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Knowledge work in the sharing economy: What drives project success in online labor markets?

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Abstract

Online labor markets are an integral part of the sharing economy. In online labor markets, firms and freelancers match up for one-off projects, or gigs. As gigs can vary in several dimensions including their complexity, uncertainty and potential for opportunism by partners, their performance may be affected by the transaction costs arising from these features. We use this logic to posit that freelancer capabilities, project complexity, employer and freelancer experience, and contract type affect employers' evaluation of project success. Using a novel and extensive dataset from the online labor-sharing platform Upwork, we find broad support for our hypotheses. Our findings suggest that factors related to transaction costs can explain the heterogeneity in project outcomes even in an online market for gigs.

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Abstract

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Keywords: sharing economy, online labor markets, transaction costs, gig economy

1 INTRODUCTION

The origins of the sharing economy lie in the utilization of underused assets and capacity, often aided by the emergence of a technological infrastructure facilitating the supply of such capacities. This has been most prevalent in the sharing of physical assets through an online platform (e.g. Uber and Lyft for taxi services or Airbnb for short-term accommodation), but it has also made inroads into the online supply of labor. In this context, the sharing economy has triggered several changes especially on the supply side: previously, services were often outsourced to professional firms on a medium- or long-term basis, while online platforms for labor make it possible for firms to hire individuals for one-off projects, or gigs, even for complex tasks requiring specific skills (Kunda, Barley, & Evans, 2002; Masters & Miles, 2002; O'Mahony & Bechky, 2006).[1] Firms therefore address an "undefined, generally large group of people in the form of an open call" (Horton & Chilton, 2010, p.1).

The gig economy as part of the wider phenomenon of the sharing economy has radically gained in importance (Agrawal et al., 2015). This is a result of broader economic trends towards outsourcing and contingent work (Belous, 1989; Cohany, 1996; Dibbern, Winkler, & Heinzl, 2008; O'Mahony & Bechky, 2006), self-employment (Steinmetz & Wright, 1989), and increasing project work (Bielby & Bielby, 1999; Hinds & Bailey, 2003), aided by technological advancements that enable geographically and temporally distributed work (Boudreau, Loch, Robey, & Straud, 1998) and makes finding potential project partners easy. However, this also means that traditional ways of assessing partners ex ante such as personal contact, repeated work relationships or referrals are less suitable for predicting the success of a particular project. This leads to transaction costs which are not typically relevant for transactions on spot markets (Ho, Slivkins, Suri, Vaughn, 2015; Rogstadius et al., 2011). Knowledge-intensive projects are essentially experience goods (Kokkodis and Ipeirotis, 2016) and subject to information

[1] We will use the terms *gig* and *project* synonymously throughout the paper.

constraints, which give rise to information asymmetries between parties. Indeed, employers in online labor markets cannot directly monitor a worker's behavior (*hidden action problem*). Further, given the anonymity and diverse backgrounds of workers, it is more difficult to assess their ability and skill proficiency in advance (*hidden information problem*). Concurring, low quality work and unexpected results have been identified as "the single biggest factor[s] in companies choosing to abandon paid crowdsourcing" (Felstiner, 2011, p. 153). Employers therefore need to leverage distinct cues relevant for these markets and possibly design contractual safeguards to ensure satisfactory project performance.

Consequently, we study the *key factors that drive project success in online labor markets*. While controlling for a variety of employer-, project-, and freelancer-specific characteristics, we posit that differences in employers' evaluation of project success can be explained by variations in the drivers of transaction costs across outsourced projects. We identify several factors at the freelancer, employer, and project level that might reduce or exacerbate certain transaction costs and consequently result in lower or higher evaluations of projects. We expect that prior success of a freelancer predicts future success due to an inherent ability to successfully complete projects (reducing uncertainty about the outcome). We also argue that more complex projects imply higher uncertainty about the outcome and therefore higher transaction costs, leading to lower performance ratings on average. Further, employers and freelancers gather experience in managing online transactions, reducing asymmetric information and therefore transaction costs, which increases expected performance ratings. Finally, the contractual design of a project also affects transaction costs. A fixed-price contract reduces the scope for opportunistic behavior of freelancers claiming more hours than actually spent, so that we expect fixed-price projects to receive higher performance ratings on average.

We hypothesize and test the above arguments in the context of *Upwork*, the world's largest online workplace. In contrast to many other online labor markets, projects on *Upwork* are often more professional, longer-term, uncertain and require specific skills, which makes the platform an ideal testing ground for project- and freelance-specific drivers of transaction costs. We find our hypotheses broadly supported with the exception that freelancer experience is negatively correlated with project success, contrary to our expectations.

We contribute to the literature in several ways: First, few studies have looked at knowledge-intensive online projects, which is a fast-growing segment of the labor market thanks to the sharing economy. Focusing on simple and low-skilled tasks, prior studies have naturally been less concerned with transaction costs arising from uncertainties (Kunda et al. 2002; Masters & Miles, 2002). By taking the lens of transaction costs economics, our analysis suits well the growing and important section of online labor markets. Second, we study performance in the post-contractual phase in one-off contracts. This is important because with increasing project complexity, contracts will inevitably be less complete, giving wider scope for post-contractual opportunism. The limited repeated interaction intensifies this issue. Third, with the exception of Leung (2014) prior work on online labor markets has overlooked complexity as a key driver of heterogeneity in transaction costs across projects. As online labor markets include more sophisticated tasks and higher skilled individuals, knowledge about the effect of complexity on expected project performance becomes increasingly important. Finally, we contribute to the literature on project-based work by studying the drivers of performance using a large-scale sample of projects across many firms and individuals. Hence, our results are not specific to a single firm or type of project.

2 ONLINE LABOR MARKETS

2.1 Defining Online Labor Markets

Over the last decades, online labor markets (OLMs) such as Amazon Mechanical Turk (MTurk), Upwork (formerly Elance-oDesk), Zooniverse, CrowdFlower and Innocentive have emerged as platforms that facilitate the allocation of productive effort across global economies. More specifically, OLMs can be defined as "a market where labor is exchanged for money, the product of that labor is delivered over a wire and the allocation of labor and money is determined by a collection of buyers and sellers operating within a price system" (Horton, 2010: p. 516). The most obvious distinguishing characteristic of OLMs is that work is entirely performed online rather than by workers that are physically collocated (Chen and Horton, 2016). Hence, OLMs offer the potential for a large number of transactions and services to be provided by suppliers who may be geographically distant from buyers (Agrawal et al., 2015). The exchanged service is thus an experience good, i.e. a product or service that is difficult to assess its value without purchasing and consuming it (Kokkodis and Ipeirotis, 2016). Further, workers can be hired by several employers at the same time. Thus, OLMs are characterized by many-to-many connections, with some connections only a few minutes long (Felstiner, 2011). Finally, many OLMs broker highly heterogeneous tasks, enabling workers to work simultaneously in diverse task categories. Workers on OLMs are also diverse in their motivation, education, and background (Manyika, Lunds, Bughin, Robinson, Mischke, & Mahajan, 2016).

