An Empirical Study of Online Software Outsourcing: Signals under Different Contract Regimes

Mingfeng Lin, Siva Viswanathan and Ritu Agarwal
Robert H. Smith School of Business
University of Maryland

* The Networks, Electronic Commerce, and Telecommunications (“NET”) Institute, http://www.NETinst.org, is a non-profit institution devoted to research on network industries, electronic commerce, telecommunications, the Internet, “virtual networks” comprised of computers that share the same technical standard or operating system, and on network issues in general.
AN EMPIRICAL STUDY OF ONLINE SOFTWARE OUTSOURCING:

SIGNS UNDER DIFFERENT CONTRACT REGIMES¹

Mingfeng Lin, Siva Viswanathan and Ritu Agarwal

Department of Decision, Operations and Information Technologies
Robert H. Smith School of Business
University of Maryland, College Park

Abstract

We study whether and how contractual arrangements (fixed price versus time-and-materials contracts) change the effect of reputation, certification, and language characteristics on the chances of winning outsourcing contracts. Using a comprehensive dataset from an online outsourcing marketplace, we model how buyers choose among bidding vendors, and how the effects of these variables change under different contract forms. Our results show that online reputation is an important predictor of success only for fixed-price contracts, but not significant for times-and-materials contracts. In other words, contract forms can potentially mitigate the typical Matthew Effect (“the rich get richer”) associated with online reputation systems. Contrary to popular belief, certifications do not increase the chances of winning regardless of the contract forms. Linguistic features of private communications from the vendor to the buyer also affect the chances of winning, and different dimensions have different effects when contract forms change. This study is one of the first to study the interaction between contract formats and different signals that vendors can reveal to buyers in the competitive bidding process, and is also one of the first to investigate how texts of private communications affect buyers’ contracting decisions.

This version: October 2010

¹ The authors thank the NET Institute for their support through the 2010 Summer Research Grant. All errors remain our own. Mingfeng Lin (contact author) can be reached at mingfeng@rhsmith.umd.edu; Siva Viswanathan, sviswana@rhsmith.umd.edu; Ritu Agarwal, ragarwal@rhsmith.umd.edu.
1. Introduction

Recent developments in Internet technologies have transformed many industries, and the market for labor, even offshore labor, is a vivid example (Autor, 2001). While previously only large businesses could outsource (or offshore) software development activities, online markets now allow small buyers as well as small software developers to engage in transactions and even build long-term relationships. The lower barriers to enter the market now allow projects of much smaller sizes to be effectively outsourced online. Meanwhile, despite the rapid growth of these markets that brings together atomistic buyers and sellers, the “virtual” and “small stake” nature of these markets exacerbates issues of information asymmetry and the likelihood of opportunistic behaviors. Our goal in this essay of the dissertation is to better understand the process through which buyers and sellers\(^2\) are matched in this marketplace, how different variables affect buyers' choice, and how these variables function differently under different contractual regimes.\(^3\)

Asymmetric information in labor markets can be shown through the ex-ante adverse selection problems, worker signaling, as well as ex-post shirking or moral hazard problems. When a market like this becomes virtualized, one great advantage is that buyers and sellers of labor can engage in transactions that are much smaller in scale, which would not have been economically justifiable otherwise. There is a much larger potential for gains from trade in the electronic marketplace. Meanwhile, all the information asymmetry described in the last paragraph still applies. In fact, buyers and sellers are faced with many additional issues when transacting online:

\(^2\) In this essay, “buyers,” “employers” and “clients” refer to individuals and companies who have software needs. “Sellers,” “vendors” and “developers” refer to programmers who work for the buyers. For consistency, we will mostly use “buyers” versus “sellers.”

\(^3\) As Section 3 will discuss in greater detail (page 6), we study two contract forms in this essay. Pay-for-deliverable (PFD) contracts are comparable to the “fixed-price” contracts in outsourcing literature. Pay-for-time (PFT) contracts are similar to the “Time-and-Materials” contracts, even though usually no materials are involved.
(1) Because some jobs are much smaller, buyers will have less incentive to conduct extensive screening prior to contracting; and if things don't work out, they will have less incentive to pursue recourse, seek arbitration, and enforce the contract. Opportunistic behavior could go unpunished and may even be encouraged.

(2) The “virtual” nature of the marketplace: buyers usually do not know the real identity behind the sellers’ online ID. And, because this is a global marketplace, buyers are unlikely to find those outside the United States.

To address these issues, almost all online labor markets (such as eLance, freelancer or oDesk) carry certain functions to improve transaction efficiencies, such as identity verification, escrow, arbitration, skill certifications, and reputation systems such as rating. Effectiveness of these systems in online labor markets, however, are often assumed rather than tested empirically. Systematic studies in this regard will be highly valuable for practitioners.

From a research point of view, there have been many academic studies on online reputation systems in websites such as eBay. Meanwhile, there have been many studies on contract formats, especially in the context of outsourcing. However, there has been little confluence between these two streams of literature. Our goal in this essay is to take a first step in that direction. We empirically examine how buyers' choice of vendors is associated with characteristics of the vendors at the time of their bids, including their reputation, certification and textual communications, and more importantly, how different contract forms change the effect of these variables.

One of the most popular research questions in the extant literature is how buyers decide which contract format to use, given that a buyer already knows which sellers to conduct business with. Much less is known about how buyers and sellers came into contact in the first place – the
process through which the buyer is matched with a seller. One possible reason is that such data is typically very hard to come by. Our study attempts to fulfill this gap in the literature by using a comprehensive dataset from an online outsourcing marketplace, where all transactions are archived and made available. We examine variables that affect buyers' choices of sellers, especially how the effects of these variables change under different contractual mechanisms – Fixed Price contracts and Time-and-Materials contracts. We focus on variables that are unique to the online environment for outsourcing. These variables include: (1) The reputation of the seller reflecting his or her prior experience with other trading partners; (2) Third-party certification; and (3) Content and sentiment of how the seller communicates with the buyer.

While the literature has documented the impact of variables (1) and (2), most studies use information about buyers and sellers who actually engaged in transactions, and very little is known about those who failed to obtain the contract in the first place. Moreover, there has been no study on how their effects change under different contract mechanisms.

The dataset from the online outsourcing market has some additional appealing features. Most important, it provides archived messages between buyers and sellers, including their initial contacts – when sellers respond to buyers’ requests for bids through an online message. Due to the limited information available to buyers at the time of their decisions, the message that sellers send to potential buyers can have important implications. Just like entrepreneurs who have to “pitch” their ideas to venture capitalists, what they write in this “first contact” can determine the outcome of their bids. To our knowledge, such information has never been studied in the literature, most likely due to a lack of data. Computerized linguistic analysis of these texts can yield interesting insights into how the transactional ties are actually formed.

