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Too Risky to Bid? Women in OLMs and STEM Competitive Environments

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Abstract

Online labor markets (OLM) are increasingly common sources for identifying trained individuals for technological work. Yet, like much of the tech industry, OLMs suffer from under-representation of women. We examine why women may choose not to participate in bidding for software development and analytics projects on OLMs. We theorize that pertinent project factors – project complexity and overall project competition – increase the risk profile of such work and disproportionately dissuade women from bidding for these projects, relative to men.

We test these hypotheses using experiments conducted on Amazon Mechanical Turk (AMT). Comparing the effect of higher project complexity, greater boundary spanning requirements, and higher competition on the propensity to bid for riskier projects for women versus men, and on the bid amount issued when they do bid, we find that women are indeed deterred by project complexity in their bid decision (and to bid lower amounts), but are more likely to bid for projects with higher boundary spanning requirements or more competition. We contribute to the IS literature by establishing the specific factors affecting women's participation and wages in OLMs and suggest several actionable managerial insights to make OLMs more inclusive and attractive to women in IT.

Keywords: Randomized Experiments; Women in IT; Online Labor Markets; IT Labor Market; Discrimination; Technological Complexity; Boundary Spanning; Competition

Introduction

Real or perceived gender differences in competitiveness (Buser et al. 2014, Croson and Gneezy 2009) or organizational constraints (Ahuja 2002, Ibarra 1997, Ibarra and Andrews 1993, Trauth et al. 2009) may explain why women and men experience differential labor market outcomes such as promotions and wages. However, does the inherent riskiness of the perceived tasks, as encapsulated in increased complexity, in a context free of the said organizational constraints affect women's participation in these markets and getting a foot in the door? There is a paucity of research examining this specific question, since the organizational or institutional context wherein economic activity is carried out has often assumed primacy. As freelancing platforms and the gig economy gather traction, gender-specific differences in and of themselves may be instrumental in determining the extent to which women choose to participate in these markets, specifically in Information Technology (IT) related projects. In this study, we ask whether women will choose to compete with men directly for more complex and therefore riskier IT projects in an online labor market (OLM). This study removes traditional organizational constraints where men could benefit from hidden biases against women in hiring and promotion and could potentially uncover specific gender differences in risk preferences in IT work.

We set our study within the institutional context of OLMs such as UpWork (formerly oDesk), Amazon Mechanical Turk, and Task Rabbit. These platforms are large and vibrant, fully online communities of clients and service providers, wherein vendor search, contracting, execution of projects, payment services and ex post assessments of performance are carried out on the platform itself (Horton 2010). These markets present an opportunity for a variety of projects, including IT and computing tasks ranging from software and web development to multimedia development (Chan and Wang 2017, Kokkodis and Ipeirotis 2016).

Research on OLMs has been growing in recent years, and currently encompasses an examination of the efficiency of such markets and persistence of reputation effects (Kokkodis and Ipeirotis 2016) as well as country differences (Hong and Pavlou 2017). Emergent research also seeks to understand whether gender stereotypes persist in these markets (e.g. Chan and Wang 2017). Beyond mere stereotypes, bias in online environments can persist in hiring and evaluation decisions: expressing bias against women or other under-represented groups is relatively costless to OLM users as they rarely come across legal or social repercussions as a result (Guryan and Charles 2013). In addition to the legal and societal ramifications that may be associated with these systematic biases, it is imperative for researchers to fully understand their sources as well as their implications for the efficient and equitable functioning of these markets.

A specific component of the freelancing OLM context that may exacerbate existing gender-based biases, both in women and in men, pertains to the uncertainty, and thus riskiness, of projects listed on the sites, instigated by the complexity of the task at hand, the boundaries that need to managed to accomplish this task, and the overall competitive environment. More to the point, despite the fact that decentralized institutions like OLMs provide mechanisms for thwarting gender stereotypes, there is a paucity of research focusing on whether task complexity or anticipated competition significantly influence equitable participation in project work across genders. In other words, even as women compete with men in OLMs for IT work, do they shun (or are shunned for) complex, more technologically advanced projects? Activity on OLMs are often characterized by variations on these dimensions, each of which may contribute to the level of uncertainty and complexity in the project. It is arguable that these factors systematically dissuade women from participating on the market, either in terms of their decisions to bid for projects or in terms of the wages they demand, relative to men.