Although different types of OLMs exist, we focus on spot markets for tasks, a particularly interesting and powerful way of accomplishing work online (Horton, 2010). There, employers can "buy discrete chunks of labor from a global pool of workers at a market price, similar to how they obtain any other factor of production" (Chen & Horton, 2016, p. 414).

2.2 Work Processes on Upwork

Upwork was founded in 2015 (formerly oDesk-Elance), and is now the world's largest freelancing website. The platform aims at "*creating economic and social value on a global scale by providing a trusted online workplace to connect, collaborate, and succeed*" (Upwork.com, 2018) and connects clients with freelance professionals from various disciplines, ranging from administrative support and graphic design to software and web development. With millions of jobs posted on *Upwork* annually, freelancers are earning more than $1 billion via the site each year and covering over 3,500 skills (Upwork.com, 2018).

In contrast to OLMs focusing on microtasks such as MTurk, *Upwork* explicitly encourages longer-term projects and prioritizes high-value, ongoing work (Pofeldt, 2016). This makes for a particularly interesting context because it enables us to study more high-skilled contingent work. In fact, few studies examine high- rather than low-skilled contingent work (Kunda et al., 2002; O'Mahony & Bechky, 2006) in general but also in the context of the sharing economy. For example, the most prominent examples of sharing economy platforms – Uber (driving service), Airbnb (renting service), TaskRabbit (handyman service) – predominantly provide job opportunities for less knowledge-intensive and largely homogenous tasks. Below, we briefly explain the work processes on *Upwork*.

To post projects on the platform, employers have to register by providing their contact details and basic information on their firm, including name, owner, and location. Once registered, employers can post as many jobs as they like. Job postings include a description of the task, the location of the employer, and the type of contract offered, either a fixed price or an hourly wage contract. The contract type has implications for monitoring and duration specifications. For hourly wage projects employers have to indicate the expected number of hours per week and the number of weeks required to complete the project. Employers can also limit the number of hours per week a freelancer can work on the project. When posting fixed-price projects, the budget and deadline has to be specified. These job postings can be made public (so that any freelancer can apply) or private (so that only freelancers the employer invites can apply).

Workers must also register on the website by giving their contact details, name, and location as well as by setting up a profile page. Profile pages serve self-marketing purposes and freelancers can include a description of skills, education, work experience outside of *Upwork*, platform-specific skill test scores, certifications, agency affiliation, and platform work history and feedback scores. Freelancers can apply for jobs by submitting cover letters and bids to job postings. A bid indicates the amount a freelancer is willing to be paid to work on a job. Employers have the option to interview and negotiate over bids with applicants before hiring and to hire as many contractors as they like.

Once hired, freelancers accomplish tasks remotely. After project completion, work can be verified in several ways. On hourly contracts, employers can review the Work Diary. It tracks billable time and records completed work. During billing hours the freelancer takes screenshots of her screen (six times per hour), allowing verification of billable hours. On fixed-price contracts, both parties agree on milestones for each project. After submitting milestones, employers review the work and release funds upon approval. Submission of deliverables and payments are done via *Upwork*, which charges a service fee of ten percent.

After completing a job, employers provide freelancers a feedback score ranging from 1 to 5 on six criteria: skills, quality, availability, deadlines, communication, and cooperation. Each freelancer also has an overall job success score, which is a job-size-weighted average of the individual scores and prominently placed on a freelancer's profile. Likewise, freelancers rate employers based on the same criteria; thus, employers have a comparable overall score.

Projects on *Upwork* are typically projects with a degree of autonomy rather than tightly specified tasks as on Amazon's MTurk. Projects are considered unique, one-off endeavors consisting of a large number of varied and interdependent activities intended to achieve a desired end result (Larson & Gray, 2013; Gido & Clements, 2012). In the context of online labor markets, projects refer to the whole process from posting a job to delivering the outcome and paying the freelancer, including collaborating with each other. Evaluating project success thus depends on more than assessing objective output quality. Rather, employers will evaluate whether the resources they invested (time, money, effort) resulted in the requested output. Specifically, they will evaluate three process-based measures of project success: whether it came in on schedule (time), whether it came in on budget (cost), and whether the requirements were met (product). Employers can also rate three outcome-based measures of success, i.e. whether the resulting product or service was actually used (use), whether the project helped prepare the organization for the future (learning), and whether the project improved efficiency or effectiveness of the client organization (value) (Nelson, 2005). Consequently, perceived project success depends on various (subjective and objective) criteria.

Importantly for our study, the performance rating given by the employer is a good indicator of post-contractual performance. If everything is as expected ex ante, the freelancer will receive the highest rating. If there are unanticipated shortcomings, the employer will penalize them.

3 PRIOR WORK ON ONLINE LABOR MARKETS

Although scholars and practitioners agree on the growing importance of OLMs (Agrawal et al., 2015; Manyika et al., 2016), relatively few studies have examined their specific nature (Chen & Horton, 2016). Most studies have used OLMs as a testing domain for broader questions (Steelman et al., 2014).

Existing research on OLMs can be divided into two dominant streams. The first looks at the ex ante contractual phase of transactions – i.e. hiring decisions – in OLMs for more skill-intensive tasks, using primary longitudinal data from oDesk or Elance. In contrast, the second stream of research focuses on ex post freelancer behavior – i.e. task performance – and relies on experimental data from less skill-intensive OLMs such as MTurk. Both, however, are interested in identifying factors that can predict future worker performance.

Work on hiring decisions in high-skill OLMs places particular emphasis on the search and screening process. This is because projects are shorter compared to offline contingent work and thus hiring decisions occur on a more frequent basis, which make both the search and screening process much more important (Chen and Horton, 2016). Studies then aim at identifying accurate signals of future performance to reduce uncertainty regarding freelancers' skills and motivation. For example, Leung (2014) studies whether the order of a freelancer's work history, i.e. the chronological order of job types and categories the freelancer has worked in, affects employers' hiring decisions. Leung (2014) finds that employers prefer applicants who move incrementally between similar jobs to those who do not move (specialize in one job category) or those with highly diverse job histories (move between highly dissimilar job categories). These results suggest that employers favor workers that are committed to a certain job area, but attempt to develop their skills and careers at the same time. Taking a more dynamic perspective, Leung (2017) finds that prior negative and positive hiring experiences with freelancers from specific countries influences an employer's subsequent likelihood of hiring applicants from those countries. Employers thus update their beliefs continuously and "learn to hire" in these markets with increasing experience. Along similar lines, Chan and Wang (2017) find evidence for a positive hiring bias towards females in OLMs. Using a matched sample and a quasi-experimental technique, the authors show that gender traits of trustworthiness, cooperativeness, and attractiveness are the main underlying factors leading to the positive hiring bias for female workers. However, this effect diminishes over time when employers gain more experience on the platform. Other studies look at how novice freelancers can overcome the "cold-start problem", i.e. how to get hired without prior experience on the platform when employers prefer more experienced freelancers (Pallais, 2014; Stanton & Thomas, 2016). For example, Stanton and Thomas (2016) find that working through an agency can help inexperienced freelancers to get their careers started. That is because agency affiliation can serve as a signal to reduce the uncertainty about a novice worker's quality and motivation. Kokkodis and Ipeirotis (2016) focus on prior task category-specific feedback ratings as a signal to predict future performance. Interestingly, review scores in other categories predict performance even in categories for which there are few observations, suggesting that there is an innate underlying ability or motivation driving performance.

