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Measuring Frictional Costs in E-Commerce: The Case of Name-Your-Own-Price Auctions

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MEASURING FRICTIONAL COSTS IN E-COMMERCE – THE CASE OF NAME-YOUR-OWN-PRICE AUCTIONS

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Abstract

Frictional costs are defined as the disutility related to the conduct of an online transaction. Thus, frictional costs can accrue through the consumer's decision-making process prior to an online transaction, e.g., bidding in interactive pricing mechanisms like auctions. We present two models for the measurement of frictional costs in Name-Your-Own-Price auctions where these costs can either be measured through a discount factor or in absolute values. We compare the fit and estimation results of these models by analyzing bidding data from a German NYOP seller. Our results show that both models are equally parsimonious, explain a comparable fraction of variance and both models yield robust and reasonable parameter estimates.

Keywords: Frictional Costs, Electronic Commerce, Name-Your-Own-Price.

1 INTRODUCTION

The Internet has changed the way business is conducted in many ways. For example, in the field of pricing, the possibility to directly interact with a trading partner has given rise to new mechanisms previously unknown in the offline world. One such interactive pricing mechanism is the Name-Your-Own-Price auction (NYOP), which lets both buyer and seller influence the price of a product. The seller offers products in his online shop but does not make a take-it-or-leave-it-offer by posting a fixed price. In contrast he allows prospective buyers to make an offer which in turn the seller can accept or reject. Depending on the design of the mechanism, single bidding or multiple bidding may be allowed. NYOP was introduced by Priceline in 1998 and is used to sell flight tickets, or to let hotel rooms and rental cars.

Recently, eBay introduced a feature called “Best Offer” which is basically similar to NYOP applied by Priceline. At Priceline, however, only a single bid is possible that is then tested against some unrevealed threshold price. If the bid surpasses the secret threshold price, the bid is accepted by the system, the credit card is immediately charged and the transaction process is initiated. At eBay, sellers can customize the mechanism and define thresholds where the system automatically accepts or rejects an offer, or they can specify a range in which the seller decides on rejection/acceptance manually. A compendious analysis of recent ongoing auctions on the US and German websites of eBay found that about 9% of auctions listed on eBay made use of the Best Offer feature.

These mechanisms, as well as other auction mechanisms, further provide the seller with information for market research purposes, since the individual bidding behaviour reveals interesting information about the buyers. In contrast to fixed prices the seller can also learn something from rejected offers when he applies interactive pricing mechanisms. The seller may calculate the demand function for his product based on the bids even when he has to reject some bids. Moreover interactive pricing yields price differentiation among buyers based on their varying bid amounts, thus increasing profits.

Previous research in Information Systems and Marketing revealed that microeconomic models can be used to derive information about the bidders’ true willingness-to-pay, their beliefs and frictional costs that prospective buyers face when they think about their optimal bids and finally submit their bids (Spann, Skiera, Schäfers 2004). Frictional costs are defined as the disutility that the consumer experiences when conducting an online transaction, such as submitting an offer (Hann and Terwiesch 2003). Such information can then be used to build Decision Support Systems or tools for market analyses (see e.g. Bernhardt and Hinz 2005; Van Heijst, Potharst and van Wezel 2008). Multiple bidding is more useful for market research purposes since every additional bid reveals more information about the bidder’s characteristics. In this paper, we therefore focus on multiple bidding in NYOP channels.

However, estimating frictional costs requires an appropriate modelling of their impact on bidding behaviour. Frictional costs can either be modelled as absolute costs subtracted from consumer surplus or as a relative factor that discounts surplus. In the first case the frictional costs are modelled as absolute costs in monetary terms. For example, a buyer that is willing to pay 100 USD for a product is successful with his second bid b of 80 USD. In case he faces frictional costs s of 2 USD, his realized consumer surplus is CS=(100 USD-80 USD)-2*2 USD=16 USD.

