personal cost to the worker unless they are hired and fail to deliver. Another friend, however, had a positive experience — their freelancer also offered a guarantee and successfully completed the job.

You've received 2 bids from two different freelancers for this job, shown in the table below.
Note: Bidder usernames were automatically generated by the platform.

	Freelancer: Zintrio	Freelancer: Lunavo
Rating	☆☆☆☆☆ (0/5)	☆☆☆☆☆ (0/5)
Jobs Completed	1	2
Bid Amount	$144	$140
Guarantee Offered	$14.4 (10%)	Not Offered

Which freelancer would you hire for this job?
Note: We have ground truth about which freelancer has really completed job after being hired. If you select the correct one, a bonus will be given.

- Freelancer: Zintrio
- Freelancer: Lunavo
- Neither

Thinking about your decision, how important were the following factors in choosing which freelancer to hire?
(1 = Not at all important, 7 = Extremely important)

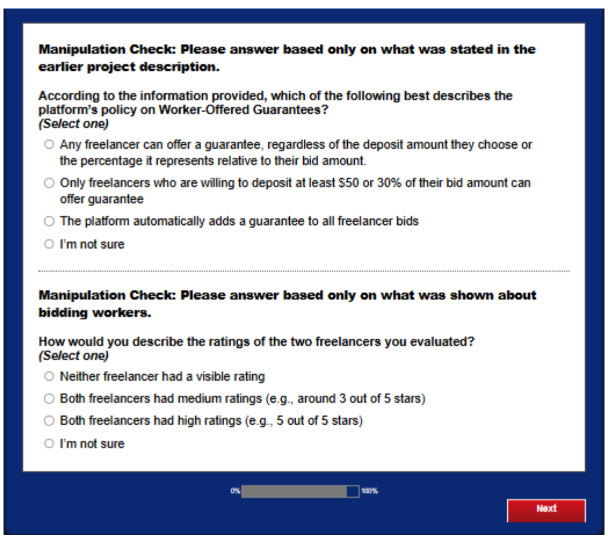
	Rating (1-7) 1	2	3	4	5	6	7
The freelancer's guarantee offer (or lack thereof)	○	○	○	○	○	○	○
The freelancer's average rating	○	○	○	○	○	○	○
The number of past job completed	○	○	○	○	○	○	○
The bid amount	○	○	○	○	○	○	○

In a few words, what was the most important reason you chose this freelancer?

0% 100%

Next

Manipulation Check



Manipulation Check: Please answer based only on what was stated in the earlier project description.

According to the information provided, which of the following best describes the platform's policy on Worker-Offered Guarantees?
(Select one)

- Any freelancer can offer a guarantee, regardless of the deposit amount they choose or the percentage it represents relative to their bid amount.
- Only freelancers who are willing to deposit at least $50 or 30% of their bid amount can offer guarantee
- The platform automatically adds a guarantee to all freelancer bids
- I'm not sure

Manipulation Check: Please answer based only on what was shown about bidding workers.

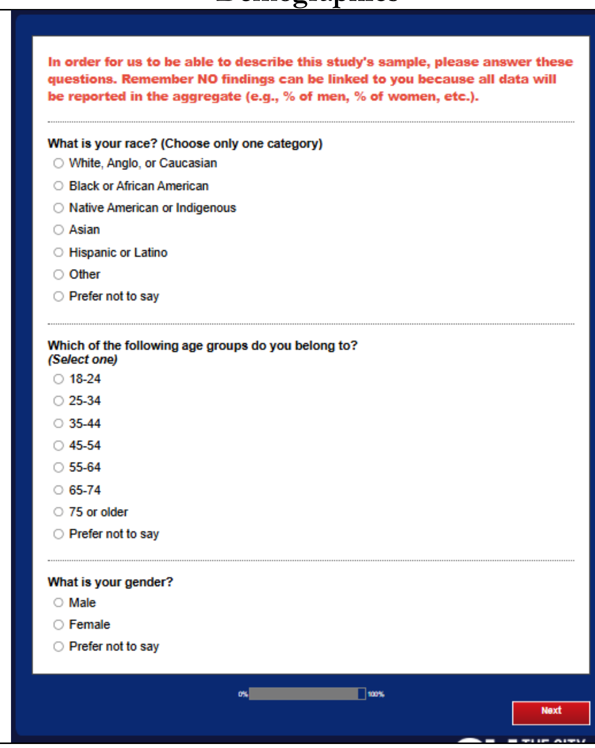
How would you describe the ratings of the two freelancers you evaluated?
(Select one)

- Neither freelancer had a visible rating
- Both freelancers had medium ratings (e.g., around 3 out of 5 stars)
- Both freelancers had high ratings (e.g., 5 out of 5 stars)
- I'm not sure

0% 100%

Next

Demographics



In order for us to be able to describe this study's sample, please answer these questions. Remember NO findings can be linked to you because all data will be reported in the aggregate (e.g., % of men, % of women, etc.).

