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Some Empirical Evidence

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Timo Heinrich[1]

Communication and Reputation in Procurement Auctions – Some Empirical Evidence

Abstract

This paper studies the role of communication and reputation in market interactions using data from online procurement auctions. Not only positive reputation ratings but also engaging in communication increases a bidder's probability of winning the auction. Messages are primarily used to reduce the asymmetric information associated with transactions.

JEL Classification: D44, D83, L14

Keywords: Communication; procurement auctions; reputation

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1 University of Duisburg-Essen. – *I am indebted to Jeannette Brosig and Joachim Weimann for their advice. I thank Erwin Amann, Kyoo il Kim, Hendrik Schmitz and an anonymous referee for helpful comments. Further, I thank the team of MyHammer for sharing their data and Sylvia Nienhaus for excellent research assistance. Part of this research was conducted at the Otto-von-Guericke University, Magdeburg.* – *All correspondence to Timo Heinrich, University of Duisburg-Essen, Faculty of Economics and Business Administration, Universitätsstr. 12, 45117 Essen, Germany, E-Mail: timo.heinrich@ibes.uni-due.de.*

1 Introduction

In order to counteract problems of asymmetric information, electronic markets often implement reputation mechanisms which allow transaction partners to rate each other's behavior after trading. Reputation mechanisms can be used by traders to communicate information about the behavior of their previous transaction partners to other market participants and can alleviate the problems of moral hazard and adverse selection (Dellarocas, 2006). But most electronic markets do not only facilitate communication about past transactions, they also help potential transaction partners to communicate with each other *before* a transaction takes place. Ebay users, for example, can contact sellers to ask questions about the goods on offer using Ebay's email system. Although there has been extensive research on the effects of reputation in electronic markets (see e.g. Bajari and Hortaçsu (2004) for a summary), little is known about the role of communication between potential transaction partners. It is surprising that this factor has been ignored in field studies of economic transactions, where several communication channels are usually available.[1]

In recent years several websites started operating that allow consumers to buy services via procurement auctions. Using these websites, consumers can find contractors for a variety of services like the remodeling of their house, the repair of their car or the relocation of their belongings.[2] This paper studies a German website called MyHammer.[3] On the website buyers describe their projects, select a category and set a starting price. Bidders are then able to bid a price and buyers can select a winning contractor from among the bidders. As in most economic exchanges the contracts are incomplete, giving rise to problems of adverse selection and moral hazard (Akerlof, 1970; Dellarocas, 2006). MyHammer therefore implements reputation mechanisms similar to those used by Ebay and other electronic markets. But unlike Ebay, MyHammer does not allow private messages to be sent between market participants. Buyers and bidders can only communicate using an auction-specific message board. This makes it possible to study the

[1] A probable explanation is that messages sent between market participants at Ebay, the most widely studied electronic market, cannot be publicly observed. To my knowledge the only study that controls for the effect of communication is by Resnick et al. (2006). In their field experiment conducted on Ebay the same seller auctioned off similar items using identities with different reputation ratings.

[2] A first experimental study of bidding in (sequences of) procurement auctions was conducted by Brosig and Reiß (2007).

[3] The website can be accessed at http://www.myhammer.de. An English version is available at http://www.myhammer.co.uk. This study covers auction rules that were in effect in 2007.

effect of communication on awarding decisions while controlling for bidder reputation using the publicly available ratings.

In theory, the role of communication by means of cheap talk depends on the nature of the interaction. As summarized by Crawford (1998): If the interests of buyer and contractor are similar, communication can be used as a coordination device; if the interests are opposed, communication will not influence the outcome. In a recent paper Jullien and Park (2010) model the interaction of reputation and pre-trade cheap talk in markets with adverse selection. They show that even though buyer and seller interests are opposed in the short-run, there is an equilibrium where bidders can credibly communicate their supplied quality due to their long-run reputational motives.

Empirically, a large body of experimental evidence shows that pre-play communication can dramatically increase cooperation between people in experimental games (see e.g. the survey by Brosig (2006)). In a related experimental paper Charness and Dufwenberg (2006) study behavior in a trust game with moral hazard in which a principal decides on hiring an agent, who in turn decides whether to exert effort. Charness and Dufwenberg (2006) find that messages sent from agents to principals lead principals to expect more agents to exert effort and agents to adjust their second-order beliefs in the same way. Accordingly, principals choose to contract agents more often and agents choose to exert effort more often than in baseline treatments without communication.