In the second case the consumer surplus CS is discounted by a factor 1-δ (with $0<\delta<1$) and the numbers of bids n that were necessary to surpass the secret threshold price, e.g. $CS=(WTP-b)*\delta^n$. Let us assume the buyer has a willingness-to-pay of 100 USD and his second bid (hence n=2) of 80 USD is successful. Further assume that the frictional costs factor is δ=0.9. Then the buyer’s consumer surplus is CS=(100 USD-80 USD)*0.9^2=16.2 USD.

These two modelling approaches are both used in various academic papers and are applied in sophisticated decision support tools (e.g. Cramton 1984, Hann and Terwiesch 2003). However, it is not clear which one of those two approaches fits better and whether the models lead to different implications. The aim of this paper is therefore to address these questions. We apply both models to bidding data from a German NYOP seller for flights from Germany to Majorca (Spain). At this NYOP seller, prospective buyers are allowed to submit an unlimited number of bids if their previous bids are rejected. They have to wait, on average, about 15 minutes for information about the acceptance or rejection of their bids. It is straightforward, that waiting infers some inconvenience on the bidders and waiting is costly and can be modelled either as a discount or an absolute loss in consumer surplus.

The remainder of this paper is therefore as follows: Next, we discuss the previous research that is relevant for this paper. In section 3 we present the bidding model and distinguish between absolute and relative frictional costs. Both models are then applied to a unique dataset from a German NYOP seller that allowed an infinite number of bids. We compare the different estimation results and evaluate the different measurement approaches. We conclude the paper with implications for research and practice.

2 PREVIOUS RESEARCH

2.1 Frictional Costs

Hann and Terwiesch (2003) define frictional costs as the disutility related to the conduct of an online transaction. Thus, frictional costs can accrue through the consumer‘s decision-making process prior to an online transaction, e.g. optimizing his bids at an NYOP seller, the consumer’s prior search effort or through the process of actually submitting the bid via a user-interface (Spann et al. 2004). Therefore, frictional costs are closely related to search costs and the modelling of consumers’ search behaviour. Consumer search behaviour can be modelled as a sequential decision on engaging in initial and possible further search steps (Ratchford, 1982). More specific, models of consumer search behaviour observe the problem of a consumer who faces varying and unknown prices at different sellers for the product she wants to buy (Stigler, 1961). Because of this, the consumer has to search for the best price at different sellers, with the search process being costly (Stigler, 1961). Based on the tradeoff between the additional revenue of search in the form of a lower price and the additional costs associated with search, the basic economic decision rule is as follows: The consumer performs an additional search step if the expected revenue of the search step is greater than the costs which occur in this search step (Goldman & Johansson, 1978; Weitzman, 1979).

In these models, the consumer assumes that prices at different sellers follow a certain distribution (in most cases a uniform distribution), enabling her to calculate the expected revenue of the search step (Ratchford, 1982). After each search step, the consumer updates the assumed price distribution based on the prices found in the previous search steps (Rothschild, 1974; Weitzman, 1979). Therefore, consumers determine the expected revenue of an additional search step based on the knowledge of their WTP and their assumptions about the price distribution. They carry out an additional search step if the expected revenue of this step is positive and exceeds the cost of search.

2.2 Name-Your-Own-Price Auctions

Likewise auctions, the innovative interactive pricing mechanism NYOP gained attention in academics from different disciplines.

In IS research, Hann and Terwiesch (2003) were the first that examined NYOP as a possibility to impute the frictional cost parameters for consumers by using the observed bidding behaviour at an NYOP seller. They model frictional costs as an absolute parameter that is subtracted from the utility a consumer receives when a deal is made. Hann and Terwiesch (2003) find that the frictional costs in E-Commerce are substantial with median values ranging from EUR 3.54 for a portable digital music player (MP3) to EUR 6.08 for a personal digital assistant (PDA). This concept of absolute frictional costs is extended in Terwiesch, Savin and Hann (2005) where the authors derive implications for an NYOP seller regarding the optimal setting of the secret threshold price.