Our work here contributes to IS literature in multiple ways. First, we address the critical issue of unequal participation in the tech sector by women, by focusing attention not only on salaries but also on the earlier decision to enter the competitive and complex arena of OLMs. Contrary to prior research, we find that women are more likely to participate and even more so for competitive projects, but less likely for more complex projects. This study thus complements and extend existing research on gender and competitive labor markets to the context of IT labor markets and more to STEM markets. Second, we address the extent to which technical and contextual complexity may differentially influence the decision to bid for projects across gender, building on prior research that shows how women may systematically shy away from more complex and riskier projects. Finally, we study how the presence of strong competition by itself may affect participation decisions as well as wage expectations; to the extent that freelancer and gig economies have low entry barriers, competitive pressures faced by participants are typically more intense. While extant wisdom suggests that the low prevalence of women here may simply be from a decision to opt out of competitive environments, our findings show that women's decision to participate in OLMs may not necessarily be driven by intrinsic or extrinsic barriers. In sum, our work here addresses the important issue of women's participation in OLMs, representing competitive and complex work environments, and has significant theoretical and practical implications for Information Systems (IS) scholars focusing on gender related research questions.

Background Theory and Hypothesis

Since we are interested in understanding why individuals may choose to bid for projects on online labor markets where there are significant technological and contextual challenges present, we draw on information processing theory (Tushman and Nadler 1978), which postulates that every organizational and economic activity entails the need for information processing, since all tasks are interdependent and require coordination. In certain settings, the information processing requirements are more pressing, thereby making such settings inherently more uncertain and riskier (Langer et al. 2014). More importantly, in our context, we argue that projects listed on OLMs tend to represent varying levels of information processing needs by virtue of their technical requirements. Even when project details are enunciated ex ante, individuals bidding for such projects rarely ever have all the pertinent information needed for decision making.

Consider, for instance, a typical IT project executed on an OLM where both vendor and client have access to only incomplete information about each other. The client posts information about the project's technology and domain specific requirements, yet the precise level of skill and expertise needed can only be partially inferred. Based on this admittedly rudimentary project description, potential vendors, who know their own skills and capabilities, choose to bid on the projects while also specifying their own desired wages. The competitive aspect of OLMs adds further uncertainty to these projects.

While all of these factors increase the uncertainty and risk embedded within the specific project, our goal here is to examine if there are differences between men and women in terms of bidding and competing for the project, contingent on factors that vary their information processing requirements. Specifically, we study whether the presence of technological complexity and competition will differentially influence the decision of women to bid on such projects (Morgan 2006, Simon 1997, Tushman and Nadler 1978).

Gender and Task Complexity

Within the information processing paradigm, a significant source of information processing needs emerges from task complexity, defined as the series of interdependent and interconnected subtasks that need to be completed in a specified order for the task to be completed (Campbell 1988). In general, task complexity is associated with greater uncertainty, since each subtask may not always be well understood or easily completed, while their interdependencies are even less predictable. Uncertainty in this setting is therefore the difference between the information available to the agent and the full complement of information needed to complete the task. Thus, the greater the task complexity, the greater is the information processing need, and hence greater is the uncertainty in the activity, all else being equal (Tushman and Nadler 1978). In the context of OLMs in particular, technologically complex projects that involve a combination of technical requirements combined with complex data processing needs are inherently more uncertain since they require high levels of information processing. Inasmuch as the technical knowhow is present in the vendor's skillset, the incremental uncertainty created by the OLM itself can add to the technical complexity faced by the prospective vendor. Thus, from an information processing perspective, technically complex projects on OLMs represent significant uncertainty for bidders. How may task complexity affect the decision by women to bid for such projects, relative to men on the OLM? Prior research argues that dynamic task environments that intrinsically generate greater uncertainty (Duncan 1972) will tend to generate gender disparities in terms of bidding behavior for such projects. Men are generally substantially more confident about their capabilities with respect to managing uncertainty inherent in more complex tasks than women (Niederle and Vesterlund 2007). Since higher complexity engenders more risk, an individual's propensity to bear risk can lead to systematic differences in response. Using this reasoning, Niederle and Vesterlund (2007) argue that women tend to display more risk-averse behavior and therefore opt for less complex undertakings, relative to men. Other scholars have also attested to the notion that when faced with complex and potentially risky activities, women and men tend to respond differently (Borghans et al. 2009, Croson and Gneezy 2009). Given the link between technical complexity, risk, and the observed prevalence of greater risk-averse behavior by women relative to men, we posit:

H1a: Ceteris paribus, relative to men, women are less likely to bid for projects with high technological complexity.

H1b: Ceteris paribus, relative to men, women are more likely to issue lower bids, if they bid, for projects with high technological complexity.

Gender and Competition

Beyond the presence of technological complexity, OLMs are characterized by intense competition as several vendors typically bid for projects and the bidding environment allows bidders to gauge the skills and capabilities of competitors bidding for the same project. Low entry barriers and network effects ensure that there are many vendors operating on the platform at any point in time, enhancing the extent to which competition is a significant factor in this setting.

In such competitive settings, do women compete in the same manner as men? Prior research has addressed gender differences in terms of how individuals respond to competitive environments, but mostly in offline settings that are not associated with IT contexts. Specifically, Gneezy et al. (2003) show that in highly competitive environments, men tend to outperform women on average. In more recent work, Saccardo et al. (2018) confirm these broad findings in the lab by showing that women tend to respond less favorably to competition while men are more eager to compete and tend to respond more positively to the presence of competition. The literature also shows that men view the presence of competition as a challenge and less as a threat; in contrast, women view competition as risk (Croson and Gneezy 2009, Eckel and Grossman 2008).

These broad attitudes to competition across genders manifest themselves when faced with the decision to either enter into employment in the presence of competition, or in demanded wages. Niederle and Vesterlund (2007) examine how women and men respond to a choice between a competitive versus a non-competitive compensation scheme and find that men are more likely to believe that they can outperform others. In contrast, women do not make the same choices and prefer the non-competitive scheme. These differences in behavior cross over to bidding behavior as well, when facing competition. Women appear to systematically respond to competition by choosing to not participate in the bidding process, and when they do bid, they bid lower than men. We formalize these in the following hypotheses:

H2a: Ceteris paribus, relative to men, women are less likely to bid for projects with greater competition.

H2b: Ceteris paribus, relative to men, women are more likely to issue lower bid, if they bid, for projects with greater competition.

Methodology and Experimental Design

We empirically test our hypotheses using a set of randomized controlled experiments that enable us to understand the bidding process by individuals. We ran the experiment on Amazon's Mechanical Turk (AMT) using crowd workers on AMT called Turkers. AMT is increasingly being used for randomized experiments in IS research (Burtch et al. 2018, Mejia and Parker 2019) and can yield samples that are arguably more diverse, geographically dispersed, and more representative of what may be encountered in a typical OLM (Buhrmester et al. 2011). Further, we randomize the project profiles between male and female "OLM bidders;" this allows us to identify the effect of the two proposed treatments: task complexity (high vs. low) and competition (high vs. low) (e.g. Bertrand and Mullainathan 2004). Because successful project completion on OLMs necessitates integration of knowledge and information across many boundaries, be they functional, technological, procedural, geographical, or organizational boundaries (Gopal and Gosain 2010, Levina and Vaast 2005), we also manipulate boundary spanning as an additional treatment, even though we do not hypothesize for it. We employ a combination of between (competition and boundary spanning) and within subjects (competition) design (Charness et al. 2012), wherein each subject is randomly assigned to one of the 8 factorial cells (A-H, Table 1). The participants were provided with project profile pages, similar to those found on OLM platforms such as freelancer.com or upwork.com, which included information provided by a potential client on the technical requirements of the project, the programming environment or technical skillset requirement that is involved, a tentative duration for the project, a short description of the expected deliverable, and other information relevant to the project. The project profile provided some client background information, such as location, prior projects posted on the platform, total project spending on the platform, and reviews left for the client by prior vendors, if applicable.