To summarize, the main research questions that we address in the paper are:
(1) What variables affect a buyer's choice among potential sellers; and

(2) How do the effects of the following variables change under different contracting mechanisms?

(a) Reputation mechanism reflecting a vendors' past performance;

(b) Third-party certification that can potentially serve as a signal; and

(c) Content and sentiment of how vendors communicate with a potential buyer.

These variables (among others) are identified from a review of the literature on reputation systems, contracts, and outsourcing. Our working hypothesis is that, not only should these factors play a role in the buyer's decision process, but their effects should differ under different contractual arrangements because of the difference in risk sharing. While the choice of contract mechanisms is not new, its interaction effects with reputation systems, semantics and certifications are much less investigated.

The rest of the paper is organized as follows. Section 2 situates our study in the broader literature in labor, contracts, outsourcing, reputation and certification. Section 3 describes the context of our study, followed by a discussion of the data collection and the variables used. Section 5 provides the empirical model and results. Implications of the study are in Section 6, and Section 7 discusses limitations and future studies related to this paper. Section 8 concludes the study.

2. Literature Review

This study is positioned at the intersection of reputation systems, certification, and contract formats, especially in the context of outsourcing. In this section, we make no attempt to
be exhaustive in the review of such enormous literature; rather, we shall focus on studies that most directly relate to the current study.

Outsourcing has attracted significant interest in many disciplines, including economics and information systems (Koh, Soon, & Straub, 2004; Levina & Ross, 2003; Tanriverdi, Konana, & Ling, 2007). Two most popular forms of contracting are Fixed Price (FP) Contracts and Time-and-Materials (TM) Contracts. Fixed Price contracts specify a fixed price for an outsourcing project, and the vendor will be paid the agreed amount upon satisfactory delivery of projects. The risk is on the vendors: if they underestimate the cost of development, they cannot charge a higher price later. Time-and-Materials contract, on the other hand, is more flexible and shifts the risk to the buyer. Sellers are paid by time and the cost incurred, instead of the pre-specified amount.\(^4\)

The distinction between Fixed Price and Time-and-Materials contracts has been subject to many theoretical and empirical studies. Gopal, Sivaramakrishnan et al. (2003) investigated the determinants of contract choice, and further relate the choice to project outcomes using data from vendors located in India. Hasija, Pinker and Shumsky (2008) employed data from an outsourcing vendor to investigate the effect of different combinations of contract features. Through content analyses of actual contracts, Chen and Bharadwaj (2009) found that contract format has a moderating effect on the relationship between contract provisions and transactional characteristics. The stylized models of Dey, Fan and Zhang (2010) suggested that Fixed-Price contracts are better for simple outsourcing projects, while Time-and-Materials contracts are better suited for complex ones. These results are echoed in Bajari and Tadelis (2001). These results indicate that in our model of seller selection, project complexity should be accounted for.

\(^4\) We will use the term “pay-for-deliverables contracts” (PFD) interchangeably with “fixed price contracts.” Pay-for-time (PFT) contracts are also equivalent to time-and-materials contracts.
A number of studies have also been conducted on the control and enforcement issues in outsourcing. For instance, Kirsch (1997) proposed that a portfolio of control modes could be adapted to outsourcing. Rustagi, King and Kirsch (2008) studied variables that lead to the use of formal controls. Meanwhile, one of the classical issues in outsourcing is the hold-up problem, where the party that makes buyer-specific investments will be at a disadvantage during negotiations. Susarla, Subramanyam and Karhade (2010) studied IT outsourcing service contracts and found that contract extensiveness could mitigate the hold-up problem, but this is moderated by the complexity of tasks.

Reputation is another important subject widely studied in outsourcing. Vendor (seller) reputation has been linked to contractual performance (Banerjee & Duflo, 2000; Lewis, 1986), since the concern for reputation can potentially “outweigh the temptation to renege on a given contract” (Tykvová, 2007). Jensen and Roy (2008) modeled the choice a trading partner as a two-stage process, in which reputation helps to decide among a bracket of alternatives.

While the issue of reputation systems in electronic commerce have been extensively studied in the context of product exchanges (such as those on eBay), there has been relatively little empirical study of reputation in the outsourcing context. One possible reason is that firms rarely share their outsourcing experience with others, and there is also no central platform for them to do so even if they wish to. By contrast, online outsourcing markets often extensively use such reputation systems to document sellers’ performances. They thus provide an ideal context to study the use of reputation systems in the choice process of buyers in outsourcing.

One of our hypotheses is that sellers’ reputation should have a much smaller effect on the choice of buyers under Time-and-Materials contracts. A typical issue in the traditional Time-and-Materials contract is that the effort level of sellers cannot be easily monitored or verified.
This restriction has been significantly changed in the online outsourcing marketplace because of new technologies that allow buyers to effectively monitor the effort level of sellers. As buyers need to approve the billing hours submitted by sellers, they can accurately evaluate sellers’ efforts if necessary. This makes it possible for them to cautiously take some risks and conduct business with sellers who have lesser experience on the marketplace, but are able to complete the task at lower costs. If they do turn out to be of low quality, the buyers will be able to terminate the contract, instead of having to wait until the deadline under a fixed-price contract, thereby reducing the loss.

Another topic that has received significant attention is the role of certifications, especially those from third-parties. One such study in the context of outsourcing is Gopal and Gao (2009), who studied the effect of ISO certification on outsourcing vendors. Similar to ISO certifications, the online outsourcing marketplace where we gathered the data provides links to a third-party certification website that tests the sellers’ skills on different subjects. When sellers pass these exams, an icon will be displayed next to their ID and prominently displayed to buyers when the seller places a bid. However, it should be noted that the threshold of such certification in this market is relatively low: Exams are available online, and sellers can take exams multiple times until they pass. Hence, the effect of such certification may not be practically significant, especially under pay-for-time contracts – as buyers can try out the sellers without paying for everything.

We further explore the role of textual communications in the buyers’ decision processes of choosing a seller – again, focusing on their differing effects under different contract mechanisms. The online market is able to archive all such communications. A study of the language used can be especially valuable to buyers who consider outsourcing. Much like
entrepreneurs “pitching” their ideas at venture capitalists, these vendors only have a limited opportunity to convince a potential buyer. Moreover, since buyers have different priorities when deciding between PFT versus PFD contracts, it is very likely that some language features are important for pay-for-time contracts, while others are more important for pay-for-deliverable contracts. We use a computerized linguistic analysis program to detect features of the vendors' communications, and incorporate resulting variables in the econometrical analyses.

Figure 1 illustrates the conceptual model for the current study.

