22 March 2017

When Do Information Signals Convey Quality in Digital Platforms?

Abstract

When do information signals convey quality in digital platforms? Inferring vendor quality in digital microsourcing platforms is challenging due to inherent information asymmetry, which can lead to adverse selection or moral hazard. Many platforms address this challenge by incorporating information signals. However, it is difficult for clients to assess whether and when such signals are true reflections of vendor quality. In this study, we test two kinds of information signals, *competency signal* and *goal signal*, as indicators of vendor quality. We argue that these two signals are stronger indicators of vendor quality in jobs of longer duration and in jobs involving greater cultural distance between vendor and client. Our empirical analysis uses a leading online microsourcing platform dataset, which contains over 5000 microsourced IT jobs completed by hundreds of vendors and clients located across dozens of countries. We obtain three main findings. First, goal signal is a more reliable indicator than competency signal without accounting for job and vendor characteristics. Second, both signals are stronger indicators of vendor quality in jobs of longer duration. Finally, both signals are stronger indicators of vendor quality in jobs with greater cultural distance between clients and vendors. This paper contributes to the literature on signaling and digital microsourcing platforms by identifying conditions under which information signals are stronger reflections of vendor quality.

Keywords: *Microsourcing, information signals, cultural distance, job duration.*

1. Introduction

Advances in computing and connectivity have enabled proliferation of digital platforms (Parker, Van Alstyne and Choudary 2016). These digital platforms encompass global microsourcing platforms such as Freelancer.com and Upwork.com which facilitate work that is worth billions of dollars annually (Lu, Hirschheim and Schwarz 2015). [1] Some studies expect the global microsourcing market to rise exponentially from $10bn to $63bn by 2020 (Kirton 2015), and part of the reason for such expected

[1] Microsourcing is "the provision of micro-tasks and other small enterprise services from an online community of providers residing in an online microsourcing platform" (Gefen and Carmel 2008; Lu, Hirschheim and Schwarz 2015, p. 604; Obal 2009).

growth is a 30-40% rise in the number of independent professionals leveraging microsourcing platforms (Cadman 2015; Gillespie and O'Brien 2015). Despite their potential, such digital platforms face challenges in that the online and remote origin of transactions makes it hard for clients to observe vendors and evaluate their quality, creating the potential for information asymmetry between vendors and clients (Bapna, Gupta, Ray and Singh 2016; Mani, Barua and Whinston 2006; Sambhara, Keil, Rai and Kasi 2011; Shih, Dedrick and Kraemer 2005). For instance, vendors are aware of the quality of their own services, but clients are not fully informed about it (Yoganarasimhan 2013). This information asymmetry generates two main challenges: adverse selection and moral hazard. Adverse selection results when a client selects an inappropriate or low quality vendor for a job (Chang and Gurbaxani 2012; Lu, Hirschheim and Schwarz 2015). Moral hazard results when vendors engage in opportunism by exerting less effort than that required to deliver what was agreed (Moreno and Terwiesch 2014).

Adverse selection and moral hazard are particularly salient in online platform environments, because platforms offer a high number of vendors increasing the likelihood of adverse selection. Further, the electronic interactions between clients and vendors hinder clients' ability to verify vendors' processes and quality of work in progress, increasing the likelihood of moral hazard (Gefen, Gefen and Carmel 2016). The digital nature of microsourcing platforms further exacerbates the lack of transparency, common standards, and clarity (Bergvall-Kåreborn and Howcroft 2014; Felstiner 2011). Although microsourcing platforms facilitate access to a large diverse pool of expertise by allowing clients to source work from a wide range of vendor backgrounds (Lu, Hirschheim and Schwarz 2015), the resultant challenges of adverse selection and moral hazard may deter optimal outcomes (Yoganarasimhan 2013).

Adverse selection and moral hazard can be mitigated when microsourcing platforms incorporate information signals that reliably indicate vendor quality (Banker and Hwang 2008). Many microsourcing platforms try to solve the challenge of vendor quality information asymmetry by providing *platform based information signals* about vendors. The inclusion of vendor quality signals is an essential design choice for microsourcing platforms to mitigate clients' difficulties in selecting vendors and identifying the job conditions that affect the reliability of quality signals. Furthermore, platforms incentivize vendors to acquire and maintain information signals in anticipation of future revenue, and to reassure clients that platform based signals are a reliable reflection of vendor quality. Prior theoretical discussions examine the use of signals as mechanisms for reducing potential adverse selection and moral hazard (Connelly, Certo, Ireland and Reutzel 2011). Signaling principles suggest that in offline environments, receivers rely on signals to avoid adverse selection (Coff 2002) and reduce moral hazards (Elitzur and Gavious 2003) to improve their sourcing decisions, an important criteria for effective decisions in supplier choice (Aral, Bakos and Brynjolfsson 2017). However, the literature has yet to explore the role of signaling and job conditions in understanding how clients resolve information asymmetry about vendor quality in microsourcing platforms or online labor markets. Furthermore, literature has proposed that signals have different strengths depending on certain factors (Higgins and Gulati 2006). However, until now, scholars have not yet analyzed when such signals convey vendor quality in microsourcing platforms.

The incomplete predictions from the signaling and microsourcing literature call for an empirical examination to reveal the conditions under which signals convey vendor quality in microsourcing platforms. Two kinds of signals are of particular importance in microsourcing platforms to reduce the information asymmetry between clients and vendors: signals that indicate competence of vendors, and signals that indicate past performance of vendors (Connelly, Certo, Ireland and Reutzel 2011; Stiglitz 2000). These signals enable clients to draw inferences about vendors' abilities and qualities, and help to ensure that the outcome of the service is of high quality and satisfaction to the client (Banker and Hwang 2008). Accordingly, in this study, we define two types of information signals: *competency signal* which is a reflection of a vendor's competence, and *goal signal* which is a reflection of a vendor's past performance. First, we define *competency signal* as the information signal that emphasizes a vendor's technical skills and process related knowledge. It is represented by benchmarking assessments of certifications and examinations. Second, we define *goal signal* as the information signal that emphasizes the vendor's job fulfillment within resource constraints of time and budget. This is represented by the vendor's on-time, within-budget, and successful completion of prior jobs, which are important indicators of high quality vendors.[2] Another motivation, albeit not the primary one, for the examination of these two signals from a theoretical standpoint is the psychology literature which finds that potential can have as much of an impact on individual evaluation as achievement (e.g., Tormala, Jia and Norton 2012). To the extent that competency signal is a reflection of potential of the vendor and goal signal is a reflection of past achievement of the vendor, examination of the role of these two signals will enhance understanding of the relative importance of potential versus achievement in microsourcing platforms.

Because microsourcing is largely used by clients and vendors with limited resources and located all around the globe (Lu, Hirschheim and Schwarz 2015), signals may be stronger indicators of vendor quality in jobs that have a longer duration or when there is greater cultural distance between client and vendor. Hence, we focus on these two salient job conditions: *longer job duration,* and *greater cultural distance* between vendor and client. First, longer jobs require interconnected tasks or coordination of multiple skillsets typical of longer engagements. Microsourcing platforms are more suitable for short duration jobs with limited scope and scale (Kaganer, Carmel, Hirschheim and Olsen 2013). Moral hazard is likely to be more pronounced in longer duration jobs because there is greater time for the vendor to slack off and not devote resources to the task assigned by the client. Moreover, adverse selection is more pronounced in longer jobs, because the impact of the choice of an inadequate vendor will be greater and the multiple interactions with the client will expose the vendors' lack of skills and knowledge. Second, microsourcing platforms facilitate the participation of vendors from all over the world. Thus, cultural distance, which is defined as the degree to which cultural norms differ between two countries (Kogut and Singh 1988), arises from physical separation of vendor and client across countries and cultures. Cultural distance hinders the efficiency and effectiveness of coordination and communication and therefore there is a higher risk of moral hazard (Jarvenpaa and Keating 2011). Adverse selection is more likely to happen when there are greater cultural differences between clients and vendors, because clients may choose vendors that are closer to their own culture regardless of vendors' quality. This principle is known as

[2] While we label this signal as "Goal Signal", it can also be interpreted as a "Past Performance Signal".

homophily and states that individuals tend to choose other individuals that are similar to themselves (McPherson, Smith-Lovin and Cook 2001), as part of a psychological tendency to identify with the similar (Lin and Viswanathan 2015).

Given the information asymmetry challenges and the nature of the transactions in a microsourcing platform, we pose the following research question: *how do job duration and cultural distance between client and vendor affect the reliability of competency signal and goal signal as indicators of vendor quality in microsourcing platforms?* Drawing on arguments related to signaling and information asymmetry, we theorize that the reliabilities of competency signal and goal signal as indicators of vendor quality in microsourcing platforms are stronger for longer jobs and jobs between vendors and clients with greater cultural distance. We empirically test our theory using a unique dataset of 5432 microsourcing jobs collected from a leading microsourcing platform and conducted across 638 distinct client-vendor country tuples. Our analysis suggests that competency signals and goal signals are stronger indicators of vendor quality in jobs involving longer duration and greater cultural distance. Interestingly, when not accounting for these conditions, we find that goal signal is a reliable indicator of vendor quality, whereas competency signal does not indicate vendor quality. Our findings contribute to the literature on (1) signaling and (2) microsourcing platforms by helping to fill the gap related to the contingencies that influence the reliabilities of signals as indicators of vendor quality in online labor markets. The results can help microsourcing clients to interpret signals and infer vendor quality taking into account job and vendor characteristics. This study also offers insights for microsourcing platform designers, managers and developers to instill a signal oriented strategy that can help clients to choose vendors.