Another stream of research studies ex post contractual behavior and examines whether financial incentives can affect task performance in OLMs for microtasks (Mason & Watts, 2010; Shaw, Horton, & Chen, 2011; Yin & Chen, 2015). For example, Mason and Watts (2009) study the effect of compensation on worker performance in the context of two experiments conducted on MTurk and find that a higher level of financial incentives increases the quantity but not the quality of work performed by participants. Studies on performance-based payments in crowdsourcing markets have produced mixed and somewhat contradictory results on the efficacy of such pay systems (Ho et al., 2015).

A series of studies also analyzes spillover effects from a focal task to subsequent tasks. For example, Chen and Horton (2016) study how wage cuts can affect subsequent task outcomes. In their field experiment on MTurk, they find that workers quickly form wage reference points and react to proposed wage cuts from one task to subsequent tasks by quitting or lower subsequent work quality. Another experimental study examines how the ordering of high- and low-skill tasks can help optimize worker performance (Cai et al., 2016). In OLMs for microtasks, tasks are not typically completed in isolation, but in a chain of microtasks in a single session. Cai et al. (2016) find only limited evidence for the effect of task order on completion time and quality.

Although these studies shed light on important aspects of OLMs, we still know little about the drivers of project success (measured as an employer's project satisfaction) in OLMs for skill-intensive work. While previous studies concentrate on task quality as the dependent variable, employers might place higher value on timely completion rather than maximum quality. Hence, employer satisfaction is a broader, but more appropriate measure of whether expectations for a particular job were met. In addition, although studies have identified signals that affect an employer's hiring decisions, we lack evidence that they indeed represent accurate signals of performance, i.e. whether employers' expectations are more likely to be met ex post.

The study closest to ours is Kokkodis and Ipeirotis (2016) who study the predictive value of past worker performance in related task categories. However, whereas the authors are interested in inferring a freelancer's ability to predict future success, we identify a broader set of success factors. Hence, we build on and expand their work by studying success factors at the freelancer, employer, and project level.

We build on transaction cost theory (Williamson, 1971, 1991) and suggest that an employer's evaluation of project success will depend on the level of unexpected (ex post) transaction costs. That is, when outsourcing knowledge work to OLMs becomes unexpected costly for the output produced, for example because monitoring and coordination costs increase due to a lack of motivation of the freelancer, employers will be less satisfied. These transaction or extra costs have also been referred to as the "hidden costs" of a transaction (Barthélemy, 2001; Overby, 2003) and have been found to account for the economic failure of a large number of outsourced projects in the offline context (Dibbern et al., 2008). Hence, we argue that certain freelancer, employer, and project characteristics might increase (reduce) drivers of transaction costs and therefore result in lower (higher) levels of project success.

4 CONCEPTUAL FRAMEWORK

4.1 Transaction Costs

Transaction cost theory posits that the choice between markets and hierarchies is determined by differences in transaction costs, which are defined as all costs in terms of time, effort, and money spent that arise from "planning, adapting, and monitoring task completion under alternative governance structures" (Williamson, 1981, p. 552). For each transaction, firms choose the governance form that minimizes the sum of production and transaction costs (Williamson, 1991). Just like other contexts, regarding their labor decisions, firms will choose to transact on the market over hierarchical governance if production cost advantages outweigh transaction costs (Carmel & Tija, 2005).

Production cost advantages materialize most readily if firms outsource labor-intensive knowledge to workers demanding lower-wage via online labor markets. Moreover, workers can be hired on-demand and for a short amount of time without having to establish a long-term employment relationship and providing physical infrastructure. However, in addition to contract-based payments, specific transaction costs for managing outsourced projects need to be taken into account when evaluating a project (Dibbern et al., 2008), as unexpected transaction costs can offset cost savings from lower contractual payments. Transaction costs are often underestimated when it comes to outsourcing IT projects in general (Carmel & Tija, 2005; Overby, 2003). Hence, while the decision to the choose markets or hierarchies is based on the ex ante sum of contractual and expected transaction costs, the realized evaluation of an outsourced project will be based on the realized costs. Hence, when facing unexpected costs to elicit requested outcomes, employers are less satisfied with project outcomes.

Transaction costs regarding labor are based on two fundamental assumptions. First, economic actors are *boundedly rational* – "behavior that is intendedly rational but only limitedly so" (Williamson, 1998, p. 81). As a result, contracts are necessarily incomplete since "it is impossible to deal with complexity in all contractually relevant aspects" (Williamson, 1981, p. 553-554). Second, individuals are *opportunistic* and intentionally take advantage of opportunities at the expense of others – this is referred to as "self-interest seeking with guile" (Williamson 1998, p. 81). Further, a transaction partner's attitude toward opportunism cannot be ascertained ex ante (Williamson, 1981, p. 554). Transaction costs then arise because actors shield themselves from opportunistic behavior of an exchange partner. The need to safeguard against such opportunism, however, is not uniform across transactions.

4.2 Transaction Costs in Online Labor Markets

Online labor markets are rife with sources of uncertainty. The literature distinguishes between *behavioral uncertainty* and *environmental uncertainty*. The latter arises if not all contingencies surrounding the contract are known, while the former is due to unverifiable performance and effort. In OLMs, employers face at least two types of *behavioral uncertainty*; first, regarding a freelancer's skill and quality, and second, about the amount of effort a freelancer will exert in the job (Leung, 2014). These forms of behavioral uncertainty create a performance evaluation problem and result from many goods and services on OLMs being experience goods – that is, even when the product has been delivered (e.g. conducting a literature review), it is difficult to ascertain ex post whether contractual compliance has taken place. Digital freelancers also typically have less at stake than traditional employees as jobs are smaller, one-off, and work experience built on the platform has only limited exchange value outside of it (Felstiner, 2011). The searching and screening process then becomes more important because it is repeated frequently. However, the heterogeneity of applicants in terms of education or job experience makes comparison difficult, creating a hidden-quality problem (Agrawal et al., 2015).

The danger of opportunism is also higher for tasks with high *environmental uncertainty*, which leads to incomplete contracts. Tasks in uncertain environments are difficult to specify upfront because there may be different ways to accomplish them. In more uncertain environments, there are also more states to be considered, which makes designing a complete contract more difficult. With incomplete contracts, transaction costs will increase because monitoring becomes increasingly imperfect, more difficult and costly.

Asset specificity is another factor which plays a key role. It refers to either physical or human assets specific to a particular transaction and of little value outside the focal transaction. The value of transaction-specific assets depends on the continuation of the exchange relationship. Transaction partners may therefore underinvest in specific assets to keep their general options open, leading to lower-than-expected benefits from a transaction.