The results presented here offer supporting field evidence for the importance of communication in market interactions: Bidders use messages to reduce information asymmetries and buyers (or principals) who can choose among several bidders (or agents) prefer those who send messages.

2 Data Set

The data set comprises 5,726 auctions for transport and relocation projects with 32,624 bids from the website of MyHammer which were conducted between January and October 2007. Transport and relocation projects account for the largest share of auctions in the time span under consideration. MyHammer's reputation mechanism allows buyers and contractors to rate each other after an auction ended. The ratings bidders had received at the time of the auction and any additional information they provided in their user profiles were available for analysis. The ratings can be positive, neutral or negative and supplemented by a comment.

In addition, bid prices and messages written by participants on the auction-specific message board were used.[4] Further information about bidders is included in the regression analyses.[5] Table 1 summarizes the main observed variables of bids placed at auctions.

The data set is restricted to projects auctioned by first-time buyers and actually assigned to one of the bidders. To be able to address potential endogeneity issues of communication, the sample was limited to auctions in which buyers sent no messages and to auctions with bidders who participated in more than one auction (this covers 65 percent of all auctions). In addition, the content of 1,950 messages accompanying a subsample of 1,167 bids was analyzed.

Table 1 - Summary Statistics

Variable	Definition	Mean (Std. Dev)	Minimum	Maximum
Winning	Dummy variable that equals 1 if the bid was successful	0.176 (0.380)	0	1
Bid	Bid amount	673.009 (838.290)	1	100000
Lowest	Dummy variable that equals 1 if the bidder offered the lowest bid amount in the auction	0.183 (0.387)	0	1
Positive1	Dummy variable that equals 1 if the bidder has received 1-4 positive ratings	0.199 (0.399)	0	1
Positive2	Dummy variable that equals 1 if the bidder has received 5-13 positive ratings	0.187 (0.390)	0	1
Positive3	Dummy variable that equals 1 if the bidder has received 14-32 positive ratings	0.192 (0.394)	0	1
Positive4	Dummy variable that equals 1 if the bidder has received 33-178 positive ratings	0.191 (0.393)	0	1
ShareProblematic	Share of neutral or negative ratings the bidder has received	0.026 (0.074)	0	1
Message	Dummy variable that equals 1 if the bidder has written 1 or more messages	0.506 (0.500)	0	1

[4] In 2007 the message board was meant to be the only way of communicating between buyers and bidders. The buyer's contact information was only made available to the winning bidder at the end of the auction. MyHammer collected a share of the bid from the winning bidder as a fee for transmitting the buyer's contact information. After 2007 MyHammer changed their rules and now explicitly allowed bidders to transfer their contact information during the auction for an additional fee.

[5] This includes the following variables: dummies for company size (1-3, 4-9, 10-20 or more than 20 employees), a dummy for holding commercial liability insurance (yes or no) and the length of the company description (number of characters). Furthermore, the distance between the reported area codes was used as a proxy to control for the geographical distance between the project locations and the bidders.

3 Model Specification

To determine which characteristics of a bid influence the probability of winning a contract, bids by different bidders in different auctions are analyzed. McFadden's conditional logit model (McFadden, 1973) is applied, which assumes an underlying random utility model where buyers choose the bid offering the highest utility. The utility a buyer in auction i obtains from a bid j is given by

$$U_{ij} = \beta' x_{ij} + \gamma' m_{ij} + e_{ij},\; i = 1, 2, ...N \text{ and } j = 1, 2, ..., J_i,$$

where x_{ij} is a vector of observed bid-specific attributes and e_{ij} is an unobserved error term. m_{ij} is a dummy variable indicating whether a bidder sent at least one message in that auction. The probability that bid j is chosen in auction i is

$$Pr(y_i = j) = Pr(U_{ij} > U_{ik}, \forall\, k \neq j).$$

If, and only if, each error term is assumed to be independently identically distributed with the type 1 extreme value distribution $F(e_{ij}) = exp(-exp(-e_{ij}))$, the probability for bid j to be selected as a winning bid in auction i is given by

$$Pr(y_i = j) = \frac{exp(\beta' x_{ij} + \gamma' m_{ij})}{\sum_{l=1}^{J_i} exp(\beta' x_{il} + \gamma' m_{il})}.$$

