DIW BERLIN

2087

Discussion Papers

Deutsches Institut für Wirtschaftsforschung 2024

Advertising in Online Labor Markets: A Signal of Freelancer Quality?

Jonas Hannane

IMPRESSUM

DIW Berlin, 2024

DIW Berlin
German Institute for Economic Research
Mohrenstr. 58
10117 Berlin

Tel. +49 (30) 897 89-0
Fax +49 (30) 897 89-200
https://www.diw.de

ISSN electronic edition 1619-4535

Papers can be downloaded free of charge from the DIW Berlin website:
https://www.diw.de/discussionpapers

Discussion Papers of DIW Berlin are indexed in RePEc and SSRN:
https://ideas.repec.org/s/diw/diwwpp.html
https://www.ssrn.com/link/DIW-Berlin-German-Inst-Econ-Res.html

Advertising in Online Labor Markets: A Signal of Freelancer Quality?*

Jonas Hannane†

June 13, 2024

Abstract

Freelancers face cold-start problems in online labor markets: getting hired is very difficult without ratings, while obtaining a rating is impossible unless already having been hired. According to economic theory and empirical evidence, advertising can serve as a signal of product quality for experience goods. As such, advertising might help skilled new freelancers without reputation on a platform to obtain a first job, by providing a quality signal to employers. This study empirically explores the role of advertising in online labor markets using transactional data from a major platform. While indeed newer freelancers tend to advertise, I find that buyers dislike ads once I control for the increased visibility of ads. This negative effect is amplified for new and unrated freelancers compared to already rated freelancers. Furthermore, I find that new freelancers who advertise do not perform significantly better in the long-run compared to similar freelancers who do not advertise. Taken together, my results contrast the hypotheses derived from signaling models of advertising.

Keywords: Online Labor Markets, Information Asymmetry, Reputation, Signaling, Informative Advertising
JEL Codes: M37, J40, D82, L15

*I thank Hannes Ullrich, Tomaso Duso, Timm Teubner, Fabian Braesemann, Otto Kässi, Viola Hilbert, Andreas Leibing, as well as conference and seminar participants at the GC Summer Workshop 2022, the DIW Berlin IO Brown Bag Seminar, and the Digital Economy Workshop 2023 in Lausanne for helpful comments and suggestions. I thank Adam Lederer for editorial support. All remaining errors are my own.
†Affiliation: DIW Berlin, Technische Universität Berlin, and Berlin School of Economics. Email: jhannane@diw.de. Address: Mohrenstrasse 58, Berlin 10117, Germany.

1 Introduction

Online Labor Market (OLM) platforms connect buyers with freelance workers for a wide range of projects that are completed remotely. Typical projects include, among others, programming, graphic design, writing, or data entry jobs. Platforms such as Upwork, Freelancer.com, or Fiverr, have attracted millions of freelancers worldwide looking for work (Kässi et al., 2021). The immense reach of OLM combined with small and flexible jobs enables individuals and small firms to access a global workforce that would be otherwise inaccessible (Gao et al., 2023). At the same time, the low costs of joining OLM platforms create information asymmetries, since employers and freelancers can hardly evaluate each other's capabilities and commitment. Employers face substantive risks when hiring a freelancer. Besides delivering low-quality services, freelancers might delay or not complete a job, and possibly even steal advance payments or intellectual property (Yoganarasimhan, 2013). Therefore, new freelancers without reputation from past performance on the platform particularly struggle to obtain work. Pallais (2014) documents the prevalence of cold-start problems in OLM: getting hired is very difficult without (good) ratings, while obtaining a review is impossible unless already having been hired.

Signaling mechanisms are crucial to reduce such frictions caused by information asymmetries. Nelson (1970, 1974)[1] argues that expensive advertising can serve as a signal of high quality for experience goods, where consumers are *ex-ante* uncertain about the quality of a product (such as freelance work). The standard signaling model predicts a positive correlation between quality, advertising, and price only for newly introduced products, when consumers are uncertain about product quality (Horstmann and MacDonald, 2003). According to the model, firms producing goods of higher quality benefit more from advertising, thanks to obtaining more repeat purchases after consumption. In the context OLM, this translates into high-quality freelancers being re-hired more frequently after the completion of a project, since they are more likely to meet employers expectations. In this case, high-quality freelancers can more easily recover the costs of advertising compared to low-quality freelancers. This can lead to an equilibrium in which only high-quality freelancers advertise, on condition that advertising is sufficiently costly so that it is unprofitable for low-quality freelancers to imitate the strategy of high-quality freelancers by advertising. The act of advertising itself thereby reveals information about quality.

This article explores the role of advertising on OLM platforms and, more specifically, whether it serves as a signal of quality, especially for new and unrated freelancers. If so, advertising can improve the

[1] Kihlstrom and Riordan (1984) and Milgrom and Roberts (1986), amongst others, expand and formalize his signaling model of advertising.

match between buyers and freelancers in OLM, while helping qualified but not yet rated freelancers to win a first job. Advertisement refers to "sponsored bids" in the context of this study. When freelancers apply for work by submitting bids to a posted job offer, they can pay a predetermined price to appear at the top position of the result list viewed by the buyer (i.e. the employer, as I refer to interchangeably). Sponsored bids are labelled "Sponsored", informing the buyer that the freelancer paid money to be displayed prominently.[2]

I empirically test three hypotheses derived from the signaling model of advertising using observational data from a leading OLM platform. More specifically, I analyze i) if advertising freelancers are less experienced; ii) if buyers have a preference for ads; and iii) whether advertising freelancers perform better in the long-run. To answer the first question, I present several descriptive statistics such as the distribution of key variables (such as the number of ratings or number of days registered on the platform), distinguishing between sponsored and regular bids. Furthermore, I estimate a logit model to determine the most important predictors of the sponsoring decision. For the second hypothesis, I estimate discrete choice models to measure hiring preferences of buyers in OLM. Finally, to measure the long-run outcomes of new freelancers for the third hypothesis, I collect data on all posted bids, awarded projects, earnings, and ratings of initially unrated freelancers during a time span of four years. I then compare these various outcomes (using regression analysis) between the groups of freelancers who sponsored (at least) one bid with freelancers who did not advertise at all.

In line with the standard signaling model, I find that advertising freelancers tend to have fewer ratings and joined the platform more recently. However, my estimation of hiring preferences suggests that buyers do not have a preference for ads. To the contrary, compared to non-sponsored bids at the top position, sponsored bids are overall 6.4 percentage points less likely to win a project, *ceteris paribus*. For unrated new freelancers, the absolute effect is even larger with a decrease of around 11.5 percentage points on the probability of winning a project. While I find heterogeneous effects depending on the type of project (less complex types of projects are characterized by a stronger dislike for sponsored bids), the negative effect persists across project types for new and unrated freelancers. Apart from salience effects, which occur due to the increased visibility by being displayed first, sponsoring thus hurts the advertiser since employers prefer regular, i.e. non-sponsored, bids. Lastly, I find that new freelancers who advertise do not perform better in the long-run compared to new freelancers who do

[2] Sponsored bids can be thought of as sponsored product listings, which are common in many online marketplaces nowadays. In contrast to regular display ads that appear outside of the content margins, sponsored listings are located within the organic content of a platform. Sponsored listings provide both sales commissions (like organic listings) as well as advertising revenues to platforms, incentivizing more online marketplaces to offer ad slots in the form of sponsored listings to third-party sellers (Joo et al., 2024).

not advertise. This finding justifies that buyers do not have a preference for sponsored bids.

My study makes several contributions. First, I contribute to the literature on online labor markets by analyzing a so far unexplored mechanism (advertising) as a possible remedy for cold-start problems faced by freelancers. Second, my findings of a dislike for advertising (especially for new unrated freelancers), as well as the observation that the act of advertising is not predictive for future success on the platform, contributes to the empirical marketing literature by contrasting the hypotheses derived from the signaling model of advertising. To the best of my knowledge, my study is the first to link advertising to the counter-signaling literature. My results indicate that advertising might be used to counter-screen sellers in online platforms suffering from strong information asymmetry where other signals, such as online ratings, play a crucial role.

The remainder of this paper is organized as follows. Section 2 reviews the related literature. Section 3 describes the study's empirical context and data used. Section 4 investigates what type of freelancers select in to advertising. Section 5 looks at hiring choices, to determine whether buyers have a preference for ads. Section 6 compares long run outcomes between freelancers who advertise and those who do not. I conclude in Section 7.

2 Related Literature

This article relates to three main strands of research. First, this paper is related to the literature on online labor markets. Second, I contribute to the empirical marketing literature testing the signaling model of sponsored product listings. Finally, the literature on counter-signaling offers an explanation for my results rejecting the predictions of the signaling model of advertising.

2.1 Online Labor Markets and Signaling

A vast body of literature focuses on the estimation of hiring preferences in OLM (e.g. Troncoso and Luo (2023); Chan and Wang (2018); Hong and Pavlou (2017), Yoganarasimhan (2013)), looking at various variables of interests such as ratings, gender, or country of residence. Pallais (2014) shows that cold-start problems are prevalent in OLM: it is difficult for new freelancers to establish themselves and compete with established freelancers who have a track record of completed projects and positive ratings. Several studies look into signaling mechanisms in OLM, which might help new freelancers overcome this barrier to entry. For instance, Stanton and Thomas (2016) analyze the role of agencies, while Kässi and Lehdonvirta (2022) analyze the role of microcredentials. Filippas et al. (2023) analyze a different form of advertising in OLM: in their empirical context, the advertisement displays the phrase "Available Now" on the advertising freelancer's profile and all search tiles in which the freelancer appears. As such, the authors focus on a different mechanism, namely the coordination of buyers toward freelancers with greater capacity, which is more important for established freelancers, in contrast to my setting. Gao et al. (2023) analyze the role of guarantee-deposits[3] as quality signals in OLM. The authors find that guarantee-deposits often reduce the chances of winning a project and that freelancers offering guarantee-deposits are less likely to deliver satisfactory work. My findings support their results of signal "boomerangs" in OLM, where the signal hurts the freelancers instead of helping them.