2. Theoretical Background and Hypotheses

2.1. Background

Even though microsourcing platforms is a relatively new phenomenon, scholars have investigated some advantages and challenges from clients' and vendors' perspectives. First, from the clients' perspective, existing literature suggests that clients engage in microsourcing not only to reduce costs but also for strategic reasons (Lu, Hirschheim and Schwarz 2015). For instance, clients that utilize microsourcing have greater flexibility as the workforce sits outside firm boundaries, and firms are not obliged to provide social protection (Bergvall-Kåreborn and Howcroft 2014). Second, clients face new organizational challenges due to difficulty in handling the capabilities of microsourcing vendors and managing multiple tasks (Corney, Torres-Sánchez, Jagadeesan and Regli 2009). Therefore, clients develop new skills and capabilities to effectively manage microsourcing vendors and tasks (Nevo and Kotlarsky 2014). Third, research has examined factors that influence vendor selection in offline transactions. One such factor is high business familiarity which may determine selection of vendors (Gefen, Wyss and Lichtenstein 2008). Finally, a tradeoff exists between reputation and price, such that buyers are willing to accept higher bids from reputable vendors (Moreno and Terwiesch 2014). In a microsourcing platform, reputation could be reflected through past clients' evaluations.

From vendors' perspective, scholars have examined characteristics of jobs and auctions that influence vendors' bidding behavior (e.g., Hong, Wang and Pavlou 2016). For instance, higher value jobs attract more bids but with a lower average quality (Snir and Hitt 2003). Nonetheless, the greater number of bids increases the cost to all participants because of costly bid evaluations. In addition, open auctions have an advantage over sealed bid auctions as they reduce service providers' valuation and competition uncertainty (Hong, Wang and Pavlou 2016). While existing work provides important insights, there has been scarce research that examines signals that vendors can display to showcase their quality. While several studies have examined reputation as a factor that influences how clients choose vendors, scholars have yet to examine the platform-based signals that can be created by vendors themselves to communicate their quality.

For example, recent research has examined issues related to information signals as reputation mechanisms in online microsourcing and e-services. It is recognized that buyers in online marketplaces place significant weight on seller reputations (Yoganarasimhan 2013). For instance, Banker and Hwang (2008) pose that accounting e-service vendors' signals on technical competence and functional ability are related to the likelihood of a client selecting a vendor. Allon, Bassamboo and Çil (2012 pose that it is important for firms owning the platforms to institutionalize information to help clients and vendors to make decisions. The lack of information on vendors' quality affects vendors' likelihood to be chosen. For example, vendors who do not have reputation ratings are less likely to be chosen, while those with higher ratings are more likely to win bids (Lin, Liu and Viswanathan forthcoming; Moreno and Terwiesch 2014). We extend this stream of research by proposing that there are specific job conditions under which information signals are more reliable indicators of vendor quality (as evaluated by the client at the end of the job) in microsourcing platforms. We also extend the literature by empirically examining how the reliability of information signals in microsourcing is contingent upon specific job conditions.

Figure 1 illustrates the job progression in microsourcing platforms and the aforementioned challenges. Although prior research has identified information asymmetry as a main challenge in platform based environments (Lin, Liu and Viswanathan forthcoming; Zhang and Zhang 2015; Zhang and Zhu 2011), we argue that microsourcing platforms face two sets of challenges that originate from this information asymmetry (adverse selection and moral hazard), which are further magnified in jobs of longer duration and in jobs between vendors and clients with greater cultural distance. Next we elaborate our key arguments.

We begin by articulating why adverse selection and moral hazard are two key challenges in microsourcing platforms. Consider adverse selection first. Adverse selection is a manifestation of information asymmetry that results from pre-job misrepresentation of the vendor's true characteristics (McAfee and McMillan 1987). Existing research notes that adverse selection can be mitigated through appropriate care in pre-contract phase in vendor selection, bidding, and quality assessments (Dibbern, Goles, Hirschheim and Jayatilaka 2004; Lacity, Khan, Yan and Willcocks 2010). However, mechanisms such as elaborate contractual arrangements and relevant planning are not in place in many microsourcing platforms. Microsourcing platforms are generally characterized by a lack of formal procedures or service level agreements (Lu, Hirschheim and Schwarz 2015). Hence, as a platform based phenomena, it requires distinct mechanisms to mitigate adverse selection.

Turning to moral hazard, it is traditionally addressed by emphasizing learning from experiences, development of extensive contracts (e.g., Benaroch, Lichtenstein and Fink 2016; Bhattacharyya and Lafontaine 1995; Elitzur, Gavious and Wensley 2012; Gefen, Wyss and Lichtenstein 2008; McAfee and McMillan 1987), and management control mechanisms (Sedatole, Vrettos and Widener 2012) that facilitate identification and monitoring of appropriate vendors. Other ways in which clients mitigate moral hazard include providing training or learning opportunities at their cost to vendors, selecting pre-trained vendors, selecting vendors with whom they have business familiarity (Gefen, Wyss and Lichtenstein 2008), or designing detailed, well specified, and measurable contractual terms (Aubert, Kishore and Iriyama 2015). However, microsourcing platforms lack personalized measurable contractual terms and service level agreements. Microsourcing clients rarely provide training or learning opportunities for vendors (Kaganer, Carmel, Hirschheim and Olsen 2013). Moreover, microsourcing clients are typically not equipped with process standards, formal employee management practices, or formal processes to monitor vendors (Lu, Hirschheim and Schwarz 2015). Vendors in microsourcing platforms may continuously engage in new jobs that require distinct technical knowledge and cultural sensitivities. Therefore, their prior experience may not be as useful (Lu, Hirschheim and Schwarz 2015).

For these reasons and due to the digital and global nature of microsourcing platforms, the challenges of moral hazard and adverse selection are critical in the microsourcing context. Without adequate signals, clients may select vendors that do not fulfill their jobs within deadlines and budget, and that do not have the necessary skills to successfully complete their jobs.

Microsourcing platforms face two additional challenges that stem from job duration and cultural distance. We focus on these two characteristics due to the following reasons. First, microsourcing vendors have limited capacity to handle jobs of large scale and scope (Kaganer, Carmel, Hirschheim and Olsen 2013). Moreover, clients often assign jobs which lack clear details of scope and work expectations (Lu, Hirschheim and Schwarz 2015). Thus, *job duration* is a characteristic that accentuates the effects of vendors' lack of technical skills because longer duration allows vendors more time to slack off and devote less resources to jobs. Job duration is a relevant aspect in this type of online environment where clients cannot see how much time and resources that vendors devote to each task. Current literature has yet to explore the effects of job duration on vendor quality signals in the microsourcing platform context. Second, cultural distance, defined as the degree to which cultural norms differ between two countries (Kogut and Singh 1988), can lead to misunderstandings, act as a barrier to interaction between people, and result in preconceived notions about people from different cultures (Ravishankar 2015; Sousa and Bradley 2008).

Cultural distance results in coordination and control costs, communication difficulties between vendor and client (Avison and Banks 2008; Su 2015), and subsequent mismatch of expectations during job execution, often resulting in failures (Heeks, Krishna, Nicholsen and Sahay 2001). In prior research, cultural distance is operationalized to incorporate differences in national culture across dimensions of individualism, uncertainty avoidance, power distance, masculinity, and long-term orientation (Hofstede 1980; Kogut and Singh 1988). Cultural distance can affect relationships and quality (Gong 2003; Manev and Stevenson 2001), establishment choices (Drogendijk and Slangen 2006), and multinational strategies (Yu, Subramaniam and Cannella 2009). Cultural issues arise from a lack of shared expectations and differences in conversations across cultures (Avison and Banks 2008). Extending this argument, clients may seek vendors from similar cultures to conduct transactions as cultural similarity, or smaller cultural distance, eases interactions between parties (Manev and Stevenson 2001; Tsui and O'reilly 1989). However, seeking culturally similar vendors may undermine clients’ evaluation of vendors’ quality. Extant research in online environments has found that bias for funding projects in the same country consistently exists in crowd-funding platforms (Lin and Viswanathan 2015). However, due to the electronic nature of these transactions and standardization of the platform this bias should not exist. The authors find that this tendency is emotionally or psychologically driven, which further emphasizes the need to examine the effect of cultural distance on platform-based signals. In addition, literature on microsourcing platforms has yet to explore the role of cultural distance in affecting how signals indicate vendor quality in electronic environments.

2.2. Hypotheses Development

Our core theoretical argument is that the reliability of vendors' competency and goal signals as indicators of vendor quality is stronger under conditions of longer job duration and greater cultural distance between vendor and client. Figure 2 depicts our research model.

Signals are fundamentally concerned with reducing information asymmetry between two parties (Spence 2002). In the absence of adequate formal communication and coordination mechanisms, signals help in reducing information asymmetry and explaining the behavior of parties (Connelly, Certo, Ireland and Reutzel 2011). In microsourcing platforms, signals can be used by vendors to convey information to clients, and clients can use the signals displayed by vendors to decrease their pre-job information asymmetry. Prior research suggests that various types of signals and situations in which they are used are important for interpretations, although their relative importance and reliabilities may differ (Banker and Hwang 2008; Donath 2007; Spence 2002). Hence, we examine how two characteristics, job duration and cultural distance, influence the reliability of platform-based signals as indicators of vendor quality. In this study we use client evaluation of the vendor's quality subsequent to the completion of a focal job as the measure of vendor quality. As argued in prior research, quality of sourcing providers, encompassing strategic, economic, technological and social factors of job success is reflected in client evaluations (Lahiri and Kedia 2009).