What is your race? (Choose only one category)

- White, Anglo, or Caucasian
- Black or African American
- Native American or Indigenous
- Asian
- Hispanic or Latino
- Other
- Prefer not to say

Which of the following age groups do you belong to?
(Select one)

- 18-24
- 25-34
- 35-44
- 45-54
- 55-64
- 65-74
- 75 or older
- Prefer not to say

What is your gender?

- Male
- Female
- Prefer not to say

0% 100%

Next

3) Manipulation Check

We conducted two manipulation checks to assess whether participants recognized the experimental manipulations related to the signaling cost of guarantees and the reputation levels of job applicants. First, we evaluated whether participants understood the manipulation of access costs associated with offering a guarantee. A one-sample proportion test indicates that 95.3% of participants correctly understood the manipulation, significantly higher than the expected 50% under the null hypothesis ($p < 0.01$). This high level of comprehension suggests that participants accurately perceived the experimental conditions. We then applied the same approach to assess whether participants accurately identified the manipulation of job applicants' reputation levels. In this case, approximately 94.9% of participants correctly interpreted the manipulation, and the proportion test was highly significant ($p < 0.01$). This confirms that the manipulation of the freelancer's reputation was effective and clearly understood by the participants.

4) Analyses and Results

In this study, we theorize that the low signaling cost associated with worker-offered guarantees reduces their perceived credibility, thereby decreasing employers' likelihood of hiring workers who offer them. To empirically test this claim, we examined how the cost of signaling through guarantees influences employers' hiring decisions and how workers' reputation moderates this relationship.

Figure F2 shows the proportion of guaranteed job applicants hired, broken down by signaling cost (Low vs. High) and reputation (Low, Medium, High). Two patterns emerge. Under high signaling cost, hiring likelihood increases with reputation. Under low cost, hiring rates are generally lower and vary less across reputations—medium-reputation applicants are favored over high, with low-reputation applicants selected least. These patterns support our theory: Costly guarantees are more effective signals, and reputation affects the relationship between guarantee offering and hiring.

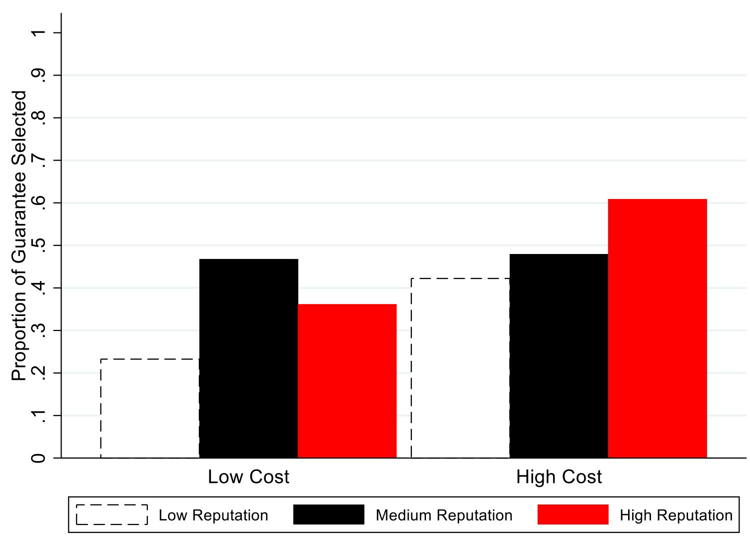


Fig. F2 Hiring Rates of Guaranteed Workers by Signaling Cost and Reputation

We conducted two participant-level analyses using the dependent variable *HiringGuarantee*, which indicates whether a participant selected the worker who offered a guarantee. In the first analysis, we assessed how hiring outcomes varied across different levels of signaling cost and reputation. In the second analysis, we also included an interaction term between signaling cost and reputation to examine the moderating role of reputation on the relationship between signaling cost of guarantee and hiring a worker who offers a guarantee.