Spann, Skiera and Schäfers (2004) show how NYOP can be used for market research and develop an analytical model that accounts for absolute frictional costs and willingness-to-pay. They apply their model to use the observed bids in order to estimate the individual's willingness-to-pay, beliefs about the threshold price and the frictional costs in absolute terms. This model is extended in Spann and Tellis (2006) to test the rationality of bidding behaviour at two different NYOP sellers.

Ding et al. (2005) examine the impact of expected excitement at winning and frustration at losing on bids in an NYOP channel. Since they apply a single bid policy in their laboratory experiments, no frictional costs are considered.

Further, several analytical papers study NYOP. Fay (2004) analyzes the optimal design of an NYOP auction in case buyers may use multiple identities and thus learn more about the secret reserve price. Wang, Gal-Or and Chatterjee (2009) study the key trade-offs driving the decision by a service provider to employ an NYOP channel or not. Amaldoss and Jain (2008) analyze joint bidding for multiple items at a reverse-pricing retailer. These studies enhance our understanding of the optimal design of NYOP but they do not estimate frictional costs.

Hinz and Spann (2008) relaxed the assumption that bidders do not communicate and information about previous bids is not available before submitting a bid. They examine information diffusion through social networks and show that exogenously acquired information significantly influences bidding behaviour. Moreover, the authors show in a field study that some bidders are at an advantage through their social position in the network. Bidders with higher centrality are more likely to bid closer to the secret threshold price since they have a higher likelihood to receive useful information about previous bids. Hinz and Spann (2008), however, do not consider frictional costs in their paper and focus on the single bid case.

In contrast to modelling absolute frictional costs, Hinz, Hann and Spann (2009) introduce a model that is based on the idea of discounting which is commonly used in Economics (e.g. Cramton 1984, Frederick, Loewenstein and O'Donoghue 2002) and apply it to the field of information systems. They allow an infinite number of bids and test the prediction accuracy of the model in a laboratory study and a field study with real purchases.

This leads to the question whether the modelling of absolute or relative frictional costs leads to better results and what implications does the modelling approach have on decision making. We therefore introduce both modelling approaches in detail in the next section before we apply them to a unique dataset of a German NYOP seller in section 4.

3 MODELLING APPROACHES

In NYOP a seller first decides about the secret threshold price and the number of possible bids (single or multiple). Prospective buyers must then decide whether they want to enter the bidding process or not. If a prospective buyer is willing to accept the frictional costs and expects a positive consumer surplus, she can place the bid which is rejected if it does not meet or surpass the secret threshold price. Otherwise the bid is accepted and the transaction is initiated. If the bid is rejected, the prospective buyer may place an additional bid depending on the number of allowed bids. She has to, however, consider again the frictional costs and must deliberate whether she wants to accept these costs or whether she wants to stop bidding without reaching an agreement. ***Figure 1*** depicts the process (process parts at the seller's side are marked grey while process parts at the buyer's side are in white).