In online labor markets, *asset specificity* issues may arise about firm-specific skills or knowledge that are acquired on-the-job by working with a single employer, and that cannot or rarely be used for another job (Becker, 1962). For example, if a job requires a freelancer to develop skills specific to a technology that is used exclusively by the employer, or to a particular contact person, these skills might be of no value for other transactions. Employer characteristics can also intensify this problem. As a temporary relationship is, by definition, expected to be short-term, employers have limited incentives to develop a temporary workers' potential (O'Mahony & Bechky, 2006), for example by investing in specific training. So despite the obvious potential payoffs, a lack of trust to share firm-specific contents and high costs of sharing knowledge may prevent employers from investing into a relationship with a specific freelancer. This might result in a suboptimal level of transaction-specific investments of both parties. In online labor markets for simple and low-skilled work, this is not an issue because it is unlikely that microtasks (such as data entry) require transaction-specific investments. However, higher-skilled tasks will require firm-specific skills and knowledge to produce output according to specific needs of the employer. Therefore, the employer has to ensure an appropriate level of knowledge transfer. This will increase communication costs, particularly for technology-enabled project work. If a freelancer underinvests in transaction-specific knowledge or skills, low service and product quality or project delays could be the result. This leads to increased monitoring costs and eventually lower benefits for the employer.

5 HYPOTHESES DEVELOPMENT

We want to to identify characteristics of online transactions and transaction partners that are correlated with the uncertainty and asset specificity of a particular transaction. This then allows us to derive conjectures about behavioral uncertainty (i.e. the potential for opportunistic behavior) and environmental uncertainty (i.e. the degree to which contracts are incomplete). Specifically, we relate prior success of freelancers, experience of both freelancers and employers, project complexity, and contract type to the uncertainty and/or asset specificity of transactions. Project success will then be affected by differences in transaction costs driven by these factors.

5.1.1 Prior Success of Freelancer

In most job markets, employers cannot be sure of the productive capabilities of an individual at the time of the hiring decision. To resolve the uncertainty regarding a freelancer's quality and effort, employers will rely on observable signals (Spence, 1973), providing cues on a worker's productive capabilities. In OLMs, one such signal is a freelancer's feedback ratings received from past employers. Thus, the performance of freelancers in past projects is visible to future employers and thus comparable across workers and task categories, due to a unified reputation system implemented by *Upwork*. The feedback score is likely to be correlated with a worker's productive capabilities and has been shown to positively affect hiring decisions in OLMs (Leung, 2014). This suggests that the success score is indeed a signal of capabilities such as skills and commitment. Further, reputation systems can be predictive of users' future performance in a wide variety of online communities, e.g., online reviews (Liu, Bian, Agichtein, 2008; Lu, Tsaparas, Ntoulas, Alexandros, & Polany, 2010). However, these studies have focused on communities with homogenous tasks, making the comparison of performance levels much easier. In the context of OLMs, however, freelancers can switch task categories (e.g. from data entry to web development) and comparison becomes more challenging. A recent study by Kokkodis and Ipereitos (2016) addresses this issue and examines how past performance can predict future performance in an environment characterized by task heterogeneity. The authors find that high performance in one task category is indeed a good predictor of future performance in a related task category. Their results suggest that freelancers have a latent ability which can be transferred to related task categories, thus being an accurate predictor of future performance in related task categories.

Many capabilities of freelancers can be of general-purpose use, and thus applicable to diverse and seemingly unrelated projects. We therefore test a more general conjecture on whether the overall success score, prominently placed on the profile of a freelancer, can predict future performance, irrespective of the task categories and their relatedness. This seems reasonable since a high feedback score indicates that a freelancer has consistently met clients' expectations. We expect that monitoring and coordination costs are lower when freelancers are better able to decipher client expectations. In sum, if the past average feedback score is high, employer's hiring uncertainty is reduced which will reduce transaction costs, for example in the form of not having to enforce the contract or by reducing monitoring effort compared to a freelancer without a high reputation score.

In sum, we expect that the prior success level of a freelancer reduces behavioral uncertainty and transaction costs and will thus lead to higher review scores. This is in line with previous findings (Kokkodis and Ipeirotis, 2016) and serves as our baseline hypothesis.

H0: The prior success record of a freelancer is positively related with project success.

5.1.2 Project Complexity

Contrary to online labor markets for microtasks, *Upwork* explicitly supports higher-value projects and employers seek to outsource more challenging and projects to the market. This would likely include projects with higher complexity on this platform. Complexity here refers to projects "consisting of many varied interrelated parts" and can be operationalized in terms of differentiation (i.e. the number of varied elements) and interdependency (i.e. the degree of interrelatedness of these elements) (Baccarini, 1996: p. 201-202). We suggest that projects on the platform differ in their complexity and consequently in their level of uncertainty and asset specificity, which has important implications for transaction costs and for managing these projects. Thus, we expect projects with higher levels of project complexity to have lower levels of project success on average.

Although employers might anticipate higher transaction costs for more complex projects, the exact cost level is unknown ex ante. Thus, the risk of hidden costs is much higher for complex projects for several reasons. First, environmental uncertainty increases as complex projects can often be completed in multiple ways and outcomes are less predictable. At the same time behavioral uncertainty increases since variability and unpredictability of the means to accomplish the task makes it unclear whether the freelancer complies with the contract. Shirking may be more likely because it is difficult to observe whether technical problems or low productivity or skills have led to unsatisfactory results. If an employer wants to ensure satisfactory project outcomes, the level of coordination, communication, and monitoring effort has to be adapted ex post and might go beyond what the employer had expected ex ante.

Besides uncertainty, complex tasks are also more likely to require higher levels of firm-specific skills and knowledge, i.e. to have higher asset specificity. In particular, they might require more input from organizational members and better knowledge of organizational parameters.

Opportunistic freelancers will avoid making transaction-specific investments since they are not valuable for other projects. This in turn reduces expected success for complex projects.

All in all, we expect that transaction costs for complex tasks result in low feedback ratings. To hypothesize and test this argument, we operationalize project complexity using three measures: whether multiple freelancers were hired for the project, the number of skills required for a project, and the length of the project description.

Multiple freelancers hired. *Upwork* allows employers to hire multiple freelancers to work on the same project as a team. The idea is to enable joint work regardless of the freelancers' locations. This is assumed to foster knowledge pooling and more creative solutions but can also ensure a continuous workflow due to time zone differences and speeding up completion time. However, hiring multiple freelancers will also increase execution complexity for employers. The emerging literature on global virtual teams (Jimenez, Boehe, Taras, & Caprar, 2017), while mostly concerned with virtual teams within organizational boundaries, reports high failure rates of meeting the objectives due to an inability to manage complexities arising from this type of collaboration. Thus, global virtual teams often fall short in handling the cultural and geographical dispersion complexities. In addition, team members in OLMs are anonymous, diverse in their motivations, and do not even belong to the same organization. Therefore, we assume that managing multi-member projects is even more complex in OLMs.

The sources of complexity mentioned above will increase uncertainty through several mechanisms. First, teamwork often cannot be well defined in a contract. At the same time, team dynamics are also unpredictable ex ante, i.e. whether team members share the same working style and get along well (even online). Relatedly, empirical evidence shows that dispersed teams experience higher levels of conflict (Hinds and Bailey, 2003). Hence, managing these social aspects will increase communication and coordination costs. Second, ascertaining that knowledge and information is distributed evenly among team members because their work is likely to be interrelated and interdependent can further increase coordination and communication costs. Finally, freeriding is more likely for projects including multiple freelancers, increasing internal conflicts and consequently monitoring and coordination costs.