![Conceptual Model Diagram]

3. Context

In this section, we describe major features of the online labor outsourcing marketplace that provided the data for our analyses, the introduction of a new contracting mechanism, the construction of matched samples for analyses, and the derivation of various variables used in our statistical models.

Data for this study are provided by one of the leading online software outsourcing marketplaces. This marketplace is headquartered in the United States, but buyers and sellers of the market come from all over the world. The largest proportion of work done on this site is customized software development, although more recently there has also been a growing need
for graphic design and other tasks. Software development programs include designing a website, 
enhancing e-commerce website features, file format conversions, and so on. Some examples of 
typical requests posted on the website are⁵:

“**We need to integrate our website with Google Checkout ... If client selects "credit card"**
as the payment method, he arrives to a custom payment page where he can enter credit card 
information. This card information is sent to bank processor, if approved, then a receipt page is 
displayed and order data is updated. If ......”

“**Small site design needs to be re-coded/optimized for newer standards. Requirements:**
1. Convert to XHTML 1.0 strict; 2. Convert all of site design to use CSS; 3. MUST be W3C 
validated...”

“I need a PHP script that will read every SQLite database in a directory. These 
databases all have the same schema. Insert their entries into a MySQL table with a similar 
schema, plus a column for file names.”

3.1 Overview

This proprietary dataset contains extensive information about software buyers, sellers, their 
transactions, communications, mutual ratings and other information from October 2001 to 
October 2010 (as we will discuss shortly, our analyses will not use the full sample). This is a 
marketplace of over 250,000 software developers (sellers) and more than 120,000 software 
buyers from around the world. These are typically small software development projects, mostly 
ranging between $150 and $300. Prior to September 2009, all projects are “fixed-price contracts”:

---

⁵ Due to non-disclosure agreements, these descriptions have been slightly changed to protect the privacy of website 
users.
Sellers are paid when they deliver satisfactory products according to buyer requirements. If the sellers underestimate the time and cost involved, they will have to bear the extra cost.

3.2 A Typical Process of Transaction

This section describes the typical process of transaction on this market.

Buyers and sellers first sign up with an email address. Before they enter any contracts, the website will verify their identity. For instance, US buyers are verified by phone, credit card, and driver’s license information. Once the verification is complete, buyers post “request-for-bids” on the site. A typical request includes a title, a summary of requirements, and a rough budget (e.g., maximum $500). Buyers also determine the form of the contract (PFT or PFD).

Software developers (sellers) can browse the requests, search for keywords, and they can be notified of new projects should they choose to receive such alert emails from the site. When they find a project of interest, they can post a bid, which is the amount they will charge for the delivered product. Along with the bid, they can (optionally) submit a text message trying to convince the buyer that they are a good candidate. This is very similar to the “pitch” that entrepreneurs make to venture capitalists when they seek funding. It should be noted that these are sealed bid auctions, in the sense that only the buyer can see the bids placed; peer sellers cannot observe each other’s bids.

Buyers can communicate with the sellers, and then choose a seller to work with by accepting his or her bid. Buyers can choose any bid he or she wants, and lower price bids do not necessarily win. This is an important feature of the online labor market that distinguishes itself from websites such as eBay.
Once the bid is accepted, the buyer will first pay the amount of the bid by credit card or electronic check into an escrow account of the site. Then, the site sends a notification to the seller that they can start working on the project. A contract is thus created.

The buyer and seller communicate with each other through the website to clarify requirements and other details. When the seller finishes the project, he or she uploads programs to the site, and the buyer can download it to test whether the requirements are met. If so, buyers accept the project as 100% complete, and the funds are released from the escrow account to the seller. Buyers and sellers can then rate each other on a scale of 1 to 10, and also provide comments on each other. These ratings become public information on their profiles, and form the “reputation” system on the marketplace.

The website deducts a percentage of fees from the escrowed amount when it is released to the vendor. These fees are not only for the provision of an infrastructure and possible arbitrations (see next paragraph), but also for taking care of paperwork related to taxes and other issues involved in paying another person, especially those in a foreign country.

If the project is not completed due to any reason, it typically enters arbitration. The arbitrator is a staff member of the site and the arbitration process can be initiated by either the buyer or the seller. The arbitrator will review all communications on site, including the original requirements, and will contact both parties. Offline communications, if any, are not considered in the process. If either party fails to respond, he or she receives a low rating, and loses.

3.3 Emergence of Pay-for-Time Micro Contracts

Up until September of 2009, all projects in this online software outsourcing marketplace are “pay-by-deliverables”; that is, the buyer and seller agree on the requirements of the project at
the beginning, and the cost of the project is fixed. This is comparable to the “fixed price” contracts in outsourcing, where the buyer’s obligation is limited a priori and the burden of risks falls on the vendors. Since September 2009, the website started to allow buyers and sellers to enter “pay-for-time” contracts. In this arrangement, sellers are merely paid by the number of hours they work on the project without guaranteeing the outcome, and the buyer can terminate the contract at any time. If mutually agreed, the contract can extend at the agreed hourly rate. This is made possible only because the website created an application to allow the buyers to closely monitor the efforts of the sellers. When the sellers start working on a pay-for-time project, they will log into the monitoring software, which will take screenshots, random keystrokes as well as webcam pictures at given intervals. The buyers can also manually take additional pictures or keystroke recordings as required by the contract. These records are kept for the purpose of arbitration; if the buyer believes that the seller has inflated the number of hours, the arbitrator can use these recordings as evidence.

This change in technology provides an interesting context for us to study how different contract formats change the effect of various seller signals (reputation, certification and communication) on winning a contract.

### 3.4 Reputation Systems

Much like eBay, the website has developed extensive reputation systems for the sellers so as to assist buyer's choice among candidates. When buyers and sellers first sign up, they have no ratings. When a project is completely successfully, buyers and sellers can rate each other. The rating has a numeric part that ranges from 1 to 10 stars, as well as a textual part that they can comment on the rating. Information about number of ratings that the seller has received up to the
time of the bids, as well as the average of those ratings, are displayed prominently to future buyers when they look at the list of sellers who placed bids.

3.5 Certifications

The website also works with a third party provider who allows sellers to take exams online on different subjects. Sellers need to pay about $50 US to take an exam. If they fail an exam, they can wait a few days before another attempt. After they pass an exam, the website will display an “Expert” icon next to their bids. It should be noted that the icon itself does not describe the subject of the exams taken, just merely the fact that the seller has taken at least one exam. Buyers need to click through the icon and find out the subject of the exams.