But if bidders who are particularly well suited to a certain project are more likely to send messages, communication is endogenous and correlated with the error term. To control for possible endogeneity, the control function approach for choice models suggested by Kim and Petrin (2010a), Kim and Petrin (2010b) and Petrin and Train (2010) was applied.[6] The aim of this approach is to derive an explanatory variable that conditions on the part of m_{ij} that depends on e_{ij}. It is assumed that m_{ij} can be expressed as $m_{ij} = g(z_{ij}, \delta) + \mu_{ij}$, where z_{ij} is a vector of instrumental variables uncorrelated with the unobserved factors μ_{ij} and e_{ij}. Therefore μ_{ij} and e_{ij} are correlated and e_{ij} can be decomposed into $e_{ij} = E[e_{ij}|\mu_{ij}] + \epsilon_{ij}$. $E[e_{ij}|\mu_{ij}]$ is referred to as the control function $f(\mu_{ij}, \lambda)$. Substituting it into the utility function together with the error

[6]Recent applications using conditional logit models include Chen and Moore (2010), Ferreira (2010) and Liu et al. (2010).

term ϵ_{ij} (which is by construction uncorrelated with m_{ij}) yields the following:

$$U_{ij} = \beta^{'} x_{ij} + \gamma^{'} m_{ij} + f(\mu_{ij}, \lambda) + \epsilon_{ij},\ i = 1, 2, ...N \text{ and } j = 1, 2, ..., J_i.$$

In a first step, $m_{ij} = g(z_{ij}, \delta) + \mu_{ij}$ is estimated as a linear probability model. The resulting residuals $\widehat{\mu}_{ij}$ are then used as estimates for μ_{ij} in the control function. In the second step the conditional logit is estimated using the simplest form of the control function given as $f(\widehat{\mu}_{ij}, \lambda) = \lambda^{'} \widehat{\mu}_{ij}$. Other functional forms yielded similar results but the resulting models were inferior according to the Bayesian information criterion. The standard errors are corrected using bootstrapping as described in Kim and Petrin (2010b).

The approach above relies on finding instruments that are correlated with the probability of communicating, but not with the buyer's utility from the bid. As in Petrin and Train (2010), a Hausman-type instrument (Hausman, 1997) is constructed: For a bid j in auction i the average number of messages the respective bidder sent in all other auctions was used in the first-stage regression. As an additional instrument, the number of messages a bidder sent in auctions in which he did not bid divided by the amount of time the bidder has been registered was included.

4 Results

The estimated coefficients for the conditional logit models described in the previous section are presented in Table 2. Column (1) reports the results of a simple model including controls for the bid amount and the reputation ratings: The dummy variables for different levels of received positive ratings and the share of a bidder's received ratings that were problematic, i.e. neutral or negative. The model in column (2) additionally includes the message dummy and its interactions with the reputation variables. The model in column (3) adds the residual of the linear probability model as the control function.

Table 2 - Conditional Logit Regressions for the Success of Bids

	Conditional Logit		
Independent variable	(1)	(2)	(3)
$Ln(Bid)$	-5.932^{***}	-5.913^{***}	-5.900^{***}
	(0.193)	(0.194)	(0.397)
$Lowest$	1.218^{***}	1.248^{***}	1.252^{***}
	(0.043)	(0.044)	(0.064)
$Positive1$	0.559^{***}	0.526^{***}	0.540^{***}
	(0.061)	(0.085)	(0.125)
$Positive2$	1.097^{***}	1.003^{***}	1.025^{***}
	(0.065)	(0.093)	(0.138)
$Positive3$	1.220^{***}	1.047^{***}	1.068^{***}
	(0.070)	(0.102)	(0.154)
$Positive4$	1.648^{***}	1.605^{***}	1.629^{***}
	(0.072)	(0.099)	(0.154)
$ShareProblematic$	-2.216^{***}	-2.152^{***}	-2.106^{**}
	(0.353)	(0.531)	(0.930)
$Message$		0.575^{***}	0.420^{***}
		(0.087)	(0.141)
$Message * Positive1$		-0.094	-0.094
		(0.124)	(0.174)
$Message * Positive2$		-0.024	-0.031
		(0.127)	(0.184)
$Message * Positive3$		0.085	0.086
		(0.133)	(0.194)
$Message * Positive4$		-0.079	-0.085
		(0.127)	(0.198)
$Message * ShareProblematic$		-0.357	-0.333
		(0.716)	(1.185)
$Residual$			0.262^{**}
			(0.116)
McFadden's Pseudo R^2	0.402	0.412	0.412
Bayesian Information Criterion	-38,597.106	-38,628.085	-38,629.195
N	32,624	32,624	32,624

The regressions include further bidder characteristics. Standard errors are given in parentheses. Standard errors for model (3) are based on 100 bootstrap replications. * p<0.10, ** p<0.05, *** p<0.01.