In sum, we expect that employers are more likely to face unexpected transaction costs in multi-member online projects. These costs will lead to lower review scores. Thus we hypothesize:

H1a: Having hired multiple freelancers to complete a project is negatively related with project success.

Number of skills required. Employers can indicate the skills required to perform a project when posting it on the platform. More skills required for a project suggest a more complex project: The higher the number of skills required, the more likely the combination of these skills is firm-specific and the less likely the employer will find an individual combining all of these skills. This will increase the asset specificity of the transaction, which amplifies the level of transaction costs. Further, a freelancer will often be proficient in only some of these skills and then has to develop skills outside his core portfolio on-the-job. This process is prone to opportunistic behavior by the freelancer in the form of underinvesting in the project. For example, if a translator has to translate a text including many uncommon and highly specific words that can probably not be used outside the focal project, she might not be willing to invest a lot of time and effort to grasp their accurate meaning. Consequently, the service and output quality is lower than expected. Employers will then increase monitoring and coordination effort to ensure a satisfactory level of transaction-specific investments by the freelancer. Given these hidden costs, we expect that employers to be on average less satisfied with project outcomes.

H1b: The number of skills required to perform a project is negatively related with project success.

Project description length. The length of a project description in the job posting might be another indicator of high project complexity. More complex projects will comprise more components and require more explanation, thus, their descriptions will tend to be longer (Leung, 2014). Much in line with the arguments above, these projects will typically increase the level of uncertainty for employers due to the high required collaboration and communication costs between parties.

Thus, we expect that project description length is negatively correlated with project success.[2] Specifically, due to increased uncertainty, the extra costs will negatively affect project success.

H1c: Project description length is negatively related with project success.

5.1.3 Prior Experience

Prior Freelancer Experience. Prior freelancer experience refers to the number of completed projects on the platform. In general, organizations hire based on work experience because they expect experienced workers to perform better (Rynes, Orlitzky, & Bretz, 1997) due to two reasons. First, more experience can be a signal for worker quality because such freelancers had more time to accumulate job-relevant skills and knowledge but also in working remotely with its unique challenges. Because the employment relationship is, by definition, contingent on a freelancer's fit with an assignment and expected to be short-term compared to offline work, employers have no incentive to develop a temporary worker's potential (Kunda et al., 2002; Lepak & Snell, 1999; Marler, Barringer, & Milkovich, 2002). Assuming that more experience is an accurate signal of future performance, employers might expect the delivery of higher-quality outputs and lower transaction costs because such freelancers need less coordination and

[2] Project description length could also indicate a better job description, i.e. more precisely formulated objectives and instructions. Investing time and resources into the specification of a project ex ante could then reduce unexpected ex post transaction costs. While we believe that employers generally want to describe their projects well, we include employer fixed-effects in our analyses, which likely covers the main source of job description heterogeneity as it accounts for differences in employers' tendency or ability to write better descriptions.

monitoring. Further, having an extensive work history serves as a credible signal of commitment, professionalism and dedication, further reducing coordination and monitoring costs. That is because these freelancers have shown their ability to accomplish tasks.

Nevertheless, we so far do not have empirical evidence that more platform experience, irrespective of the task category it was gained in, serves as an accurate signal of future performance. Existing research has focused on how inexperienced freelancers can overcome information frictions to get their careers started (e.g. Leung, 2014; Pallais, 2014; Stanton & Thomas, 2016). We are, however, interested in testing whether more platform experience can indeed reduce the behavioral uncertainty of transactions and result in more satisfactory outcomes. Thus we hypothesize:

H2a: Prior work experience of a freelancer is positively related with project success.

Prior Employer Experience. Besides the freelancer's experience, we expect an employer's experience in accomplishing projects on the platform to improve future project success by reducing uncertainty due to four reasons. First, we expect that employers get better at monitoring and collaborating with freelancers. For example, employers might establish communication routines and improve knowledge transfers to and onboarding of new hires. At the same time, they may get better at establishing an appropriate monitoring system for this unique setting. Relatedly, they might get better at managing these projects by making more realistic budget plans, defining necessary input factors and scheduling of their projects. Second, the selection technology of freelancers might get better over time. Recent work shows that employers learn from negative and positive past hiring experiences and avoid hiring freelancers from social categories who struggled to meet their expectations, resolving some of the hiring uncertainty (Leung, 2017). Inexperienced employers, on the other hand, will have more difficulty in assessing the quality of freelancers from a diverse labor pool and have a less accurate understanding of how this market works and of its realistic outcomes. Third, it seems reasonable to assume that with increasing platform experience, employers also become better at negotiating, evaluating performance, and designing contracts. Fourth, they might learn which types of tasks they can outsource on OLMs and how to market them on the platform.

To conclude, we suggest that with increasing project experience, employers reduce the uncertainty surrounding transactions in these markets and will less likely face unexpected hidden costs, resulting in more successful projects.

H2b: An employer's prior experience is positively related with project success.

5.1.4 Contract type

We are also interested whether the type of contracts in OLMs affects project success. Specifically, we asl if fixed-price projects achieve higher review scores than hourly paid projects. In fixed-price projects, both parties negotiate a bid for the full project or break it down into several milestones. The freelancer submits the agreed deliverable and the employer reviews and approves the milestone. After completion, the freelancer receives final payment.

We conjecture that fixed-price contracts reduce uncertainty because both parties agree ex ante on deliverables that employers can review during project execution. At the same time, employers have to plan these projects more precisely, and think about appropriate and realistic milestones in advance. Thus, projects tend to be better specified in terms of outcomes and process steps, providing freelancers with some guidance and cues on an employer's expectations. This will reduce the likelihood of misunderstandings and ex post opportunistic behavior. This contract type also simplifies performance evaluation and can help intervene in early project stages if the freelancer has gone into wrong directions.

Thus, although fixed-price contracts increase ex ante coordination and negotiation costs, they prevent unexpected results and hidden ex post costs. Thus, we expect that working under a fixed-price contract will lead to more successful projects by reducing transaction uncertainty.

H3: Using fixed-price contracts is positively related with project success.

6 DATA AND METHODS

6.1 Sample

We use transaction-level data from the platform *Upwork* to test our hypotheses. The original dataset was downloaded in 2017 using a Python script and includes data on 255,393 freelancers with a minimum of one job. The sample was reduced to 71,030 freelancers with 10 to 100 jobs. Due to missing data, the panel dataset was reduced further to 234,212 transactions, covering 59,534 freelancers and 126,123 firms.

6.2 Variables

Dependent variable. We measure project success by taking the average total feedback score a project was rated by the hiring firm based on six dimensions, each ranging from 1 (worst) to 5 (best): Skills, quality, availability, deadlines, communication, and cooperation. Since we cannot observe the job success rate shown on a freelancer's profile, we use the average feedback score as a proxy. This seems reasonable since the average feedback score takes into account all possible ways in which a project falls short of initial expectations. Thus, it indicates how satisfied an employer was with the project outcome overall.