4. Sample Construction

To understand the factors affecting buyers’ choices of vendors and rule out alternative explanations, we constructed two samples of auctions that consummated in actual contracts (i.e., buyers matched to a seller). We then extracted all bids placed in those auctions, information about buyers and sellers as of the time of the contract, as well as project descriptions and communications. The next paragraph describes additional details about how these two samples are constructed. We will test whether effects of various variables on a bidder’s success change under different contract regimes using these samples, both jointly and separately.

Sample #1: Pay-for-time (PFT) contracts (cf. time-and-materials contracts)

Although PFT is a promising new mechanism, it has not yet gained traction in this online marketplace. One year after PFT contracts are allowed, there were still less than 200 such
contracts. To allow for meaningful statistical analysis, we try to retain as many PFT contracts as reasonably possible.

We first removed PFT requests that did not result in an actual contract. While we have data on bid requests (auctions) that do not have any winning bids at all, we decided to exclude them because a contract failing to consummate may be due to unrealistic requirements of the buyers, instead of any characteristics of the vendors. Focusing on contracts that were actually created eliminates confounding factors from the buyer's side.

Less than 1% of the PFT contracts are between buyer-seller pairs who had prior relationships. We removed these observations as buyers are faced with much lower levels of uncertainty in those cases; this is also to ensure consistency with sample #2.

Sample #2: Pay-for-deliverable contracts (fixed-price contracts)

Pay-for-deliverable contracts are the original format used on the website, and it is also what most users are accustomed with. Hence, even after pay-for-time contracts are made available; many users (buyers and vendors) continue to use pay-for-deliverable contracts. This is especially true among buyer-vendor pairs that already have repeated transactions. Almost all pay-for-time contracts (one year after the implementation of the new method) are between buyer-seller dyads that do not have prior transactions. Hence, for Sample #2 (PFT contracts), we also removed the contracts between parties with prior experience. This ensures that buyers in these two samples face comparable degrees of uncertainty when they choose among the vendors.

We then retained only PFD contracts in the three months prior to the introduction of PFT contracts (June - August 2009). This was to ensure that vendors did not face resource constraints and had to choose between PFD and PFT auctions posted at the same period of time.
Then, we took a random sample of PFD between June and August 2009 so that there was approximately the same number of contracts in Sample #2 as in Sample #1.

Once both samples were constructed, we extracted all bids related to those auctions, all comments posted by the vendors in their “first contact” with the potential buyer, information about the vendors at the time of their bids, and requirement documentations related to these projects. The textual comments were then submitted to two programs for textual analyses. The first one was GNU Aspell, which contains a dictionary of English words. We compared each word contained in the vendors' emails, and counted the number of typos contained therein: it is possible that more typos may reflect difficulty of communication, which could affect the chances that the bids are accepted. The second one is LIWC (Linguistic Inquiry and Word Count), a specialized program for computational linguistic analyses that generate variables characterizing the texts on a large number of dimensions. These and other variables are explained in greater details in the next section.

4.1 Level of Analysis and Dependent Variable

The level of analysis in our model is each bid; we study how characteristics of sellers’ (reputations; certifications) and their comments are associated with the outcome of their bids. The dependent variable is a dichotomous variable that takes on a value of 1 when a bid wins the buyer’s contract; 0 otherwise.

4.2 Independent variables:

6 http://aspell.net/
(1) *ExpertCertification*: Indicates whether or not there is an “Expert Certification” icon next to the sellers’ bids. As described earlier, these icons do not directly indicate whether the exams that the seller has taken were on a subject relevant to the current project. Nevertheless, the icon does increase the visibility of a seller, and could potentially create an advantage for them. On the other hand, the cost of obtaining the signal is relatively low, which casts doubts on its signaling value. Whether or not this is a useful signal is an empirical question. In a robustness test, we also included the number of tests that the seller has taken up to the time that the bid was placed.

(2) *noRating*: An indicator variable that the seller has not yet received any ratings.

(3) *AvgRating*: The mean of ratings that the seller has received up to the time that the bid was placed.

(4) *logRatingsCount*: Logarithm of the number of ratings that the seller has received up to the time of the bid.

(5) *BuyerSellerSameCountry*: An indicator variable that the buyer and seller are residents of the same country. The literature typically suggests that buyers and sellers in the same country are more likely to interact with each other (Hillberry & Hummels, 2003), either due to homophily (Reagans, 2005) or lower transaction costs (Redding & Sturm, 2008). This is, in fact, closely related to the “home bias” concept that we studied in the second essay of this dissertation.

(6) *BuyerSellerBothUS*: An indicator that both parties are from the United States.

(7) *logSellerMonth*: Logarithm of the number of months that the seller has signed up on this market.

(8) *logExpertiseLength*: Each seller has a “resume” page where they can post their resumes or further describe their experiences and expertise (which are not verified by the site). This variable captures the length of the document.
(9) \textit{logBidAmount}: Logarithm of the dollar amount of the bid.

(10) \textit{logBidOrder}: Logarithm of the order in which the bid was placed. A larger number suggests that the bid was placed later. Since the bids are displayed in the order they are received by default, earlier bids are more likely to be noticed and accepted.

(11) \textit{noCommentBid}: An indicator variable that the bid does not come with a message.

(12) \textit{noTypo}: An indicator variable that there is no typo in the first message from the seller to the buyer.

(13) \textit{ProjectAmtRange}: controls for the size of projects, we first calculated the final project cost that the buyer actually paid for each project in the sample. For pay-for-time contracts, this is the hourly rating that the seller bid, multiplied by the estimated number of hours. This amount is then “binned” into different intervals: 1 if it's lower than $100, 2 if it's between $100 and $200, 3 if between $200 and $300, 4 if between $300 and $400, and 5 for $400 and above.\footnote{These are then included in the estimation as a series of dummies in a saturated model specification.}

(14) Variables of linguistic features. We use LIWC 2007 to parse bid comments that accompany the bids placed by sellers. LIWC is a computational text analysis program developed by psychologists James W. Pennebaker and his colleagues. LIWC takes the text files as input, and produces numerical characterization of the file by categorizing words and phrases into approximately 80 output variables. These include “4 general descriptor categories” such as word count, and number of words longer than six letters; “22 standard linguistic dimensions,” which include percentage of words that are nouns, auxiliary verbs, adverbs and so on; “32 word categories tapping psychological constructs” such as affect and cognition; “7 personal concern

\footnote{The examples of projects on page 10 cover different ranges of the project costs.}
categories” such as home, leisure, work; and 3 “paralinguistic dimensions” such as fillers (“um”, “you know”); as well as 12 punctuation categories.

This study is one of the first attempts to apply such analysis to vendors’ private communications with the buyers in an outsourcing process. We focused on the following variables because the other variables either cannot be theoretically justified in this context, or they occurred very rarely in the sample (such as those representing biological processes). In addition to the count of each category of words, we also normalized them using the total number of words in each message. This yielded highly consistent results.