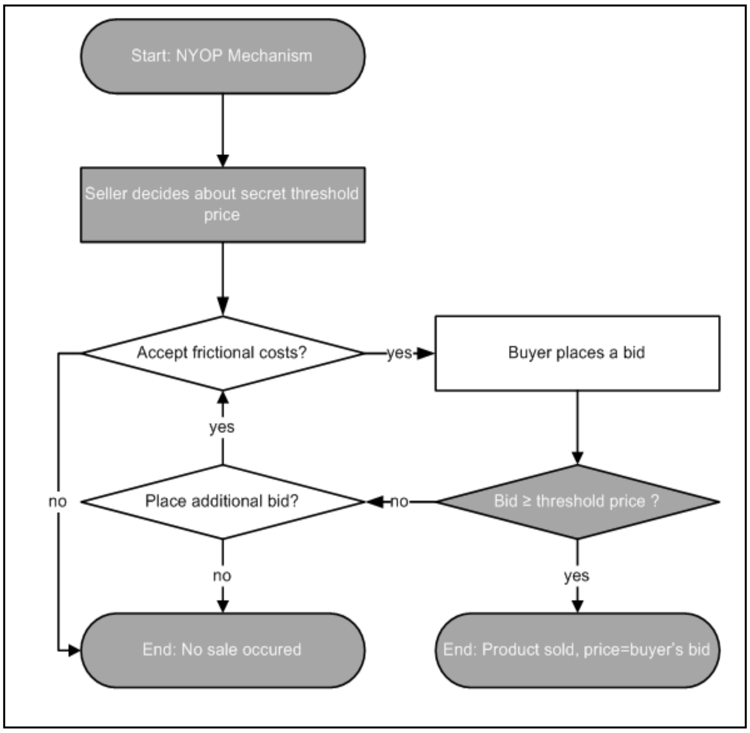

Figure 1. Bidding Process in the Name-Your-Own-Price mechanism

Economic intuition suggests that consumers with low frictional costs are more likely to submit bids using small increments, and consumers with high frictional costs are more likely to submit bids in large increments (Hann and Terwiesch 2003). If bidding was frictionless, consumers could identify the threshold price by incrementing their bid in small steps in each round, leaving little surplus to the seller. Vice versa the NYOP seller can infer from the bidding behaviour the frictional costs that bidders have to face. This information can be used to optimize the design of the website or the optimal setting of the secret threshold price (Terwiesch, Savin and Hann 2005).

We introduce the economic model which describes the optimal bidding behaviour from a buyer's perspective. We assume the following: The buyer has a willingness-to-pay *WTP* for a given product that is on sale by an NYOP-seller. We assume that buyers correctly expect an exogenous and constant threshold price of the seller. Buyers are considered to be risk-neutral.

The decision rule is that a prospective buyer submits a bid b for a product if the expected consumer surplus *ECS* of the bid is positive. However, the prospective buyer has to account for frictional costs that can either enter as absolute costs c or as a discount factor $1-\delta$ (with $0<\delta<1$). The bidder wants to maximize his expected consumer surplus *ECS* by optimizing his bid.

The bid amount influences both, the surplus and the success probability. The success probability depends on the buyer's assumption regarding the probability distribution $g(p_T)$ of the unknown threshold price p_T. Hereby, the buyer increases his success probability by increasing the amount of the bid. However, at the same time, a higher bid decreases consumer surplus in case of a successful bid. The buyer optimizes the expected consumer surplus of the bid *ECS* over the bid amount. Buyers have a reservation price r for the product. This reservation price is determined by prospective buyer's willingness-to-pay *WTP*. However, in case a buyer expects a highest possible value for the secret threshold price which is below her willingness-to-pay, she will use this highest expected threshold price value as reservation price.

Prospective buyer's decision:

$$\max_b ECS = \begin{cases} \delta \cdot E(r-b) = \delta^n \cdot \int_0^b (r-b) \cdot g\,(p_T) dp_T & \text{for relative frictional costs} \\ E(r-b) - c = \int_0^b (r-b) \cdot g\,(p_T) dp_T - c & \text{for absolute frictional costs} \end{cases}$$

$$s.t.\ \ ECS \geq 0;\ b \leq r \ \text{ with } \ r = \min\left\{WTP, \max\left\{g(p_T)\right\}\right\}$$

The buyer's belief regarding the probability distribution $g_j(p_T)$ can have different functional forms including a normal distribution or a uniform distribution. We can derive a closed form solution for the consumer's optimal bid in case of a uniform distribution of the expected threshold price on the interval [*LB*, *UB*]. This assumption is in line with Stigler (1961), Hann and Terwiesch (2003), and Ding et al. (2005) and results also hold for the most common distributional assumptions. In case of the uniform distribution between a lower bound LB and an upper bound UB, the probability density for the secret threshold price p_T is 1/(UB-LB).