2.2 Signaling Model of Advertising

Sahni and Nair (2020) run a field experiment on a restaurant-search portal, where the authors randomly vary the disclosure to consumers of whether a restaurant's listing is a paid ad. They find that the disclosure increases calls to the restaurant, thus, according to the authors, confirming the signaling hypothesis. In contrast, Joo et al. (2024) and Rallabandi (2022) find negative effects of sponsored listings on conversion rates using data from an online retail platform and an online hotel booking platform, respectively. Rallabandi (2022) argues that consumer responses to advertisement in high consideration purchase occasions (such as vacation stays) may be different compared to low consideration purchase occasions such as restaurant deliveries, which could explain his opposite findings compared to Sahni and Nair (2020). Abhishek et al. (2022) find heterogeneous effects of sponsored listings on clicks and conversion rates. The authors document negative effects for product categories such as electronics,[4] where the degree of information asymmetry between the seller, the platform, and the consumer is expected to be intrinsically low. However, categories with a higher degree of information asymmetry, such as clothing, as the authors argue, display positive effects of advertising on clicks and conversion. These results are in line with the canonical signaling models (Kihlstrom and Riordan (1984); Milgrom and Roberts (1986)), which focus on experience goods. I contribute to this strand of research by looking at a particular type of experience good, namely freelance work, which is characterized by severe information asymmetries (Horton, 2010). Furthermore, I focus on the effect of advertising for new participants that have not yet built up a reputation. In principle, advertising should be a valuable signal in this particular setting according to the signaling model of advertising.

2.3 Counter-Signaling

The economic literature on counter-signaling offers an explanation for my results rejecting the predictions of the signaling model of advertising. Feltovich et al. (2002) show, in a theoretical model, that counter-signaling can occur in situations of information asymmetry where multiple signaling tools ex-

[3] Freelancers providing guarantee-deposits who win a project but fail to complete it remain unpaid. Instead, the special guarantee-deposit is given to a charity chosen by the platform.

[4] Categories rather corresponding to search goods than experience goods.

ist. In such situations, high-quality firms may conceal certain information that mid-level quality firms might disclose. This counter-signaling behavior occurs when high quality firm withholding signals to potential customers are confident that other information about them will be favorable. Feltovich et al. (2002) illustrate this by showing that high-quality job candidates may choose not to disclose their GPA when recommendation letters from previous letters are available to distinguish themselves from medium candidates. Several empirical studies find evidence of this counter-signaling behavior as described by Feltovich et al. (2002). For instance, Luca and Smith (2015) show that prestigious business schools are less likely to reveal their rankings compared to mid-tier schools. The authors argue that this behavior stems from the established brand recognition, which acts as an alternative signal, enjoyed by the former. Bederson et al. (2018) find that high-quality restaurants that received a rating of A from hygiene inspections are less likely to disclose this rating than lower-quality restaurant of the same hygiene rating. Yelp ratings serve as an alternative signal for restaurants to stand out in that context. A closely related study from Gao et al. (2023) shows that employers in OLM platforms counter-screen freelancers who use guarantee deposits when applying for work. My study contributes to this strand of literature, by showing that advertising can be used as a counter-signal in markets characterized by strong information asymmetry where other signals (such as online ratings or text messages included in the bid) exists.

3 Empirical Context and Data

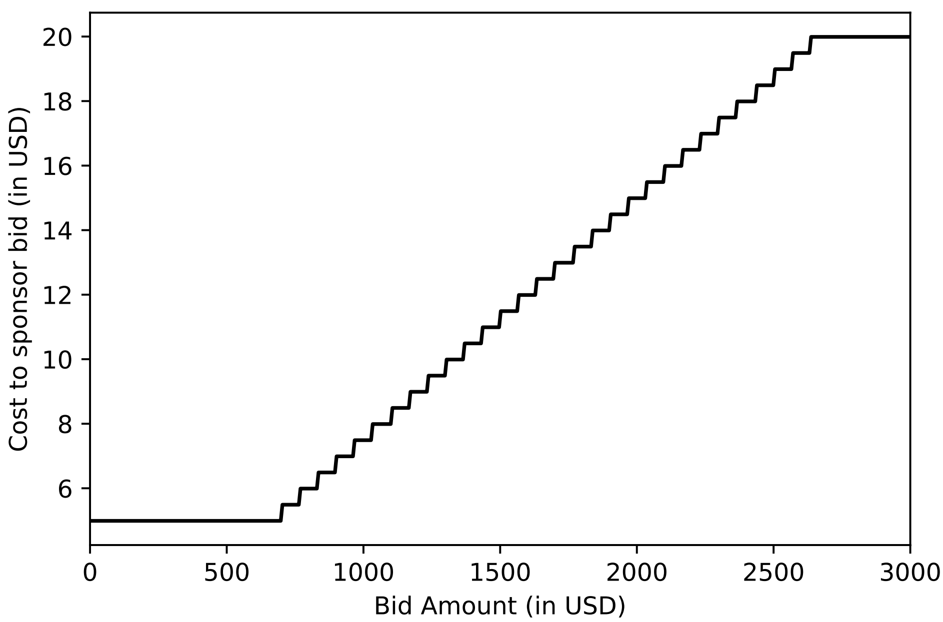
3.1 Empirical Context: OLM Platforms

Many OLM platforms deploy buyer-determined, reverse auctions (Hong et al., 2016). A buyer, who wants to hire a freelancer, can post a project as a call for bids (CFB). Buyers make several decisions when posting CFBs, such as setting a project budget, auction duration, and auction design format. Freelancers can apply to a CFB by submitting bids including a price and text message to the buyer. The buyer then decides to whom she awards the project.

The OLM platform under consideration in this study ranks all bids in a CFB based on a score calculated by an undisclosed, proprietary algorithm of the platform. Per default, the bids are shown to the buyer in a descending order of this score. Eight bids are shown per page to the buyers. While the exact formula of the bid score is kept secret, the platform informs about the relevant factors impacting the score: i) reviews and feedback; ii) previous payments received on the platform; iii) a freelancer's responsiveness; and iv) quality of a profile. Therefore, a freelancer cannot immediately (or just to a very limited extent) influence her bid score when applying for a project, since it is mostly based on past performance on the platform and does not take into account the bid price or message to buyer from the freelancer.

One sponsored bid is allowed per CFB, which is allocated on a first come first serve basis. A sponsored bid is pinned on top of the result list shown to the buyer and labeled "Sponsored", informing the buyer that the freelancer paid to be displayed prominently. Contrary to most other online marketplaces, the ad slot is not allocated to a seller via an auction. Instead, the price to sponsor a bid directly depends on the bid price set by the freelancer in the CFB. More specifically, the cost to sponsor a bid corresponds to 0.75% of the bid price or USD 4.99 (whichever is higher), for a maximum of USD 19.99. The price to sponsor is furthermore rounded up to the next USD cents 50. Figure 1 illustrates how the costs to sponsor a bid evolve according to the price set by a freelancer in her bid. In my data, the median price set by the freelancer equals 50 USD, with 90% of the bids having a price below 410.25 USD. The median price of sponsored bids equals 100 USD (and 555 USD for the top decile). Given the fact that many CFBs end up not being awarded (Yoganarasimhan, 2013), the costs to sponsor a bid appear rather expensive.

Figure 1: Costs to Sponsor a Bid



However, if a freelancer wins a CFB and gets a good rating by producing satisfactory work, she not only earns her bid amount for the project completion but also has a higher chance of receiving future job offers both directly[5] by being re-hired by the same employer or by being contracted by other

[5]It is possible for a buyer to hire a specific freelancer directly, without posting a CFB.

buyers with similar projects and indirectly thanks to her good rating, which improves her winning chances in CFBs.

3.2 Data

I collected bid-level data using the API of a major OLM platform on all CFBs posted between March and June 2018, in which the buyer selected a freelancer.[6] Appendix A.1 provides more details about the data collection procedure.

Table 1: Full Sample Overview

Observation Period	2018-03-01 to 2018-06-30
Number of Projects	96,150
Number of Bids	2,562,015
Number of Distinct Freelancers	255,795
Number of Distinct Employers	65,970
Number of Sponsored Bids	1,678
Number of Sponsored Awarded Bids	109

Table 1 gives an overview about the data collected for this paper. I collect data on 96,150 CFBs posted by 65,970 employers during a four months period. I observe 2,562,015 bids submitted by 255,795 different freelancers. Only 1,678 projects (1.75% of all projects) feature a sponsored bid, which is much lower than the prevalence of sponsored listing on other e-commerce marketplaces where they typically constitute around 20% of all listings (Abhishek et al., 2022). My findings from section 5 of a negative signaling effect from advertising might offer an explanation for this low proportion of sponsored bids. If many freelancers detect the poor effect of advertising on the likelihood of winning a CFB by themselves, the low percentage of sponsored bids follows trivially.

The data contains a large set of information about the bids and freelancers who submitted them. I observe the registration date of the freelancer on the platform, the type of account (if it is a corporate account), the country where the freelancer is based, her ratings in various categories as well as the price, message, and time to complete the project indicated in each bid. Furthermore, I observe the bid score computed by the platform. This variable not only serves as a proxy for a freelancer's profile quality but also informs about the position of a bid in the result list shown to the buyer.

As a large OLM platform, the freelancers and buyers observed in my data come from various countries around the world. Table 2 lists the top-15 freelancer and employer countries. In line with Braesemann et al. (2022), I find that most freelancers are based in South Asia,[7] while employers are based, to a

[6] These projects did not necessarily ended up being completed. Some projects were rejected by freelancers, others were cancelled by buyers, and a few projects were revoked by the platform, if it violated the platform's terms and conditions.

[7] Freelancers from India, Pakistan, and Bangladesh account for over 1.8 million bids in my sample, which is more than 70% of all bids.

larger extent, in developed countries.

Table 2: Top 15 Freelancer and Employer Countries

Freelancer Country	Number of Bids	Employer Country	Number of Projects
India	1,318,974	United States	22,356
Pakistan	328,115	India	15,227
Bangladesh	165,181	United Kingdom	7,392
United States	68,771	Australia	7,224
Egypt	44,871	Canada	4,190
China	43,921	Germany	1,952
United Kingdom	35,890	Saudi Arabia	1,640
Kenya	35,484	Pakistan	1,639
Philippines	29,340	Spain	1,581
Ukraine	28,438	United Arab Emirates	1,537
Sri Lanka	27,094	Italy	1,245
Nigeria	24,523	Singapore	1,233
Venezuela	21,900	France	1,120
Vietnam	20,949	Malaysia	1,051
Canada	20,048	Bangladesh	1,041

