

Stoll, Sebastian; Zöttl, Gregor

Conference Paper

Information Disclosure in Dynamic Buyer-Determined Procurement Auctions: An Empirical Study

Beiträge zur Jahrestagung des Vereins für Socialpolitik 2012: Neue Wege und Herausforderungen für den Arbeitsmarkt des 21. Jahrhunderts - Session: Procurement, No. B05-V1

Provided in Cooperation with:

Verein für Socialpolitik / German Economic Association

Suggested Citation: Stoll, Sebastian; Zöttl, Gregor (2012) : Information Disclosure in Dynamic Buyer-Determined Procurement Auctions: An Empirical Study, Beiträge zur Jahrestagung des Vereins für Socialpolitik 2012: Neue Wege und Herausforderungen für den Arbeitsmarkt des 21. Jahrhunderts - Session: Procurement, No. B05-V1, ZBW - Deutsche Zentralbibliothek für Wirtschaftswissenschaften, Leibniz-Informationszentrum Wirtschaft

This Version is available at:

<https://hdl.handle.net/10419/62044>

Standard-Nutzungsbedingungen:

Die Dokumente auf EconStor dürfen zu eigenen wissenschaftlichen Zwecken und zum Privatgebrauch gespeichert und kopiert werden.

Sie dürfen die Dokumente nicht für öffentliche oder kommerzielle Zwecke vervielfältigen, öffentlich ausstellen, öffentlich zugänglich machen, vertreiben oder anderweitig nutzen.

Sofern die Verfasser die Dokumente unter Open-Content-Lizenzen (insbesondere CC-Lizenzen) zur Verfügung gestellt haben sollten, gelten abweichend von diesen Nutzungsbedingungen die in der dort genannten Lizenz gewährten Nutzungsrechte.

Terms of use:

Documents in EconStor may be saved and copied for your personal and scholarly purposes.

You are not to copy documents for public or commercial purposes, to exhibit the documents publicly, to make them publicly available on the internet, or to distribute or otherwise use the documents in public.

If the documents have been made available under an Open Content Licence (especially Creative Commons Licences), you may exercise further usage rights as specified in the indicated licence.

Information Disclosure in Dynamic Buyer-Determined Procurement Auctions: An Empirical Study

Sebastian Stoll*, Gregor Zöttl†

February 29, 2012

Abstract. The outcome of non-binding reverse auctions critically depends on how information is distributed during the bidding process. We use data from a large European procurement platform to study the impact of different information structures, specifically the availability of quality information to the bidders, on buyers' welfare and platform turnovers. First we show that on the procurement platform considered bidders indeed are aware of their rivals' characteristics and the buyers preferences over those non-price characteristics. In a counterfactual analysis we then analyze the reduction of non-price information available to the bidders. As we find, platform turnovers would decrease from around 10 million euros to around 7 million euros and the buyers' welfare would increase by the monetary equivalent of around 2.7 million euros.

Keywords: Procurement, Bidding, Reverse Auctions, Multi-Attribute Auctions, Non-Binding Auctions, Information Revelation, Structural Estimation

JEL Classification Numbers: D44, D82, L11, L15

*Sebastian Stoll, Department of Economics, University of Munich, Kaulbachstr. 45, D-80539 Munich, Germany. Email: sebastian.stoll@lrz.uni-muenchen.de.

†Gregor Zöttl, Department of Economics, University of Munich, Ludwigstr. 28, D-80539 Munich, Germany. Email: zoettl@lmu.de. Sebastian Stoll gratefully acknowledges financial support by the Deutsche Forschungsgemeinschaft (DFG) through GRK 801.

1 Introduction

When procuring a contract the buyer often is not only interested in the price of an offer but also in other, non-monetary dimensions such as technical characteristics of the good or time of delivery. A by now quite well studied multidimensional auction format is given by scoring auctions where buyers prior to the bidding process establish a binding scoring rule. Besides such highly structured auctions recently “non-binding” or “buyer-determined” auctions became increasingly important. In these auctions buyers can freely assign the contract after bidding has taken place. Currently this auction format seems to establish itself as the most prominent one for online marketplaces both for private and commercial contractors.¹

When designing non-binding procurement auctions, typically no structure is imposed on the buyer’s decision process - he is entirely free to choose any of the submitted bids. Important design questions arise, however, with respect to the optimal information structure for the bidding process. First of all, bidders can be provided with different levels of information regarding the buyers preferences over both the price and the non-price characteristics of their offers. Second, bidders can be provided with different levels of information regarding the identity of rival bidders and the detailed characteristics of their rivals’ bids.

