Online Reverse Auctions for Outsourcing Small Software Projects: Determinants of Vendor Selection

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ABSTRACT

Online service marketplaces have enabled small firms to efficiently outsource small-scale IT projects by providing reduced transaction costs and increased competition among bidders. This paper presents an explanatory study that examines the vendor selection process using data from a large online service marketplace. Theories from production economics, resource dependency, and software risk management are applied in a small-firm context. The empirical results suggest that a client's utility function increases with a lower bid price, shorter lead-time, higher vendor average feedback rating, higher degree of vendor experience, and domestic (U.S.) location. There was not sufficient evidence to support strategically differentiated vendor selection behavior with respect to project value (or price). This study's findings help understand patterns of bid evaluation in online auctions, where a large percentage of transactions consist of small IT projects.

Keywords: *Electronic commerce, Online service marketplaces, IT outsourcing, Small projects, Vendor selection*

INTRODUCTION AND MOTIVATION

Recently, online reverse auctions have become a popular means when sourcing professional services through Internet marketplaces. By maximizing competition among bidders, reverse auctions in online marketplaces offer clients lower costs and improved profitability (Samuelson, 1986). Examples of such online service marketplaces include *ElanceOnline* (www.elance.com), *RentACoder* (www.rentacoder.com), *Guru* (www.guru.com), *eWork* (www.eworkmarkets.com), *German Contract Information Service* (www.dtad.de), *NeoIT* (www.neoit.com), and *Smarterwork* (www.smarterwork.com). The reduced transaction costs these marketplaces provide have enabled firms to efficiently outsource small-scale IT projects and other professional services, such as marketing and legal consulting. This study focuses on the small-size IT projects. In online service marketplaces, such a project is procured as follows: A client (i.e., buyer or auctioneer) posts a request for proposal (RFP) describing the project requirements, and service providers subsequently prepare a bid package describing their capabilities and bid prices. When the auction is complete, the client evaluates the received bids and selects a winner. The selected vendor provides the service as described, and the client pays the agreed-upon amount. The goal of this explanatory study is to identify and understand vendor selection determinants for small IT projects.

Application development, Web site and database design, script writing, and system administration are commonly contracted via online marketplaces. These projects share properties, such as highly standardized or commoditized configurations, which existing literature (Grover et al., 1996) suggests make them extremely attractive for outsourcing. Contract prices of IT projects transacted through online marketplaces are relatively low; the data used in this study shows an average $955.00 bid price. The high concentration of small IT projects is primarily due to the fact that the user group in these markets mainly consists of small businesses (Radkevitch et al. 2006). In general, these firms lack the resources for in-house software development and, consequently, outsource more to leverage the providers' economies of scale (Ang and Cummings, 1997; Ang and Straub, 1998; Carmel and Nicholson, 2005; Ono and Stango, 2005). High searching costs and entry barriers are the biggest challenge faced by small firms in the outsourcing process (Dean et al., 1998), but in online marketplaces, both costs are far lower (Radkevitch et al. 2006). These advantages in both production and transaction cost attract a critical mass of small firms to online marketplaces. Small firms' innovative entrepreneurship (Dean et al., 1998) also makes them favor the online sourcing method. Given the high population of small firms sourcing small projects, it is important to apply theories in the correct context to explain the vendor selection behavior, since the strategic management literature suggests that the study of small firms requires a different model than that applied to large firms (Dean et al., 1998). In this study, theories from the general software outsourcing literature are applied to build hypotheses and careful attention is paid to verify whether they are supported in this context.

Understanding the vendor selection process in online marketplaces is essential for a better market design. Selecting a vendor for IT involves a multi-attribute auction that enables negotiation on multiple attributes of a deal. The winner in this type of auction may not necessarily be the one who bids lowest, because the client's utility is determined by a combination of the bid price and non-price attributes. Prior analytical work on designing multi-attribute auction mechanisms assumes a certain function of the buyer's utility. Despite ample analytical work (Bichler, 2000; Bichler and Kalagnanam, 2005; Chen-Ritzo et al., 2005; Strecker and Seifert, 2004), the actual components of a buyer's utility function have not been investigated empirically in the online software outsourcing context. Identifying the vendor selection determinants also helps vendors prepare bid packages efficiently. This is now more important than ever, given the increased competitiveness and vendor participation in auctions. Empirical assessment of vendor selection behavior will fill the gap in the IS and multi-attribute auction literatures by revealing the buyer's utility function with a rich, real-world dataset.