To vary technical **task complexity**, we manipulate the technical requirements of the project itself, based on parameters associated with the depth of data manipulation required, the sophistication of the programming languages and interfaces required, the function points involved in the project, the complexity of the data itself, and the output requirements. The less complex project was significantly simpler in terms of the technical environment, the output requirements, and the extent to which data manipulations are needed to complete the project. The experiment captured the presence of **competition** by providing information on how many other bidders were currently in the running for the same project. The low competition setting showed only four other bidders with average ratings, while the high competition setting showed twenty other bidders with some variation in their overall ratings. These numbers are based on the archival data that we studied across the two OLMs – freelancer.com and upwork.com. Figure 1 illustrates the competition treatment.

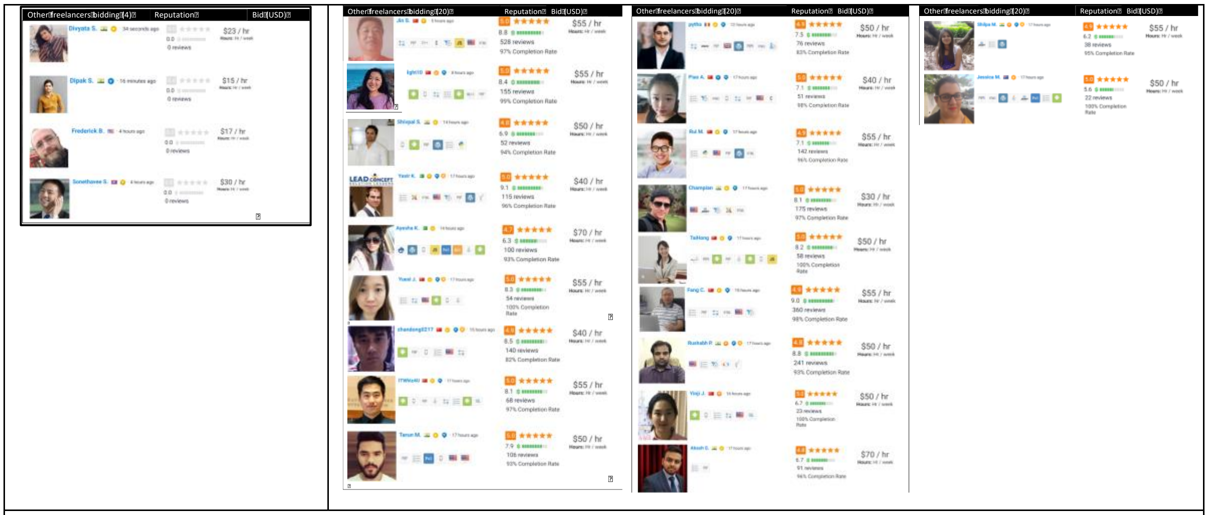

Figure 1. Illustrating Low v. High Competition Scenarios

We also manipulate boundary spanning conditions of the project: the high boundary spanning condition required managing across time-zones, language barriers, and more stringent requirements for coordination and communication between the client and vendor. Alternatively, the low boundary spanning condition was significantly easier with fewer clear fault-lines and boundaries at play in the project profile.