We then can easily derive the optimal bid for both models. We will first derive the optimal bid for absolute frictional costs, thus c>0. In section 3.2 we derive the optimal bidding behaviour when frictional costs are captured through a discount factor 1-δ (with 0<δ<1).

3.1 Optimal Bidding Behaviour when Frictional Costs are modelled as Absolute Costs

For expositional easy, we start with the single bid case. The prospective buyer has only one chance to surpass the secret threshold price and thus submits one optimal b*.

$$ECS = \int_{LB}^{b} (r-b) \cdot \frac{1}{UB-LB} dp_T - c = (r-b) \cdot \frac{b-LB}{UB-LB} - c$$

$$\Rightarrow \ \max ECS \ = \frac{dECS}{db} = \frac{1}{UB-LB} \cdot \left[(-1) \cdot (b) + LB + (r-b) \cdot 1\right] \stackrel{!}{=} 0$$

$$\Leftrightarrow b^* = \frac{r+LB}{2} \ \text{ with } \ r = \min\left\{WTP, \max\left\{g(p_T)\right\}\right\} = \min\left\{WTP, UB\right\}$$

If prospective buyers can submit two bids, the optimal bidding behavior is as follows:

$$ECS_1 = (WTP - b_1) \cdot \frac{b_1 - LB}{UB - LB} + ECS_2 \cdot \frac{UB - b_1}{UB - LB} - c$$

$$= (WTP - b_1) \cdot \text{Prob}\left(b_1 \geq p_T\right) + ECS_2 \cdot \text{Prob}\left(b_1 < p_T\right) - c \ \text{ with } \ ECS_2 = (WTP - b_2) \cdot \frac{b_2 - b_1}{UB - b_1} - c$$

The first part of the term equals the expected consumer surplus if the first bid b_1 surpasses the threshold price. If the bid b_1 is rejected, then the prospective buyer knows that the secret threshold price must be higher than b_1. Using Bayesian updating the new lower bound equals the rejected bid b_1 and thus the second bid b_2 is higher than the first bid.

The (unrestricted) optimization of this equation for the two-bid model results in the following equations for the optimal first and second bid b_1^* and b_2^*:

$$b_1^* = \frac{2}{3} LB + \frac{2}{3} c + \frac{1}{3} WTP$$

$$b_2^* = \frac{1}{3}LB + \frac{1}{3}c + \frac{2}{3}WTP$$

The optimal bidding behaviour can easily be determined for more than 2 bids. See Spann, Skiera and Schäfers (2004) who derived the optimal bids for up to 6 possible bids.

3.2 Optimal Bidding Behaviour when Frictional Costs are modelled as Discount Factor

We use the same assumptions as before but replace the absolute frictional costs *c* with relative frictional costs modelled as discount factor 1-δ (with 0<δ<1). For the single bid case the expected consumer surplus that needs to be maximized from a buyer's perspective is given as:

$$ECS = \delta \cdot \int_{LB}^{b} (r-b) \cdot \frac{1}{UB-LB} dp_T = \delta \cdot (r-b) \cdot \frac{b-LB}{UB-LB}$$

$$\Rightarrow \max ECS = \frac{dECS}{db} = \frac{\delta}{UB-LB} \cdot [(-1)\cdot(b) + LB + (r-b)\cdot 1] \overset{!}{=} 0$$

The optimal bid b* is then also given by:

$$b^* = \frac{r+LB}{2} \quad \text{with } r = \min\{WTP, \max\{g(p_T)\}\} = \min\{WTP, UB\}$$

This means that in the single bid case there are no differences between the outcomes of the two models. The outcomes in terms of optimal bidding, however, change when more bids are allowed. For the two-bid-case the optimal bids b_1^* and b_2^* are given by:

$$\max_{b_1,b_2} ECS_1 = \frac{\delta}{UB-LB}\left[(WTP-b_1)\cdot(b_1-LB) + \delta(WTP-b_2)\cdot(b_2-b_1)\right]$$

$$b_1^* = \frac{WTP\left(1-\frac{1}{2}\delta\right)+LB}{\left(2-\frac{1}{2}\delta\right)} \text{ and } b_2^* = \frac{WTP(3-\delta)+LB}{(4-\delta)}.$$

This can be extended analogously to the n-bid case (details on the optimal bids for higher bid cases are available upon request from the authors).