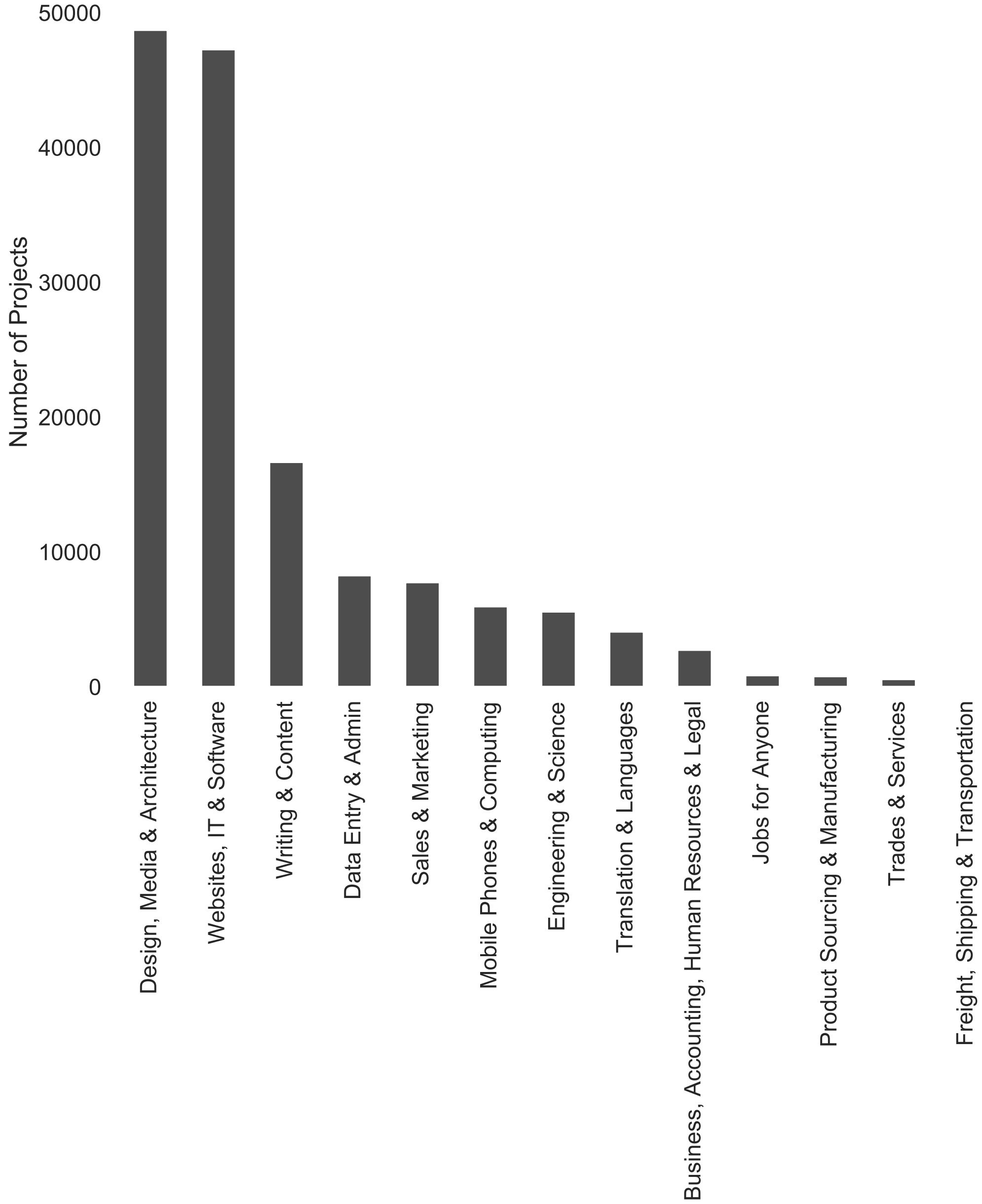
The CFBs in my sample encompass a large variety of project categories. The bar chart in figure 2 depicts the different project categories and their respective frequencies. These categories are not mutually exclusive, 47.5% of CFBs fall into 2 or more categories. Design and IT-related projects constitute by far the two largest categories, accounting for more than 60% of the posted CFB in my sample. I exploit the heterogeneity of project categories in section 5.1.2, to analyze how hiring decisions vary depending on the job complexity.

To estimate the hiring decisions in section 5, I reduce the sample by matching projects with a sponsored bid to similar projects without a sponsored bid using propensity score matching (PSM). Appendix A.2 describes the matching procedure in more detail. The full sample is however useful to analyze the determinants of the sponsoring decision in the following section 4.

4 Selection into Advertising

According to the signaling model of advertising, we would expect that rather new freelancers with little or no reputation on the platform tend to advertise. More established freelancers, who already obtained ratings, should be less in need of an additional way to signal their quality. To assess this hypothesis and to gain a better understanding about the selection mechanism into advertising in general, subsection 4.1 provides some descriptive evidence about the freelancers characteristics, distinguishing between freelancers who advertise and those who do not. Section 4.2 examines which factors are the most important predictors that a freelancer will choose to advertise.

Figure 2: Project Categories Frequency



4.1 Summary Statistics

Freelancers who advertise differ from those who do not. Table 3 compares sponsored bids to regular bids, based on reputation variables (bid score, number of ratings and ratings in different categories), account specific variables, bid specific variables (such as the price, the length of the description, and position of the bid in the result list), and geographic location variables.

In line with the signaling model of advertising, I find that sponsored bids are posted by less experienced freelancers. On average, a sponsored bid has 29.5 ratings (compared to 137 for non-sponsored bids), and a bid score of .66 (compared to .8 for non-sponsored bids). Due to their lower scores, sponsored bids would have been displayed lower in the results (if they were not sponsored), namely on the 31st place on average compared to 24.4 for non-sponsored bids. Furthermore, freelancers who sponsor a bid are registered for a shorter time period on the platform, namely 620 days on average (median of 159.5 days) compared to 971 days (median of 708 days) for non-sponsored bids.

Table 3: Bid-Level Summary Statistics

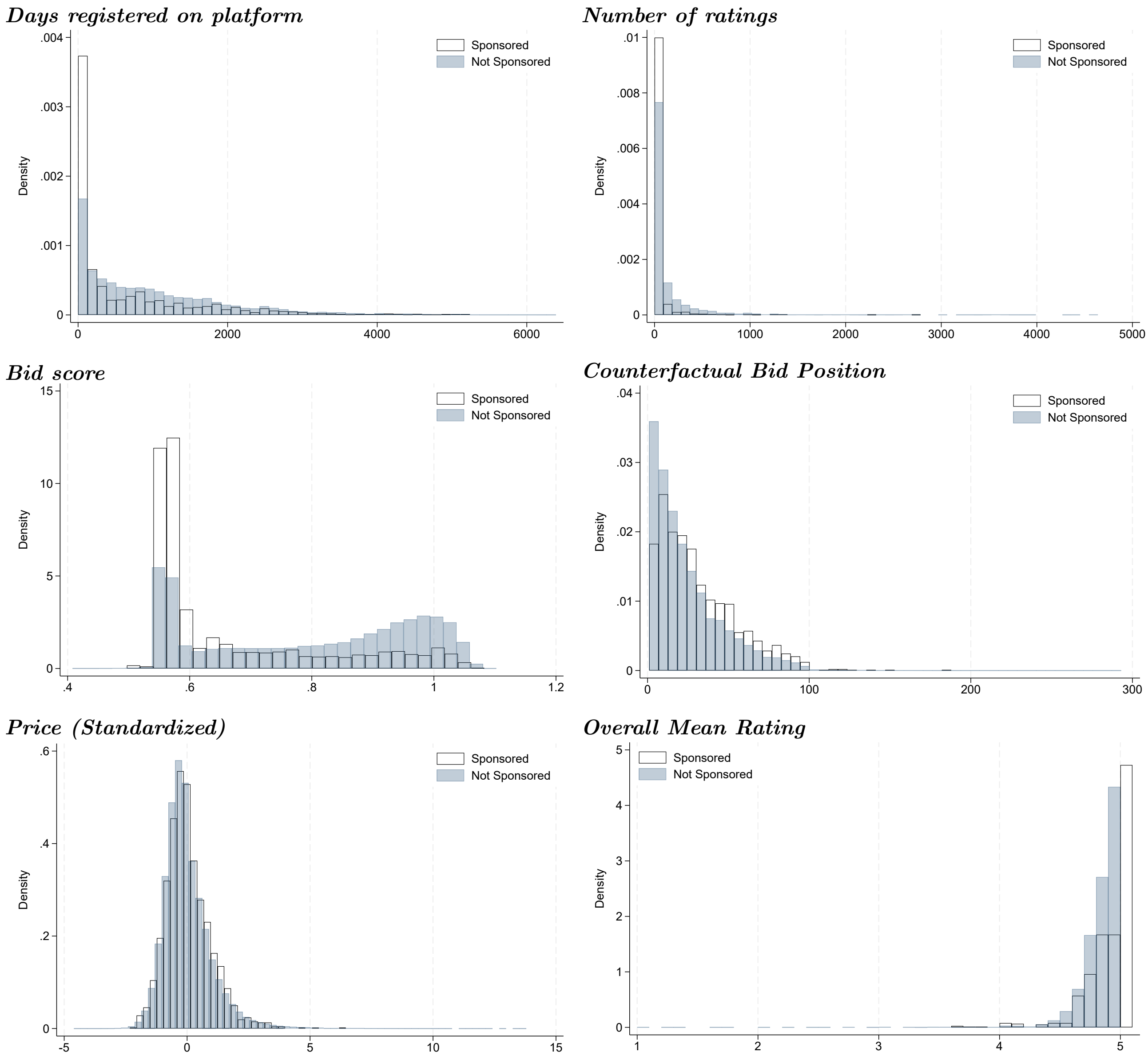
	Non-sponsored (mean)	Sponsored (mean)	Difference	BM t-statistic	p-value
Reputation Variables					
Bid Score	0.80	0.66	0.13	–34.81	0.00
Number of Ratings	137.00	29.53	107.48	–42.19	0.00
Mean Rating: Overall	4.84	4.89	–0.05	12.64	0.00
Mean Rating: Communication	4.85	4.88	–0.04	13.46	0.00
Mean Rating: Quality	4.84	4.89	–0.05	12.68	0.00
Mean Rating: Expertise	4.84	4.89	–0.06	13.66	0.00
Mean Rating: Professionalism	4.86	4.90	–0.04	12.94	0.00
Mean Rating: Hire Again	4.82	4.88	–0.06	13.86	0.00
Account Specific Variables					
Days registered on Platform	970.64	619.69	350.95	–20.97	0.00
Corporate Account	0.22	0.19	0.04	–3.95	0.00
Bid Specific Variables					
Bid Price (Standardized)	–0.00	0.05	–0.05	3.68	0.00
Duration (Standardized)	–0.00	0.09	–0.09	3.31	0.00
Bid Description Length (Standardized)	0.00	–0.05	0.05	–3.57	0.00
Counterfactual Bid Position	24.40	31.23	–6.82	14.55	0.00
Location Variables					
Timezone Difference	5.16	4.85	0.31	–3.36	0.00
Same Country	0.09	0.12	–0.03	3.90	0.00
Same Language	0.91	0.86	0.04	–5.22	0.00

Note: Bid price, duration and the bid description length are standardized on a project level, to account for project differences. The BM t-statistic and p-value are based on the Brunner Munzel test (also known as generalized Wilcoxon test), to account for the non-normal distribution of (some) of these variables.