Table 1. 2x2x2 Experimental Stimuli

			Variation	
			Low	High
Task complexity	Low Competition	High	B	D
		Low	A	C
	High Competition	High	F	H
		Low	E	G

Table 1. 2x2x2 Experimental Stimuli

Following Mejia and Parker (2019), we ascertained the suitability of the subject pool to assess IT projects using a pre-screening questionnaire, which had 15 questions related to database design, SQL, and programming languages such as Python, this and the sample project profiles we used in the experiments are available from the authors upon request. Before administering the experiments, the stimuli were examined by three experienced raters with experience in software development in general (Espinosa et al. 2007, Langer et al. 2014). Subsequently, they were pre-tested by a set of 20 IS graduate students at a large four-year university in the United States to ensure that they were reasonable for the purposes of the study.

For the actual AMT study, we trained the subjects on two sample projects so as to clarify all questions related to the main experimental procedure. Subsequently, each subject was presented with a randomly chosen project profile and then asked two specific questions of importance that inform our two dependent variables:

1. Would you like to **bid** for this project (Yes/No)?

2. If you chose to bid for this project, what **hourly wage rate (in $)** would you choose to enter?

We then asked a series of questions as manipulation checks to ensure that the purported treatments have indeed registered with the subject. We finally concluded the experiment with a set of demographics questions to gather information about the subject's age, gender, race, education, work experience, and years of experience in STEM. As with all research with human subjects, the experiments were run following approval from the Institutional Review Board at the authors' respective universities. The Turkers were paid amounts consistent with prior studies (Mejia and Parker 2019). We obtained a usable sample size of roughly 387 participants on AMT yielding a total of 773 usable observations, where the unit of analysis is the individual project.

Randomization Checks

An important aspect of a randomized experiment is that the treatment should indeed be random across treatment and control groups (Bertrand and Mullainathan 2004, Lalonde 1986). We compared the means and standard deviations of gender, age, race, and educational background for the three treatments and found no statistically significant differences between the two groups, allowing us to conclude that the treatment was indeed random. We present these randomization checks for the AMT experiment in Table 2.

Table 2. Randomization Checks

	Complexity		Competition		Boundary Spanning	
	High	Low	High	Low	High	Low
Female	0.27 (0.45)	0.45 (0.27)	0.27 (0.45)	0.45 (0.27)	0.27 (0.44)	0.44 (0.27)
Age 18-24	0.22 (0.42)	0.42 (0.22)	0.23 (0.42)	0.42 (0.22)	0.22 (0.42)	0.42 (0.23)
Age 24-34	0.52 (0.5)	0.5 (0.52)	0.51 (0.5)	0.5 (0.53)	0.52 (0.5)	0.5 (0.51)
Degree-Bachelor	0.25 (0.43)	0.43 (0.25)	0.26 (0.44)	0.44 (0.24)	0.25 (0.43)	0.43 (0.26)
Degree-Masters	0.71 (0.46)	0.46 (0.7)	0.72 (0.45)	0.45 (0.69)	0.7 (0.46)	0.46 (0.72)
Degree-Professional	0.16 (0.37)	0.37 (0.16)	0.14 (0.35)	0.35 (0.18)	0.16 (0.37)	0.37 (0.14)
Degree – Non Professional	0.06 (0.24)	0.06 (0.24)	0.06 (0.24)	0.06 (0.25)	0.07 (0.25)	0.06 (0.23)
Race=White	0.13 (0.34)	0.34 (0.13)	0.14 (0.35)	0.35 (0.13)	0.13 (0.34)	0.34 (0.14)
Race= Asian	0.32 (0.47)	0.47 (0.32)	0.34 (0.47)	0.47 (0.3)	0.32 (0.47)	0.47 (0.34)
Notes: Standard deviations in parentheses.						

Table 2. Randomization Checks

Table 3 shows the summary statistics for the study. The AMT sample indeed seems more representative of the IT industry, with women constituting 28.1% of the sample. The correlations between the variables of interest for the sample did not show any significant relationships; the correlations data are available from the authors upon request.