In the present article we shed light on the optimal design of the information structure of non-binding reverse auctions, using an extensive dataset from a large European online procurement platform. Our analysis focuses on the impact of transparency of the auction design with respect to the buyers’ valuation of all the bidders’ non-price characteristics. As one of the main results we find that buyers’ expected welfare is higher when they keep information about their preferences over the bidders’ non-price characteristics private. The reverse result obtains for the expected turnovers of the procurement platform, which are higher in case information with respect to the non-price characteristics and the buyers’

¹See Jap (2002, 2003); Jap and Haruvy (2008) and compare for example the platform FedBid, Inc., where US government agencies have procured more than \$4.1 billion worth of purchases since 2008 using non-binding auctions.

preferences over bidders' non-price characteristics is conveyed.

Our analysis proceeds as follows. First, we establish two different formal frameworks which describe two limiting cases of information structures: in the first case bidders are fully informed both about all rival bids and about buyers' preferences over their rivals' non-price characteristics. In consequence, bidders know about the quality of their own and their rivals' bids as perceived by the buyers. In the latter case, bidders are not informed at all with respect to the non-price characteristics and thus behave as if they were bidding in a regular open price-only auction. Whether or not it is beneficial for the buyers (respectively the auction platform) to reveal information with respect to all non-price aspects depends on the precise characteristics of the market considered.

Our analysis in the main part of the article is based on a detailed data set of an online procurement platform, where subscribed buyers post their tenders and can freely choose among the posted bids. For the observed period bidding on the platform is completely open, that is both price and non-price characteristics of all bids are commonly visible. As a first step of our empirical analysis we verify whether bidders indeed are aware of the buyers' preferences over their own and their rivals' non-price characteristics. Thus, we test whether observed behavior is in accordance with the predictions of our theoretical framework where bidders are informed with regard to all non-price aspects. In this case the bids should directly take into account the non-price characteristics of rivals' bids. By exploiting the fact that a subset of bidders is observed to participate in several auctions we are able to identify the bidders' reactions to changing compositions of their rivals' characteristics. We find that bidders submit significantly lower bids when confronted with rivals' characteristics which are more valuable for the buyer.

These insights finally allow us to conduct a counterfactual analysis and determine the impact of reducing the availability of non-price information on buyers' welfare and platform profits. Based on our formal framework where bidders are informed with respect to all non-price aspects we derive estimates of the bidders' cost. Based on our formal framework where

bidders are not informed about non-price characteristics of the contract to be procured, we then determine the counterfactual buyers' utility and the counterfactual platform turnovers. We find that if non-price information was not available to the bidders, platform turnovers would decrease by 30% from 10 million euros to 7 million euros. In contrast, buyers would be better off, with a relative utility increase of the monetary equivalent of 2.6 million euros. Our analysis thus shows that the decision whether or not to reveal quality information to the bidders has quite significant consequences on the welfare of the buyers and the platform.

Our work adds to a strand of literature which is concerned about efficient ways to procure contracts when the buyer's valuation of an offer depends on additional dimensions besides the price. A specific procurement mechanism which has already received some attention in the economic literature and is quite well understood are scoring auctions. Asker and Cantillon (2008, 2010) showed that for the case when suppliers have multi-dimensional private information this procurement mechanism dominates others like sequential bargaining and price-only auctions. Different scoring auction designs are compared in Che (1993), Branco (1997), Chen-Ritzo et al. (2005) and Kostamis et al. (2009). Empirical analysis of scoring auctions can be found in Athey and Levin (2001) and Lewis and Bajari (2011), the first using data from US timber auctions and the second data from US highway procurement auctions.