2.2.1. Platform Signals as Indicators of Vendor Quality

Signals help disclose private information to clients, and allow high ability vendors to differentiate themselves from low ability ones (Rao, Qu and Ruekert 1999). When capabilities of vendors are not directly visible, signals help overcome problems associated with adverse selection (Hölmstrom 1979). Variations in information signals on microsourcing platforms are key mechanisms for differentiation because signals plausibly should be indicators of vendors' expertise and behavior (Banker and Hwang 2008; Wells, Valacich and Hess 2011).

First, competency signal suggests that the vendor performs jobs with competency acquired through certifications and exams. Competency signals on microsourcing platforms are manifested through a vendor's completion of technical and managerial exams, or assessment tests. These examinations show that the vendor has higher technical and managerial competency. Such verified knowledge credentials suggest that the client may feel more confident about choosing vendors that display competency signals, because signals motivate clients to believe that vendors with higher certifications can offer superior solutions to satisfy clients' needs (Lee, Miranda and Kim 2004). Thus, clients experience a lower risk of adverse selection.

Second, goal signal suggests the goal-focused nature of the vendor to complete jobs on time and within budget. Goal signal is a signal of past performance of the vendor and enables the client to draw inferences of the vendor's quality (Banker and Hwang 2008). Moreover, goal signal can enhance clients' trust on the efficiency and productivity of the vendor, because vendors' goal signal illustrates their dependability and signal a lower risk of moral hazard. Furthermore, vendors that provide their services on time and within budget are more likely to get better client evaluations than those who do not.

Therefore, we expect that competency signal and goal signal increase the likelihood of a high quality job by fulfilling the information voids that may enhance adverse selection and moral hazard. In this study, we focus on contingent conditions under which these signals are stronger indicators of vendor quality. Thus, we do not make specific hypotheses for direct effects of competency signal and goal signal.

2.2.2. Signals as Indicators of Vendor Quality for Longer Jobs and Culturally Distant Actors

We propose that the reliability of information signals as indicators of vendor quality is stronger in jobs of long duration and jobs between culturally distant vendors and buyers. Our first consideration is competency signal, which is an indication of the vendor's verified expertise through certifications, technical and managerial exams, or assessment tests. Competency signal reflects the traits of vendors to handle technology-, task-, or work- related aspects more strongly in complex jobs (Susarla, Subramanyam and Karhade 2010).

Long duration jobs in microsourcing platforms are a challenge for vendors due to lack of scale, standardized processes, and advanced coordination and communication mechanisms (Kaganer, Carmel, Hirschheim and Olsen 2013). Competency signal, which is reflected through tests that verify technical know-how, business process understanding, and communication abilities, helps vendors to project their ability to overcome these challenges. In longer duration jobs, vendors need to possess more specific knowledge and techniques to manage the job and clients interactions (Lee, Miranda and Kim 2004; Ravindran, Susarla, Mani and Gurbaxani 2015). Hence, longer duration jobs would benefit more from verified credentials of vendors because clients would have the perception that the verified knowledge and expertise are being applied to overcome difficulties of the longer job duration. Hence, information asymmetry between clients and vendors will be reduced assuming that highly qualified vendors will not represent a moral hazard in jobs of longer duration.

Similarly, in jobs involving higher cultural distance, clients need to manage vendors with differing beliefs and norms. Prior research recognizes that individuals' misconceptions about other individuals at a greater cultural distance can create biases (Manev and Stevenson 2001) and halter objective evaluations (Lin and Viswanathan 2015). Competency signals act as a standard benchmark of verified knowledge notwithstanding language, cultural barriers and decreasing biases that may lead to adverse selection. These signals indicate that the vendor has technical and managerial competency, as reflected through certifications or tests. Vendors who radiate higher expertise levels face less hurdles while interacting with clients at greater cultural distance. For these vendors, competency signals not only indicate abilities through certifications and examinations, but also indicate independently verified knowledge and hence high quality to manage jobs involving greater cultural differences. Vendors with greater cultural distance may require greater details about specifications and other aspects of the IT job (Dibbern, Winkler and Heinzl 2008). Hence, jobs involving greater cultural distances between clients and vendors are likely to benefit more from vendors with stronger competency signal because such vendors may be more likely to overcome biases and non-objective assessments by relying on their technical and managerial skills. Furthermore, clients will also benefit from an objective representation of vendors' skills and knowledge, because competency signal will reduce any biases that clients may have towards choosing culturally similar vendors regardless of their skills. Hence, clients can rely on competency signals as indicators of vendor quality under conditions of longer job duration and greater cultural distance. In sum, we argue that in jobs involving higher duration or cultural distance, the independently verified knowledge represented by the competency signal would be more likely to be reflected in higher vendor quality in the job. Hence, we hypothesize:

Hypothesis H1a: Competency signal is a stronger indicator of quality of microsourcing vendors in jobs with <u>longer duration</u> than in jobs with shorter duration.

Hypothesis H1b: Competency signal is a stronger indicator of quality of microsourcing vendors in jobs involving <u>higher cultural distance</u> than in jobs involving lower cultural distance.

We contend that goal signal is a stronger signal of high vendor quality in jobs involving longer job duration and greater cultural distance than in jobs of shorter duration or lower cultural distance. Goal signal represents the vendor's ability to meet targets and commitments. It indicates the extent to which the vendor has met the final deliverables as per clients' specifications, as reflected in the vendor's ability to successfully complete jobs in time and within budget. We argue that the moderating effect of job duration on the reliability of goal signal is manifested through three mechanisms. First, in jobs with a longer duration, there is greater benefit to vendors for meeting clear deadlines and understanding clients' requirements for each deadline. Vendors with higher goal signal will likely focus on having a high quality information exchange with clients as a critical step towards meeting job timelines and budgets. This information shared between vendors and clients will create complementary knowledge and understanding, decreasing the risk of moral hazard and therefore resulting in higher evaluation of vendor quality by clients, especially in longer duration jobs (Kishore et al. 2003).

Second, goal focused vendors will tend to cultivate their relationship with clients resulting in development of shared goals and a sense of trust (Palvia, King, Xia and Palvia 2010). As highlighted by prior literature, relationship quality and shared goals are essential factors for successful sourcing (Levina and Ross 2003). Consequently, clients and goal focused vendors are likely to maintain good communication in longer duration jobs, thereby reducing information asymmetry.

Third, a vendor emitting a strong goal signal is likely to handhold the client through a long duration job due to vendor's ability to efficiently manage its skills and resources. This not only enhances client's confidence in the vendor's ability to eventually meet goals, but also reduces uncertainty and anxiety during course of the longer job. This process reassures that the client selected an adequate vendor (no adverse selection) and that the vendor is devoting adequate resources to the job (no moral hazard). Thus, the client will eventually evaluate vendor quality in a longer duration job more favorably.

Likewise, we posit that goal signal is a stronger indicator of high vendor quality in jobs characterized by higher cultural distance. First, cultural distance can enhance the challenges to maintain focus on goals and objectives due to disagreements on priorities (Ramasubbu, Mithas, Krishnan and Kemerer 2008; Su 2015). As a result, activities that deviate from original specifications may arise, which can result in time and budget overruns, causing low client evaluations. For instance, negotiations regarding IT job specifications may be more cumbersome when cultural distance is higher (Giannetti and Yafeh 2012). In presence of such potential distractions, a higher goal signal by the vendor can be more valuable as it would preempt the surge of deviating activities by focusing job priorities on completion within cost and time constraints.

Second, a goal focused vendor is likely to adapt the jobs' goals and direction, or even transform its services to provide value added outcomes to customers effectively (Lengnick-Hall 1996). As the goal-oriented vendor focuses on providing services that satisfy customers' needs and demands, clients and vendors will start sharing strategies and interdependencies. Such characteristics are more valuable in jobs of higher cultural distance between vendors and clients as initially clients and vendors may have different communication styles, demands and expectations (Schneider and Bowen 2010). Thus, goal signal can considerably reduce the challenges of moral hazard and adverse selection in jobs of longer duration and greater cultural distance. In line with these arguments, we hypothesize:

Hypothesis H2a: Goal signal is a stronger indicator of quality of microsourcing vendors in jobs with longer duration than in jobs with shorter duration.

Hypothesis H2b: Goal signal is a stronger indicator of quality of microsourcing vendors in jobs involving higher cultural distance than in jobs involving lower cultural distance.

3. Methodology

3.1. Data and Variables

To test our hypotheses, we collected data from January 2013 to September 2013 from freelancer.com, a leading global online microsourcing platform. We used a time structure design relevant to the job progress to capture information and code our variables. The time structure design is illustrated in Figure 3. The platform information signal variables were collected prior to execution of the focal job, while the dependent variable was collected after completion of the job. This temporal ordering reduces concerns due to reverse causality in our analysis.

To collect our data, we followed a recursive process of scraping information from the platform. First, we used multiple software tools and custom scripts to automatically scrap information on all jobs that were posted on the platform during the data collection period. We then shortlisted all jobs that were categorized as web, web services, software, or mobile app development jobs. This ensured that our dataset covered all forms of IT jobs that were conducted through the platform. We collected information at the completion of each job in our shortlist, which included attributes of the vendor. For vendors for which we had scraped information, we again collected all information regarding all jobs completed by the vendor during this period that could be categorized as IT jobs. By following such a recursive process, we were able to gather information on jobs that may have been incorrectly categorized as non-IT jobs.

Overall, our dataset covers 6452 IT jobs. After removing duplicates, incomplete jobs and jobs for which information was not completely available, the final dataset covers 5432 IT service jobs executed prior to August 2013. The jobs were assigned by 3221 clients across 64 countries, and completed by 642 vendors from 49 countries, encompassing 638 distinct client-vendor country tuples (see Appendix B, Table B1 for country distributions).