Table F1 presents the results. First, the coefficients for *HighSignalingCost* are positive and statistically significant in both columns, indicating that when the cost to offer a guarantee is high, employers are more likely to hire freelancers who include one. This finding supports our theoretical argument that costly guarantees are perceived as more credible signals. Second, in Column 1, the coefficients of both *Reputation (medium)* and *Reputation (high)* are positive and statistically significant at .05 level, while the coefficient of *Reputation (high)* is relatively greater (0.671 vs. 0.623), suggesting that overall guarantees are more effective when offered by more reputable freelancers.

Third, in Column 2, the coefficient of *Reputation (medium)* is statistically significant and greater than the coefficient of *Reputation (high)*, which is only marginally significant, indicating that when signaling cost is low, guarantee is most helpful for the medium-reputation workers. Notably, the interaction term between *HighSignalingCost* and *Reputation (medium)* is negative and marginally significant in a one-tailed test ($\beta = -0.836$, $p < .10$), suggesting that such advantage for medium-reputation workers weakens when the cost of offering a guarantee is high. The interaction term between *HighSignalingCost* and *Reputation (high)* is small and not statistically significant ($\beta = 0.130$), indicating that the effect of high reputation does not substantially change across signaling cost conditions.

Overall, these results support the theoretical prediction that higher signaling costs increase the credibility of worker-offered guarantees. Moreover, the influence of reputation interacts with cost: Guarantees are especially effective when either reputation or signaling cost is high, but the combination of both may not yield additive effects.

Table F1. Effect of Signaling Cost and Reputation Levels on Employers' Hiring Decisions

DV: *HiringGuarantee*	No Interaction Terms	Interaction Terms
HighSignalingCost	0.619**	0.880*
	(0.249)	(0.471)
Reputation (medium)	0.623**	1.066**
	(0.310)	(0.464)
Reputation (high)	0.671**	0.626ǂ
	(0.311)	(0.472)
HighSignalingCost×Reputation (medium)		-0.836ǂ
		(0.625)
HighSignalingCost×Reputation (high)		0.130
		(0.636)
Constant	-1.043***	-1.194***
	(0.269)	(0.361)
# of Observations	276	276

Note. Standard errors in parentheses.
*** p<0.01, ** p<0.05, * p<0.1, ǂ p<0.1 in one-tailed tests

5) Mechanism: Perceived Importance of Guarantees

To explore the mechanisms underlying participants' hiring preferences, we asked participants—acting as employers—to rate the importance of several factors that may influence their hiring decisions. These factors included whether a guarantee was offered (or lack thereof), the freelancer's average rating, the number of jobs completed, and the requested payment to complete the job. Participants rated each factor on a 7-point Likert scale (1 = Not at all important, 7 = Extremely important).

To assess whether perceptions of the importance of guarantees differed by signaling cost condition, we conducted a Pearson chi-square test. Table F2 presents the distribution of importance ratings for guarantees, disaggregated by signaling cost condition (low vs. high). The results revealed a statistically significant association between signaling cost and perceived importance of guarantees, $\chi^2(6, N = 276) = 14.36$, $p = .026$. This suggests that participants' evaluations of the guarantee's importance varied meaningfully between the two conditions.

In the low signaling cost condition, importance ratings were more evenly distributed, with a notable concentration in the lower part of the scale—for example, 22 participants rated the importance of guarantees as "2," while only 12 rated it as "5." In contrast, in the high signaling cost condition, participants were more likely to assign higher importance to guarantees, particularly at scale point 7 (n = 24 vs. 7 in low cost). This pattern supports the intended effect of the signaling cost manipulation: When offering a guarantee involves a real financial commitment, participants interpret it as a more credible and meaningful signal of reliability.