Efficient market design for online service marketplaces is important to prevent a market failure, because the vendor selection process inherently entails severe information asymmetries. The highly intangible, highly customizable nature of IT products makes it difficult for clients to identify the cost structure or quality of vendors prior to the contract (Snir and Hitt, 2004). Severe information asymmetries may result in market failure, known as the "lemons problem" (Akerlof, 1970), where there is no credible signal for high quality products, resulting in aggressive sales of only low-quality products. Buyers naturally refrain from purchasing, and the market eventually collapses. Similarly, if online service marketplaces are not able to provide their clients with credible signals for high-quality vendors, market failure will be unavoidable. The continuous growth of these marketplaces indicates that they may have implemented credible signaling devices to mitigate severe information asymmetries. This study identifies currently implemented signal devices, such as feedback systems.

This study's theory basis is rooted in production economics, resource dependency, and software development risk management, and developed in a small firm context. The remainder of this article is organized as follows: First, the theoretical basis is presented and six major determinants of vendor selection are identified. Then, the data collected from an online service market is described. In the following sections, an explanation is given of how the discrete choice model is implemented and the test results are presented. Finally, the implications and conclusions are discussed.

THEORETICAL BASIS AND RESEARCH HYPOTHESES

Vendor selection is a decision making process that assesses the likelihood of successful and unsuccessful outcomes of an outsourcing project for a given vendor. A successful outcome is assessed in terms of the benefits achieved, which can be categorized into economic and technological benefits (Grover et al., 1996; Lee and Kim, 1999). An unsuccessful outcome can be predicted and assessed by examining the risks associated with a particular vendor (Barki et al., 1993). Therefore, we argue that vendor selection determinants are affected by the predicted benefits and risks associated with individual vendors. This rationale is also carefully verified from the perspective of small-firms economics.

Economic Benefits

Production economics views firms as profit-maximizing organizations trying to minimize production costs (Tirole, 1988; Williamson, 1981). This view suggests that firms choose outsourcing instead of internal production to seek production cost advantages provided by external IT vendors (Ang and Straub, 1998; Loh and Venkatraman, 1992). Such economic benefits, or production cost advantages, have been acknowledged as one of the primary benefits of outsourcing (Grover et al, 1996; Lacity and Hirschheim, 1993; Lee and Kim, 1999). Furthermore, the IT outsourcing and strategic management literatures suggest that small firms are financially motivated when they outsource IT functions because of the lack of financial slack that would allow them to invest in their internal information systems (IS) department or afford expensive vendors (Ang and Cummings, 1997; Ang and Straub, 1998; Dean et al., 1998; Loh and Venkatraman, 1992). Besides the challenges in production costs, small firms often face high coordination costs because they lack specialized human resources to prepare or monitor a contract (Carmel and Nicholson, 2005). Thus, small firms with these disadvantages will seriously consider a vendor who can provide cost advantages. Therefore, we posit cost advantages as a determinant of vendor selection.

There are two cost-related attributes that a client considers when evaluating bids in this type of marketplace: a service price to be paid to a vendor and time until the service is delivered. The price and lead-time are also considered as important attributes that determine costs in the physical-goods procurement literature (Chen-Ritzo et al., 2005), because clients' cost minimization is achieved through both a lower price and a shorter lead-time. The positive relationship of lower bid price and shorter lead-time is postulated as factors leading to winning a contract. Therefore, H1 and H2 are formulated to identify cost-related attributes:

*H1: **A lower bid price** is positively related to the probability of winning a contract.*

*H2: **A shorter lead-time** is positively related to the probability of winning a contract.*

Technological Benefits

Grover et al. (1996) define technological benefits as the ability of a firm to gain access to leading-edge IT from a vendor. Resource dependency theory suggests that a firm seeks external resources and capabilities that complement the firm's deficient resources in order to gain competitive advantages (Grant, 1991; Grover et al., 1996). Small firms typically lack technological resources because obtaining technological capabilities often requires economies of experience, i.e., learning from experience, and small firms cannot afford high costs related to learning (Carmel and Nicholson, 2005; Ono and Stango, 2005). Thus, small firms actively seek vendors' resources to access necessary technologies. In order to select a vendor who will provide such technological benefits, clients should first evaluate vendor quality. We refer to vendor quality in this paper as a vendor's technical and social skills accumulated through experience, as well as the ability to minimize conflicts.