We created our variables from the objective data available on the microsourcing platform. Table 1 provides a description of the variables. We measure *Competency Signal* as a sum of the number of examinations completed by the vendor prior to the focal job. These exams included technical exams (e.g., programming exams) and process related exams (e.g., employer orientation), and are indicative of the extent to which competency signals are captured in the platform. We measure *Goal Signal* by the product of proportion of on-time, on-budget, and successfully completed jobs by the vendor.

A client announces a job with a description and tentative budget on the website; and then seeks, selects and awards the job to a vendor. The job start date and completion date are captured on the website; we used the difference of these dates to code *Job Duration*. We capture the country names of client and vendor for the focal job and use a standard measure to calculate *Cultural Distance* (see Appendix A for details). We follow prior studies that have used cultural distance between countries to operationalize cultural distance between individuals (Manev and Stevenson 2001).

We use client evaluation score of the vendor quality in the focal job as the measure of *Vendor Quality*, consistent with prior research (Domberger, Fernandez and Fiebig 2000). Clients evaluate vendor quality after completion of the job on a 0 to 5 continuous rating scale. This is an effective measure of quality of microsourcing providers (Lahiri and Kedia 2009) because client satisfaction is derived from services provided by vendors (Grover, Cheon and Teng 1996; Levina and Ross 2003; Saunders, Gebelt and Hu 1997). Client evaluations after a job is completed are widely used as a quality measure in existing literature in several contexts (Bowen and Jones 1986; Brady and Cronin Jr 2001; Liao and Chuang 2004). A related measure, client satisfaction has been established as having a positive relationship with customer loyalty and repurchase levels (Bolton, Kannan and Bramlett 2000), project success (Petter, DeLone and McLean 2013; Rai, Maruping and Venkatesh 2009), customer acquisition and retention, revenue and cash flow (Gruca and Rego 2005), and equity value (Fornell, Mithas, Morgeson and Krishnan 2006), justifying this as an important and valid quality measure.

We include a number of control variables. To account for the vendor's experience with the platform, we control for vendor's average prior ratings across all jobs (*Vendor Prior Rating)*, prior vendor experience as number of projects completed by the vendor in the past (*Vendor Experience)*, and number of prior reviews received by the vendor (*Vendor Reviews*). Because quality evaluations may be influenced by the clarity of the job specification, we control for the clarity in the job specification (*Job Spec. Clarity*) which is rated by the vendor on a scale of 0 to 5. We also control for the extent to which the client may have under-bid or over-bid for the job relative to the average bid of other bidders for the same job (*Job Bid Deviation*). Further, we control for the extent to which the job may have overrun or underrun its budget by measuring the percentage difference the final job price and initial budgeted price (*Job Price Diff.*). In addition, we use a dummy control for mobile apps related jobs (*Mobile Job)*. Finally, we include dummy variables for client and vendor continents to control for potential geographical influences (*Client Location*, and *Vendor Location*).

Table 2 presents descriptive statistics and correlations. The average evaluation of vendor quality by clients is around 3.7, within the 0 to 5 scale of evaluations. In terms of *Competency Signal*, vendors have on average completed around 3 examination and certifications. The *Goal signal* statistics suggests that a regular vendor only completes 66% of the jobs on-time and on budget.

In terms of locations, maximum number of clients are from United States (34%), followed by Australia (10.18%), Canada (4.66%), and India (3.88%) (see Table B1, Appendix B). Maximum number of vendors are from India (37.24%), Vietnam (11.67%), and Pakistan (10.01%). In terms of continent-wise tuples, the maximum client-vendor tuples are between North America and Asia (1646), followed by Europe and Asia (1224) (see Table B2, Appendix B). Interestingly, many clients from South and Central America and Africa are sourcing jobs from the developed world, e.g., African clients hiring North American (3), European (9), and Asian (60) vendors; which is a significant change from the typical unilateral direction of traditional sourcing.

3.2. Empirical Model

The dependent variable *Vendor Quality* is left-censored at 0, and right-censored at 5. Hence Ordinary Least Squares estimates would be less appropriate. Similarly, ordered probit estimation is not appropriate because our dependent variable is not discrete. To account for the double-censoring of the dependent variable, we use double-censored Tobit maximum likelihood estimator, which explicitly accounts for nonlinearity introduced by a double-censored dependent variable (Cameron and Trivedi 2005). We specify the double-censored Tobit model equation as:

$$y_i = \beta x_i + \varepsilon_i$$

Where, β is the vector of coefficient parameters, x_i is vector of independent variables, and ε_i is the error term. The double-censored Tobit model supposes that there is a latent unobservable variable y_i^*. The observable variable y_i is defined as:

$$y_i = \begin{cases} L & \text{if } y_i^* \leq L \\ y_i^* & \text{if } L < y_i^* < U \\ U & \text{if } y_i^* \geq U \end{cases}$$

Where, L and U are respectively the lower and upper bounds on y_i^*.

4. Results

4.1. Estimation Results

Table 3 presents the estimation results. Column 1 shows direct effects of the signals; columns 2 and 3 include interaction terms of the signals with *Job Duration* and *Cultural Distance* respectively; and column 4 includes all the four interaction terms.

Although we do not postulate hypotheses for the direct effects, the results show that *Goal Signal* has a positive and significant relationship with *Vendor Quality* (column 1, $\beta = 5.30, p < 0.01$), suggesting that goal signal is a reliable indicator of high vendor quality such that they get higher client evaluations in the focal jobs. However, we find that *Competency Signal* (column 1, $\beta = NS$) has a non-significant coefficient, suggesting that competency signal is not a reliable indicator of vendor quality when one does not account for complexity conditions.

In the interaction model, we find that the interaction term (*Competency Signal* × *Job Duration*) is positive and significant (column 4, $\beta = 0.01, p < 0.05$), consistent with H1a. This suggests that competency signal serves as a stronger indicator of vendor quality in longer duration jobs. The interaction term (*Competency Signal* × *Cultural Distance*) is positive and significant (column 4, $\beta = 0.18, p < 0.01$), consistent with H1b. This suggests that competency signal is a stronger indicator of vendor quality in jobs involving higher cultural distance.

We also find support for H2a, as the interaction term (*Goal Signal* × *Job Duration*) is positive and significant (column 4, $\beta = 0.16, p < 0.01$). This finding suggests that goal signal serves as a stronger indicator of quality of vendors engaged in longer duration jobs. Similarly, the interaction term (*Goal Signal* × *Cultural Distance*) is positive and significant (column 4, $\beta = 2.16, p < 0.01$), supporting H2b. This finding suggests that goal signal serves as a stronger indicator of vendor quality in jobs involving higher cultural distance. Among other results, we find that the main effect of *Cultural Distance* is negative and significant, consistent with the argument that cultural distance hinders coordination and communication effectiveness (Gefen and Carmel 2008). Furthermore, the control variables are largely in expected directions. For example, vendor experience, number of prior reviews of vendor, and clarity of job specifications have positive and significant coefficients.

Figure 4 depicts a graphical interpretation of the interactions. These graphs provide more insights and suggest that the interactions effects are practically significant. Figure 4a and figure 4b show that at low levels of job duration or cultural distance, competency signal is not a good indicator of quality; however, at high levels of job duration or cultural distance, the reliability of competency signal as a signal of quality is high. On the other hand, figure 4c and figure 4d show that at low levels of job duration or cultural distance, goal signal is a reasonable indicator of quality; however, at high levels of job duration or cultural distance, the reliability of goal signal as a signal of quality is substantially higher.

4.2. Robustness Check: Accounting for Endogeneity of the Signals

A potential concern in our study may be that the signals are endogenous. Such endogeneity can occur if there are unobserved (to the researcher) factors that affect the level of vendor signals as well as vendor quality. For example, if vendors possess unobserved personality traits (e.g., intrinsic motivation) that make them prone to signal more as well as more likely to perform jobs with high quality, it could be a source of potential endogeneity.

To assess the robustness of our findings, we accounted for potential endogeneity by using Garen's (1984) methodology which is a residual analysis technique to correct for selection bias and used in several recent studies in management literature (e.g., Ghosh, Dutta and Stremersch 2006; Mooi and Ghosh 2010). The rationale for the selection mechanism is that *Competency Signal* and *Goal Signal* may be endogenous due to factors, some observable to researchers (e.g., average prior vendor rating), and others unobservable (e.g., vendor intrinsic motivation). If such potential endogeneity is not accounted for, estimates can be inconsistent. Garen (1984) provides a generalization of Heckman's (1979) two-stage estimator and accounts for the continuous nature of the selection variable. Consistent with Bharadwaj et al. (2007), we created a variable (named *SigSum*) that is sum of standardized *Competency Signal* and *Goal Signal*. Intuitively, this variable represents the level of signaling of the vendor. Then, we estimated the first stage regressing *SigSum* on factors likely to impact the extent to which vendors signal (eq. i). We then calculated residuals $\tilde{\eta}$ from the first stage, and included $\tilde{\eta}$ and interaction term $\tilde{\eta} \times SigSum$ as endogeneity correction terms in the quality equation (eq. ii). $\tilde{\eta}$ corrects for selection bias, and $\tilde{\eta} \times SigSum$ accounts for unobserved heterogeneity over the range of the selection variable (Garen 1984). The equations are:

$$\text{Stage 1: } SigSum = \text{f}\,(\beta_a + \beta_r W + \eta) \qquad \text{...(i)}$$

$$\text{Stage 2: } VendorQuality = \text{f}(\textit{independent variables, interaction terms}, \tilde{\eta}, \tilde{\eta} \times SigSum, \text{controls}, \varepsilon) \quad \text{...(ii)}$$

where W is the vector of variables in the first stage; η and ε are error terms; and $\tilde{\eta}$ is the estimate of residuals from the first stage. Vendor and job characteristics are used as regressors in the first stage. Among the variables in the first stage, we include an additional variable, which serves as an exclusion restriction and aids in model identification (Greene 2008). This variable (*VenDescLen*) is the log of the length of the description that the vendor provides about itself. This is a reasonably good exclusion restriction in our study because, theoretically, the length of the description that the vendor provides is likely to also suggest a high propensity of the vendor to signal his competency and goal, but is not likely to, by and of itself, influence vendor quality in the focal job. As the results show, this variable is positive and significant in the first-stage equation, suggesting that it is valid for inclusion in the first stage, and it was non-significant when we included it in the second-stage quality equation. Table 4 shows estimates of the second stage (eq. (ii)) which addresses endogeneity by including the endogeneity correction terms calculated from the first stage.[3] We find that the results of our hypotheses tests are qualitatively unchanged, suggesting that the findings are robust to endogeneity.