Table F2. Cross-tabulation of Guarantee Importance by Signaling Cost Condition

Importance of Guarantee	Low Signaling Cost (n=137)	High Signaling Cost (n=139)	Total
1 (Not at all important)	28	16	44
2	22	15	37
3	21	20	41
4	15	18	33
5	12	14	26
6	32	32	64
7 (Extremely important)	7	24	31
Total	137	139	276

Note. Pearson $\chi^2(6) = 14.36$, p = .026

6) Qualitative Evidence Supporting Theoretical Mechanisms

To complement our quantitative findings, we examined participants' open-ended responses explaining their hiring decisions. These comments provide compelling qualitative evidence that the mechanisms outlined in our theoretical development are not only analytically valid but also intuitively recognized by participants acting as employers. Below, we summarize how participants' reasoning maps onto key aspects of our theoretical framework.

Worker-offered guarantees fail to transfer risk from buyer to seller. Several participants expressed skepticism about the practical value of the guarantee mechanism, particularly in the low-cost, low-reputation condition. One participant noted, *"I don't place much value on the guarantee since it doesn't compensate me if the work fails,"* highlighting that the guarantee did not shift risk in a meaningful way. Another participant echoed this concern, stating, *"The guarantee, while seemingly a sign of good faith, ultimately doesn't provide direct financial protection to the employer."* Even under high-cost conditions, the same sentiment was evident: *"I chose Lunavo because the guarantee offered by Zintrio doesn't provide direct compensation and may not reflect actual commitment."* These responses support our theoretical claim that employers are aware that the guarantee mechanism fails to provide true protection and therefore discount its value.

Guarantees are not perceived as credible quality signals. In both low- and high-reputation conditions, participants questioned the signaling value of guarantees. For example, one participant remarked, *"I do not feel the guarantee offer (or lack thereof) is a good indicator of whether the freelancer is able to do the job,"* reflecting our theoretical claim that guarantees, especially when low-cost, are not interpreted as credible signals of ability. Another stated, *"A guarantee only becomes costly in case Zintrio ends up being hired and fails to deliver,"* suggesting awareness that the signal's cost is conditional and thus may not reflect the worker's actual confidence at the time of bidding.

Counter-screening: Employers penalize guarantees from high-reputation workers. Consistent with our counter-screening hypothesis, participants frequently penalized reputable freelancers for offering a guarantee. In low-cost, high-reputation conditions, one participant stated, *"He has completed more jobs and has a slightly cheaper rate. I think since the rating is five stars and there are over 30 jobs, the guarantee isn't really needed."* Another put it more bluntly: *"I don't really support the idea behind [the guarantee] and felt that the freelancer who did not have the guarantee offer was the better option."* This pattern persisted even under high-cost conditions. One employer remarked, *"I'm running a business and want a potential freelancer to feel strong enough in their work without having to offer a cash guarantee,"* while another observed, *"The guarantee may be misleading; Lunavo relies on proven performance, not tactics."* These responses suggest that for highly reputable workers, offering a guarantee may signal insecurity or overcompensation, reducing perceived credibility rather than enhancing it.

High signaling cost increases credibility. In contrast, when signaling cost was high and reputation was low, participants viewed the guarantee more favorably, consistent with signaling theory. One participant wrote, *"Zintrio, however, stood to lose $50 if he did not deliver the requested product,"* acknowledging the real financial risk involved. Another commented, *"The freelancer offered a guarantee with a significant deposit, which signaled strong commitment despite limited work history."* A third participant stated, *"The $50 was their commitment to getting the job completed. Without it, you are at their mercy, and there is no commitment on their end."* These examples validate our core argument that costly guarantees restore signaling credibility, particularly for workers who lack other indicators of competence.

Our experimental findings support the conclusion that the low signaling cost associated with worker-offered guarantees is a key reason why employers view this mechanism with skepticism. These results suggest a potential solution to mitigate the unintended consequences of the guarantee mechanism: Increasing the signaling cost to enhance its credibility. The study offers important practical implications for online labor platforms, employers, and freelancers, highlighting the role of platform design in shaping trust and hiring outcomes.