Table 3. Summary Statistics

Variable Name	Mean (SD)	Min	Max
Bid Decision	0.76 (0.43)	0	1
Bid Amount ($)	23.68 (29.6)	0	250
Complexity	0.5 (0.5)	0	1
Competition	0.52 (0.5)	0	1
Boundary Spanning	0.53 (0.5)	0	1
Female	0.27 (0.44)	0	1
Age 18-24	0.22 (0.42)	0	1
Age 25-34	0.52 (0.5)	0	1
Race=White	0.17 (0.38)	0	1
Race=Asian	0.08 (0.26)	0	1
Degree=Bachelor	0.32 (0.47)	0	1
Degree=Masters	0.57 (0.5)	0	1
Degree=Professional	0.11 (0.31)	0	1
Degree=Non Professional	0.71 (0.46)	0	1

Table 3. Summary Statistics

Results and Discussion

We use a linear probability model to analyze our experimental data for the bidding decision (Chatla and Shmueli 2016), and a tobit model to ascertain the effect of treatment and demographic variables on the bidding amount, if the subject decides to bid (Greene 2003). Our primary focus is to ascertain differences between participation of men and women on OLMs when faced with task complexity and competition. The regression analysis allows us to use interaction effects to ascertain these differences. Further, it also allows us to control for within subject treatment of task complexity by clustering standard errors for the experiment participant (Abadie et al. 2017).

Results

We report the regression results for the AMT sample for our two dependent variables, the propensity to bid and the bid amount in Tables 4 and Table 5 respectively. We first ran the baseline model with the treatment and other demographic variables. We then added interaction effects for Female*Treatment, where treatment would be high task complexity and more competition as well as high boundary spanning requirements. Finally, based on past literature that stresses the differences between socio-economic structures in Asia versus US, the two regions our Turkers came from (Ahuja 2002, Langer et al. 2020), we also added an interaction effect with female and Asian participants (Female*Race_Asian). Our results are largely stable across the specifications; therefore, in the interest of space, we discuss results from the full model (column III) for both Table 4 and 5.

We find that project complexity increases the likelihood of bidding (β=0.0703, p<0.01), perhaps because vendors may perceive such projects to be more lucrative if they bid. Both boundary spanning and competition decrease the propensity to bid (β_{BS}=-0.0939, p<0.01; β_{COMP}=0.0865, p<0.01). Despite the OLMs being platforms where vendors necessarily have to be boundary spanners, higher such requirements dissuade them. Not surprisingly, vendors are also less likely to bid when there is higher competition, which in turn decreases the likelihood that they will be hired. We found that younger age group (18-24) years is more likely to bid for OLM projects (β=0.0473, p<0.01) but undergraduates are less likely to bid (β=-0.0508, p<0.01), compared with those with graduate or professional degrees. We also find that Asians are more likely to bid on IT projects on OLMs (β=0.3663, p<0.01).

Gender effects: We find that women are more likely to bid on OLM projects compared to men (β=0.3238, p<0.01). OLMs provide an employment opportunity that is more in tune with the work-life balance that many women seek in their careers. As shown in prior IS and social sciences literature (e.g., Ahuja et al. 2007), women shoulder a greater burden of housework (Bianchi et al. 2012), and a typical IT career with unpredictable hours may not be feasible for many women. OLMs, on the other hand, provide a more flexible career option where women can work according to their own schedule and possibly in the comfort of their homes, making freelancing on OLMs an attractive alternate career trajectory.

We find that H1a is supported in that women are less likely to bid for more technologically complex projects (β=-0.0725, p<0.01). Contrary to H2a, we find that women are more likely to bid for projects in the presence of higher competition (β=0.0843, p<0.01). We offer two explanations for this unlikely finding. First, prior research compared women to men in a general labor market context, whereas similar findings may not necessarily apply to women in IT; women in IT (analogously, women in STEM fields) are arguably more competitive because they have chosen to be part of a traditionally male dominated industry. Thus, we extend and complement prior research on gender and competition(Croson and Gneezy 2009, Niederle and Vesterlund 2011) to the context of IT and more fluid labor markets. Second, they do not have to contend with organizational constraints and biases that are likely to inhibit them. The online context sufficiently mitigates any such constraints, even if these are not eradicated entirely. Hence, they are more willing to compete with men when they know themselves to be capable and proficient. We also find that women are more likely to bid for projects with higher boundary spanning needs (β=0.0984, p<0.01), perhaps because they are able to communicate effectively with global clients and manage these projects well. Our results suggest that OLMs should encourage women to participate by instituting mechanisms that hinder any inherent hiring biases. Finally, our most interesting finding suggests that Asian women shy enough from OLMs and are less likely to bid for OLM projects (β=-3597, p<0.001), paving the way for future work.