Independent variables. We measure freelancer capabilities for our baseline hypothesis by using the prior freelancer success record, i.e. the average total feedback score achieved by the freelancer before the focal project. We use three different measures of our independent variable project complexity: Whether multiple freelancers were hired, the number of required skills for a project as indicated in the job posting, and the description of a project in the job posting. The first measure is a binary variable equal to 1 if the project was accomplished by more than one freelancer. The number of required skills is the logarithm of the count of the skills attached to a job posting. The third measure, description length, refers to the logarithm of the number of characters of the project description written by the hiring firm. Our experience variables for H3 are measured as the logarithm of the number of prior projects conducted by the freelancer or the employer, respectively. Contract type is the independent variable of H4 and measured as binary variable where a value of 1 indicates a fixed-price contract and 0 an hourly paid contract.

Control variables. We control for several factors. First, our binary variable different country captures the possibility of cross-country collaborations, which are likely to influence project success due to language barriers, time zone differences and alike. The variable is 1 if the freelancer and the hiring firm are located in different countries. The control variable *category pay* is measured using the average hourly pay in USD in the category of the focal project to task heterogeneity between job categories, which can affect the evaluation of projects. We further control for the use of an agency, which is 1 if the freelancer is represented by an agency. As shown by Stanton and Thomas (2016), agency membership has an effect on freelancer careers. In addition, we control for the number of applicants, i.e. the number of freelancers who have applied for the focal project (logarithm). A larger pool of applicants can affect the quality of freelancers and should thus be taken into account. Relatedly, we control for tertiary education, a dummy variable equal to 1 if the freelancer reports having tertiary education (undergraduate, graduate, or PhD), 0 otherwise.

Insert Table I about here.

6.3 Analysis

We test our hypotheses estimating a fixed-effect ordinary least squared (OLS) model. Using fixed effects at the level of the hiring firm lets us account for time-invariant characteristics of firms that might affect overall feedback ratings, such as country of origin, firm culture, and industry affiliation as well as remaining unobserved heterogeneity across firms.[3]

7 RESULTS

Table II gives summary statistics and *Table III* pairwise correlations for all variables.

Insert Table II about here.

Insert Table III about here.

The distribution of both success variables (project success and prior freelancer success) is highly skewed toward positive ratings, i.e. 5-star ratings, with a mean value of 4.76 (project success) and 4.83 (prior freelancer success). This bias is common in marketplaces with implemented reputation systems (Kokkodis & Ipereitos, 2016; Hu, Zhang, & Pavlou, 2009). Intuitively, this can be explained by user survival patterns in online communities: users that receive low feedback scores are unable to get hired again, so they leave the marketplace (Jerath, Fader, & Hardie, 2011). Thus, the majority of active marketplace users have high feedback scores. Moreover, it is an indication that most projects are fulfilled as expected, while a negative rating indicates an ex post (unexpected) shortfall in freelancer performance. Fixed-pay contracts are used more often (65%) than hourly paid contracts (35%). This might suggest that the majority of tasks outsourced on *Upwork* are more long-term oriented, ongoing work, as opposed to OLMs focused on short-term microtasks. Further, most projects (88%) involve cross-country collaborations, i.e. employers and freelancers from different countries. This is in line with Agrawal et al. (2015) who find that OLMs are dominated by long-distance north-south trade. Most exchange relationships involve employers from developed countries (mostly

[3] For example, we do not observe a firm's financial performance and thus the financial resources available to setup a monitoring system or project management tools for OLM projects.

U.S.) outsourcing tasks to freelancers from emerging or developing countries (mostly India, Pakistan, and Philippines). Realizing cost savings by outsourcing to low-wage countries thus a key motivation to use *Upwork*. Freelancers in our sample are highly educated with 73% reporting to have tertiary education (undergraduate, graduate, or PhD), suggesting that these markets generally offer access to a highly skilled virtual workforce. Overall, the independent variables show considerable variance, and the correlation matrix indicates low pairwise correlations among the independent variables.

Table IV reports the regression results of our fixed-effects OLS model. Models 1-4 show the results for each variable category (prior success, experience, complexity, and contract type) separately. Model 5 shows the full model, including all independent variables.

Insert Table IV about here.

In H0, we proposed that prior success of freelancers is positively associated with project success. The coefficient of prior success is positive and highly significant (*** $p<0.001$) in Model 1 and the full Model 5, supporting our hypothesis and serving as a plausibility check.

To test Hypotheses 1a-c, which predict that our three dimensions of task complexity (multiple freelancers hired, number of required skills, and description length) are negatively associated with project success, we included all three in Model 2. All three coefficients are negative and highly significant (*** $p<0.001$) in Model 2 and in the full Model 5, supporting our hypothesis

In Hypotheses 2a and 2b, we predicted that more experience, both at the freelancer (H2a) and the employer (H2b) side, is related to higher review scores. Unexpectedly, the coefficient of freelancer experience is negative and highly significant (*** $p<0.001$) in Model 3 and the full Model 5, not supporting H3a and even in the opposite direction. Conversely, firm experience has a positive and highly significant correlation (*** $p<0.001$) with project success in Models 3 and 5, i.e. firms become better at managing their projects with increasing experience.

Finally in Hypothesis 3, we propose that projects with fixed-payment contracts receive higher review scores. Consistent with our hypothesis, we find a positive and significant (*** $p<0.001$) association between fixed-paid contracts on project success. Thus, employers are more satisfied with projects with fixed ex ante payments.

Our controls behave mostly as expected. Cross-country collaborations receive slightly more negative review scores, the coefficient is highly significant. This might be explained by cultural and geographical dispersion as well as time zone differences and language barriers still remaining a management challenge for firms. Average category pay has a negative and significant although economically very small effect (-0.003) on project success, suggesting that projects in task categories with higher pay levels are less successful in meeting employers' expectations. This could result from the fact that pay level and task complexity are correlated, or alternatively that higher pay increases employers' expectations. The coefficient of agency affiliation is negative and significant. That is somewhat surprising because recent work has found that agencies signal to employers that inexperienced workers are high quality. However, our results suggest that this might not be an accurate signal of future performance. One reason may be that lower-quality workers self-select themselves into agencies while high-quality workers are more confident in their skills and self-marketing skills. The number of applicants has no significant effect on project success. Thus, larger applicant pools do not improve freelancer selection or matching and project outcomes. Finally, a higher level of education does not result in higher review scores. Since OLMs are skill-focused and skills are acquired on the job rather than in educational programs, more education need not translate into better results.[4]

[4] Note that the educational level is self-reported by freelancers so that the data might be somewhat noisy.

8 DISCUSSION AND CONCLUSION

In 2006, *The Economist* reported that "*The way people work has changed dramatically…*" and called for corresponding *"… new kinds of organization that are more appropriate to modern working methods*" (The New Work Organization, Economist, Jan 19th, 2006). In line with the "sharing economy" trend in other fields, advancements in information technology enabled work settings based on distributed and project-based collaboration. This required new forms of labor markets as online platforms of collaborative exchange. Our study targets a fundamental question on these platforms: the drivers of project success in OLMs. By addressing this question, we contribute to the larger question of "*how, when, why, where and under what conditions an emerging form of collaborative consumption, popularly known as the "sharing economy" affects the creation and capture of value*".