4.3. Additional Robustness Checks

We conducted several additional tests to assess the robustness of our results. First, we used an alternate measure of cultural distance, based on Euclidean distance (see Appendix A). The findings remained qualitatively unchanged. Furthermore, we repeated the analysis using only the first four of Hofstede's cultural dimensions (instead of five) and found similar results. Likewise, we repeated the analysis using the original Kogut and Singh (1988 index without adjusting for the variance of each dimension, and found substantively unchanged results.

Second, we checked for F-tests of joint significance of interaction terms, and found that the tests are rejected, suggesting rejection of the null that interaction terms are jointly zero. The F-test comparisons for the models with and without the interaction terms were significant, suggesting that the interaction terms have added value towards the model specification.

Third, we assessed the sensitivity of our results to clustering by vendors and clients. In our reported results (Tables 3 and 4), we clustered the standard errors by vendors because our sample has fewer vendors than clients, and because our sample contained several vendors who performed multiple jobs. Nevertheless, the results remained qualitatively unchanged when we cluster the standard errors by clients. Further, the results with and without clustering of standard errors remained similar.

[3] Appendix C shows first-stage estimates (eq. (i)). The model is significant, and several variables are significant. For example, as expected, vendors with high average prior rating and who have provided a longer description of themselves have higher signals.

Fourth, because the independent, dependent, and control variables are from different sources (vendor, client, microsourcing platform, and external sources for cultural distance measures), concerns of common method bias are substantially alleviated. Nonetheless, to assess common method bias, we performed Harman's one-factor test (Podsakoff and Organ 1986) and the marker variable test (Lindell and Whitney 2001). In Harman's test, no single major factor emerged, and in marker variable test, the correlations among the variables did not change significantly after accounting for common method variance. Thus, results of both tests suggested that common method bias is not a significant concern. Moreover, since our core theory pertains to interaction effects, common method variance is of even less concern because common method variance reduces the likelihood of detecting interaction effects (Wall, Jackson, Mullarkey and Parker 1996).

Fifth, we checked for multicollinearity by examining variance inflation factors (VIF). The maximum and average VIFs were well below suggested limits (Greene 2008), indicating that multicollinearity is not problematic. Moreover, we performed several diagnostic checks including testing for outliers and influential observations, and found no problems or violations of assumptions (Greene 2008). Finally, as an additional control variable, we included the number of past transactions between the same client and vendor. We found similar results. Overall, these tests suggest that the results are robust.

5. Discussion

5.1. Findings

Our study demonstrates when various types of platform based information signals (competency and goal signal) convey vendor quality in microsourcing platforms. Table 5 provides a summary and interpretation of our main findings. Specifically, our results show that both signals are stronger indicators of vendor quality for vendors engaged in longer duration jobs and in jobs with higher cultural distance. Because vendor quality is measured based on client evaluations of quality at the post-completion stage of the job, we infer that vendors with higher goal signals, or signals indicating completion of past jobs on-time and within-budget, have been able to complete and perform the jobs well enough to get higher evaluations of quality. In other words, in jobs that are of longer duration and characterized by greater cultural distance, the quality of vendors indicated through goal signals and competency signals on the platform is true to the extent that quality has remained intact during the course and completion of the focal job. Interestingly, without accounting for job characteristics, goal signal is a reliable indicator of vendor quality on a microsourcing platform, whereas competency signal is not a reliable indicator.

5.2. Theoretical Contributions

This research contributes to literature on (1) signaling and (2) microsourcing or online labor markets by offering empirical evidence from a leading microsourcing platform. Specifically, we help fill the gap in the literature on the contingencies (job duration and cultural distance) that influence the effectiveness of signaling (competency and goal signal) as indicators of vendor quality in microsourcing platforms or online labor markets.

Our study offers two main theoretical contributions. First, our study provides insights to the signaling literature with regard to when various information signals convey quality in microsourcing platforms. This addresses a salient question in the signaling literature, under which conditions can clients trust the reliability of information signals? The effectiveness of competency signal and goal signal as indicators of vendor quality is not straightforward as we counter-intuitively found that competency signal has no significance in explaining vendor quality when one does not account for job conditions (job duration and cultural distance) whereas goal signal is a reliable indicator. Our study builds on several seminal studies that proposed signals as a way to reduce information asymmetry in traditional labor markets. Notably, our study extends the seminal work of Spence (1973) to online labor markets. Spence (1973) suggested that job candidates (signalers) obtain education to signal their quality and reduce information asymmetries. However, in the microsourcing platform context, education credentials (competency signal) may fall short in signaling the actual quality of signalers (vendors). Our findings suggest that there may be a gap between competency portrayed in signals and the actual quality of the vendor. On similar lines, research in psychology has found that people often prefer potential rather than achievement when evaluating others (Tormala, Jia and Norton 2012). To the extent that competency signal is a reflection of potential of the vendor whereas goal signal is a reflection of actual achievement or performance of the vendor, our findings suggest that in the context of microsourcing, achievement matters more than potential when it comes to vendor quality. This effect is magnified under situations involving higher job duration and cultural distance.

Second, our study has significant implications for signal availability in microsourcing platforms as a relevant platform design problem. Platform design is an important example of IS design that involves strategy, economics and software engineering (Tiwana, Konsynski and Bush 2010) and it has a relevant role in clients' selection strategy and vendors' information disclosure. In spite of the proliferation of microsourcing platforms, research on the design of information signals and conditions in which they reflect vendor quality is lacking. We theoretically suggest that job conditions in microsourcing platforms have an important influence on the effectiveness of signals as indicators of vendor quality. With jobs of longer duration and of greater cultural difference between clients and vendors, clients benefit from observing vendors' competency and goal signals, which allow them to make inferences about vendors' quality, resulting in more optimal vendor selection. For vendors, since the effects of signals is substantial, deploying competency and goal signals considerably reduces information asymmetry which enables vendors to better depict their quality.

5.3. Managerial Implications

The findings of this study have a number of actionable managerial implications. First, vendors' choice has been seen as a relevant but difficult problem for clients in microsourcing platforms. The plethora of vendors in the platform highlight the need to identify platform based information signals that reliably represent vendor quality. The direct implication for clients is that the importance of goal signal and competency signal depends on the duration of the job and the cultural distance between vendor and client. Another implication of our findings for clients is that capturing this information and interpreting vendor quality based on goal signal and competency signal may be a good strategy in jobs that are longer and of greater cultural distance.

Second, adding reliable vendor quality signals into the platform may be a good strategy to encourage clients to commission jobs in online environments. Hence, platforms must consider what kinds of signals provide best indicators of vendor quality, depending on the kind of jobs. In other words, platforms can indicate to clients that in jobs involving culturally different vendors and longer jobs, they would be well advised to consider goal and competency criteria more carefully. Our results also suggest that goal signal is a stronger indicator of vendor quality than competency signal. Thus, platform designers may need to focus on devising appropriate goal signals that can highlight not only the on-time, on-budget completion of jobs, but also potentially more granular attributes such as task management capabilities and job monitoring of vendors. The findings of this study suggest that clients need to be prudent and avoid following a boiler-plate approach to scrutinize vendors based on competency alone. In microsourcing platforms, clients often choose vendors based on a preliminary scrutiny of competency (e.g., through exams and certificates). Rather, microsourcing platform designers need to implement vendor signals that go beyond competency based criteria.

Overall, our findings shed new light on the role of platform information signals as indicators of vendor quality in microsourcing. The findings provide implications to platform designers, developers, and managers to instill a signal oriented strategy that can help clients to select vendors appropriately.

5.4. Limitations and Future Research

Our study has some limitations which present opportunities for future research. First, we focused on microsourcing jobs on one specific platform. Although this enhances internal validity, future studies can examine other platforms in order to assess generalizability. Second, the cross-sectional nature of the study hinders us from categorically inferring temporal ordering. However, because our dependent variable is captured after the job is completed and platform signal variables are measured prior to the start of the focal job (see Figure 3), concerns regarding direction of causation are substantially alleviated. Nonetheless, future research extending our analysis to longitudinal settings may yield additional insights. Future studies can also examine other kinds of information signals and other kinds of job conditions such as customization levels. Finally, future research can consider quality interpretations of various information signals as pertaining to other emergent organizational forms that are temporary and distributed in nature, such as jobs in the shared economy (Malone and Laubacher 1999).