(a) “We” words including “we,” “our,” “us” and so on. “We” could refer to the seller themselves, in which case this variable indicated that the seller was a group of developers. Alternatively, it can be used to address the buyer as well (“We can start working soon”). An examination of the sample of bid comments indicated that the previous use is much more frequent. But in either case, the use of “we” can indicate either the resources of the seller, or as a subjective way of reducing the psychological distance from the buyer, which has been documented in the theory of social identities (Bagozzi & Dholakia, 2006; Hardy, Lawrence, & Grant, 2005; Kilker, 1999). This has been further documented in the context of outsourcing as well (Levina, 2006). Either rationally or emotionally, this category of words can potentially affect buyers’ choice.

(b) Words with more than 6 letters. Long words (which are often jargon as well) can increase the difficulty of communication, and hence likely to reduce the chances of winning.

(c) Auxiliary verbs such as “will, am, have.”

(d) Adverbs such as “quickly” “shortly” and “satisfactorily.”
(e) “Time” words such as “time,” “end,” “until.” While time should be an important factor for both contract forms, it has as higher priority in Pay-for-Time contracts than in Pay-for-Deliverable contracts. Hence, the frequency of these words should have a higher impact on chances of winning in PFT than in PFD contracts.

(f) “Money” words such as “owe” and “cash.” Note that the bid amount itself is not included in this analysis. Hence, “money” words refer to the discussion of budget-related issues in the body of the text. Again, even though the budget should be important for both PFT and PFD contracts, it is of higher priority in PFD contracts compared to PFT ones. Therefore, the frequency of “Money” words should have a higher impact on the bids’ odds of winning in PFD (fixed price) contracts.

(15) One other linguistic variable that we are interested in is the prevalence of typos in the comment submitted by vendors. It is possible that too many typos make it difficult to communicate; therefore, a higher number of typos can make a seller less attractive. Meanwhile it is equally likely that buyers can be tolerant of these typos in search of a good deal. We use open-source software GNU Aspell to achieve this by submitting these text files (via Perl scripts) to an English dictionary\(^8\) associated with GNU Aspell, and compared each word against the dictionary. The number of typos was recorded for each comment associated with bids. We used logarithm of this number in the statistical model to reduce dispersion. We further calculated the percentage of typos (i.e., normalized by the total number of words in the text) as a candidate variable.

5. Model

---

\(^8\) Copyright Kevin Atkinson, [http://wordlist.sourceforge.net/](http://wordlist.sourceforge.net/)
The main goal of this study is to understand how buyers' choice criteria of potential sellers change under different contract mechanisms. The dataset used in this study has some very appealing features that suit this purpose very well. First, since we focused on buyers and sellers who do not have prior relationships, all information that led to a buyer's decision is captured in the data. Unobserved factors that may have contributed to these choices are minimized, and can be considered orthogonal to our variables of interest. This is consistent with the identification strategy in Angrist (1998). Second, whereas most prior studies only have information about sellers that were ultimately chosen, we have information about others who are rejected by the buyer. Such information sheds light on how buyers made their decisions. Third, this website uses a sealed auction format; only the buyers see who the bidders are, and how much the bid amount is. This ensures that the bids among sellers are largely independent of each other, allowing for proper statistical modeling.

Given these features, we used maximum likelihood estimation of logistic models to estimate the probability that the buyer accepts a bid. Independent variables are virtually all the information that buyers had access to when they decide whom to contract. Although all bids placed in these auctions are independent of each other, we estimated the standard errors using clustered sandwich estimators to allow for intragroup correlation, where a cluster is specified to be an auction (a request for bid).

5.1 Main model of buyers’ choice: Full sample analysis

Our main working hypothesis is that the effect of reputation, certification, and linguistic variables change when contract forms change. Hence, we incorporated in the logistic regression a dummy variable indicating a Pay-for-Time contract, which was then interacted with other
variables of interest. For the overall sample – which includes bids from bidders who have no ratings, no expert certifications, or bids that were placed without textual comments – we estimated the following model:

$$\text{Prob}(\text{BidWins} = 1 | x) = \beta_0 + \beta_1 \text{noRating} + \beta_2 \text{PFT} \times \text{noRating}$$

$$+ \beta_3 \text{ExpertCertified} + \beta_4 \text{PFT} \times \text{ExpertCertified}$$

$$+ \beta_5 \text{noBidComment} + \beta_6 \text{BuyerCoderSameCountry}$$

$$+ \beta_7 \log \text{BidAmount} + \beta_8 \log \text{BidOrder}$$

$$+ \beta_9 \log \text{CoderMonths} + \beta_{10} \log \text{ExpertiseLength}$$

$$+ \beta_{11} \text{PFT} + \epsilon$$

In other words, we multiplied the PFT dummy with dichotomous variables that indicated no rating bids, no comment bids, and no certification bids – respectively. Results of this model are shown in Table 1. We can see that PFT itself is statistically significant, suggesting that the intercept term for the PFT and PFD are different. Its interaction with the no-rating dummy is also significant; the other two interactions are however not. It appears that ratings play a different role under different contract forms, but certification and comment dummies are less clear.

To delve deeper into the differences across these contract forms, we then excluded interaction terms and estimate the model separately on the PFT contract subsample (Sample #1), and the PFD contract subsample (#2). Unreported results show highly consistent patterns with Table 1: dummy variables indicating whether or not there is no comment, and whether or not there is no certification, are statistically insignificant for both subsamples. The dummy variable for no-Rating also shows a pattern consistent with our hypothesis: sellers (developers) with no ratings are significantly disadvantaged under Pay-for-Deliverables (or fixed-price) contracts, but only marginally significant for PFT contracts. In addition, the magnitude of the effect is also stronger for PFD contracts: placing a bid without a rating reduces the odds of winning by over 58%
in PFD (cf. Fixed Price) contracts, but by only about 30% in PFT (cf. Time and Materials) contracts.

Some auxiliary results are also interesting. We found evidence that on average, buyers prefer sellers who are from their same country, a phenomenon consistent with the “home bias” literature. The tendency to offshore is actually less than what mass media would have us believe: The odds that a same-country vendor is chosen are actually over 250% of that of someone in a foreign country. This pattern persists in many more specifications that we shall discuss, and is robust to the inclusion of variables such as the time zone difference and whether English is the official language. In addition, when we replaced this variable with a dummy that took the value of 1 when both buyer and seller are from the United States, the same result was obtained. In other words, under comparable degrees of uncertainty (first time interactions), US buyers also prefer domestic sellers rather than foreign ones.