Figure 3 shows the distribution of the variables mentioned above. The number of days registered on the platform, number of ratings, and position in the result list are strongly right skewed. For sponsored bids, this skewness is even more pronounced. Positive skewness is known to yield smaller median values compared to arithmetic means. In fact, most sponsored bids actually do not have a single rating and 75% of all sponsored bids have less than 4 ratings. Over a third of all sponsored bids are made by freelancers registered less than 28 days on the platform. The median score for sponsored bids is equal to .58, which is smaller than the lowest quartile for non-sponsored bids (25%-quantile at .60). This underlines that a significant proportion of freelancers who advertise are new freelancers without reputation.

Inexperienced sellers selecting into advertising is rather atypical for online marketplaces. Sun et al. (2020) empirically analyze advertising strategies from third-party sellers on the largest online marketplace in China, and find that sellers with longer tenure are more likely to advertise. Even in the context

Figure 3: Histograms - Sponsored bids vs regular bids



of another type of experience good, namely restaurants, Sahni and Nair (2020) find that restaurants with more ratings and longer tenure are more likely to advertise (Online Appendix A). The severeness of cold-start problems in OLM might explain my opposite finding of newer freelancers choosing to advertise.

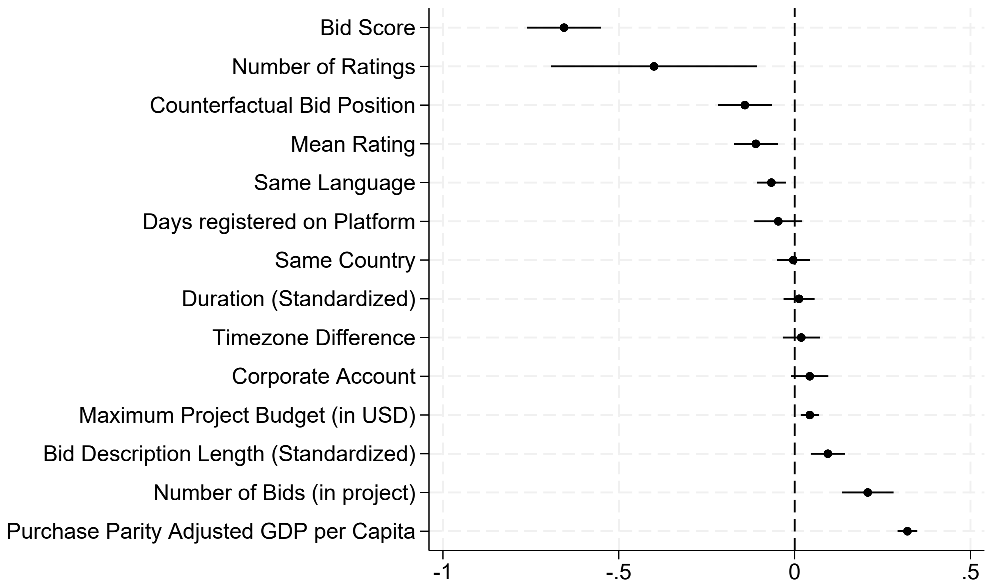
Interestingly however, sponsored bids stemming from already rated freelancers have better reviews than non-sponsored bids, not only in terms of overall ratings but also across all different categories (panel on the bottom left of figure 3). Furthermore, sponsored bids are priced slightly higher than non-sponsored bids (panel on the bottom right of figure 3).

The summary statistics from table 3 and figure 3 suggest that new freelancers, with fewer ratings and being ranked lower by the platform, might choose to advertise as an attempt to improve the salience of their bid and to convey a signal about quality.

4.2 Feature Importance Analysis

To further investigate the drivers of a freelancer's decision to sponsor a bid, I run a logistic regression where the outcome is an indicator variable equal to one if a bid is sponsored and zero otherwise. I standardize the independent variables (mean 0 and 1 standard deviation) and use them as predictors in the logistic regression. Standardization allows for comparing the relative importance of the predictors in the model.

Figure 4: Coefficient Plot of a Logit Estimation of the Sponsoring Decision



Note: All variables are standardized (mean 0 and 1 standard deviation) and used as predictors in the logistic regression. Standardization allows for comparing the relative importance of the predictors in the model.

Figure 4 reports the obtained coefficients, ordered in an ascending manner. As the summary statistics from section 4.1 suggests, the bid score and number of ratings are important predictors for the sponsoring decision. Bids with a lower score or fewer ratings are more likely to be sponsored, suggesting that freelancers might use advertisement as a remedy against the cold-start problems they confront. Another important factor predicting the decision to sponsor is the purchase parity adjusted GDP per capita of the freelancer's country of residence.[8] The price to sponsor a bid only depends on the bid price set by the freelancer but is capped at a minimum of 4.99 USD. Although everyone incurs the

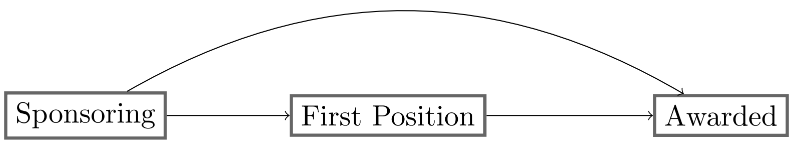
[8]Obtained from the World Development Indicators database, World Bank (accessed in June 2022).

same nominal costs, the real cost of sponsoring a bid depends on the freelancer's residing country (more specifically the purchasing power of that country). As such, it is unsurprising that, everything else equal, freelancers from wealthier countries are more likely to advertise.

5 Hiring Preferences

In this section, I analyze the role of advertising on hiring decisions. The question of interest is whether buyers prefer sponsored bids compared to non-sponsored bids, *ceteris paribus*. To measure a "pure" preference for advertisement, which would support the existence of a signaling effect, it is necessary to account for the increased visibility of sponsored bids. Recall from section 3.1 that sponsored bids are pinned at the top of the result list (i.e. on the first position of the first page) shown to the buyer, which otherwise displays bids in a descending order based on their score per default. This improved visibility needs to be accounted for, given potential buyer inattention and search costs. Narayanan and Kalyanam (2015) find that position effects are of economic significance, increasing click-through rates by 10-20% in the context of search advertising. Therefore, we should expect that sponsoring a bid impacts the likelihood of winning a CFB through i) an indirect effect of increased visibility by being posted on top of the result list viewed by the buyer; and ii) a direct effect, i.e. via the disclosure that the bid is sponsored (the signaling effect) as depicted by the simplified directed acyclic graph (DAG) in figure 5.

Figure 5: Simplified Directed Acyclic Graph (DAG)



Due to the scarce number of sponsored bids, I first reduce my sample by matching each project with a sponsored bid to a similar project without a sponsored bid in terms of project budget and number of bids received.[9] This leaves me with a dataset of 3,356 projects with a total number of 157,675 bids. Each CFB is characterized by an employer hiring a freelancer from a choice set of a varying number of freelancer applicants. I estimate both linear probability models (LPM) and conditional logit models, in which buyer's i choice of a freelancer j for a project t is given by:

$$Awarded_{ijt} = \alpha_t + \beta_1 Sponsored_{jt} + \beta_2 FirstPosition_{jt} + \gamma Controls_{ijt} + \varepsilon_{ijt} \tag{1}$$

[9] Appendix A.2 describes the matching procedure in detail.

LPM allow straightforward calculations of marginal effects on the probability of winning a CFB, whereas the coefficients from the conditional logit (which represent the change in the log-odds of winning a CFB) are more challenging to interpret. However, conditional logit is better suited to model how choices are made among a set of alternatives (bids in this context) with varying characteristics such that the agent (buyer in this context) maximizes utility from his or her choice (McFadden, 1973).[10]

Table 4: Hiring Choices Estimation

	(1) Linear Model	(2) Linear Model	(3) Conditional Logit	(4) Conditional Logit
Sponsored	0.027***	-0.064***	0.237*	-0.469***
	(0.007)	(0.011)	(0.135)	(0.155)
First Position Dummy		0.073***		0.597***
		(0.009)		(0.082)
First Page Dummy		0.031***		0.373***
		(0.002)		(0.067)
Bid Position	-0.001***	-0.000**	-0.068***	-0.052***
	(0.000)	(0.000)	(0.006)	(0.007)
Bid Position Squared	0.000***	0.000**	0.000***	0.000***
	(0.000)	(0.000)	(0.000)	(0.000)
Observations	157,231	157,231	157,231	157,231
Num. Sponsored Bids	1678	1678	1678	1678
Project FE	Yes	Yes	Yes	Yes
Bid-Level Controls	Yes	Yes	Yes	Yes

Standard errors in parenthesis are clustered at the project level
*** p<0.01, ** p<0.05, * p<0.1

Note: Projects with sponsors are matched to similar projects without sponsors based on i) their category; ii) their budget; and iii) their competitive structure. The bid-level control variables include *inter alia* the project-level standardized bid price, the number and mean rating of the freelancer, a quality score calculated by the platform, the number of days registered on the platform, the length of the bid text, differences in time zones, as well as dummies indicating whether the employer and freelancer live in the same country, speak the same primary language, and whether the freelancer has a company profile. The full regression results are shown in Appendix B.

Table 4 shows the results of both the linear probability model (columns 1-2) and the conditional logit (columns 3-4). If we do not account for the increased salience of sponsored bids, which appear on top of the bid list shown to the buyer, we might erroneously conclude that buyers exhibit a preference for advertising. Once I add dummy variables for being displayed on top of the results ("First Position Dummy" and "First Page Dummy"), the coefficient for "Sponsored" becomes negative and significant. The linear regression specification (column 2) suggests a reduction of 6.4 percentage points for sponsored bids on the likelihood of winning a CFB, while the conditional logit model indicates a 37.4 % decrease in the odds of winning a CFB, all else equal. This suggests that buyers have a preference for non-sponsored bids, when controlling for position effects. Nonetheless, sponsoring a bid usually improves the chances of being hired: the advantage of being displayed on top (First Position

[10] In contrast to LPM, condtional logit transforms the linear combination of independent variables into probabilities between 0 and 1.

Dummy) offsets the disliking of advertisement in both specifications. Only bids which would have been displayed on top anyway (i.e. bids with the highest bid score) reduce their chance of winning when being sponsored.

5.1 Heterogeneous Effects

5.1.1 Freelancer Reputation

The previous results suggest that sponsored bids have a negative effect on the likelihood of winning a CFB once we account for being displayed on top of the bid list shown to the buyer. However, buyers might react differently to sponsored bids depending on the reputation of the freelancer who advertises. According to the signaling model of advertising, we would expect a positive effect of advertising on the probability of winning a CFB for new freelancers without reputation.