Appendix G: Full Estimation Results

Table G1. Effects of *Guarantee* on Employer's Hiring Decision (Table 2 in Main Paper)

DEP. VAR.	*Selected*		*Selected*	
MODEL	Clogit	SE	FE-LPM	SE
Guarantee	-0.275***	0.040	-0.008***	0.001
#OfRatings	0.233***	0.006	0.012***	0.000
AvgRating	0.075***	0.003	0.003***	0.000
Certified	0.197***	0.039	0.015***	0.003
WorkerTenure	-0.054***	0.007	-0.003***	0.000
HavingPic	0.022*	0.013	-0.000	0.001
MsgLength(log)	0.483***	0.011	0.021***	0.000
MsgReadability(fog)	-0.401***	0.017	-0.019***	0.001
MsgConcreteness	0.738***	0.040	0.029***	0.002
MsgSentiment	-0.226***	0.028	-0.014***	0.001
BidAmount	-8.952***	0.153	-0.281***	0.004
BidOrder	0.413***	0.011	0.017***	0.000
HavingSimiJobs	-0.010	0.027	-0.005***	0.001
SameCountry	0.620***	0.022	0.032***	0.001
BidSameEmployer	-0.245***	0.024	-0.014***	0.001
Constant			0.020***	0.003
# of Observations	372,531		669,728	
# of Jobs	37,353		87,236	
Job fixed effects	YES		YES	
Year-quarter fixed effects	YES		YES	

Note. *** p<0.01, ** p<0.05, * p<0.1. Robust standard errors are clustered at the job level.

Table G2. Effects of *Guarantee* on Job Rating Given by Employers (Table 4 in Main Paper)

	Ordered Models				Linear Models			
DEP. VAR.	*JobRating*		*JobRating*		*JobRating*		*JobRating*	
MODEL	Ordered Logit	SE	Ordered Probit	SE	Random Effects	SE	Fixed Effects	SE
Guarantee	-0.596***	0.054	-0.375***	0.031	-1.155***	0.100	-1.191***	0.121
#OfRatings	0.048***	0.007	0.029***	0.004	0.098***	0.013	0.068***	0.016
AvgRating	0.118***	0.003	0.067***	0.002	0.211***	0.006	0.192***	0.007
Certified	0.049	0.043	0.032	0.026	0.104	0.083	0.027	0.104
WorkerTenure	0.025***	0.009	0.015***	0.005	0.040**	0.016	0.049***	0.019
HavingPic	0.083***	0.016	0.055***	0.009	0.155***	0.030	0.148***	0.036
BidAmount	-0.963***	0.095	-0.595***	0.056	-1.777***	0.171	-2.004***	0.245
BidOrder	0.093***	0.009	0.058***	0.005	0.172***	0.016	0.139***	0.020
HavingSimiJobs	-0.308***	0.034	-0.175***	0.020	-0.582***	0.060	-0.427***	0.070
SameCountry	0.112***	0.025	0.069***	0.015	0.199***	0.046	0.123**	0.060
BidSameEmployer	-0.087***	0.026	-0.055***	0.015	-0.144***	0.048	-0.030	0.053
EmployerTenure	-0.008	0.011	-0.005	0.006	-0.019	0.019	0.463***	0.082
EmployerExperience	0.004	0.010	0.002	0.006	0.013	0.017	-0.448***	0.054
JobDesLen	-0.019*	0.011	-0.011*	0.007	-0.037*	0.021	-0.097***	0.030
Constant					4.583***	0.140	4.531***	0.228
# of observations	49,949		49,949		49,949		49,949	
# of employers	14,986		14,986		14,986		14,986	
Job value fixed effects	YES		YES		YES		YES	
Job category fixed effects	YES		YES		YES		YES	
Employer fixed effects	NO		NO		NO		YES	
Year-quarter fixed effects	YES		YES		YES		YES	

Note. *** p<0.01, ** p<0.05, * p<0.1. Robust standard errors are clustered at the employer level.

Table G3. Workers' Reputation and Their Use of Guarantees (Table 6 in Main Paper)

DEP. VAR.	*Guarantee*	
VARIABLES	FE-LPM	SE
Reputation [Low]	-0.035***	0.002
Reputation [High]	-0.028***	0.002
#OfRatings	-0.001***	0.000
Certified	-0.028***	0.002
WorkerTenure	0.068***	0.003
HavingPic	-0.005***	0.000
BidAmount	-0.032***	0.001
BidOrder	-0.002**	0.001
HavingSimiJobs	-0.009***	0.001
SameCountry	0.002	0.005
BidSameEmployer	-0.001**	0.000
Constant	-0.007***	0.001
# of Observations	669,728	
# of Jobs	87,236	
Job fixed effects	YES	
Year-quarter fixed effects	YES	

Note. *** p<0.01, ** p<0.05, * p<0.1. Robust Standard Errors are clustered at the job level.

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