The regression results in column (1) are in line with previous results on reputation mechanisms in electronic markets. They show a positive effect of positive ratings and a negative effect of problematic ratings on the probability of winning. Adding the message dummy and its interactions in column (2), the effects of reputation ratings remain significant while messages also have a positive influence on the probability of winning. This effect is not driven by endogeneity, as the results in column (3) show. After including the residual the size of the $Message$ coefficient decreases, but neither its sign nor the significance level change.

Table 3 - Average Probabilities of Winning for Model (3)

	$Message = 0$		$Message = 1$	
	Probability	95% CI	Probability	95% CI
$Lowest = 0$				
No positive ratings	0.037	[0.032, 0.041]	0.049	[0.045, 0.052]
$Positive1 = 1$	0.052	[0.047, 0.058]	0.066	[0.060, 0.073]
$Positive2 = 1$	0.069	[0.063, 0.075]	0.084	[0.077, 0.091]
$Positive3 = 1$	0.070	[0.064, 0.076]	0.086	[0.079, 0.092]
$Positive4 = 1$	0.091	[0.085, 0.097]	0.107	[0.100, 0.115]
$Lowest = 1$				
No positive ratings	0.495	[0.464, 0.527]	0.570	[0.548, 0.592]
$Positive1 = 1$	0.591	[0.562, 0.620]	0.663	[0.635, 0.690]
$Positive2 = 1$	0.673	[0.647, 0.699]	0.737	[0.712, 0.763]
$Positive3 = 1$	0.680	[0.649, 0.711]	0.743	[0.716, 0.770]
$Positive4 = 1$	0.762	[0.738, 0.787]	0.812	[0.789, 0.837]

The 95% confidence intervals (CI) are based on 100 bootstrap replications.

Table 3 presents the predicted probabilities of the model in column (3). To facilitate predictions the sample is split up into bidders offering the lowest price in an auction ($Lowest = 1$) and those offering prices above ($Lowest = 0$). First, the results highlight the importance of prices: On aggregate, lowest-price bidders have an average probability of winning of 64 percent while those offering higher prices have an average probability of winning of only 7 percent. Second, the results show that bidders can gain from additional positive ratings. On the one hand, the difference in the probability of winning due to received positive ratings can be as large as 26 percentage points when comparing a not-communicating lowest-price bidder without any positive ratings to one with 33 to 178 positive ratings ($Positive4 = 1$). On the other hand, the gain for bidders who move from the range of 5 to 13 positive ratings ($Positive2 = 1$) to the range of 14 to 32 positive ratings ($Positive3 = 1$) is negligible, as suggested by the overlapping confidence intervals. Third, in all cases bidders who send messages have a higher probability of winning. Lowest-price bidders can increase their probability by 5 to 8 percentage points by communicating, while other bidders gain between 1 and 2 percentage points.

What do bidders say in their messages? A first analysis of the messages sent by bidders in the subsample reveals that 95 percent of their bids are complemented by the bidder's contact information. As Bajari and Hortaçsu (2004) point out in their survey, the anonymity of sellers is "[p]erhaps the most important source of information asymmetry on online auctions" (p. 469). In line with this conjecture bidders use messages to reduce the anonymity of transactions. In addition, bidders try to reduce asymmetric information in two ways: First, they hope to learn more about the job on offer by initiating further communication (31 percent) or asking about project characteristics directly (8 percent). Second, they specify their own bids in detail (64 percent). This way many bidders take into account the multi-dimensional nature of the auction, though there is little variation among the offers in dimensions other than price. Few bidders explicitly offer more (4 percent) or less (6 percent) than the buyer asks for in the project description. Further, 25 percent of bids were combined with promises or advertisement messages. Only 2 percent of bids were sent along with a mention of reputation ratings (of which more than half were due to one bidder who included a reference to his own ratings in all messages). None of the bidders in the sample asked about the buyers' award criteria.

5 Conclusion

This study highlights the importance of communication in market interactions with asymmetric information, revealing that buyers in procurement auctions prefer to contract bidders who engage in communication and write messages. This evidence from the website of MyHammer is in line with the theoretical results by Jullien and Park (2010) and the experimental results by Charness and Dufwenberg (2006). An analysis of the message content reveals that bidders use messages primarily to reduce the asymmetric information associated with transactions. In line with previous research on reputation in electronic markets the reputation of bidders is shown to have a significant effect on the success of bids. Earning positive ratings increases the probability of winning, while a higher share of problematic ratings decreases it.

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