This subsection addresses this question by analyzing if the effect of sponsoring differs for new freelancers without reputation compared to already rated freelancers. For this purpose, I partition my data into a sample of new freelancers (registered less than 31 days on the platform) without a rating who sponsored a bid as well as another sample of already rated freelancers who sponsored a bid. I add the matched projects without a sponsored bid to both sample respectively. Then, I estimate equation 1 for the two samples separately, using again both a linear probability model as well as conditional logit. Table 5 displays the results: column 1 and 2 show the results for new and unrated freelancers who sponsored a bid, estimated via LPM and conditional logit respectively. Column 3 and 4 show the results for already rated freelancers who sponsored a bid.

Comparing the "Sponsored" coefficients from columns 1 and 2 with columns 3 and 4, it appears that freelancers who already have been reviewed are less penalized when sponsoring a bid compared to freelancers without reviews. Sponsored bids from new and unrated freelancers are 11.5 percentage points less likely to win a project (odds ratio of .255) compared to an insignificant effect from the LPM and an odds ratio of .66 for already rated freelancers. In fact, new freelancers without ratings might be worse off by sponsoring a bid. The dislike of advertising (coefficient of "Sponsored") is larger in absolute terms than the advantage of being displayed on top (adding up the coefficients of "First Position Dummy" and "First Page Dummy").

In contrast, already rated freelancers benefit from advertising due to the increased visibility from being displayed on top of the result list. In the linear probability model specification (column 3), I find no statistically significant coefficient for "Sponsored." In the conditional logit specification, I find an odds ratio of .66 which is however over-compensated by the first position dummy odds ratio of 2.

This exercise suggests that new, unrated, freelancers do not benefit from sponsoring a bid. On the

Table 5: Hiring Preferences Estimation - Freelancer Reputation

	(1) New Unrated Freelancers	(2) New Unrated Freelancers	(3) Rated Freelancers	(4) Rated Freelancers
Sponsored	-0.115***	-1.367***	-0.025	-0.413**
	(0.019)	(0.449)	(0.018)	(0.199)
First Position Dummy	0.076***	0.624***	0.083***	0.700***
	(0.018)	(0.150)	(0.014)	(0.119)
First Page Dummy	0.038***	0.499***	0.025***	0.293***
	(0.003)	(0.108)	(0.003)	(0.083)
Bid Position	-0.000**	-0.055***	-0.000	-0.052***
	(0.000)	(0.007)	(0.000)	(0.006)
Bid Position Squared	0.000***	0.000***	0.000*	0.000***
	(0.000)	(0.000)	(0.000)	(0.000)
Observations	43,468	43,468	73,585	73,585
Model	Linear	Cond. Logit	Linear	Cond. Logit
Num. Sponsored Bids	459	459	772	772
Project FE	Yes	Yes	Yes	Yes
Bid-Level Controls	Yes	Yes	Yes	Yes

Standard errors in parenthesis are clustered at the project level
*** p<0.01, ** p<0.05, * p<0.1

Note: Projects with sponsors are matched to similar projects without sponsors based on i) their category; ii) their budget; and iii) their competitive structure. The bid-level control variables include *inter alia* the project-level standardized bid price, the number and mean rating of the freelancer, a quality score calculated by the platform, the number of days registered on the platform, the length of the bid text, differences in time zones, as well as dummies indicating whether the employer and freelancer live in the same country, speak the same primary language, and whether the freelancer has a company profile. The full regression results are shown in Appendix B.

contrary, the strong negative coefficient measured in column 1 and 2 of table 5 suggests that these freelancers might be worse off despite the advantage of increased salience by being positioned on top of the bid list. The negative effect of "Sponsored" contrasts the signaling hypothesis of advertising. Instead of helping the signal senders (advertising freelancers), the signal receivers (i.e. the buyers) counter-screen the former.

5.1.2 Project Categories

Lukac (2021) shows that OLM are fragmented into two segments: a reputation-driven and a price-driven segment. He argues that reputation (and therefore by extension also signaling) only matters in the former segment. The price-driven segment is characterized by fierce competition, in which freelancers try to undercut in each other. Lukac (2021) classifies different project categories into the price or reputation-driven segments. He finds that projects related to writing and research or programming and databases have the lowest probability to be in the price-driven segment. On the other hand, advertising and marketing, translation, and design jobs have the highest probability to fall into the price-driven segment.

Based on Lukac (2021)'s classification exercise, I distinguish in this subsection between high-skill and low-skill projects when estimating hiring preferences. More specifically, I consider projects labelled as "Websites, IT & Software", "Mobile Phones & Computing", "Engineering & Science", and "Writing &

Content" as high-skill projects. Projects labelled "Jobs for Anyone", "Data Entry & Admin", "Sales & Marketing", and "Design, Media & Architecture",[11] are considered as low-skill projects. Using the same specifications as before, I estimate again equation 1 by differentiating now between high-skill and low-skill project CFBs, using both linear probability models and conditional logit models. I focus again on the new and unrated freelancers for which a signaling mechanism is particularly crucial to obtain a first job and hence a possible first rating.

Table 6 shows the results. For high-skill project CFB's (column 3 and 4), the negative coefficient becomes significantly smaller compared to "All Categories" (column 1 and 2). The linear model suggests that sponsored bids are 6.1 percentage points less likely to win a CFB for high-skill projects compared to 11.9 percentage points for low-skill projects. In the conditional logit model, the effect of sponsoring is not significant for high-skill projects, while low-skill projects exhibit a stronger dislike for sponsored bids with an odds ratio of .209.

Table 6: Hiring Preferences Estimation - Project Categories

VARIABLES	(1) All Categories	(2) All Categories	(3) High-Skill	(4) High-Skill	(5) Low-Skill	(6) Low-Skill
Sponsored	-0.115***	-1.367***	-0.061**	-0.496	-0.119***	-1.567***
	(0.019)	(0.449)	(0.025)	(0.610)	(0.023)	(0.554)
First Position Dummy	0.076***	0.624***	0.036*	0.237	0.077***	0.718***
	(0.018)	(0.150)	(0.021)	(0.232)	(0.022)	(0.180)
First Page Dummy	0.038***	0.499***	0.026***	0.278*	0.043***	0.682***
	(0.003)	(0.108)	(0.005)	(0.163)	(0.004)	(0.129)
Bid Position	-0.000**	-0.055***	-0.001**	-0.059***	-0.000*	-0.048***
	(0.000)	(0.007)	(0.000)	(0.013)	(0.000)	(0.008)
Bid Position Squared	0.000***	0.000***	0.000***	0.000**	0.000**	0.000***
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
Observations	43,468	43,468	19,564	19,564	34,048	34,048
Model	Linear	Cond. Logit	Linear	Cond. Logit	Linear	Cond. Logit
Num. Sponsored Bids	459	459	202	202	327	327
Project FE	Yes	Yes	Yes	Yes	Yes	Yes
Bid-Level Controls	Yes	Yes	Yes	Yes	Yes	Yes

Standard errors in parenthesis are clustered at the project level
*** p<0.01, ** p<0.05, * p<0.1

Note: Projects with sponsors are matched to similar projects without sponsors based on i) their category; ii) their budget; and iii) their competitive structure. Projects labelled "Websites, IT & Software", "Mobile Phones & Computing", "Engineering & Science", and "Writing & Content" are considered as High-Skill projects. Projects labelled "Jobs for Anyone", "Data Entry & Admin", "Sales & Marketing," and "Design, Media & Architecture" are considered as Low-Skill projects. The bid-level control variables include *inter alia* the project-level standardized bid price, the number, and mean rating of the freelancer, a quality score calculated by the platform, the number of days registered on the platform, the length of the bid text, differences in time zones, as well as dummies indicating whether the employer and freelancer live in the same country, speak the same primary language, and whether the freelancer has a company profile. The full regression results are shwon in Appendix B.

Although we do not observe a preference for advertisement, these findings are (to some degree) consistent with the signaling model. The latter predict a stronger impact of signaling for products with a higher degree of information asymmetry between buyers and sellers. In the context of OLMs, we

[11] I include "Design, Media & Architecture" CFBs to low-skill projects since Lukac (2021) classifies design-related jobs as price-driven jobs. Omitting this category from the analysis does not alter the interpretation of the results.

would expect that buyers face more uncertainty about the ability of a worker to complete a project successfully in the context of high-skill projects. Therefore, any form of quality signal (e.g. ratings), should be more valuable when applying for a high-skill projects.

5.2 Empirical Challenges and Limitations

Advertising is a strategic choice. Firms usually try to show ads to those consumers who are more likely to be interested in their products. Such non-randomness in the assignment of advertising causes endogeneity due to selection bias. From the perspective of a buyer in OLM, the presence of endogeneity would imply a correlation between the exposure to a sponsored bid and the error term ε in the hiring decision model from equation 1. If consumers more likely to purchase in the first place are targeted with ads, an estimation of returns to advertising based on observational sales data is upward-biased without a proper identification strategy (Rutz and Watson, 2019). Therefore, the "Sponsored" coefficients in tables 4 - 6 cannot be interpreted as causal effects.

Various approaches have been developed to address endogeneity in empirical settings. Several marketing studies conduct field experiments on online platforms to create exogenous variation regarding consumers' ad exposure, in order to eliminate the selection bias of targeted ads (e.g. Sahni and Nair (2020) or Joo et al. (2024)).

Quasi-experimental methods, on the other hand, are challenging to implement in this context. Importantly, advertising is not the only endogenous variable. The bid price set by the freelancers is a strategic choice as well, which moreover cannot be considered as independent of the advertising decision.[12] Thus, it is necessary to handle it as a second endogenous variable, since it cannot be omitted from the estimation due to its dependence with the advertising choice.[13] Therefore, at least 2 instrumental variables are needed for the hiring decision estimation of equation 1. Figure 6 illustrates the empirical setting using a DAG. The price and sponsoring decisions are jointly determined by each freelancer to maximize her chances to win a project. Multiple factors influence these two decisions, such as the mean and number of ratings.[14] If there exist other influential variables (denoted by η in figure 6) that are not observed by the econometrician, e.g. the gender of a freelancer,[15] which possibly influences both the chance of winning (Chan and Wang, 2018) as well as the price and advertising decisions, the estimation of hiring choices yields distorted coefficients.

Under the presence of a selection bias caused by targeted sponsoring, we should expect that the true

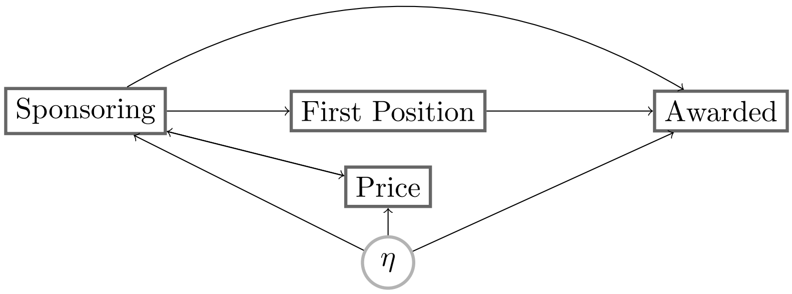
[12] Recall from section 3.1 that the cost to sponsor a bid directly depends on the bid price.