However, intangible characteristics of IT projects and information asymmetry make it difficult to identify which vendor is capable of providing services of the desired quality level, prior to signing a contract. Furthermore, information asymmetry often motivates vendors to misrepresent their quality (Snir and Hitt, 2003; Tirole, 1998). Online auctions also increase the level of information asymmetry because many transactions on the Internet are likely to be one-shot relationships between strangers (Bolton et al., 2004), compared to traditional transactions, where sellers and buyers tend to establish long-term relationships. To overcome uncertainty augmented by the environment, many auction sites provide reputation mechanisms by which sellers' reputations are accumulated and become public (Ba and Pavlou, 2002; Pavlou and Gefen, 2004).

Among the reputation devices implemented in online service markets, there are two signaling tools for vendor quality: average feedback rating, and total number of feedback ratings. The average feedback rating systems have been acknowledged as an effective sanctioning tool against a vendor's moral hazard in online environments (Dellarocas, 2005; Pavlou and Gefen, 2004). This mechanism also establishes the client's trusting intention, despite a lack of interaction history with and incomplete information about the vendor, by visualizing vendors' average performance on their projects (Grover et al., 1996).

However, a client needs a tool to distinguish between two vendors with identical average rating, but different numbers of ratings. For example, the high average feedback rating of vendor *A*, who has completed only one or two projects, cannot be a reliable signal to decide between vendors *A* and *B,* when vendor *B* has similar or even slightly lower average rating but has completed hundreds of projects. Therefore, the average feedback rating system must be complemented by the vendor's accumulated history, which essentially indicates the vendor's experience level. The level of a vendor's accumulated experience can be represented by the total number of completed projects. Many online marketplaces currently publicize this information to aid clients' decision processes. Hypotheses to test the relationship of the quality-related attributes to the likelihood of winning an auction have been formulated as:

*H3: **A higher average feedback rating** is positively related to the probability of winning a contract.*

*H4: **A higher total number of feedback ratings** are positively related to the probability of winning a contract.*

Software Development Risks

Besides the successful outcome expected from a potential vendor, clients should consider risks, defined as the likelihood and magnitude of an unsuccessful outcome associated with a particular vendor. Outsourcing an IT project inherits risks and has a long history of high failure rates (Lacity and Hirschheim, 1993; Xia and Lee, 2005). Small firms do not have sufficient resources to bear such failures because the failure would have a significant impact on the firm's finances, given the lack of economies of scale (Carmel and Nicholson, 2005; Dean et al., 1998). The failure would also slow down the firm's reactions to competitors, which is the essential capability by which small firms gain competitive advantages (Carmel and Nicholson, 2005; Chen and Hambrick, 1995; Dean et al., 1998). Thus, small clients are highly motivated to minimize risks, and the vendor selection process involves identifying a vendor who demonstrates fewer risk factors. Clients would also pay special attention to vendor selection if the project being procured entails considerable risk factors. To draw hypotheses in a systematic manner, we adopt the software risk management literature's definition of risk as the magnitude of the potential loss times the probability of loss (Barki et al., 1993). Thus, we propose that vendor selection is affected by these two parameters as a proxy of potential risks: probability of loss and magnitude of loss.

First, probability of loss increases with the complexity of managing a project. To reduce risks, clients prefer a vendor with lower managerial complexity. Managerial complexity increases when there are high transaction (coordination) costs, which is the case in offshore outsourcing (Carmel and Nicholson, 2005; 19, Radkevitch et al., 2006; Walsham, 2001). Managerial complexity of offshore outsourcing originates from communication difficulties due to cultural differences and language abilities (Walsham, 2001), operational difficulties due to unreliable telecommunication infrastructure (Carmel and Nicholson, 2005), uncertainty in intellectual property and legal penalties (Carmel and Nicholson, 2005), coordination difficulties due to time-zone and geographical differences (Carmel, 1999), and a lack of domain knowledge of the offshore team (Krishna et al., 2004). Therefore, the managerial risks associated with offshore outsourcing have been formulated as the following hypothesis:

*H5: **The geographical distance** between vendor and client is negatively related to the probability of winning a contract.*

Second, the magnitude of a potential loss increases with project value, or project price as a proxy. Project value is determined by many factors: degree of technical complexity, difficulty in customization, project size, etc. Project size and technical complexity are two major sources of uncertainty and failure in an IT project (Barki et al, 1993; McFarlan, 1981; Zmud, 1980). If an expensive project fails, the subsequent loss becomes larger. Thus, a client with a higher-value project perceives a higher risk than those with a lower-value, standardized, commodity-like project. When the client perceives higher risk due to the nature of the project, he is more interested in determining a vendor who is likely to minimize that risk. Therefore, in the presence of higher risk, the client will weigh each determinant of vendor selection differently, in a way that minimizes the risks, even with a premium price. Thus, hypotheses to test the relationships of the risks stemming from the project value to the vendor's likelihood of winning the auction have been formulated as:

H6: ***Clients with higher value projects*** *will consider quality-related attributes more and price-related attributes less than clients with lower value projects.*
H7: ***Clients with higher value projects*** *will prefer US vendors over non-US vendors.*

EMPIRICAL MODEL

A discrete choice model has been implemented to estimate the clients' utility-maximizing behavior. The dependent variable is a binary variable that depends on whether client i awards a contract to bid j or not. Since a client chooses a particular bid as a winner after evaluating all bids that he receives, the empirical model must estimate the effect of each bid attribute on the probability of the client choosing the bid over the rest of the bids in the given auction. Therefore, a conditional logistic regression model has been used. The conditional logistic model is based on a random utility model (Greene, 2003). The utility of choosing bid j for client i is

$$U_{ij} = \beta X_{ij} + e_{ij}.$$

X_{ij} is a vector of explanatory variables for client i and bid j. X_{ij} can be the attributes of the choices, which is specific to each bid, as well as the characteristics of the individual client, which vary across the auctions but do not vary across alternative bids, given the auction (Gopal et al., 2003). β is a vector of estimated parameters; e_{ij} is the random error term. It is assumed that the client i chooses bid j if its utility, U_{ij}, is the maximum among the utilities of other bids. Then, the probability that client i will choose bid j is given by

$P(U_{ij} > U_{ik})$ for all other $k \neq j$.

Conditional logit model assumes that the random disturbances, e_{ij}, are independently and identically distributed with a Weibull distribution. Then, the probability that client i will award a contract to bid j is given by:

$$P(Y_i = j) = \frac{\exp(\beta X_{ij})}{\sum_{j=1}^{J} \exp(\beta X_{ij})}.$$

The parameters are estimated by maximizing the likelihood function for n observed auctions:

$$L = \prod_{i=1}^{n} \prod_{j=1}^{J} \frac{\exp(\beta X_{ij})}{\sum_{j=1}^{J} \exp(\beta X_{ij})}.$$

The conditional logit model does not allow correlation of the error terms over alternatives, and therefore imposes the independence of irrelevant alternatives (IIA) assumption (Greene, 2003). The IIA assumption implies that the odd ratio of choosing Bid A and choosing Bid B remains constant, regardless of whether other alternative bids are added or removed. The IIA assumption might or might not be a strong restriction in some brand or location choice problems (Go and List, 2004; Lemon and Nowlis, 2002). Unlike in the brand or location choice problems, where individuals face an identical and predetermined choice set such as *Brand A* and *B*, or *Location A* and *B*, auction data does not have fixed *Bid A* or *Bid B* across auctions; each auction receives a different set of bids with different configurations. Because of this nature of the auction data applied in this work, it is hard to determine if such correlations between two irrelevant alternatives could exist in this type of data set. To confirm the IIA property, an additional test using the mixed logit regression, which is also known as random coefficient model and which relaxes the IIA assumption, has been performed. The result did not show systematic differences in terms of the significance of the variable effects.

DATA

Data on recently completed projects were collected from ElanceOnline, an Internet-based services procurement intermediary for small businesses. (For larger businesses such as *American Express, BP, GE,* and other Fortune 500 companies, *Elance* used to provide on-demand Services and Contract Management solutions. In 2006 *Elance* sold this business to *Click Commerce*, another fast-growing technology company.) ElanceOnline is a large e-marketplace for services with more than 100,000 business customers.