Table 4. Regression Results: DV = Decision to Bid

	I		II		III	
Complexity	0.05**	(0.02)	0.07**	(0.03)	0.07**	(0.03)
Competition	-0.07***	(0.02)	-0.09***	(0.03)	-0.09**	(0.03)
Boundary Spanning	-0.07**	(0.02)	-0.09**	(0.03)	-0.09**	(0.03)
Female	0.08***	(0.02)	0.02	(0.03)	0.32***	(0.05)
Age 18-24	0.06**	(0.02)	0.06**	(0.02)	0.05**	(0.01)
Race=Asian	0.29***	(0.04)	0.28***	(0.04)	0.37***	(0.05)
Degree=Bachelor	-0.07**	(0.02)	-0.07**	(0.02)	-0.05**	(0.02)
Degree=Master	0.03	(0.02)	0.02	(0.03)	0.05+	(0.03)
Degree=Professional	0.03	(0.04)	0.02	(0.04)	0.04	(0.05)
Female*Complexity			-0.07**	(0.03)	-0.07**	(0.03)
Female*Competition			0.08**	(0.03)	0.08**	(0.03)
Female* BndrySpan			0.09**	(0.03)	0.10***	(0.03)
Female*Asian					-0.36***	(0.05)
N	464		464		464	
R-sq	0.32		0.33		0.39	

Notes: Standard errors in parentheses. + p<0.1, * p<0.5, ** p<0.01, *** p<0.001.
Model I estimates the base line model; Models II and III add treatment and race interaction effects.

Table 4. Regression Results: DV = Decision to Bid

In Table 5, we examine the factors affecting bidding amount, if the subject chose to bid for the project. We find that more complex projects elicit higher bids (β=18.76, p<0.001), more boundary spanning reduces the project bids (β=-10.19, p<0.01), but competition did not have any significant effect on bidding amount (β=1.23, p>0.1). Younger vendors bid less for OLM projects (β=-17.54, p<0.001), as did undergraduates (β=-9.95, p<0.1). Contrary to our expectations, women did bid more for OLM projects (β=16.64, p<0.1), but as we argued in H1b, they bid less for more complex projects (β=-13.15, $p<0.05$). There were no significant differences in bidding amount between men and women for more competition or higher boundary spanning; these interaction coefficients were positive but insignificant (β_{COMP}=6.45, $p>0.1$; β_{BS}=9.67, $p>0.1$). Interestingly, we again find that Asian women bid less for projects (β=-15.37, $p < 0.1$). Overall, our findings suggest that women on OLMs seek to mitigate the ubiquitous wage gap but may be deterred by competition.

Table 5. Regression Results: DV = Bid Amount ($)

	I		II		III	
Complexity	14.99***	(2.21)	18.80***	(2.41)	18.76***	(2.43)
Competition	2.7455	(2.76)	0.97	(3.29)	1.23	(3.29)
Boundary Spanning	-7.71**	(2.83)	-10.11*	(3.26)	-10.19**	(3.26)
Female	5.84	(3.70)	3.74	(5.48)	16.64+	(8.93)
Age 18-24	-16.91***	(3.13)	-16.92***	(3.13)	-17.54***	(3.13)
Race=Asian	1.17	(4.24)	0.86	(4.20)	4.59	(5.01)
Degree=Bachelor	-10.49*	(5.33)	-10.86*	(5.51)	-9.95+	(5.44)
Degree=Master	-7.81	(6.14)	-8.18	(6.32)	-6.94	(6.36)
Degree=Professional	-14.25	(13.58)	-15.23	(12.88)	-14.47	(13.36)
Female*Complexity			-13.11*	(5.42)	-13.15*	(5.41)
Female*Competition			6.42	(5.88)	6.45	(5.80)
Female* BndrySpan			9.36	(6.74)	9.67	(6.69)
Female*Asian					-15.37+	(8.71)
N	464		464		464	