Some auction variables are also significant predictors of bidding outcomes, and their results are largely to be expected: bids placed earlier are more likely to be successful, and higher amount of bids are less likely to be chosen.

Also in unreported analyses, we investigated the interaction effect between some other variables. For instance, even though the model above suggests that having no ratings is a bad signal, it is probably much worse if the seller has been on the market for a long time. The fact that a seller has been on the market for a long time but has obtained no contracts can indicate bad quality. Future buyers can simply “herd” and choose to ignore those sellers.

To test this effect, we included another interaction term between the indicator variable for “no rating,” and “number of months since vendor signed up.” While “no rating” is shown to be negatively associated with the chances of winning, it is significantly worse for sellers who are on
the market longer. In other words, between two sellers who are not rated, the ones who joined the site earlier are even less likely to win a contract. No-rating suggests that the seller has not been chosen by any other buyer so far. The longer they stay in that situation, the less attractive they become.

5.2 Modeling buyers’ choices: Volume and valence of ratings

The above analyses, however, only use dichotomous variables for comment and rating. This may be sufficient for Expert Certification (bids either have an “expert” icon next to it, or it does not), but it is certainly worth exploring the actual level of rating and the number of ratings. In addition, among the bids that do include textual messages, we further investigate how linguistic features of those messages affect the choice of buyers.

We first analyze the number of ratings as well as the average rating of sellers when they place bids. These variables are displayed prominently to buyers when bids are placed. We replaced the dummy variable of “no rating” with two new variables: (1) logarithm of the number of ratings that the seller has at the time of the bid; and (2) the average of ratings that the seller has received at the time of the bid. While results are consistent whether the analysis is done on both subsamples or sequentially, they are easier to interpret on subsamples. We therefore reported the results using subsamples instead of the overall sample with interaction terms (see Table 2). In addition, we excluded auctions that choose sellers who did not have ratings at the time of the request in this estimation.

From Table 2 we can see that variables examined previously display very consistent results: certification is insignificant, while bidding order and bid amount matters. On the other hand, ratings variables show some interesting patterns. For instance, while having a large number
of ratings in PFD (Fixed Price) contracts significantly increases the chances of securing the contract, the effect is statistically insignificant in PFT (cf. Time and Materials) contracts. Meanwhile, while the average rating has a positive and statistically effect on the chances of winning a contract under PFD arrangements, the effect is insignificant for PFT contracts as well. In fact, the magnitudes of these coefficients are also smaller in PFT contracts.

More specifically, the results above suggest that sellers who entered the market earlier, established good reputations and accumulated a long work history had a significant advantage when they competed in the market, especially under pay-for-deliverables (fixed price) contracts. This in turn gave them more opportunities to increase the volume of their ratings. The cumulative advantage for established sellers in the online market can be very significant, consistent with the predictions of Matthew Effects (Merton, 1968). This effect exists both for the volume of ratings that the seller has, as well as the valence of ratings. The more jobs you did in the past, and the better you did on those jobs, the more likely you are going to get jobs in the future. While this is not entirely surprising, it does have a detrimental effect on the competitiveness of the market. New entrants will find it very difficult to compete with the incumbents. This can also be harmful for the development of the marketplace itself, as it competes with other online outsourcing platforms to attract new users.

Our results under Pay-for-Time contracts, by contrast, show that it is possible to mitigate the market’s tendency to polarize by implementing new contract forms. By redistributing the burden of risk between buyers and sellers, pay-for-time contracts allows buyers to “experiment” with sellers who are less experienced on the market, giving them a chance at the competition.

---

9 It should be noted, however, that a lack of experience on this market does not mean the developer him/herself lacks experience. They may simply be new to this marketplace, and it is difficult for these online markets to verify the validity of their resumes.
5.2 Modeling buyers’ choices: Textual contents of “first contact”

We now turn to the textual content of comments that accompany bids, and identify characteristics that are associated with better chances of winning under different contract formats. Textual content of such communications could play an important role as this is a virtual marketplace, and each seller has only a limited opportunity to compete for the contracts. What they place in their first communication to the buyer can affect their chances of winning due to the limited amount of information that a buyer has of the seller. To this end, we estimated the model on the subsample of auctions that do not choose a bid without comments. The goal of the analysis is to understand linguistic features that are important to the buyers when they are not simply choosing the lowest amount of bid.

The first variable that we examined is the number of typos. We studied two alternative metrics for typos: the total number of typos in the vendor's message, and the ratio of this number to the total number of words. While the odds ratios associated with these variables were indeed smaller than 1, they were not statistically significant in all specifications described earlier. It thus appears that buyers in this market seemed to be tolerant of typos; they either did not consider them a signal of communication difficulties, or fully anticipated them in this market.

The second set of variables is generated from LIWC (Linguistic Inquirer and Word Count), a computerized linguistic analysis program. The two main variables that we are interested in are “Time” and “Money” variables, as they represent two of the main dimensions that buyers consider when they choose a vendor. We find that “time” words are a statistically significant predictor of bid success only for pay-for-time contracts, but insignificant in pay-for-deliverable (fixed price) contracts. For PFT contracts, a larger number of “time” words are associated with higher chances of winning. “Money” words, on the other hand, are also
significant only for PFT contracts. By contrast, a larger number of “Money” words are associated with lower chances of winning.

These results suggest that buyers are looking for different contents in the sellers’ messages when screening transaction partners under different contracts, consistent with the risk that they are bearing. Under pay-for-time contracts, buyers will pay for the number of hours that the developer will be working. Therefore, a more detailed discussion of time will alleviate buyers’ concerns on that dimension, and can increase a seller’s chances of winning the contract. On the other hand, when the contract is “pay-for-deliverables,” buyers tend to be more concerned about the budget size, and “time” is only secondary. Hence, more discussions to justify the total budget will enhance the seller’s chance of winning.

A few other variables also show some noteworthy patterns. We found that the number of words with more than 6 letters is negatively associated with chances of winning, although the odds ratio is relatively small in scale. “We” words were not significant predictors in either PFT or PFD contracts. While this contrasts with the literature (Levina 2006), this result may simply reflect the nature of jobs being outsourced on this market, which are a lot smaller than the multimillion dollar projects reported in prior empirical studies. Many of these results are robust to specifications. For instance, removing Auxiliary verbs does not change the results, especially the other categories of words. Their effects seem to be orthogonal to each other.