[13] The omission of price when estimating equation 1 would create an omitted variable bias to its correlation with the sponsoring decision.

[14] As shown in section 4.2 for the advertising decision.

[15] Which can be possibly revealed by the name or profile picture of a freelancer profile

Figure 6: Directed Acyclic Graph (DAG)



effects of sponsoring are even more negative than the reported coefficients from tables 4 - 6. Such an upward-bias would actually reinforce the evidence of an absence of a signaling effect presented in this section. Nonetheless, supplementary experimental evidence is necessary to confirm these findings.

6 Evaluation of Freelancer Performance

6.1 Reviews of Awarded Bids

The previous results indicate that buyers are less likely to hire a freelancer who advertises, *ceteris paribus*. A natural follow-up question is whether this distaste for sponsored bids can be justified *ex-post*. To do so, I analyze the reviews obtained by the freelancers who won CFBs from the sample used during the analysis in section 5. I identify 1,699 reviews posted for non-sponsored awarded bids and 71 reviews posted for sponsored awarded bids. Note that there are fewer reviews than awarded projects, since not all awarded projects end up being completed and not every completed project gets a review.

Sponsored bids have a mean rating of 4.68 (with median of 5) while non-sponsored bids have a mean rating of 4.74 (with median of 5). A generalized Wilcoxon test cannot reject the null-hypothesis of no difference between the two groups. However, the small number of sponsored bids which got reviewed makes statistical inference difficult based on in this sample.

In the following subsection, I focus on long run outcomes, covering a time span of four years. Collecting a larger amount of data enables me to focus on new and unrated freelancers who advertise and compare *ex-post* their performance measured by various outcomes with new freelancers who did not advertise.

6.2 Long Run Outcomes of New Freelancers

The signaling model of advertising posits an equilibrium where high-quality firms choose to advertise while low-quality firms do not. For the existence of such an equilibrium, it is necessary that high-quality firms generate higher profits than low-quality firms. Otherwise, costly advertising is not incentive compatible, since high-quality firms could increase their earnings by mimicking the behavior of low-quality firms, i.e. by simply choosing not to advertise.

In this subsection, I compare long run outcomes of unrated freelancers who advertise with those who do not. The goal of this exercise is to detect a possible selection of freelancers with a higher number of future hires, earnings, or better ratings into advertising. I do not aim to establish a causal effect of advertising on these long run outcomes, but rather to check for a correlation between them. A positive correlation would indicate that advertising can serve as a predictor for future success,[16] in line with what signaling models of advertising hypothesize.

I identified 714 freelancers who sponsored at least one bid during the four months observation period and did not have a single rating at this point, as well as 1,023 freelancer who also applied for work during the same period without having a rating, but never sponsored a bid throughout their history on the platform. I collect their entire history on the platforms until June 2022, i.e. I collect data on every posted bid, all awarded projects, all earnings and all ratings for these freelancers. Then, I compare various outcomes between both groups, taking into account differences in activity levels.

Table 7: User History Data Descriptives

Variable	Sponsorer: Mean	Control Group: Mean	Sponsorer: SD	Control Group: SD
Total Revenue (in USD)	73.40	51.71	889.28	618.88
Number of Sponsored Bids	1.98	0.00	2.92	0.00
Number of Bids	71.66	87.15	443.14	1,124.40
Number of HireMe Projects	0.47	0.39	2.12	3.02
Number of Awarded Projects	0.43	0.64	2.57	7.33
Mean Rating	3.98	4.02	1.58	1.52
Mean Number of Competitors	50.65	50.51	24.34	24.80
Mean Budget	170.73	126.04	461.01	230.41
Share of "Low-Skill" Projects	0.17	0.21	0.23	0.24
Share of "High-Skill" Projects	0.27	0.28	0.27	0.27
Got Awarded (Indicator)	0.14	0.11	0.35	0.31
Number of Active Days	422.08	434.87	671.54	642.01
Observations	714	1,023		

Note: The user history data is aggregated on a freelancer-level.

Table 7 shows descriptive statistics of the data collected on the user histories. In my sample, sponsoring freelancers earned more money throughout their career on the platform, but won less projects, submitted fewer bids and were active during a shorter time period on the platform. The descriptive statistics furthermore underline the difficulty to acquire a first job as a new freelancer in OLMs. Only 11% of the freelancers who never sponsored a bid in my sample were awarded at least a single project (14% for those who sponsored a bid).

The groups of freelancers who sponsored and those who did not sponsor bids differ in their activity levels (i.e. number of bids and active days). I run several regression models to measure the correlation

[16] In the sense that more high-quality freelancers, who receive better ratings and more offers later on, choose to advertise at the beginning of their career.

between various outcomes and whether a freelancer selected into advertising, while controlling for these differences in the activity levels.

Table 8: Regression Analysis - Long Run Outcomes

VARIABLES	(1) Got Awarded	(2) Total Earnings	(3) Mean Rating	(4) Number of Direct Hires
Sponsored	0.166*	30.875	0.289	0.113
	(0.086)	(34.529)	(0.294)	(0.091)
Number of Regular Bids	0.004***	0.463***	0.000**	0.002***
	(0.001)	(0.117)	(0.000)	(0.001)
Number of active Days on Platform	0.000***	0.072***	0.001***	0.000***
	(0.000)	(0.026)	(0.000)	(0.000)
Mean Number of Competitors per Project	-0.010***	-0.179	-0.010	-0.001
	(0.003)	(0.413)	(0.013)	(0.002)
Share of Low-Skill Projects	0.595***	6.438	0.516	-0.027
	(0.180)	(53.048)	(0.744)	(0.151)
Share of High-Skill Projects	0.185	67.917	-0.707	0.124
	(0.158)	(68.286)	(0.547)	(0.159)
Constant	-1.314***	-31.233	3.782***	0.054
	(0.147)	(23.930)	(0.757)	(0.101)
Observations	1,737	1,737	74	1,737
R-squared		0.335	0.184	0.448
Model	Probit	OLS	OLS	OLS

Robust standard errors in parentheses
*** $p<0.01$, ** $p<0.05$, * $p<0.1$

Note: The unit of observation is on the freelancer level. The number of active days on the platform corresponds to the number of days between the first and last posted bid on the platform. Low- and high-skill projects are defined as in section 5.1.2.

Table 8 presents the results for the aforementioned regressions, where the variable of interest Sponsored" (first row) is an indicator equal to 1 if a freelancer sponsored at least one bid and 0 otherwise. Across all outcomes, I do not find a statistical difference between both groups. Taken together, freelancers who sponsored at least one bid are not more likely to i) to win at least one project; ii) receive higher earnings; iii) obtain a better rating; or iv) being directly hired. These findings directly contrast the underlying incentive compatibility condition of signaling models of advertising, which posit that advertising firms should have more repeat purchases leading to higher revenues.

7 Conclusion

This article empirically analyzes whether advertising serves as a quality signal in online labor markets. Economic models of informative advertising based on Nelson (1970, 1974) predict that costly advertising can be a valuable quality signal for freelance services, since it is an experience good characterized by severe information asymmetry. Section 4 confirms that rather new and unrated freelancers choose to advertise, consistent with the signaling model. However, my empirical analysis based on transactional data in section 5 suggests that buyers dislike advertising once I control for the increased visibility of sponsored bids in CFB auctions. For unrated freelancers, this negative effect of advertising on the probability of winning is even more pronounced. Due to the absence of a clean identification strategy, my estimates of advertising on hiring probabilities cannot be interpreted as causal. However, selection biases impacting the estimation of returns to advertising would usually lead to upward-biased results. Therefore, my results can be interpreted as lower-bounds, which strengthens the evidence of an absence of a preference for advertising in OLM. Finally, in section 6, I find that new freelancers without reputation, who chose to advertise, are not more successful (based on various outcomes) over the course of the subsequent four years on the platform compared to similar freelancers who do not advertise. This finding justifies that buyers do not have a preference for sponsored bids, This finding justifies that buyers do not have a preference for sponsored bids, *ex-post*.

From a managerial perspective, this study underscores the challenges when designing signaling tools. The advertising mechanism, in its current implementation within my study, does not function as the platform suggests. By preferring regular bids over sponsored bids, *ceteris paribus*, buyers use sponsored bids to counter-screen advertising freelancers. Counter-signaling can arise in situations of information asymmetry where multiple possible signaling tools are available. In the context of online labor markets, the scientific literature identifies existing reputation (displayed through ratings) as a crucial signal of quality. For new and unrated freelancers, who cannot rely on reputation from past performance on a platform, different signaling mechanisms seem better suited to convey information about quality than advertising, in light of my results. For instance, Stanton and Thomas (2016) show that outsourcing agencies[17] serving as intermediaries in OLM help inexperienced workers to signal to employers that they are of high quality. Another possible signal are microcredential schemes that, according to Kässi and Lehdonvirta (2022), help less experienced freelancers to obtain jobs. An interesting additional mechanism to study in future work could be the role of text descriptions included in bids for CFBs, by focusing explicitly on new and unrated freelancers.

[17] According to Stanton and Thomas (2016), outsourcing agencies are typically constituted by a small number of workers, often from the same geographic location. Agency affiliates tend to know each other offline and often have similar backgrounds. Agencies build up a collective reputation, based on the feedback received by their individual workers.