5.5. Conclusion

Platforms have changed the interactions between vendors and clients and the way jobs are sourced globally. One relevant issue facing microsourcing platforms is how platform based information signals with regard to vendors' competency and goal orientation are a true reflection of vendor quality. In spite of recent progress in the microsourcing platforms, the importance and reliability of information signals under specific job conditions remain inconclusive. By using a unique dataset of 5432 microsourcing jobs spread across 638 unique country tuples, we demonstrated the conditions under which vendors' competency and goal signal reliably reflect vendors' quality. Interestingly, job duration and cultural distance between clients and vendors strengthen the reliabilities of competency and goal signals as indicators of vendors' quality, which make platforms that display these information signals a superior option for clients that want to reduce their information asymmetry and the risks of adverse selection and moral hazard. Given the importance of platforms in global job markets, we hope that our study can serve as a springboard for scholars and practitioners to further analyze other platform design features and their effects on the reduction of information asymmetry with regard to vendor quality.

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Figures and Tables

Figure 1. Microsourcing Challenges, Signals, and Quality

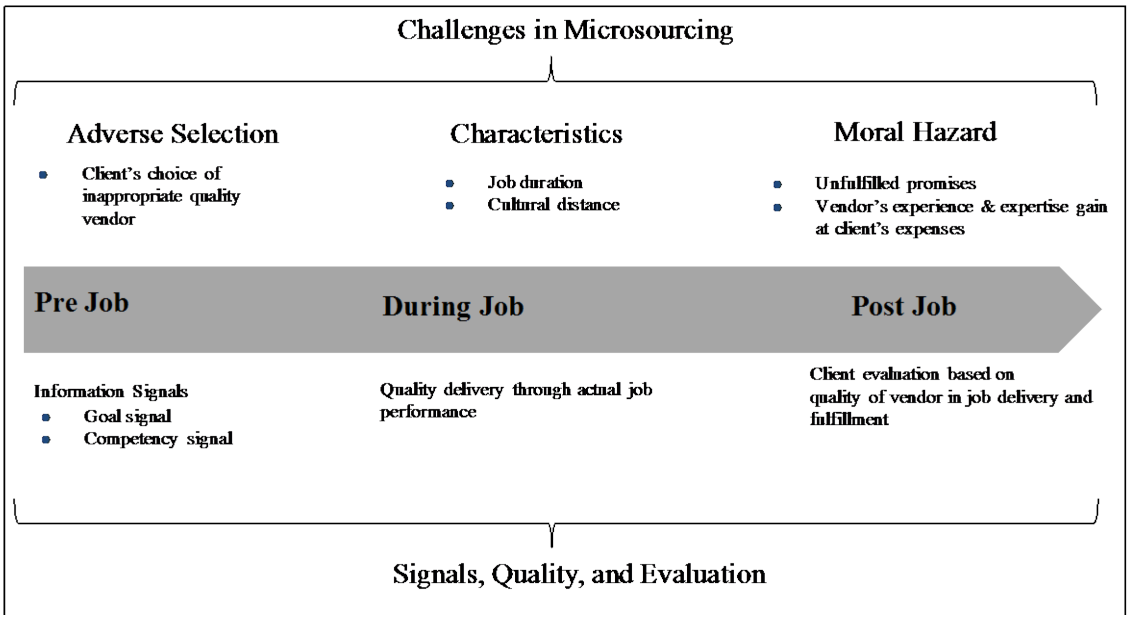

Figure 2. Research Model

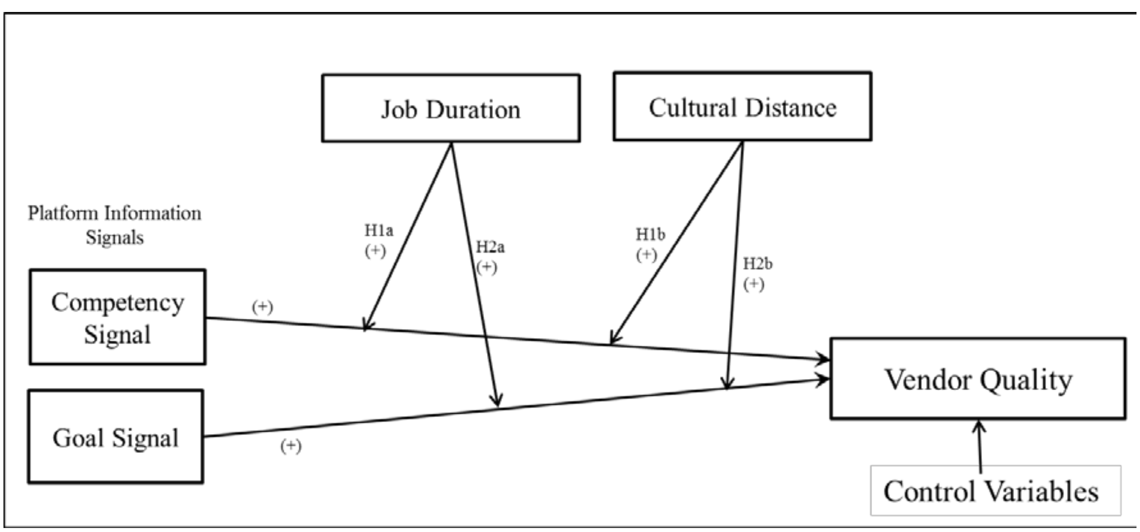

Figure 3. Time Structure of Research Design and Data Collection

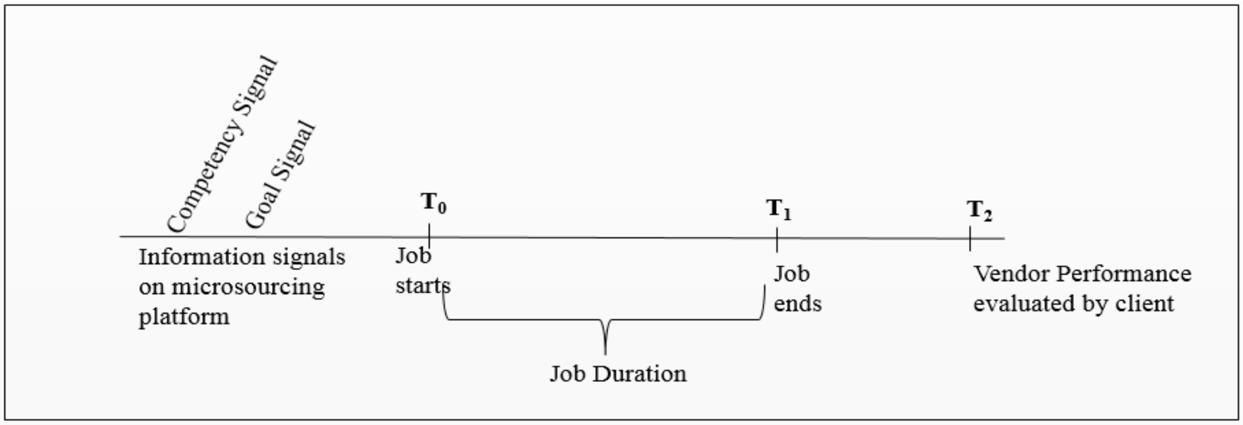

Figure 4. Graphical Interpretation of Interaction Effects

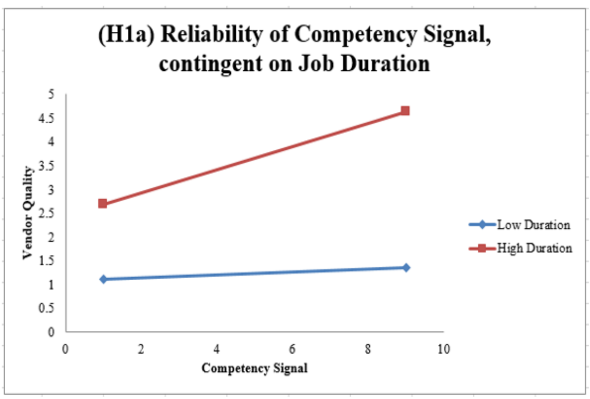

Figure 4a

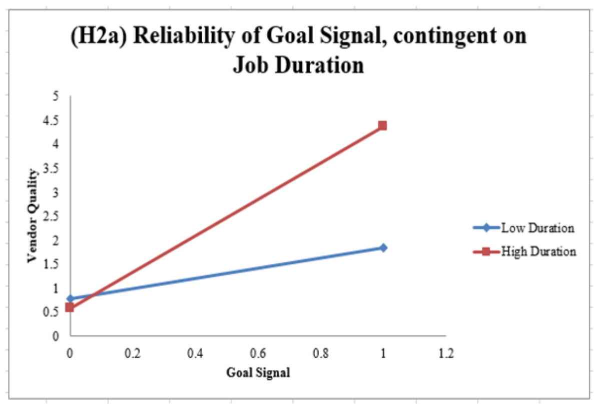

Figure 4c

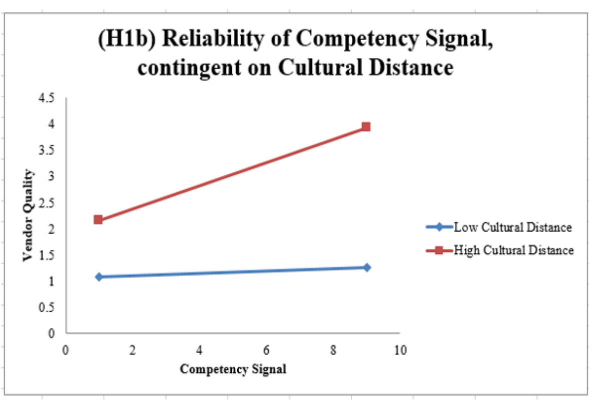

Figure 4b

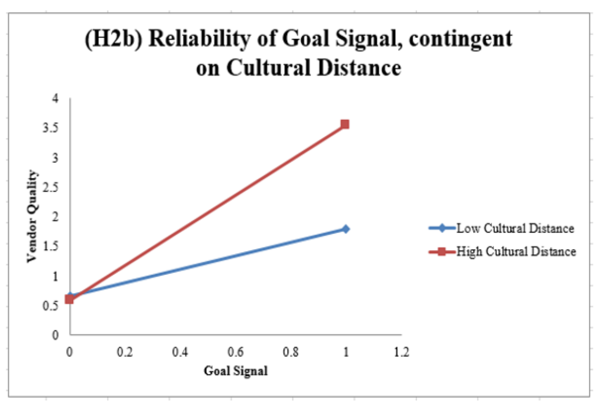

Figure 4d

Table 1. Description of Variables

Variable	**Definition and Operationalization**	**References**
Vendor Quality	The overall evaluation rating provided by the client for the vendor's quality in the focal job after the job's completion. The measurement is on a continuous scale from 0 to 5, where 0 is the lowest and 5 is the highest evaluation. This variable is log transformed as log (1+ Vendor Quality) to account for skewness.	(Domberger, Fernandez and Fiebig 2000; Lahiri and Kedia 2009)
Competency Signal	Competency signal indicates how competent the vendor is. This variable is measured as the number of IT exams (e.g., PHP programming, iPhone software development) and process-related exams (e.g., vendor orientation, employer orientation) completed by the vendor prior to the focal job. For ease of interpretation, we used the standardized value in the estimations.	(Banker and Hwang 2008; Gao, Gopal and Agarwal 2010; Wells, Valacich and Hess 2011)
Goal Signal	Goal signal is measured as the three-way product of proportion of jobs completed on time, the proportion of jobs completed on-budget, and the proportion of successfully completed jobs in the past. Goal signal = (on-time proportion) x (within-budget proportion) x (completion rate proportion). For ease of interpretation, we used the standardized value in the estimations.	
Job Duration	Duration of the focal job, measured in number of days.	(Susarla, Subramanyam and Karhade 2010)
Cultural Distance	Cultural distance between the country of location of the vendor and country of location of the client, calculated based on the cultural dimensions identified and used in prior studies. Prior studies have used country cultural distance to operationalize individual's cultural distance. Please see Appendix A for detailed description and calculations of this variable.	(Kogut and Singh 1988; Manev and Stevenson 2001; Sousa and Bradley 2008)
Vendor Prior Rating	Average rating received by the vendor on all jobs done by the vendor prior to the focal job. Calculated and provided by the platform, on a continuous scale of 0 to 5, where 0 is lowest rating, and 5 is highest rating.	
Vendor Experience	Prior experience of the vendor measured as the total number of jobs undertaken by the vendor prior to the focal job.	
Vendor Prior Reviews	The total number of prior reviews of the vendor prior to starting the focal job.	
Job Spec. Clarity	Indicates clarity of the job specification. The specification for the focal job is posted by the client on the website prior to the start of the job. Vendor rated the clarity of the job, on a continuous scale of 0 to 5, with 0 being the lowest clarity, 5 being the highest clarity.	