The initial data set consists of observations of 60,737 bids involved in 8,369 IT projects, closed between 4/17/2005 and 4/16/2006 from the Software and Technology category. The Software and Technology category has more than 50,000 registered software developers, and includes various subcategories of IT projects. The first column of Table 1 shows the details about the project distributions across the subcategories within the Soft-

Table 1. Project frequencies in sub-categories

Software & Technology sub-categories	Number of projects: Filtered data (Open-bid, not-invitees-only auctions with a winner and more than two bids received)		Initial data	
Application Development	575	(44.40%)	4121	(49.24%)
Scripts & Utilities	234	(18.07%)	1108	(13.24%)
Database Development	196	(15.14%)	892	(10.66%)
Other - Software & Technology	110	(8.49%)	919	(10.98%)
System Administration	55	(4.25%)	306	(3.66%)
Linux	45	(3.47%)	168	(2.01%)
Handhelds & PDAs	26	(2.01%)	234	(2.80%)
Technical Support	24	(1.85%)	177	(2.11%)
Networking	13	(1.00%)	113	(1.35%)
Wireless	9	(0.69%)	137	(1.64%)
Security	8	(0.62%)	112	(1.34%)
Enterprise Systems	0	(0.00%)	82	(0.98%)
Total	1,295	(100%)	8,369	(100%)

Table 2. Descriptive Statistics

	Variable	Mean	Std Dev	Min.	Max.
Bid-choice specific (N=8936)	Bid price (US$)	954.86	1996.77	50	100000
	Time to deliver (days)	17.62	20.42	1	270
	Vendor experience (Number of projects previously completed.)	9.31	11.78	0	51
	Vendor feedback rating (1 is the lowest; 5 is the highest)	4.68	0.64	1	5
	Vendor size (Number of employees)	64.58	105.95	1	749.5
	Vendor age (Years since founded)	6.45	4.19	0	35
	Number of prior contracts between the client and vendor during the recent one year	0.02	0.18	0	5
	US vendors (1 if the vendor is from the U.S., otherwise 0.)	0.16	0.37	0	1
Auction specific (N=1295)	Client experience (Number of contracts previously awarded)	9.30	20.60	0	298
	Project value (Average bid, US$)	954.86	1365.91	83.33	20930.2
	Number of bids	11.09	8.61	2	62

ware and Technology category. ElanceOnline also operates several non-IT-related professional service categories such as marketing and legal consulting, which are not included in the analysis. Website Development is another IT-related category with market liquidity similar to the Software and Technology category, with 7,494 projects posted during the same period. The Website Development category is not included in the current analysis.

Each bid information shows to which project the bid belongs, whether a contract was awarded, bid price, time it would take to deliver the service if awarded, vendor's geographical location, vendor's recent six-month feedback ratings, vendor's total earnings through the particular online marketplace, and number of feedback ratings that the vendor has received regarding the projects he completed. The information about each project includes the client's experience level (the number of project awarded), and average bid amount of the project.

The initial data was filtered to eliminate inappropriate data for testing the hypotheses. There were only 9,224 bids with 1,583 projects remaining after deleting sealed-bid auctions, invitees-only auctions, auctions without any winner, and auctions with multiple winners. Among this filtered data, auctions that had received only one valid bid were also deleted as a client of a one-bid auction would not have any alternatives to choose from. The final data set consists of 8,936 bids with 1,295 projects. Table 1 compares the project frequencies between the initial data and the filtered data, indicating no significant difference in terms of the distributions across subcategories.

The descriptive statistics are presented in Table 2. The average bid price is $954.86 and average proposed lead-time proposed is about 18 days, indicating projects procured in this market are simple and short-term, compared to typical IT projects. The average number of bids received per project is 11, and average number of projects awarded by a client is 9, demonstrating active market liquidity.

EMPIRICAL RESULTS

To test the proposed hypotheses, control variables were added: vendor's size in terms of number of employees, and existence of prior contracts between the given vendor and client. The model specification forms as follows, after including these control variables. Model 1 formulates hypotheses H1 through H5 and control variables:

Model 1: *Prob [A vendor wins a contract] = f (Price, Time-To-Deliver, Average-Feedback, Vendor-Experience, Vendor-Distance, Vendor-Size, Prior-Relationship).*

Hypotheses H6 and H7 include interaction terms of project value with each explanatory variable. The average bid price of a given project is used as a proxy for project value to test hypotheses H6 and H7, as in Snir and Hitt (2003) since the client's perceived value is unavailable to measure.