We focused on the transaction costs arising in online labor markets, specifically on the potential for ex post performance shortfalls due to incomplete contracts and the associated environmental and behavioral uncertainty. We examined how freelancer, employer and project characteristics are correlated with a project's success in online labor markets. Our findings suggest that hiring freelancers with a prior success record and under a fixed-price contract result in more positive project ratings. Project complexity has a negative effect on project success, for a variety of complexity measures, suggesting an increased potential for unexpected performance shortfalls in such cases. Our results also highlight that employers learn how to manage their projects over time; firm experience is positively and significantly related with project success. Finally, and contrary to our hypothesized outcome, freelancer experience is negatively and significantly associated with project success. Our results disclose the factors that increase the benefits of using OLMs for employers even for more knowledge-intensive tasks like the ones on the platform we study. By discussing the drivers of transaction costs in this setting, we highlight the factors limiting these benefits. As a robustness check, we controlled for a variety of other factors (splitting up experience in five quintiles and estimate the dummies separately, skill-specific experience, time since last project, average amount in USD earned in prior projects to account for average project size). The direction and significance of the coefficient does not change, pointing to a robust puzzle.

Our findings have important implications for both the freelancer and employer side in OLMs. By drawing attention to these implications, we shed light on *"what strategies, resources and capabilities are needed to effectively compete in the sharing economy?"* On the freelancers' side, our results underline the importance of quality signals (prior success) in these contexts. At the same time, freelancers can learn that working on more complex projects and in teams including multiple freelancers increases the risk of negative feedback ratings. However, the negative relation between experience and project success is a curious finding. This result may point to a potential distinction between the drivers of success in traditional versus OLMs and may be a result of several dynamics. First, the review scores in OLMs are noisier and less tangible compared to success outcome measures in traditional markets. Therefore, given the difficulty for employers to distinguish between close review scores (e.g. 4.5 vs. 4.7), freelancers might learn over time that aiming for a perfect score in every project might not be worth the effort. Consequently, they might adapt, i.e. reduce, their effort level to a minimum that is still sufficient to get hired again. Relatedly, freelancers are likely to become better at selling themselves to employers in applications, resulting in getting hired for jobs where they do not perfectly match and consequently in lower review scores.. Second, more experienced freelancers might self-select themselves into more complex jobs. As we have seen, more complex projects tend to receive more negative feedback ratings. If there are other elements of complexity not picked up by our independent variables, this dynamic would lead to a negative effect of experience. This is supported by anecdotal evidence from interviews conducted by Horton and Tambe (2017) suggesting that freelancers strategically apply to more complex jobs later in their career to advance their career. Finally, recent work shows that experience does not always positively affect future performance when employees work across firm boundaries. Dokko, Wild, and Rothbard (2009) argue that prior work experience can also lead to habits, routines, and other cognitions and behaviors that are not necessarily useful for performance when applied in a different context. Developing expectations about how work should be done and what behavior is appropriate from different employers may be counterproductive in a new employment relationship. Thus, more experienced workers might carry a larger "baggage" with them and are worse at adapting to employer expectations in a short amount of time. We encourage future research to dig deeper into the potential mechanisms of this effect.

Our findings on the positive effect of prior freelancer success on project success correspond with prior findings that high past performance levels in one task categories can be transferred to future performance in related task categories (Kokkodis & Ipereitos, 2016). We contribute to these prior findings by showing that the overall success record of a freelancer already represents an accurate and easy-to-assess signal of future performance, irrespective of the task categories someone has worked in. Previous studies have suggested that employers use freelancers' work history to assess their skills and commitment, preferring those with more specialized and consistent portfolios (Leung, 2014). However, our results indicate that the signaling effect of specialization (Spence, 1973) might become less important in OLMs because past performance is transparent to future employers. That means untalented and multi-talented generalists can be clearly distinguished from one another, conditional on an employer's trust in the reputation system. In offline labor markets general ability is more difficult to assess from CVs so that employers often hire more specialized individuals to lower the risk of hiring. Finally, although more successful freelancers may negotiate higher contractual payments, ex post transaction costs may be lower due to lower monitoring and coordination efforts. These additional contractual costs seem to pay off for firms since prior success is by far the strongest driver of project success in our empirical results.

Our study has further implications for employers, highlighting which type of hiring projects/contracts may better perform in an OLM. We show that more complex projects, with complexity either stemming from monitoring or content-related issues, receive lower review scores, i.e. are less likely to meet firm’s expectations. We suggest that this is mainly driven by the need for more firm-specific knowledge to make outcomes valuable to and useful for employers. As transaction cost logic suggests, asset specificity can result in higher transaction costs, making market solutions less attractive. Our results are of course conditional on having chosen an online labor market as the preferred governance mode. We cannot observe whether these projects would have been more successful in an offline context. However, since *Upwork* enables firms to rehire freelancers, complex tasks might best be managed with a more hybrid or quasi-employment relationship. Recent experimental evidence suggests that the ordering of high- and low-complexity tasks might be important (Cai et al., 2016) and firms might first use simpler but related tasks to build a trusting relationship with an employee and assess skill and effort level. After successful completion and the corresponding increase in trustworthiness (Vanneste, Puranam,& Kretschmer, 2014), firms may then outsource more complex tasks to the freelancer. This would also benefit freelancers looking for more stable and continuous employment relationships. Nevertheless, our results might suggest that spot markets for tasks might have certain limits. This question has also been raised and examined for crowdsourcing markets, a different type of OLMs. In that context, crowdsourcing is only more efficient and effective in solving problems under certain conditions (Afuah & Tucci, 2012). However, for spot markets, we know very little about which types of tasks can be outsourced more easily. Thus, we hope that our results spark further research interest in studying this pressing question. Our results regarding the positive effect of fixed-price contracts on project success are interesting as managing projects via a fixed-paid contract seems to require far more additional resources in terms of time and effort than hourly paid jobs. Employers have to think more profoundly about milestones, deliverables, and scheduling. In turn, this enables them to exert more control and provides freelancers with more concrete instructions. This is likely to lead to results more in line with employer expectations, but employers might also anticipate these additional coordination costs in advance. More precisely, they will less likely face hidden or unexpected extra costs resulting from managing occurring problems in projects with less specified contracts. Hence, the additional upfront costs in setting up a mutual agreement and reviewing work seems to pay off and leads to more satisfactory project results.

Another potentially fruitful area for future research could be to take a more differentiated look at project success. In fact, future research could decompose the aggregate score in its six dimensions (skills, quality, availability, deadlines, coordination, communication) to see what drives them separately. Since we cannot observe the realized transaction costs ex post (for example coordination and communication costs), it might be worth analyzing whether the failure to meet expectations originates from negative deviations in these dimensions. Similarly, future research could study whether certain freelancer characteristics serve as accurate signals of freelancer quality (combining the dimensions skills and quality) or motivation (combining the dimensions availability and deadline).