4 EMPIRICAL STUDY

The aim of this empirical study is the empirical comparison of the two different modeling approaches for frictional costs. Therefore, we compare the estimations of frictional costs as well as individual WTP and the assumptions about the distribution of the threshold price for the empirical data of a name-your-own-price seller (Spann et al. 2004). Thus, we test the applicability of both modeling approaches with respect to their convergent validity and how well they fit the data.

We use the observed bid sequences of a bidder to estimate his or her characteristics, i.e., frictional costs, willingness-to-pay and assumptions about the threshold price distribution. For the estimation of absolute frictional costs, we use the approach of Spann et al. (2004). Thereby, we fit the predicted sequence of bids according to the optimal bidder behaviour to the observed bid sequence, thus imputing the bidders' characteristics via least squares estimation. The optimal bidding behaviour is derived according to the models for absolute and frictional costs outlined in section 3 above, respectively.

Since we estimate four consumer specific parameters, we need at least an equal number of observations (i.e. bids) per consumer for the model to be identified. We further assume constant frictional costs across all search bids of a consumer. Thus, we can use all consumers who submit at least four bids.

We empirically compare the two modelling approaches by analyzing the bidding data from a German NYOP seller for flights from Germany to Majorca (Spain) for a eight month period. At this NYOP seller, consumers are allowed to submit an unlimited number of bids if their previous bids are rejected. They have to wait, on average, about 15 minutes for information about the acceptance or rejection of their bids. Since Spann et al. (2004) used this data set before, we can compare their estimates for the model of absolute frictional costs to the estimates from a model with relative frictional costs.

Table 1 and Table 2 display the estimation results for the two models for consumers with four, five or six bids. It is interesting to note that the mean, min and max estimates of willingness-to-pay are almost identical between the two models. The estimate upper and lower bound for the distribution of the threshold price are similar, but slightly lower in the model with relative frictional costs compared to the model with absolute frictional costs. The model with absolute frictional costs estimates a mean value of 6.23 DM for these costs per bid. Contrary, the model with relative frictional costs measures a discount rate of 1-80.64%=19.36%. This value is rather high and is another evidence for hyperbolic discounting, meaning that consumers highly discount delayed outcomes (see e.g. Frederick, Loewenstein and O'Donoghue 2002). However, the absolute values for frictional costs are also rather high. This indicates that the approaches are comparable. The average fit of the estimated bids according to the models obtained similar explained variances of 67.88% and 65.53%, respectively.

Parameter*	*WTP* [in DM]	*UB* [in DM]	*LB* [in DM]	*c* [in DM]
Mean	353.07	441.25	177.94	6.23
Standard Deviation	90.68	282.97	68.40	7.95
Minimum	129.00	212.30	0.00	0.00
Maximum	614.00	1788.61	346.15	36.13
Model fit: R^2-mean=67.88%; R^2-median=80.00%; N=68				

Note: Results for 68 consumers with four, five or six bids for a flight from Germany to Majorca.

Table 1: Parameter Estimates for Absolute Frictional Costs (cf. Spann et al. 2004)

Parameter*	*WTP* [in DM]	*UB* [in DM]	*LB* [in DM]	δ [in %]
Mean	355.24	410.03	152.03	80.64
Standard Deviation	96.14	107.12	86.66	34.91
Minimum	125.00	150.00	0.00	0.00
Maximum	614.00	736.80	392.86	100.00
Model fit: R^2-mean=65.53%; R^2-median=78.82%; N=68				

Note: Results for 68 consumers with four, five or six bids for a flight from Germany to Majorca.