References

Abhishek, V., Jerath, K., and Sharma, S. (2022). “The impact of sponsored listings on online marketplaces: Insights from a field experiment.” *Working paper.* 4, 7

Bederson, B. B., Jin, G. Z., Leslie, P., Quinn, A. J., and Zou, B. (2018). “Incomplete disclosure: Evidence of signaling and countersignaling.” *American Economic Journal: Microeconomics*, *10*(1), 41–66. 5

Braesemann, F., Stephany, F., Teutloff, O., Kässi, O., Graham, M., and Lehdonvirta, V. (2022). “The global polarisation of remote work.” *PLOS ONE*, *17*(10), 1–22. 7

Chan, J., and Wang, J. (2018). “Hiring preferences in online labor markets: Evidence of a female hiring bias.” *Management Science*, *64*(7), 2973–2994. 3, 18

Feltovich, N., Harbaugh, R., and To, T. (2002). “Too cool for school? signalling and countersignalling.” *RAND Journal of Economics*, 630–649. 4, 5

Filippas, A., Horton, J. J., and Urraca, D. (2023). “Advertising as coordination: Evidence from a field experiment.” *Working paper.* 3

Gao, Q., Lin, M., and Liu, Y. (2023). “When” signals” boomerang: Employers’ reactions to a novel signaling mechanism.” *Working paper.* 1, 4, 5

Hong, Y., and Pavlou, P. A. (2017). “On buyer selection of service providers in online outsourcing platforms for it services.” *Information Systems Research*, *28*(3), 547–562. 3

Hong, Y., Wang, C. A., and Pavlou, P. A. (2016). “Comparing open and sealed bid auctions: Evidence from online labor markets.” *Information Systems Research*, *27(1)*, 49–69. 5

Horstmann, I., and MacDonald, G. (2003). “Is advertising a signal of product quality? evidence from the compact disc player market, 1983–1992.” *International Journal of Industrial Organization*, *21*(3), 317–345. 1

Horton, J. J. (2010). “Online labor markets.” In A. Saberi (Ed.), *Internet and Network Economics*, 515–522. 4

Joo, M., Shi, J., and Abhishek, V. (2024). “Do sellers benefit from sponsored product listings? evidence from an online marketplace.” *Marketing Science.* 2, 4, 18

Kihlstrom, R. E., and Riordan, M. H. (1984). "Advertising as a signal." *Journal of Political Economy*, *92*(3), 427–450. 1, 4

Kässi, O., and Lehdonvirta, V. (2022). "Do microcredentials help new workers enter the market? evidence from an online labor platform." *Journal of Human Resources*. 3, 22

Kässi, O., Lehdonvirta, V., and Stephany, F. (2021). "How many online workers are there in the world? a data-driven assessment." *Open Research Europe*, *1*. 1

Luca, M., and Smith, J. (2015). "Strategic disclosure: The case of business school rankings." *Journal of Economic Behavior & Organization*, *112*, 17–25. 5

Lukac, M. (2021). "Two worlds of online labour markets: Exploring segmentation using finite mixture models and a network of skill co-occurrence." *Working Paper*. 16, 17

McFadden, D. (1973). "Conditional logit analysis of qualitative choice behaviour." In P. Zarembka (Ed.), *Frontiers in Econometrics*, 105–142, New York, NY, USA: Academic Press New York. 14

Milgrom, P., and Roberts, J. (1986). "Price and advertising signals of product quality." *Journal of Political Economy*, *94*(4), 796–821. 1, 4

Narayanan, S., and Kalyanam, K. (2015). "Position effects in search advertising and their moderators: A regression discontinuity approach." *Marketing Science*, *34*(3), 388–407. 13

Nelson, P. (1970). "Information and consumer behavior." *Journal of Political Economy*, *78*(2), 311–329. 1, 21

Nelson, P. (1974). "Advertising as information." *Journal of Political Economy*, *82*(4), 729–754. 1, 21

Pallais, A. (2014). "Inefficient hiring in entry-level labor markets." *The American Economic Review*, *104*(11), 3565–3599. 1, 3

Rallabandi, K. C. (2022). *Consumer Perceptions of Sponsored Listing and their Impact on Online Marketplaces*. Ph.D. thesis, UCLA. 4

Rutz, O. J., and Watson, G. F. (2019). "Endogeneity and marketing strategy research: an overview." *Journal of the Academy of Marketing Science*, *47*(3), 479–498. 18

Sahni, N. S., and Nair, H. S. (2020). "Does advertising serve as a signal? evidence from a field experiment in mobile search." *The Review of Economic Studies*, *87*(3), 1529–1564. 4, 11, 18

Stanton, C. T., and Thomas, C. (2016). "Landing the first job: The value of intermediaries in online hiring." *The Review of Economic Studies*, *83*(2), 810–854. 3, 22

Sun, H., Fan, M., and Tan, Y. (2020). "An empirical analysis of seller advertising strategies in an online marketplace." *Information Systems Research*, *31*(1), 37–56. 10

Troncoso, I., and Luo, L. (2023). "Look the part? the role of profile pictures in online labor markets." *Marketing Science*, *42*(6), 1080–1100. 3

Yoganarasimhan, H. (2013). "The value of reputation in an online freelance marketplace." *Marketing Science*, *32*(6), 860–891. 1, 3, 6

A Data Collection and Preparation

A.1 Data Collection

The empirical analysis is based on observational data from an undisclosed OLM platform, collected via its API. The data collection proceeds as follows:

1. I collected data on all projects which were posted (last updated, more precisely) during the four months of March through June 2018 together with their corresponding bids.[18] I focus on projects in which the buyer selected one freelancer. I only consider the first freelancer who was awarded a project the winner, in the few instances where a CFB was later awarded to a different freelancer.[19] The CFBs in my sample do not necessarily end up being completed: Some projects are rejected by the freelancers, others were cancelled by the employer, and a few projects were revoked by the platform, if the projects violated its terms and conditions. Furthermore, I exclude 20 outlier projects with a budget over 50,000 USD. This leaves me with 96,150 projects posted by 65,970 employers for which I observe 2,562,015 bids submitted by 255,795 different freelancers.

2. Freelancer ratings collected during the first step reflect current ratings (as of 2022) instead of ratings from the point in time when the bid was posted. To obtain accurate ratings at the time of bidding, I went through all freelancer profiles in my sample to collect all their individual reviews (in form of ratings on a 5-star scale) received by buyers, and re-calculated their past ratings on a daily-level for the four month observation period. I then matched these ratings to the bid-level data collected during the first step to update the rating variables.

3. For the analysis in section 6.1, I collected all reviews posted by buyers for completed projects from the sample of CFBs collected in step 1. I restricted the sample for the analysis to the matched projects with and without a sponsored bid (see appendix A.2).

4. To measure the long run outcomes in section 6.2, I went through 714 profiles of freelancers who sponsored a bid and did not have a rating at this point from my sample (as treatment group), and additionally randomly selected 1,376 freelancers without a rating and who did not advertise in my observation period (as control group). For both groups, I collected data on each bid they submitted, on all their earnings and all their received reviews throughout their career. I

[18] The platform enables freelancers to "seal" their bids in more recent CFB (as of 2021), which hides prices and messages for a significant number of bids. Therefore, I decided to scrape past data from 2018 using the platform's API by filtering for projects last updated during that time span. Collecting older transactional data enables me furthermore to conduct the *ex-post* evaluation in section 6.2.

[19] Which can happen, for instance, when the initially awarded freelancer rejects the offer.

dropped freelancers from the control group who, at some point, sponsored a bid, thus reducing the number of freelancer profiles to 1,023 in the control group.

A.2 Propensity Score Matching

Given the severe imbalance between sponsored and regular bids, I restrict the sample by matching projects with sponsored bids to similar projects without sponsored bids. More specifically, I use propensity score matching (PSM) to find similar projects in terms of project budget, number of bids, and project categories. I estimate a logistic regression to predict the probability that a project includes a sponsored bid, based on the aforementioned variables. The predicted probability is called the propensity score. Projects with and without sponsored bids are then matched based on their propensity scores. This approach enables me to account for selection on observables regarding the sponsoring decision at the project level.

Table 9 reports a balance check of all covariates pre- and post-PSM. The first column indicates the covariate used in PSM, the second column the sample (before or after PSM), the third and fourth columns the mean of our treated (i.e. sponsored) and control groups and the last column the standardized mean difference (SMD).[20] Sponsoring typically occurs in more competitive (measured by the number of bids) and more expensive or larger projects (measured by the maximum budget in USD). Furthermore, some project categories are under-represented (e.g. Mobile Phones & Computing) while others are over-represented (e.g. Data Entry & Admin) in projects with sponsored bids. The SMDs suggests that PSM yields a comparable control group of projects without a sponsored bid compared to the projects with a sponsored bid, since the SMDs are below 0.1 across all covariates. The distribution of propensity scores across both groups shown in figure 7 further confirms that the covariates are balanced across both groups after matching.

[20] SMDs allow to compare the means of two groups on a continuous variable, regardless of the original units of measurement. It is defined as the ratio of mean to standard deviation of the difference of two random values respectively from two groups:

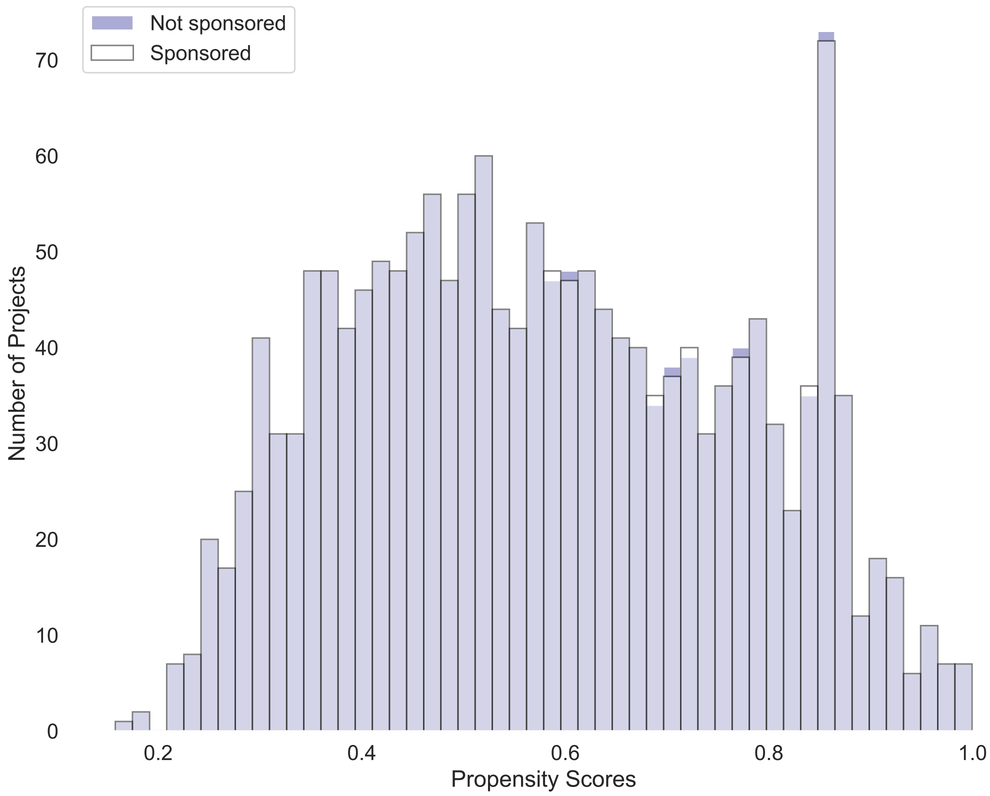
$$SMD = \frac{\mu_t - \mu_c}{\sqrt{\sigma_t^2 + \sigma_c^2 - 2\sigma_{tc}}}$$

where μ and σ^2 denote the mean and variance of group t and c respectively, and σ_{tc} denotes the covariance between both groups. SMDs help assess how well balancing has been achieved for each covariate in the context of matching. An SMD of 0.1 or below is a widely used benchmark and suggests good covariate balance.