Notes: Standard errors in parentheses. + p<0.1, * p<0.5, ** p<0.01, *** p<0.001.
Model I estimates the base line model; Models II and III add treatment and race interaction effects.

Table 5. Regression Results: DV = Bid Amount ($)

Overall, our results indicate that OLMs are not the same as the typical IT jobs, and women are more willing and eager participants in these markets. The differences we identify between Asian and other women encourage us to conduct the next study focusing on these very factors in Asian regions. We are indeed in the process of designing and conducting the next set of experiments.

Conclusion

The issue of equitable participation by women within the IT and STEM professions has remained a challenge, whether these include academic communities or for-profit firms. The policy-based solutions to remedying this situation have, for the most part, tackled wage disparity issues as well as issues of work-life balance that may disproportionately affect women's careers (Sirimanne 2019). Alternatively, hostile work environments have been identified as reasons for why women may choose to leave IT and STEM environments (Funk and Parker 2018). Arguably, the advent of OLMs could be viewed as a pragmatic solution to some of these concerns, since the impact of toxic workplaces, work-life balance, and wage disparities may be significantly reduced. OLMs thus present a credible alternative to women as they seek non-traditional career paths that provide more flexibility, money-making opportunities, and less office politics and biases (Horowitz 2015). However, research suggests that even in OLMs, there is under-representation of women. In this paper, we examine potential reasons for why women may choose to not compete for projects on the OLM platform, contingent on factors that are visible and relevant.

We found that women are more likely to bid for OLM projects in general, are deterred more by complexity but contrary to prior research, less so by the project's competitive environment. They are also more likely to bid higher for these projects. These findings overwhelmingly women in IT are willing and able to take on the uncertainty and risks that are the necessary features of OLMs. Given our most interesting finding suggests that Asian women shy away from OLMs and less likely bid for OLM projects, further work could investigate the roles of culture differences, tech experience, platform experience and/or education impact on women's willingness to compete on OLMs.

As researchers uncover and understand factors that may discourage or encourage women in IT, this study provides critical insight into the antecedents of labor market participation. Our study thus complements and extends existing scholarship on gender and competitive labor markets to IT labor markets and more generally to STEM labor markets. We specifically address the extent to which contextual complexity of technical projects and inherent competition to OLMs may differentially influence the decision to bid for OLM projects across gender and show that women's decision to participate in OLMs may not necessarily be driven by intrinsic or extrinsic barriers. These findings also have implications for academics as they train and educate the next generation of women in IT.

Further, in as much as OLMs are true marketplaces, our findings are also likely to be of import to senior managers at OLMs, as they look to increase platform participation and use and cater to the increasingly diverse and global clients and service providers. Furthermore, from a policy perspective, our results have implications for how platform policies and sociological factors pertinent to women from certain parts of the world may interact in ways to either enhance or reduce the propensity to participate on OLM platforms. Clearly, more work is needed to fully examine these questions.

As with all research, we are limited by the scope of our experiments. While both sets of experiments were randomized and had effective manipulation of the treatment, they do not capture the opportunity costs of bidding on a real, live project. Although our subject pools were more representative of OLMs, racial and national differences may yet play a role in the decision process that we are unable to discern.

Despite these limitations, we believe ours to be one of the first studies to examine the motivation and identify the specific factors relevant to the IT industry that deter or encourage women in IT to participate in OLMs. We hope that future research will find mechanisms to motivate these platforms to be even more inclusive and attractive to women in IT. Addressing these systemic imbalances within the IT and STEM professions is beneficial to all. We hope that the research described helps towards furthering these goals.

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