Job Price Diff.	Unit difference between the job price and the budgeted price of the focal job. Job Price Diff. = (job budget – job price)/ (job budget).	
Job Bid Deviation	This variable is calculated as the unit deviation of the vendor's bid amount from mean bid amounts for the focal job. Job Bid Deviation = (Mean bid amount – Vendor's bid amount)/(Mean bid amount).	
Mobile Job	Whether the job is related to cell phone or mobile device, such as coding an application for the android or iTunes market. The variable is binary, where 1 indicates a mobile application related development job; 0 indicates otherwise.	
Client Location and Vendor Location	Dummy variables indicating continent of location of the client and continent of location of the vendor. We coded binary dummy variables, one each for a) North America, b) Europe, c) Asia, d) South/Central America, e) Australia and New Zealand, and f) Africa. Dummy for Africa is omitted from the empirical model to prevent perfect collinearity.	
Vendor Description Length	Log of the length of the description provided by the vendor	

Table 2. Descriptive Statistics and Correlations

Variable		Mean	SD	1	2	3	4	5	6	7	8	9	10	11	12
1	Vendor Quality	3.71	0.98	1.00											
2	Job Duration	10.83	12.11	-0.07*	1.00										
3	Cultural Distance	1.98	1.15	-0.17*	-0.06*	1.00									
4	Competency Signal	2.81	2.09	0.00	0.03*	0.07*	1.00								
5	Goal Signal	0.66	0.23	0.17*	0.03*	0.02	0.05*	1.00							
6	Vendor Prior Rating	3.63	0.78	0.05*	0.02	0.04*	0.10*	0.46*	1.00						
7	Vendor Prior Reviews	22.78	72.18	0.05*	-0.05*	0.03*	0.03*	0.06*	-0.01	1.00					
8	Vendor Experience	46.86	137.22	0.01	-0.07*	0.01	0.02	0.05*	-0.01	0.25*	1.00				
9	Job Spec. Clarity	4.70	1.07	0.24*	-0.02	0.04*	-0.01	0.04*	0.02	0.08*	0.05*	1.00			
10	Job Price Diff.	-0.43	3.19	0.05*	-0.09*	0.01	0.07*	-0.09*	0.08*	-0.02	-0.01	-0.14*	1.00		
11	Job Bid Deviation	0.16	0.36	-0.00	-0.17*	-0.01	-0.05*	-0.01	-0.01	-0.01	-0.01	-0.00	0.05*	1.00	
12	Mobile Job	0.92	0.26	0.00	0.08*	0.04*	0.08*	-0.05*	-0.02	-0.07*	-0.05*	0.02	0.04*	0.03*	1.00
13	Vendor Desc. Length	5.50	1.11	-0.02	-0.00	0.04	0.11*	0.17*	0.02	0.03	0.02	-0.03	-0.02	-0.02	-0.02

*Number of observations, N = 5432. * indicates significance at 5% level.*

Table 3. Estimation Results

	(1) Vendor Quality	(2) Vendor Quality	(3) Vendor Quality	(4) Vendor Quality
Competency Signal	0.004 (0.03)	-0.07 (0.05)	-0.14 (0.13)	-0.04 (0.12)
Goal Signal	5.30*** (0.79)	3.47** (0.73)	0.87** (0.42)	0.72** (0.35)
Competency Signal × Job Duration		0.01** (0.003)		0.01** (0.003)
Goal Signal × Job Duration		0.16*** (0.05)		0.16*** (0.05)
Competency Signal × Cultural Distance			0.18*** (0.04)	0.18*** (0.04)
Goal Signal × Cultural Distance			2.16*** (0.47)	2.16*** (0.46)
Job Duration	-0.008*** (0.003)	-0.04*** (0.01)	-0.007*** (0.003)	-0.04*** (0.01)
Cultural Distance	-0.10*** (0.03)	-0.10*** (0.03)	-0.57*** (0.08)	-0.58*** (0.08)
Vendor Prior Rating	0.06 (0.06)	0.05 (0.06)	0.07 (0.05)	0.05 (0.05)
Vendor Prior Reviews	0.01*** (0.002)	0.01*** (0.002)	0.01*** (0.002)	0.01*** (0.002)
Vendor Experience	0.001*** (0.0003)	0.001*** (0.0003)	0.001*** (0.0002)	0.001*** (0.0002)
Job Spec. Clarity	0.22*** (0.03)	0.21*** (0.03)	0.20*** (0.03)	0.19*** (0.03)
Job Price Diff.	-0.005 (0.02)	-0.02 (0.02)	-0.00 (0.02)	-0.01 (0.02)
Job Bid Deviation	-0.12 (0.08)	-0.13 (0.08)	-0.11 (0.08)	-0.11 (0.08)
Mobile Job	0.06 (0.12)	0.04 (0.12)	0.04 (0.11)	0.02 (0.11)
Log pseudo-likelihood	-2929.01	-2912.48	-2846.10	-2828.14
F-statistic	6.76***	6.67***	7.42***	8.25***
F-test of significant coefficients of interaction		7.78***	21.70***	14.47***
Akaike Information Criterion	5904.01	5874.96	5742.21	5710.28
Bayesian Information Criterion	6055.81	6039.96	5907.21	5888.48
Number of observations	5432	5432	5432	5432

Double-censored Tobit models used for estimations. Significance levels: ***p < 0.01, **p < 0.05, *p < 0.10; Parentheses show robust standard errors clustered by vendor. Dependent variable is log transformed as log (1+ *Vendor Quality*). Because *Vendor Quality* ranges from 0 to 5, left censoring is at log (1 + 0) and right censoring is at log (1 + 5). Each model includes an intercept and controls for location (continent) of client and vendor. F-test comparison of the interaction models with baseline models (with and without interaction terms) gives significance at p < 0.001 levels for all models. Models with each interaction term added individually in the model produce similar results. As an additional control variable, we added the number of past transactions between the same vendor and client. Results remained qualitatively the same.