Model 2: *Prob [A vendor wins a contract] = f (Price, Time-To-Deliver, Average-Feedback, Vendor-Experience, Vendor-Distance, Vendor-Size, Prior-Relationship, Price*Project-Value, Time*Project-Value, Feedback*Project-Value, Vendor-Experience *Project-Value, Vendor-Distance* Project-Value, Vendor-Size, Prior-Relationship).*

In addition to the above analysis, a possible confounding effect, the level of client's market experience, is also controlled. The result might be confounded if heterogeneity in buyer's market experience affected their vendor selection behavior. When clients are inexperienced in the given online market, they do not have sufficient knowledge about the proper use of the market signals. However, experienced clients who have posted RFPs and awarded contracts through the online markets must have learned how to identify credible signals, and what the signals mean. The model, after controlling the heterogeneity of client's market experience levels, is specified by adding the client experience-specific interaction terms for each explanatory variable.

Model 3: *Prob* [A vendor wins the contract] = *f (Price, Time-To-Deliver, Average-Feedback, Vendor-Experience, Vendor-Distance, Vendor-Size, Prior-Relationship, Price*Project-Value, Time*Project-Value, Feedback*Project-Value, Vendor-Experience*Project-Value, Vendor-Distance*Project-Value, Price*Client-Exp, Time*Client-Exp, Feedback*Client-Exp, Vendor-Experience * Client-Exp, Vendor-Distance* Client-Exp).*

The estimation results of the conditional logistic regression are shown in Table 3. The results of Model 1 show that hypotheses H1 through H5 are supported. All of the vendor selection determinant variables have the expected signs. PRICE and TIME-TO-DELIVER have negative coefficients; it suggests that the probability of winning a contract increases with lower values in these variables. VENDOR-EXPERIENCE and

FEEDBACK have positive coefficients, indicating that the high values in both quality and quantity of feedback ratings are perceived as important signals of vendor quality by clients. Clients prefer U.S. vendors to foreign vendors when other parameters are equal. It suggests that U.S vendors have advantages over foreign vendors in this market and the foreign vendors may have to offer a better bid package through a price discount or a faster delivery date to compete with the U.S. vendors of the same quality. In summary, the propensity to be selected as a winning bid increases with a lower bid price, shorter time to deliver the service, higher average feedback rating, higher cumulated experience, and domestic location.

The project value hypotheses H6 and H7 were not supported; the result appears as Model 2 in Table 3. The reason that H6 and H7 are not supported can be explained by the market's high concentration on relatively simple, small IS development projects. The range of the project value in this market may not be broad enough to observe differentiations in clients' vendor selection strategy. From the client's perspective, most of the projects in this market may be classified as a commodity-like and inexpensive project category accompanying a small magnitude of potential risk.

The result of Model 3 shows that the control of buyer experience heterogeneity does not change the previous results. Without significant effects of buyer experience heterogeneity, the results still support H1 through H5 but do not support H6 and H7. This implies that experienced clients do not adopt the market signals differently from inexperienced ones. A possible interpretation of this result can be that this particular online marketplace (i.e., *eLance.com*) from which the data is collected is designed so that inexperienced clients can easily identify the market signals suggested by the marketplace. Clients keep using the same set of signals as they get experienced. For example, when a client evaluates the vendors' bids, quantifiable information available to the client include bid price, lead time, number of feedback ratings and average value of feedback rating. These measures are comparable among different vendors and easily accessible to the clients. Therefore it is likely that the clients consider using them when selecting a vendor. This result and interpretation are not limited to only the dataset used in this research, because a similar setting for similar market signal measures is observed in other online service marketplaces such as *guru.com* or *rentacoder.com*.