Table 2: Parameter Estimates for Relative Frictional Costs

We find a correlation of .360 (p<.01) between the estimated willingness-to-pay and absolute frictional costs but only a correlation of .091 (p>.4) between the estimated willingness-to-pay and relative frictional costs. As expected, we observe that bidders with high willingness-to-pay have higher frictional costs. Waiting is more costly for them than for bidders with lower willingness-to-pay, thus increasing the opportunity costs of time. This finding is in line with previous research in management science (e.g., Tellis 1986) and indicates that a model that captures this relation through a discount factor is reasonable. If frictional costs are measured through a discount factor, we find that the correlation is not significantly different from zero. Thus, the relative discount factor adequately captures the relationship between willingness-to-pay and frictional costs.

5 CONCLUSION

In this paper we show how frictional costs can be measured in absolute or relative terms in an application for NYOP markets. Both models are equally parsimonious and our results indicate that both models deliver similar results in terms of model fit (i.e., explained variance: see R^2-values). Further, the parameter estimates for the remaining three other bidders' characteristics, i.e. willingness-to-pay and beliefs about the secret threshold price seem to be quite robust for the different model specifications.

Both models can be used to infer the bidders' characteristics based on the observed bidding behaviour. This data can either be used for market research and pricing decisions or for the optimization of web sites. Since frictional costs measure the inconvenience that prospective buyers have to face, it can also be used to evaluate the optimality of the bidding process enabled by the applied software. These frictional costs are foregone surplus for both market sides. For example NYOP sellers like Priceline could optimize their website and thus the bidding process to decrease the frictional costs for their bidders. This allows higher surpluses for both, prospective buyers and seller (in this case Priceline). Interestingly, Priceline introduced a support tool for consumer decision making in form of a link "Not Sure What to Bid?" where prospective buyers can compare prices. Another example is Gimahhot.de, a German negotiation platform, where new products are on sale through a double auction mechanism and where frictional costs are also substantial. This platform provides a suggested bid value and an evaluation of bid values which is given before the submission. This saves haggling time for both market sides and thus lowers frictional costs (see ***Figure 2***).

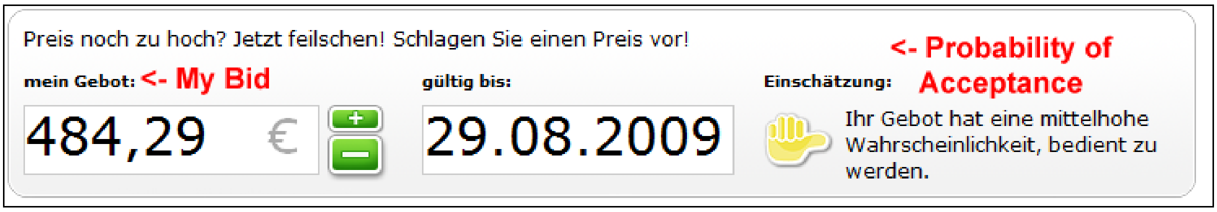

Figure 2. Tool to Decrease Frictional Costs in Bidding Processes

Such features are most likely helpful and should decrease the frictional costs. Since high valuation buyers have high frictional costs, an optimization would especially help to increase the utility of these valuable prospects. It would be interesting to measure frictional costs (either in absolute or relative terms) before the introduction of such a feature and afterwards. This would allow for the calculation of the monetary value of such software changes. Further, since suggested bid values are also external reference prices for bidders, reference price effects of such tools need to be delineated from the effects of reduced frictional costs. In any case, both effects appear to be beneficial for the seller if reference prices induce higher bid values (Wolk and Spann 2008) as well as less deadweight loss due to decreased frictional costs. The study of these aspects opens interesting avenues for future research.

Our approach presented can also be used in IS research in other contexts. For example, microeconomic models like the bidding model presented here, can be used to improve the quality of business processes and further can be used to calculate the utility of software improvements in monetary terms. This should help IT project managers to justify their development costs.

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