Table 4. Robustness Test: Estimations Accounting for Endogeneity

	(1) Vendor Quality	(2) Vendor Quality
Competency Signal	-0.01 (0.04)	-0.30 (0.66)
Goal Signal	1.11*** (0.38)	1.15** (0.49)
Competency Signal × Job Duration		0.01*** (0.001)
Goal Signal × Job Duration		0.04*** (0.01)
Competency Signal × Cultural Distance		0.08*** (0.02)
Goal Signal × Cultural Distance		0.50*** (0.11)
Job Duration	-0.002 (0.007)	-0.037*** (0.01)
Cultural Distance	-0.11*** (0.04)	-0.59*** (0.08)
Vendor Prior Rating	0.05 (0.06)	0.05 (0.06)
Vendor Prior Reviews	0.007*** (0.002)	0.007*** (0.002)
Vendor Experience	0.0006 (0.0006)	0.0004 (0.0006)
Job Spec. Clarity	0.25*** (0.05)	0.23*** (0.05)
Job Price Diff.	0.0001 (0.0003)	0.00 (0.00)
Job Bid Deviation	-0.03 (0.12)	-0.04 (0.12)
Mobile Job	-0.04 (0.15)	-0.11 (0.15)
$\tilde{\eta}$	-0.66 (0.71)	-0.81 (0.72)
$\tilde{\eta}$ × SigSum	-0.03 (0.10)	-0.15 (0.10)
Log pseudo-likelihood	-2927.56	-2823.88
F-statistic	6.19***	6.69***
F-test of significant coefficients of interaction		14.88***
Akaike Information Criterion	5905.12	5705.76
Bayesian Information Criterion	6070.12	5897.16
Number of observations	5432	5432

Double-censored Tobit models used for estimations. Garen (1984) methodology used for estimations. Terms containing $\tilde{\eta}$ are endogeneity correction terms calculated from the first stage. Significance levels: ***$p < 0.01$, **$p < 0.05$, *$p < 0.10$. Parentheses show robust standard errors clustered by vendor. Dependent variable is log transformed as log (1+ *Vendor Quality*). Because *Vendor Quality* ranges from 0 to 5, left censoring is at log (1 + 0) and right censoring is at log (1 + 5). Each model includes an intercept and controls for location (continent) of client and vendor. F-test comparison of the interaction models with baseline models (with and without interaction terms) gives significance at $p < 0.001$ levels for all models. Models with each interaction term added individually in the model produce similar results. As an additional control variable, we added the number of past transactions between the same vendor and client. Results remained qualitatively the same.

Table 5. Summary of Findings

Hypothesis		Finding	Implications
H1a	Competency signal is a stronger indicator of quality of microsourcing vendors in jobs with longer duration than in jobs with shorter duration.	Supported	- Both signals are more reliable indicators of quality for vendors who deal with jobs of longer duration. - Microsourcing platforms should institutionalize both signals, particularly when they deal with longer jobs. - For longer jobs, clients should infer vendor quality using both signals rather than relying on one signal only.
H2a	Goal signal is a stronger indicator of quality of microsourcing vendors in jobs with longer duration than in jobs with shorter duration.	Supported	
H1b	Competency signal is a stronger indicator of quality of microsourcing vendors in jobs involving higher cultural distance than in jobs involving lower cultural distance.	Supported	- Clients dealing with global job sourcing from culturally distant vendors should rely more on goal and competency signals. - Microsourcing motivation may not be solely for cost arbitrage, but competency and goal relying behavior of vendors. Rewarding for such behavior through microsourcing platforms may need to evolve.
H2b	Goal signal is a stronger indicator of quality of microsourcing vendors in jobs involving higher cultural distance than in jobs involving lower cultural distance.	Supported	

Appendices

Appendix A: Cultural Distance Description and Calculations

For measuring *Cultural Distance*, we used the widely used measure similar to Kogut and Singh (1988)'s index (Manev and Stevenson 2001), following adaptations recommended by prior research (Shenkar 2001). This measure is calculated using dimensions of culture based on work of Geert Hofstede, which has emerged as a standard measure of difference in national cultures (Hofstede 1980; Manev and Stevenson 2001; Sousa and Bradley 2008). The index is used in several prior studies (e.g., Griffith, Harmancioglu and Droge 2009; Handley and Benton 2013) and is based on deviation of the vendor's country from the client's country along the five Hofstede (1980) cultural dimensions (i.e., power distance, individualism/collectivism, masculinity/femininity, uncertainty avoidance, long-term orientation). These differences are adjusted for differences in variance of each dimension and then arithmetically averaged. Algebraically:

$$Cultural\ Distance_{jk} = \sum_{i=1}^{5} \left(\frac{(I_{ij} - I_{ik})^2}{V_i} \right) / 5$$

where *Cultural Distance*$_{jk}$ is cultural distance of country of vendor j's from country of client k's; I_{ij} is index for ith cultural dimension of jth country; and V_i is variance of the ith dimension.

For robustness, we also used an alternate measure of cultural distance and found similar results. This alternate measure is a Euclidean distance index based on Hofstede (1980) (Drogendijk and Slangen 2006; Morosini, Shane and Singh 1998; Yu, Subramaniam and Cannella 2009). Unlike the Kogut and Singh (1988) index, this measure does not assume that differences in scores on each of Hofstede's dimensions are equally important in determining cultural distance between countries. Instead, in line with the concept of Euclidean distance, it computes their distance in a five dimensional space as the square root of the sum of squared differences in scores on each cultural dimension. The Euclidean measure is calculated as:

$$Cultural\ Distance_{jk} = \sqrt{\sum_{i=1}^{5} \left(\frac{(I_{ij} - I_{ik})^2}{V_i} \right)}$$

Although the original index proposed by Kogut and Singh (1988) consisted of the first four Hofstede dimensions, we followed prior research which suggests including the fifth dimension as well (Griffith, Harmancioglu and Droge 2009; Shenkar 2001). For further robustness, we repeated the analysis using just the first four dimensions and found similar results. Likewise, we repeated the analysis using the original Kogut and Singh (1988) index without adjusting for variance of each dimension, and found qualitatively unchanged results.

Appendix B: Sample Characteristics

Table B1. Global Characteristics of Vendors and Clients in Sample

Country	Number (#) of vendors	% of vendors	# of clients	% of clients		Country	# of vendors	% of vendors	# of clients	% of clients
Argentina	9	0.17	10	0.18		South Korea	52	0.96	0	0.00
Australia	36	0.66	553	10.18		Malaysia	42	0.77	67	1.23
Austria	19	0.35	23	0.42		Malta	0	0	11	0.20
Bangladesh	248	4.57	17	0.31		Mexico	2	0.04	27	0.50
Belgium	2	0.04	26	0.48		Morocco	0	0	5	0.09
Brazil	6	0.11	41	0.75		Netherlands	1	0.02	89	1.64
Bulgaria	36	0.66	8	0.15		New Zealand	3	0.06	43	0.79
Canada	53	0.98	253	4.66		Nigeria	90	1.66	5	0.09
Chile	0	0.00	16	0.29		Norway	0	0	58	1.07
China	516	9.50	36	0.66		Pakistan	544	10.01	32	0.59
Colombia	3	0.06	6	0.11		Peru	0	0	6	0.11
Croatia	41	0.75	17	0.31		Philippines	15	0.28	12	0.22
Czech Republic	1	0.02	11	0.20		Poland	48	0.88	14	0.26
Denmark	3	0.06	48	0.88		Portugal	3	0.06	9	0.17
Egypt	155	2.85	17	0.31		Romania	105	1.93	22	0.41
El Salvador	2	0.04	3	0.06		Russia	71	1.31	0	0.00
Estonia	18	0.33	2	0.04		Serbia	22	0.41	4	0.07
Finland	6	0.11	11	0.20		Singapore	39	0.72	104	1.91
France	0	0.00	62	1.14		Slovenia	0	0.00	7	0.13
Germany	12	0.22	156	2.87		South Africa	0	0.00	45	0.83
Greece	0	0.00	29	0.53		Spain	58	1.07	57	1.05
Hong Kong	0	0.00	68	1.25		Sweden	1	0.02	72	1.33
Hungary	4	0.07	4	0.07		Switzerland	12	0.22	81	1.49
India	2023	37.24	211	3.88		Taiwan	0	0.00	29	0.53
Indonesia	43	0.79	15	0.28		Thailand	16	0.29	39	0.72
Iran	1	0.02	0	0.00		Trinidad &Tobago	0	0.00	3	0.06
Ireland	2	0.04	63	1.16		Turkey	18	0.33	65	1.20
Israel	0	0.00	96	1.77		UAE	55	1.01	61	1.12
Italy	16	0.29	136	2.50		United Kingdom	130	2.39	562	10.00
Japan	2	0.04	47	0.87		United States	193	3.55	1847	34.00
Kenya	21	0.39	9	0.17		Uruguay	0	0.00	6	0.11
Latvia	0	0.00	13	0.24		Venezuela	0	0.00	9	0.17
Lithuania	0	0.00	5	0.09		Vietnam	634	11.67	28	0.52
Luxembourg	0	0.00	1	0.02		TOTAL	5432	100	5432	100

Note: The sample has 638 distinct client-vendor country tuples.

Table B2. Continent-wise Distribution of Tuples in Sample

		Vendor Continent					
		North America	Europe	Asia	Australia and New Zealand	South and Central America	Africa
Client Continent	North America	140	231	1646	17	8	58
	Europe	59	193	1224	5	7	113
	Asia	16	86	760	4	5	56
	Australia and New Zealand	24	77	463	12	1	19
	South and Central America	4	15	95	1	1	11
	Africa	3	9	60	0	0	9

Appendix C: Selection Equation Estimates for Robustness to Endogeneity

	SigSum
Job Duration	-0.0005 (0.002)
Cultural Distance	0.01 (0.02)
Vendor Prior Rating	0.07*** (0.02)
Vendor Prior Reviews	0.001** (0.0004)
Vendor Experience	0.00 (0.00)
Job Spec. Clarity	0.04** (0.02)
Job Price Diff.	0.0004* (0.00023)
Job Bid Deviation	-0.12** (0.05)
Mobile Job	-0.51*** (0.07)
Vendor Summary Description Length	0.09*** (0.01)
F-statistic	63.76***
R-square	0.49
Number of observations	5432

OLS model used for estimations. Significance levels: ***$p < 0.01$, **$p < 0.05$, *$p < 0.10$. Model includes an intercept and controls for location (continent) of client and vendor.