Table 9: PSM Balance Check

Covariate	Sample	Mean (Sponsored)	Mean (Not Sponsored)	SMD
Number of Bids	Before PSM	47.21	26.28	0.887
Number of Bids	After PSM	47.21	46.76	0.015
Max Budget (in USD)	Before PSM	365.04	325.78	0.020
Max Budget (in USD)	After PSM	365.04	435.36	-0.032
Business, Accounting, Human Resources & Legal	Before PSM	0.03	0.03	0.002
Business, Accounting, Human Resources & Legal	After PSM	0.03	0.03	-0.014
Data Entry & Admin	Before PSM	0.14	0.08	0.204
Data Entry & Admin	After PSM	0.14	0.13	0.024
Design, Media & Architecture	Before PSM	0.54	0.51	0.062
Design, Media & Architecture	After PSM	0.54	0.52	0.025
Engineering & Science	Before PSM	0.06	0.06	-0.003
Engineering & Science	After PSM	0.06	0.07	-0.037
Freight, Shipping & Transportation	Before PSM	0.00	0.00	0.020
Freight, Shipping & Transportation	After PSM	0.00	0.00	0.035
Jobs for Anyone	Before PSM	0.01	0.01	-0.017
Jobs for Anyone	After PSM	0.01	0.01	-0.020
Mobile Phones & Computing	Before PSM	0.03	0.06	-0.133
Mobile Phones & Computing	After PSM	0.03	0.04	-0.043
Product Sourcing & Manufacturing	Before PSM	0.01	0.01	-0.016
Product Sourcing & Manufacturing	After PSM	0.01	0.01	-0.039
Sales & Marketing	Before PSM	0.07	0.08	-0.056
Sales & Marketing	After PSM	0.07	0.07	-0.002
Trades & Services	Before PSM	0.00	0.01	-0.045
Trades & Services	After PSM	0.00	0.00	0.028
Translation & Languages	Before PSM	0.05	0.04	0.057
Translation & Languages	After PSM	0.05	0.06	-0.013
Websites, IT & Software	Before PSM	0.42	0.49	-0.148
Websites, IT & Software	After PSM	0.42	0.44	-0.046
Writing & Content	Before PSM	0.21	0.17	0.106
Writing & Content	After PSM	0.21	0.22	-0.027

Figure 7: Distribution of propensity scores



B Complete Regression Tables

Table 10: Complete Regression Table - 4

VARIABLES	(1) Linear Model	(2) Linear Model	(3) Conditional Logit	(4) Conditional Logit
Sponsored	0.027***	-0.064***	0.237*	-0.469***
	(0.007)	(0.011)	(0.135)	(0.155)
First Position Dummy		0.073***		0.597***
		(0.009)		(0.082)
First Page Dummy		0.031***		0.373***
		(0.002)		(0.067)
Bid Position	-0.001***	-0.000**	-0.068***	-0.052***
	(0.000)	(0.000)	(0.006)	(0.007)
Bid Position Squared	0.000***	0.000**	0.000***	0.000***
	(0.000)	(0.000)	(0.000)	(0.000)
Bid Price (Standardized)	-0.007***	-0.007***	-0.429***	-0.439***
	(0.000)	(0.000)	(0.027)	(0.027)
Duration (Standardized)	0.001**	0.001*	0.036	0.036
	(0.000)	(0.000)	(0.024)	(0.024)
Bid Score	0.051***	0.025***	0.589**	0.101
	(0.008)	(0.006)	(0.286)	(0.267)
Number of Ratings	0.000***	0.000***	0.000***	0.000***
	(0.000)	(0.000)	(0.000)	(0.000)
Mean Rating (Standardized)	0.004***	0.005***	0.517***	0.518***
	(0.000)	(0.000)	(0.040)	(0.040)
Bid Description Length (Standardized)	0.000	0.001*	0.021	0.027
	(0.000)	(0.000)	(0.018)	(0.018)
Days registered on Platform	-0.000**	-0.000*	-0.000*	-0.000*
	(0.000)	(0.000)	(0.000)	(0.000)
Timezone Difference	-0.000	-0.000	-0.011	-0.010
	(0.000)	(0.000)	(0.010)	(0.010)
Same Country	0.019***	0.019***	0.784***	0.779***
	(0.003)	(0.003)	(0.108)	(0.108)
Same Language	-0.001	-0.001	-0.008	-0.010
	(0.002)	(0.002)	(0.121)	(0.122)
Corporate Account	-0.001	-0.001	-0.043	-0.043
	(0.001)	(0.001)	(0.045)	(0.045)
Observations	157,231	157,231	157,231	157,231
Num. Sponsored Bids	1678	1678	1678	1678
Project FE	Yes	Yes	Yes	Yes

Standard errors in parenthesis are clustered at the project level
*** p<0.01, ** p<0.05, * p<0.1

Table 11: Complete Regression Table - 5

VARIABLES	(1) New Unrated Freelancers	(2) New Unrated Freelancers	(3) Rated Freelancers	(4) Rated Freelancers
Sponsored	-0.115***	-1.367***	-0.025	-0.413**
	(0.019)	(0.449)	(0.018)	(0.199)
First Position Dummy	0.076***	0.624***	0.083***	0.700***
	(0.018)	(0.150)	(0.014)	(0.119)
First Page Dummy	0.038***	0.499***	0.025***	0.293***
	(0.003)	(0.108)	(0.003)	(0.083)
Bid Position	-0.000**	-0.055***	-0.000	-0.052***
	(0.000)	(0.007)	(0.000)	(0.006)
Bid Position Squared	0.000***	0.000***	0.000*	0.000***
	(0.000)	(0.000)	(0.000)	(0.000)
Bid Price (Standardized)	-0.007***	-0.390***	-0.007***	-0.471***
	(0.001)	(0.049)	(0.001)	(0.041)
Duration (Standardized)	0.000	0.012	0.001*	0.047
	(0.001)	(0.043)	(0.001)	(0.036)
Bid Score	0.011	-0.109	0.025**	-0.197
	(0.010)	(0.493)	(0.010)	(0.383)
Number of Ratings	0.000*	0.000***	0.000***	0.000***
	(0.000)	(0.000)	(0.000)	(0.000)
Mean Rating (Standardized)	0.006***	0.466***	0.004***	0.555***
	(0.001)	(0.072)	(0.001)	(0.070)
Bid Description Length (Standardized)	0.001	0.039	0.001	0.029
	(0.001)	(0.034)	(0.001)	(0.026)
Days registered on Platform	-0.000*	-0.000**	-0.000	-0.000
	(0.000)	(0.000)	(0.000)	(0.000)
Timezone Difference	-0.000	-0.016	-0.000	-0.013
	(0.000)	(0.018)	(0.000)	(0.014)
Same Country	0.021***	0.906***	0.019***	0.767***
	(0.005)	(0.194)	(0.005)	(0.167)
Same Language	-0.001	-0.031	-0.000	0.037
	(0.003)	(0.218)	(0.003)	(0.198)
Corporate Account	-0.001	-0.063	-0.000	-0.006
	(0.002)	(0.087)	(0.001)	(0.066)
Observations	43,468	43,468	73,585	73,585
Model	Linear	Cond. Logit	Linear	Cond. Logit
Num. Sponsored Bids	459	459	772	772
Project FE	Yes	Yes	Yes	Yes

Standard errors in parenthesis are clustered at the project level
*** p<0.01, ** p<0.05, * p<0.1

Table 12: Complete Regression Table - 6

VARIABLES	(1) All Categories	(2) All Categories	(3) High-Skill	(4) High-Skill	(5) Low-Skill	(6) Low-Skill
Sponsored	-0.115***	-1.367***	-0.061**	-0.496	-0.119***	-1.567***
	(0.019)	(0.449)	(0.025)	(0.610)	(0.023)	(0.554)
First Position Dummy	0.076***	0.624***	0.036*	0.237	0.077***	0.718***
	(0.018)	(0.150)	(0.021)	(0.232)	(0.022)	(0.180)
First Page Dummy	0.038***	0.499***	0.026***	0.278*	0.043***	0.682***
	(0.003)	(0.108)	(0.005)	(0.163)	(0.004)	(0.129)
Bid Position	-0.000**	-0.055***	-0.001**	-0.059***	-0.000*	-0.048***
	(0.000)	(0.007)	(0.000)	(0.013)	(0.000)	(0.008)
Bid Position Squared	0.000***	0.000***	0.000***	0.000**	0.000**	0.000***
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
Bid Price (Standardized)	-0.007***	-0.390***	-0.008***	-0.453***	-0.006***	-0.430***
	(0.001)	(0.049)	(0.001)	(0.074)	(0.001)	(0.061)
Duration (Standardized)	0.000	0.012	0.001	0.030	-0.000	-0.027
	(0.001)	(0.043)	(0.001)	(0.062)	(0.001)	(0.056)
Bid Score	0.011	-0.109	0.031	-0.126	0.014	0.373
	(0.010)	(0.493)	(0.019)	(0.763)	(0.011)	(0.596)
Number of Ratings	0.000*	0.000***	-0.000	-0.000	0.000**	0.000***
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
Mean Rating (Standardized)	0.006***	0.466***	0.005***	0.504***	0.004***	0.408***
	(0.001)	(0.072)	(0.001)	(0.112)	(0.001)	(0.082)
Bid Description Length (Standardized)	0.001	0.039	0.001	0.018	0.000	0.015
	(0.001)	(0.034)	(0.001)	(0.049)	(0.001)	(0.041)
Days registered on Platform	-0.000*	-0.000**	-0.000	-0.000	-0.000**	-0.000**
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
Timezone Difference	-0.000	-0.016	-0.000	-0.007	-0.000	-0.016
	(0.000)	(0.018)	(0.001)	(0.024)	(0.000)	(0.025)
Same Country	0.021***	0.906***	0.025***	0.837***	0.018***	0.919***
	(0.005)	(0.194)	(0.010)	(0.281)	(0.005)	(0.255)
Same Language	-0.001	-0.031	-0.006	-0.232	0.002	0.217
	(0.003)	(0.218)	(0.006)	(0.285)	(0.003)	(0.289)
Corporate Account	-0.001	-0.063	-0.004	-0.183	0.000	-0.003
	(0.002)	(0.087)	(0.003)	(0.131)	(0.002)	(0.100)
Observations	43,468	43,468	19,564	19,564	34,048	34,048
Model	Linear	Cond. Logit	Linear	Cond. Logit	Linear	Cond. Logit
Num. Sponsored Bids	459	459	202	202	327	327
Project FE	Yes	Yes	Yes	Yes	Yes	Yes

Standard errors in parenthesis are clustered at the project level
*** $p<0.01$, ** $p<0.05$, * $p<0.1$