6. Implications

Sociologists have long identified the Matthew Effects (Merton, 1968) in economic life: in a competitive environment, individuals, organizations and entities that were previously in an advantageous position can continue to enjoy their advantage. This is similar to the idea of
“preferential attachment” (Hills, Maouene, Maouene, Sheya, & Smith, 2009), or the phenomenon of “the rich grows richer, while the poor grows poorer.” Sociologists also refer to this as Cumulative Advantage (DiPrete, Eirich, Cook, & Massey, 2006). For electronic commerce websites, such tendency may not be ideal as it is likely to drive away new vendors, yet it is indeed happening: Consumers are more likely to buy from sellers with more ratings and higher ratings. Our data reveals an analogy in online outsourcing: Pay-for-deliverables contracts, a dominant form of contract on this marketplace, very much favors sellers (developers) with longer job history on the marketplace, and those with higher average ratings. The cumulative advantage inherent in these online rating systems has significant implications for market design, competition, and public policies as well, as it can easily lead to higher market concentrations over time, and limit the competitiveness of new entrants.

One implication of this study is that changing contractual forms, at least in the labor and outsourcing markets, can partially mitigate Matthew Effects. By redistributing the burden of risk between buyers and sellers, buyers will have an incentive to take some risks and hire less-known, less-experienced sellers under pay-for-time contracts. This is because they are allowed to stop the transactions if the sellers turn out to be of low-ability. More broadly speaking, electronic commerce websites concerned about expanding their customer base can consider incentive mechanisms to redistribute the risks between buyers and sellers.

The second implication from the findings discussed above is that certifications may not always be effective. It is possible that this is unique only to this website, and only to the particular types of certifications. However, given the popularity of third-party certifications in decentralized online markets such as eBay, the current study suggests that we should not take
certifications' effectiveness for granted. Although such certifications do provide an extra “icon,” they do not necessarily increase vendors' chances of obtaining contracts.

Last, but not least, our analyses show some interesting potentials for computerized text analysis. Textual analysis is still an emerging field. Our analyses show that buyers do appear to take into account what was written by the vendors, and their considerations change under different contract regimes. For platforms such as online outsourcing markets, implementing automatic text analyses programs can potentially help buyers increase the efficiency of screening vendors, especially as when we are able to link textual cues to project outcomes. This will be addressed in a separate paper.

7. Limitations and Future Research

Software projects in our context are on a much smaller scale compared to typical outsourcing contracts, and this could constrain the generalizability of our findings. Indeed, many outsourcing contracts that we read about in the mass media involved millions of dollars over multiple years. By contrast, the contracts in this marketplace are much smaller. Therefore, readers have to take these findings with a grain of salt when they apply them to larger contracts. Replicating our analyses on datasets of larger vendors and clients will be certainly highly desirable, especially if we are also able to obtain information about reputation, certifications, and communications between vendors and their clients, including vendors who are unsuccessful in their bids for contracts.

Our primary goal in this paper is not about the choice of contract formats. By constructing two non-overlapping subsamples of different contractual forms, we sought to understand how contract forms moderate the relationship between a vendor's reputation and their
chance of winning a contract. A natural extension of this analysis is certainly to go beyond dyads of first-time interactions and better understand the endogenous choice of contractual forms in this context, especially between buyers and sellers who have repeated interactions. As described in the paper, the proportion of buyer-seller pairs that switched from pay-for-deliverables to pay-for-time contracts is very small. It is possible, however, that as users become more familiar with this new arrangement, we will observe more “switching” of contract forms. At that time, we will be able to extend the analyses in this paper to model the contract choice endogenously.

A second extension of the current study will be incorporating some metrics for the outcome of projects. We addressed the outcome metrics of projects in a separate paper.

Our analysis of the textual comments is one of the first efforts to study the effect of written language on buyer choice of vendors. Though there are much more advanced text mining techniques available, LIWC has been broadly used in psychology and management, and it yields similar results to other packages such as General Inquirer (Tetlock, Saar-Tsechansky, & Macskassy, 2008). Yet another valid critique of our analysis is comparable to the “Lucas Critiques” in economics: when vendors realize how buyers respond to their wordings in the communications, they may accordingly change how they write in the future, which can potentially change how buyers screen vendors. These are certainly interesting dynamic interactions that can be explored in future research. However, it does not affect the validity of the current research; these communications are private between buyers and vendors. These communications are only obtained under a non-disclosure agreement, and neither this website nor its competitors has done analyses like this before. And, at least in the time frame that we studied, no such results were revealed to vendors.
8. Conclusions

The advancement of information technologies, especially Internet technologies, promises to change the landscape of labor markets forever (Autor, 2001). How buyers and sellers (workers) are matched, how services are delivered, and how efforts are monitored, all these dimensions that economists have long studied, will be dramatically different in the online market. The monitoring technologies used on the website that we described here is but one such development. All these changes create an abundance of new research arenas. For instance, while researchers have extensively investigated contract forms as well as online reputation systems, these two literatures rarely cross paths. The unique dataset used in the current study allows me to investigate whether and how the effect of reputation systems, certifications, and text features change under different contract regimes. Given the popularity of reputation, certification and abundance of text in electronic markets, the findings here have much wider implications beyond this website itself.
Table 1: Full model with interactions

Dependent variable is whether a bid was successfully chosen by the buyer. Modeled with a logistic regression, with standard errors estimated using clustered sandwich estimators to allow for intra-auction correlation. Odds ratio (exponentiated coefficients) reported as they are easier to interpret for binary variables; standard errors in parentheses. An odds ratio greater than 1 suggests that a higher value of the explanatory variable is positively associated with the probability of winning. Dummies for project amount range suppressed for brevity. * p<0.1; ** p<0.05; *** p<0.001

<table>
<thead>
<tr>
<th>Variable</th>
<th>Odds Ratio</th>
</tr>
</thead>
<tbody>
<tr>
<td>ExpertCertified</td>
<td>1.195</td>
</tr>
<tr>
<td></td>
<td>(0.768)</td>
</tr>
<tr>
<td>noRating</td>
<td>0.339***</td>
</tr>
<tr>
<td></td>
<td>(0.093)</td>
</tr>
<tr>
<td>noCommentBid</td>
<td>0.899</td>
</tr>
<tr>
<td></td>
<td>(0.250)</td>
</tr>
<tr>
<td>BuyerSellerSameCountry</td>
<td>2.036***</td>
</tr>
<tr>
<td></td>
<td>(0.391)</td>
</tr>
<tr>
<td>logBidAmount</td>
<td>0.636***</td>
</tr>
<tr>
<td></td>
<td>(0.038)</td>
</tr>
<tr>
<td>logBidOrder</td>
<td>0.628***</td>
</tr>
<tr>
<td></td>
<td>(0.029)</td>
</tr>
<tr>
<td>logSellerMonths</td>
<td>1.592***</td>
</tr>
<tr>
<td></td>
<td>(0.132)</td>
</tr>
<tr>
<td>logExpertiseLength</td>
<td>1.038</td>
</tr>
<tr>
<td></td>
<td>(0.043)</td>
</tr>
<tr>
<td>PFT</td>
<td>2.846***</td>
</tr>
<tr>
<td></td>
<td>(0.363)</td>
</tr>
<tr>
<td>PFT*Expert</td>
<td>1.025</td>
</tr>
<tr>
<td></td>
<td>(0.683)</td>
</tr>
<tr>
<td>PFT*Rating</td>
<td>2.380***</td>
</tr>
<tr>
<td></td>
<td>(0.793)</td>
</tr>
<tr>
<td>Intercept</td>
<td>0.116***</td>
</tr>
<tr>
<td></td>
<td>(0.049)</td>
</tr>
</tbody>
</table>