In practice non-binding auctions have established themselves as the most prominent type of procurement auctions. Che (1993) shows that when bidders bid on all dimensions of their offers, from the buyer's perspective scoring auctions dominate non-binding auctions. In contrast, Engelbrecht-Wiggans et al. (2007) show that when bidders' non-price characteristics are exogenously given and they only bid on price, the non-binding auction format is preferred by the buyer when the number of participating bidders is high enough. Katok and Wambach (2011) find that when bidders are uncertain about the exact way different criteria enter the final decision of the buyer, there are cases where a non-binding auction enables them to coordinate on high prices. In that case the buyer would prefer binding price-only auctions over non-binding auctions.

We are specifically interested in the effect of different information structures in non-binding auctions. Several theoretical papers analyze the conditions under which it is beneficial for the buyer to inform the bidders about their quality. Gal-Or et al. (2007) show that under simultaneous bid submission and some assumptions regarding the distribution of the bidders' qualities the buyer is better off when he discloses quality information to the bidders. Complementing technical remarks to their work and an extension to risk averse bidders are provided in Doni and Menicucci (2010). Colucci et al. (2011) extend the setting of Gal-Or et al. (2007) by introducing heterogeneity in bidders' costs. They demonstrate that for the case of large cost differences and a comparatively small weighting of quality aspects it is in the best interest of the buyer to conceal quality information. In the opposite case, he is better off disclosing information about the bidders' quality.² To shed more light on these theoretical results, Haruvy and Katok (2010) conduct laboratory experiments to analyze both open and sealed bid buyer-determined auctions. For the environments chosen in their experiments they find that in their open auction design buyers are better off if they keep information about bidders' qualities concealed. To the best of our knowledge our article is the first one to analyze non-binding auctions based on field data. Interestingly, with our real world data we confirm that buyers are better off if all information with respect to non-price characteristics is concealed.

The article is organized as follows: In the next section we establish the formal frameworks describing two limiting information structures for open non-binding auctions. Section 3 then analyzes under what conditions it is beneficial for the buyers (respectively the auction platform) to disclose quality information. Section 4 introduces the dataset and the framework for our empirical analysis. Based on our analysis of the buyers' preferences in section 5, in section 6 we examine whether bidders are informed about their qualities. Finally, in section 7, we perform a counterfactual analysis to determine the impact of non-price information on

²Interestingly, for a similar setting Rezende (2009) shows that when the buyer and the suppliers have the possibility to renegotiate, it can be optimal for the buyer to fully reveal the information about the suppliers' qualities.

buyers' welfare and platform profits. Section 8 concludes.

2 Theoretical framework

We analyze an open non-binding reverse auction in which after a certain bidding period the buyer is free in his decision among the offers of the participating bidders. The bidders bid on prices only, but besides the prices the buyer has available information about exogenous bidder characteristics, and we assume that the buyer bases his final decision on both the prices put forward and these characteristics. The valuation of a bidder's non-price characteristics by the buyer will be termed that bidder's quality in the following. Our research interest lies in the implications of the availability of quality information to the bidders. We look at two limiting cases of information structures. In the first case, which we call no information case, bidders are not informed at all with respect to the non-price characteristics and thus behave as if they were bidding in a regular open price-only auction. In the second case, which we call information case, bidders have full information about both their own quality and their rivals' qualities and take that information into account when forming their bidding strategies.

The rest of this section is dedicated to theoretical descriptions of the two information cases. We start backwards by first analyzing the buyer's choice process and then we derive the different implications of the no information case and the information case on the behavior of the bidders.

■ **The buyer's behavior.** We assume that a buyer can choose among J bidders, that he receives a certain amount of utility u_j when he chooses bidder j , and that this amount of utility depends on the price p_j put forward by this bidder and the bidder's exogenous quality q_j . We model the utility a buyer receives from a certain bidder as being linearly dependent

on the price p_j , the bidder's quality q_j , and an idiosyncratic term ϵ_j :

$$\begin{aligned} u_1 &= q_1 - p_1 + \epsilon_1 \\ &\vdots \\ u_J &= q_J - p_J + \epsilon_J \end{aligned} \tag{1}$$

We introduce the idiosyncratic terms ϵ_j for two reasons: First, on an online reverse auction platform like that we consider bidders encounter not only one but several buyers who surely do not value the bidders' characteristics all in the exact same way. Second, later on this assumption will allow us to build our empirical model in close analogy to our theoretical framework.