The negative coefficient of Vendor-Size is an interesting result. The negative coefficient implies that increases in vendor size (i.e., number of employees) reduce the chance of winning a contract. It can be explained by the fact that bargaining powers of clients increases when they select a smaller-size vendor (Carmel and Nicholson, 2005; Gopal et al., 2003). The clients in this market, who are mainly small size businesses, appear to strongly prefer having bargaining powers over their service providers. Another explanation is that the clients, who are mostly small businesses in this particular market, may find it costly to deal with larger vendors because larger firms tend to be more bureaucratic and have strict guidelines (Dean et al., 1998). One may suspect a possible correlation

Table 3. Results of the Discrete Choice Model to Predict Vendor Selection Behavior

	Variables	Model 1	Model 2	Model 3
Cost Saving	ln(PRICE)	-0.3647 ** (0.058)	-0.3561 ** (0.0623)	-0.3515 ** (0.0624)
	ln(TIME-TO-DELIVER)	-0.2595 ** (0.048)	-0.2604 ** (0.0481)	-0.2584 ** (0.0482)
Adverse selection	FEEDBACK	0.3774 ** (0.0846)	0.3759 ** (0.0859)	0.3717 ** (0.0861)
	ln(VENDOR-EXPERIENCE)	0.0274 ** (0.00283)	0.0273 ** (0.00285)	0.0274 ** (0.00285)
Managerial complexity	USVENDOR	0.5612 ** (0.0941)	0.5582 ** (0.0947)	0.5328 ** (0.096)
Interaction with project value	ln(PRICE)* ln(PJTVALUE)		-0.0261 (0.0393)	-0.0225 (0.0395)
	ln(TIME)* ln(PJTVALUE)		0.0165 (0.0368)	0.0194 (0.0372)
	FEEDBACK* ln(PJTVALUE)		0.00971 (0.0404)	0.00868 (0.0405)
	ln(VEXP)* ln(PJTVALUE)		0.00973 (0.0322)	0.00767 (0.0324)
	USVENDOR* ln(PJTVALUE)		0.0139 (0.0406)	0.00291 (0.041)
Interaction with client experience	ln(PRICE)* ln(CLIENT-EXP)			0.0428 (0.0406)
	ln(TIME)* ln(CLIENT-EXP)			0.0432 (0.0399)
	FEEDBACK* ln(CLIENT-EXP)			-0.0135 (0.0427)
	ln(VEXP)* ln(CLIENT-EXP)			-0.0112 (0.0343)
	USVENDOR* ln(CLIENT-EXP)			-0.0963 (0.0448)
Control variables	ln(VENDOR-SIZE)	-0.289 ** (0.0318)	-0.2897 ** (0.0318)	-0.2886 ** (0.0319)
	PRIOR-RELATIONSHIP	17.4551 (252.2)	17.4452 (253)	17.3691 (255.4)
	N	8936	8936	8936
	AIC	3660.232	3669.611	3671.393
	-2LogL	3646.232**	3645.611**	3637.393**

Table 4. Correlation matrix of key variables

Parameter	ln(PRICE)	ln(TIME-TO-DELIVER)	FEEDBACK	ln(VENDOR-EXPERI-ENCE)	US VENDOR	ln(VENDOR-SIZE)	PRIOR-RELATIONSHIP	ln(PRICE)* ln(PJT VALUE)	ln(TIME)* ln(PJT VALUE)	FEEDBACK* ln(PJT VALUE)	ln(VEXP)* ln(PJT VALUE)	USVENDOR* ln(PJT VALUE)
ln(PRICE)	1	-0.423	-0.084	-0.060	-0.089	-0.048	0.000	-0.303	-0.083	-0.038	-0.004	0.009
ln(TIME-TO-DELIVER)	-0.423	1	0.062	0.085	0.040	0.010	0.000	0.023	-0.027	0.014	-0.033	0.014
FEEDBACK	-0.084	0.062	1	-0.064	0.016	0.071	0.000	-0.029	0.013	-0.161	-0.040	0.011
ln(VENDOR-EXPERI-ENCE)	-0.060	0.085	-0.064	1	0.266	-0.302	0.000	0.025	-0.021	-0.010	-0.074	-0.083
USVENDOR	-0.089	0.040	0.016	0.266	1	-0.041	0.000	0.010	0.017	0.023	-0.086	-0.092
ln(VENDOR-SIZE)	-0.048	0.010	0.071	-0.302	-0.041	1	0.000	0.019	-0.017	-0.038	0.009	-0.026
PRIOR-RELATIONSHIP	0.000	0.000	0.000	0.000	0.000	0.000	1	0.000	0.000	0.000	0.000	0.000
ln(PRICE)* ln(PJTVALUE)	-0.303	0.023	-0.029	0.025	0.010	0.019	0.000	1	-0.370	-0.034	-0.083	-0.145
ln(TIME)* ln(PJTVALUE)	-0.083	-0.027	0.013	-0.021	0.017	-0.017	0.000	-0.370	1	0.038	0.093	0.038
EEDBACK* ln(PJTVALUE)	-0.038	0.014	-0.161	-0.010	0.023	-0.038	0.000	-0.034	0.038	1	0.087	0.062
ln(VEXP)* ln(PJTVALUE)	-0.004	-0.033	-0.040	-0.074	-0.086	0.009	0.000	-0.083	0.093	0.087	1	0.207
USVENDOR* ln(PJTVALUE)	0.009	0.014	0.011	-0.083	-0.092	-0.026	0.000	-0.145	0.038	0.062	0.207	1