N (number of bids) 5670
Table 2: Effect of Ratings on PFD and PFT samples

Dependent variable is whether a bid was successfully chosen by the buyer. Modeled with a logistic regression, with standard errors estimated using clustered sandwich estimators to allow for intra-auction correlation. Odds ratio (exponentiated coefficients) reported as they are easier to interpret for binary variables; standard errors in parentheses. An odds ratio greater than 1 suggests that a higher value of the explanatory variable is positively associated with the probability of winning. Dummies for project amount range suppressed for brevity. * p<0.1; ** p<0.05; *** p<0.001

<table>
<thead>
<tr>
<th>Variable</th>
<th>Odds Ratio under Pay-for-Delivery Contracts</th>
<th>Odds Ratio under Pay-for-Time Contracts</th>
</tr>
</thead>
<tbody>
<tr>
<td>ExpertCertified</td>
<td>1.017</td>
<td>1.170</td>
</tr>
<tr>
<td>logRatingsCount</td>
<td>1.229***</td>
<td>1.094</td>
</tr>
<tr>
<td>AvgRating</td>
<td>1.255*</td>
<td>1.166</td>
</tr>
<tr>
<td>BuyerSellerSameCountry</td>
<td>1.395</td>
<td>3.378***</td>
</tr>
<tr>
<td>logBidAmount</td>
<td>0.665***</td>
<td>0.553***</td>
</tr>
<tr>
<td>logBidOrder</td>
<td>0.725***</td>
<td>0.553***</td>
</tr>
<tr>
<td>logSellerMonths</td>
<td>1.616**</td>
<td>1.354**</td>
</tr>
<tr>
<td>logExpertiseLength</td>
<td>1.093</td>
<td>0.975</td>
</tr>
<tr>
<td>Intercept</td>
<td>0.004***</td>
<td>0.400</td>
</tr>
</tbody>
</table>

N (number of bids) 2607 974
Table 3: Effect of Communication under Pay-for-Deliverable vs. Pay-for-Time Contracts

Dependent variable is whether a bid was successfully chosen by the buyer. Modeled with a logistic regression, with standard errors estimated using clustered sandwich estimators to allow for intra-auction correlation. Odds ratio (exponentiated coefficients) reported as they are easier to interpret for binary variables; standard errors in parentheses. An odds ratio greater than 1 suggests that a higher value of the explanatory variable is positively associated with the probability of winning. Dummies for project amount range suppressed for brevity. * p<0.1; ** p<0.05; *** p<0.001

<table>
<thead>
<tr>
<th>Variables</th>
<th>Odds Ratio Under Pay-for-Deliverable Contracts</th>
<th>Odds Ratio Under Pay-for-Time Contracts</th>
</tr>
</thead>
<tbody>
<tr>
<td>ExpertCertified</td>
<td>0.988</td>
<td>1.300</td>
</tr>
<tr>
<td></td>
<td>(0.658)</td>
<td>(0.260)</td>
</tr>
<tr>
<td>noRating</td>
<td>0.450***</td>
<td>0.708</td>
</tr>
<tr>
<td></td>
<td>(0.126)</td>
<td>(0.161)</td>
</tr>
<tr>
<td>BuyerSellerSameCountry</td>
<td>1.861***</td>
<td>2.538***</td>
</tr>
<tr>
<td></td>
<td>(0.506)</td>
<td>(0.811)</td>
</tr>
<tr>
<td>logBidAmount</td>
<td>0.632***</td>
<td>0.591***</td>
</tr>
<tr>
<td></td>
<td>(0.063)</td>
<td>(0.062)</td>
</tr>
<tr>
<td>logBidOrder</td>
<td>0.707***</td>
<td>0.545***</td>
</tr>
<tr>
<td></td>
<td>(0.047)</td>
<td>(0.042)</td>
</tr>
<tr>
<td>logSellerMonths</td>
<td>2.152***</td>
<td>1.340***</td>
</tr>
<tr>
<td></td>
<td>(0.350)</td>
<td>(0.138)</td>
</tr>
<tr>
<td>logExpertiseLength</td>
<td>1.099*</td>
<td>1.033</td>
</tr>
<tr>
<td></td>
<td>(0.060)</td>
<td>(0.072)</td>
</tr>
<tr>
<td>Sixltr</td>
<td>0.969***</td>
<td>0.987</td>
</tr>
<tr>
<td></td>
<td>(0.011)</td>
<td>(0.012)</td>
</tr>
<tr>
<td>we</td>
<td>0.972</td>
<td>0.994</td>
</tr>
<tr>
<td></td>
<td>(0.027)</td>
<td>(0.039)</td>
</tr>
<tr>
<td>auxverb</td>
<td>0.959***</td>
<td>0.971</td>
</tr>
<tr>
<td></td>
<td>(0.014)</td>
<td>(0.021)</td>
</tr>
<tr>
<td>adverb</td>
<td>1.022</td>
<td>1.063**</td>
</tr>
<tr>
<td></td>
<td>(0.027)</td>
<td>(0.032)</td>
</tr>
<tr>
<td>time</td>
<td>0.981</td>
<td>1.049**</td>
</tr>
<tr>
<td></td>
<td>(0.017)</td>
<td>(0.020)</td>
</tr>
<tr>
<td>money</td>
<td>1.005</td>
<td>0.897**</td>
</tr>
<tr>
<td></td>
<td>(0.030)</td>
<td>(0.049)</td>
</tr>
<tr>
<td>noTypo</td>
<td>0.745</td>
<td>0.843</td>
</tr>
<tr>
<td></td>
<td>(0.190)</td>
<td>(0.230)</td>
</tr>
<tr>
<td>Intercept</td>
<td>0.080***</td>
<td>1.348</td>
</tr>
<tr>
<td></td>
<td>(0.062)</td>
<td>(0.965)</td>
</tr>
</tbody>
</table>

N (number of bids) 3653 1490
References