A buyer is assumed to choose the option which maximizes his utility, i.e. the option k for which

$$u_k > u_j \quad \forall j \neq k, \quad j, k \in \{1, \dots, J\}.$$

We assume that the unobservables ϵ_j follow some kind of distribution, which implies that a buyer chooses option j with a certain probability P_j .

■ **The bidders' behavior in the information case.** In the information case we assume that every bidder j knows his own quality q_j , his rivals' qualities q_k , and the prices p_k they put forward. In consequence, bidder j can derive his own winning probability, P_j , and that of every rival, P_k (given some bid p_j of his own). We assume each bidder puts forward a bid p_j which maximizes his expected profit π_j ,

$$\pi_j = P_j(p_j - c_j).$$

Ceteris paribus, by lowering his bid p_j bidder j faces a trade-off between increasing his winning probability, P_j , and lowering the markup over his costs, $(p_j - c_j)$.

We apply the Nash equilibrium concept here, meaning we assume that in equilibrium each bid is chosen as best reply to all rival bids.³ In terms of the bidders' first order conditions,

$$p_j + \frac{P_j}{\partial P_j / \partial p_j} - c_j = 0, \quad \forall j \in \{1, \dots, J\}, \quad (2)$$

this is equivalent to the statement that the bids p_1, \dots, p_J simultaneously solve equation system (2).⁴ A short rearrangement of bidder j 's first order condition shows that in equilibrium bidder j 's bid p_j is given by

$$p_j = c_j + \frac{P_j}{|\partial P_j / \partial p_j|}. \quad (3)$$

Note that we make the assumption that (*ceteris paribus*) the buyer prefers lower prices, meaning that the derivative $\partial P_j / \partial p_j$ is of negative value. So, in the information case bidder j 's bid p_j equals his costs c_j plus a mark-up which depends on his winning probability P_j . As the bids of bidder j and his rivals are endogenously determined by the equation system (3), in the end P_j depends on the relation of bidder j 's quality to his rivals' qualities. The "better" bidder j is in comparison to his rivals in terms of quality, the higher is his mark-up on his costs. Vice versa, the "worse" he is in comparison to his rivals, the more competitive he will bid. In terms of our model this means that $\frac{\partial p_j}{\partial q_k} < 0$.⁵

■ **The bidders' behavior in the no information case.** In the no information case we assume that bidders are not informed at all with respect to their and their rivals' qualities. We model this situation by making the simplifying assumption that the only information the bidders have about the buyer's decision process is that *ceteris paribus* he prefers lower prices. In effect, we assume that the bidders have no information about their probability of winning the auction, and that they have to resort to the assumption that the bidder with

³This assumption is justified as in the open auction format under consideration the time the bidders have to react to their rivals' prices should be sufficient to guarantee the installation of the Nash equilibrium. As can be seen from the figures in table 1, sniping plays no role at the auction platform we consider.

⁴Note that the winning probability of bidder j , P_j , depends on all the prices put forward in the auction, i.e. $P_j = P_j(p_1, \dots, p_J)$.

⁵The proof that this statement holds given a weak regularity condition can be found in the appendix.

the lowest price gets the job contract awarded.

In consequence, in the no information case bidders behave as in a regular open price-only auction. That means in equilibrium all bidders but the one with the lowest costs bid exactly their costs, and the bidder with the lowest costs bids the costs of the bidder with the second-lowest costs. For the rest of the paper, we will assume without loss of generality that the bidders are ordered according to their costs c_j , $c_1 \leq c_2 \leq \dots \leq c_J$. With this assumption, bidder j 's behavior in the no information case can be expressed as

$$p_j = \begin{cases} c_2 & \text{if } j = 1, \\ c_j & \text{if } j \in \{2, \dots, J\}. \end{cases}$$

Thus, in the no information case the bids are solely determined by the bidders' costs. The bidders' qualities influence the buyer's decision, but they play no role at all for the bidders' behavior.