Our paper has some limitations. Our analysis may face potential endogeneity concerns mostly stemming from omitted variables. While fully addressing these concerns require exogenous discontinuities (which we lack in our context) or quasi-experimental settings, we have to mitigate them by including a wide range of controls and fixed-effects. Also, a freelancers' decision to join a project is not random, which may cause self-selection issues.

Our study is an early attempt at shedding light on the drivers of project success in OLMs. In doing so, our results underline distinctions between successes factors in traditional markets vs. OLMs. We however, do not directly compare projects' outcome in these two market forms. An interesting future direction would be to fill this gap and to explore which projects are more suited for each of these markets. This has been tested for offline market vs. hierarchical solutions but not in the context of OLMs (Masters and Miles, 2002). Also, our study analyzes OLMs in their current form. As OLMs develop, more tasks and individuals will join these markets. The change in project and agents (employer and employee) type may eventually alter the success factors, which also calls for future research on this topic.

TABLES

Table I: Variable Definitions

Variable Name	Description
Dependent Variable	
Project Success	Review score given by the hiring firm to the freelancer, average of six 1 (worst) to 5 (best) ratings on skills, quality, availability, deadlines, communication, and cooperation
H1: Capabilities	
PriorProjectSuccess	Average project success achieved by the freelancer before the focal project
H2: Project Complexity	
MultFreelancers	Dummy variable equal to one if multiple freelancers have been hired for the project
NumberRequiredSkills	Number of required skills that have been included by the hiring firm in the project description (log)
DescriptionLength	Number of characters of the project description written by the hiring firm (log)
H3: Experience	
FreelancerExperience	Number of prior projects conducted by the freelancer (log)
FirmExperience	Number of prior projects conducted by the hiring firm (log)
H4: Contract Type	
FixedPriceContract	Dummy variable if the project is a fixed pay contract as opposed to a contract with hourly pay
Controls	
DifferentCountries	Dummy variable equal to one if freelancer and hiring firm are located in different countries
CategoryPay	Average hourly pay in USD in the category of the focal project
AgencyUsed	Dummy variable equal to one if the freelancer is represented by an agency
NumberApplicants	Number of freelancers who have applied for the focal project (log)
TertiaryEducation	Dummy variable equal to one if the freelancer reports a tertiary education (undergraduate, graduate, or PhD)

Table II: Descriptive Statistics

Variable Name	Mean	Std, Dev.	Min	Max
Dependent Variable				
Project Success	4.76	0.62	1	5
H1: Capabilities				
PriorProjectSuccess	4.83	0.25	1	5
H2: Project Complexity				
MultFreelancers	0.21	0.41	0	1
NumberRequiredSkills	0.93	0.67	0	3.91
DescriptionLength	6.03	0.90	0	8.91
H3: Experience				
FreelancerExperience	1.44	0.82	0	3.95
FirmExperience	1.55	1.16	0	3.91
H4: Contract Type				
FixedPriceContract	0.65	0.48	0	1
Controls				
DifferentCountries	0.88	0.33	0	1
CategoryPay	14.46	5.15	3.93	68.36
AgencyUsed	0.11	0.31	0	1
NumberApplicants	2.95	1.08	0	8.71
TertiaryEducation	0.73	0.45	0	1

Note: The number of observations for all variables is 234,212

Table III: Pairwise correlations

Variable Name		1	2	3	4	5	6	7	8	9	10	11	12
Dependent Variable													
Project Success	1	1.00											
H1: Capabilities													
PriorProjectSuccess	2	0.18	1.00										
H2: Project Complexity													
MultFreelancers	3	-0.05	-0.03	1.00									
NumberRequiredSkills	4	-0.05	-0.02	0.11	1.00								
DescriptionLength	5	-0.06	-0.04	0.11	0.19	1.00							
H3: Experience													
FreelancerExperience	6	0.00	-0.01	0.01	0.06	-0.03	1.00						
FirmExperience	7	0.07	0.02	0.04	-0.01	-0.03	0.03	1.00					
H4: Contract Type													
FixedPriceContract	8	0.15	0.15	-0.09	-0.04	-0.04	0.06	0.00	1.00				
Controls													
DifferentCountries	9	-0.03	-0.05	-0.01	-0.02	-0.02	0.03	0.04	-0.05	1.00			
CategoryPay	10	0.06	0.09	-0.13	-0.01	-0.03	0.02	0.00	0.14	-0.08	1.00		
AgencyUsed	11	-0.08	-0.15	-0.04	0.02	0.01	-0.03	-0.01	-0.14	0.07	0.01	1.00	
NumberApplicants	12	0.00	0.03	0.30	0.14	-0.02	0.07	0.02	-0.08	0.02	-0.14	-0.03	1.00
TertiaryEducation	13	-0.02	-0.04	0.00	0.01	0.00	0.00	0.00	-0.05	0.04	0.00	0.04	0.00

Table IV: Regression results

Independent Variables	(1)	(2)	(3)	(4)	(5)
		Dependent Variables: ProjectSuccess			
H1: Capabilities					
PriorProjectSuccess	0.317***				0.292***
	(0.011)				(0.010)
H2: Project Complexity					
MultFreelancers		-0.056***			-0.047***
		(0.006)			(0.006)
NumberRequiredSkills		-0.025***			-0.021***
		(0.004)			(0.003)
DescriptionLength		-0.035***			-0.029***
		(0.003)			(0.003)
H3: Experience					
FreelancerExperience			-0.018***		-0.015***
			(0.002)		(0.002)
FirmExperience			0.032***		0.025***
			(0.002)		(0.002)
H4: Contract Type					
FixedPriceContract				0.141***	0.117***
				(0.006)	(0.006)
Controls					
DifferentCountries	-0.020***	-0.029***	-0.023***	-0.022***	-0.016**
	(0.006)	(0.006)	(0.006)	(0.006)	(0.006)
CategoryPay	0.004***	0.005***	0.005***	0.004***	0.003***
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
AgencyUsed	-0.094***	-0.120***	-0.119***	-0.108***	-0.081***
	(0.008)	(0.008)	(0.008)	(0.008)	(0.008)
NumberApplicants	-0.005*	0.002	-0.006**	0.001	0.001
	(0.002)	(0.002)	(0.002)	(0.002)	(0.002)
TertiaryEducation	-0.009*	-0.012**	-0.013**	-0.009*	-0.005
	(0.004)	(0.004)	(0.004)	(0.004)	(0.004)
Number of Observations	234,212	234,212	234,212	234,212	234,212
Number of Firms	126,123	126,123	126,123	126,123	126,123
R^2 (within)	0.025	0.010	0.008	0.014	0.035
R^2 (between)	0.045	0.018	0.015	0.031	0.067
R^2 ‘(overall)	0.038	0.016	0.014	0.027	0.057

Notes: Fixed-effect OLS point estimates with fixed effects on the level of the hiring firm. Standard errors in parentheses are clustered on the level of the firm. A constant is included but not reported. Asterisks denote significance levels (* p<0.05, ** p<0.01, *** p<0.001).

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