between Vendor-Size and Price as a cause of the negative coefficient of Vendor-Size. However, this explanation is inappropriate, as there is no significant correlation between those variables, as shown in the correlation matrix in Table 4.

The coefficients do not exhibit systematic changes after adding a series of variables to Model 1, as shown in Table 3, suggesting that there is no evident multicollinearity problem. To minimize potential multicollinearity problems, centered values have been used to generate the interaction terms and the project value is measured by only one measure, as in Lemon and Nowlis (2002). Hocking (1996) suggests, as a rule of thumb, that if any variance inflation factor (VIF) is greater than 10, the multicollinearity problem is evident. The data in this analysis satisfies the VIF test.

CONCLUSIONS AND DISCUSSIONS

Online service marketplaces have reduced global boundaries by facilitating communication and delivery of software, and created a venue where clients and vendors are connected globally. Reduced transaction costs and entry barriers have attracted a high population of small clients and vendors for trading small IT projects (Radkevitch et al., 2006). This paper presents an explanatory study that examines the vendor selection process using data from a large online service marketplace. Theories from production economics, resource dependency, and software risk management are applied in a small-firm context. The empirical results suggest that a client's utility function increases with a lower bid price, shorter lead-time, higher vendor average feedback rating, higher degree of vendor experience, and domestic (U.S.) location. There was not sufficient evidence to support strategically differentiated vendor selection behavior with respect to project value (or price). One of the possible explanations for this is that the scope of projects procured in this market is narrowly focused on an inexpensive, less complex, and small project category; the scope is therefore not broad enough to exhibit strategic diversity in client's vendor selection behavior.

Findings of this study can help online market designers ensure an efficient market mechanism. Designers must take care to make their signaling mechanisms accurate, so clients have correct information regarding the selection determinants. These devices should allow high-quality vendors to signal their quality effectively, in a way that lower-quality vendors cannot mimic. Market designers should ensure a healthy environment where a client can truthfully leave feedback based on their observed quality of a given vendor. If a client is afraid of any potential disadvantages by leaving negative feedback, the feedback information would be distorted, and the market would not function efficiently, unless the client disregards the feedback rating system when choosing their service providers. In addition, the results suggest that offshore vendors appear to be less attractive to U.S. clients than domestic vendors. Marketplace designers need to consider fortifying contract assistant services, legal advices, and secured payment systems throughout IT project contracting in order to promote the pool of high quality offshore vendors.

Among the factors influencing IS project success, such as the governance of contractual agreement and client-supplier relationship (Gopal et al., 2003, Lacity and Hirschheimk, 1993), efficient vendor selection is a prerequisite to others. To design or guide a successful IT vendor selection process, one must understand the bid evaluation process, especially the kind of market signals that clients prioritize when determining a vendor. Given the high percentage of auctions that end without achieving a contract in online service markets (Lacity and Hirschheimk, 1993), the IS literature calls for improving market efficiency for more contracts to be awarded. This article contributes to the online service market literature by empirically exploring vendor selection determinants for small IT projects. The present study does not aim to propose an optimal vendor selection strategy. Instead, an attempt has been made to explore important determinants, and help understand patterns of bid evaluation in online auctions, where a large percentage of transactions consist of small IT projects. Also, the focus of the study is online sourcing of small projects, and careful attention must be paid when applying the results to a large project context; the vendor selection determinants and significance of individual determinants may change when the market primarily deals with large projects.

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