3 Comparison of information structures

In this section we analyze under what conditions it is beneficial for the buyers (respectively the auction platform) to disclose quality information. As for any reasonable choice of distribution for ϵ_j equation system (2) is either transcendental (e.g. for the choice of a normal or a type I extreme value distribution) or its solution gets intractable (e.g. for a uniform distribution), we do not present analytical results. Instead, we assume the ϵ_j to be iid type I extreme value distributed and use numerical simulations to get an understanding of the connection between our model parameters (namely the bidders' costs c_j and qualities q_j) and the ranking of the information structures from the perspective of the buyer respectively the platform. (Simulation details can be found in the appendix.) We show that neither from the point of view of the buyer nor the platform there is a dominant information structure over the whole parameter space. Instead, whether the information case (disclosure of qual-

ity information) or the no information case (concealment of quality information) is favored depends on the relationship between the difference in the bidders' costs and the difference in their qualities.

For both the information and the no information case we simulate the bidding behavior for an auction with two participants. One of the participants (bidder 2) is assumed to have costs $c_2 > 0$ and to be in possession of a valuable characteristic and thus quality $q_2 > 0$, while the other participant (bidder 1) is assumed to have costs $c_1 = 0$ and no valuable characteristic (i.e. $q_1 = 0$).⁶ These particular assumptions exemplify the more general assumption that higher quality correlates with higher costs - an assumption which should be sensible for a large range of applications. For both cases and for $q_2 = 1$ figure 1 depicts the bidding behavior as a function of the difference in the bidders' costs. In the no information case both bidders simply bid the costs of bidder two. In the information case, both bidders can be observed to bid their costs plus a markup. It can be seen that from a certain cost difference on in the information case the strength of bidder 2 forces bidder 1 to bid below c_2 , which would be his bid amount in the no information case.

Figure 2 displays two indifference lines over the difference in the bidders' costs: the solid line shows the values of q_2 for which the buyer is indifferent between the two information cases, and the separated line shows the values of q_2 for which the platform is indifferent.⁷ For all combinations of cost difference and quality below the solid line, the buyer prefers the information case over the no information case, and vice versa for all other combinations. In analogy, for all combinations below the separated line the platform prefers the no information case. For all other combinations it prefers the information case.

There are two main points which can be made from the inspection of figure 2: First, for small cost differences the buyer always prefers the no information case over the information

⁶Note that what drives our results is solely the fact that bidder 2 has higher costs and higher quality than bidder 1. $c_1 = 0$ and $q_1 = 0$ is simply a harmless normalization.

⁷We assume that the profit of the platform increases with turnovers generated in the auctions. This assumption corresponds with the widespread custom to charge a certain percentage of the winning bid as commission.

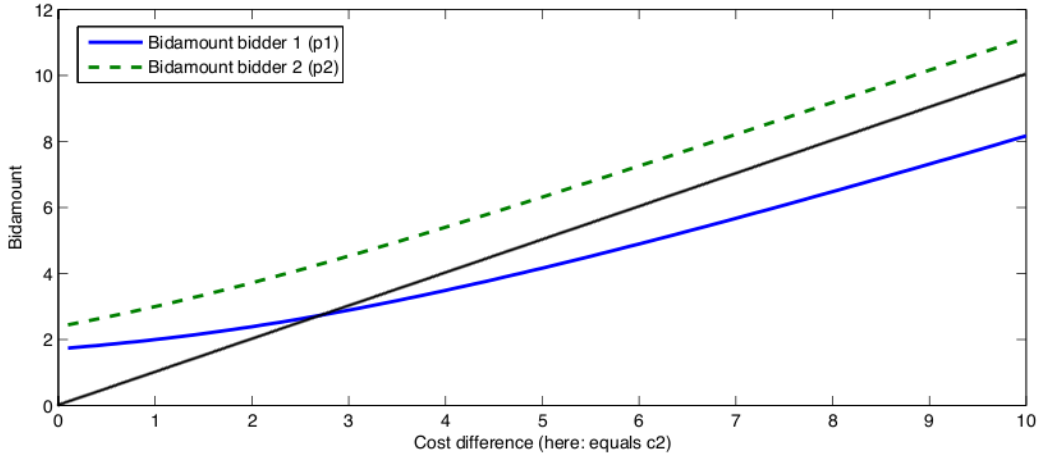


Figure 1: **Bid amounts in dependence on the cost difference.** Bidder 2 is assumed to be of quality 1 in the eyes of the buyer, bidder 1 of quality 0. Bidder 1's costs are normalized to 0. Thus the cost difference equals bidder 2's costs. The two plotted lines show the bid amounts of bidder 1 and 2 in the information case. For comparison the 45° line is drawn in. This line marks the bid amounts of both bidder 1 and bidder 2 in the no information case. Simulation details can be found in the appendix.

case. From a certain cost difference on, whether the buyer prefers the information case or the no information case depends on the value of q_2 : If q_2 is small enough compared to the cost difference, the buyer prefers the information case. Otherwise, he favors the no information case. The intuition behind is that the buyer will only prefer the information case if the threat from the stronger rival forces bidder 1 to lower his bid far enough. However, bidder 1 can only lower his bid to his own costs. If the value of q_2 is too high compared to the cost difference, bidder 1 cannot lower his bid far enough to remain a valid option to the buyer, and the buyer will prefer the no information case where bidder 2 cannot demand a markup on his costs.

Second, for small and for large cost differences the platform favors the information case over the no information case. Only for an intermediate range of cost differences and only if q_2 is small enough the platform prefers the no information case. The explanation is that for low cost differences in the information case bidder 1 cannot be forced by bidder 2 to lower his bid so far that the expected turnover in the information case is lower than in the no

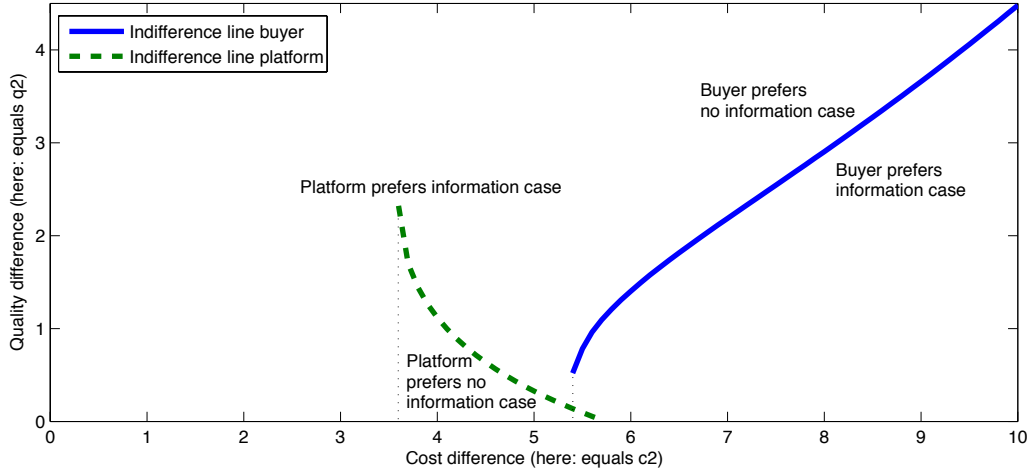


Figure 2: **Indifference lines for the buyer and the auction platform.** The solid line shows for a given difference in costs the difference in bidders' qualities for which the buyer would be indifferent between the no information and the information case. The dashed line shows the respective indifference line for the auction platform. As bidder 1 is normalized to have costs of zero and to be of quality zero, here the quality difference equals bidder 2's quality and the cost difference equals bidder 2's costs. Simulation details can be found in the appendix.

information case. For an intermediate range of cost differences bidder 2 bids aggressive and forces bidder 1 to lower his bid significantly below bidder 2's costs. If in this intermediate range of cost differences the value of q_2 is not too high, then bidder 2 will not bid too far above his own costs, and together with the fact that bidder 1 bids significantly below bidder 2's costs this renders the expected turnover in the information case lower than that in the no information case (which equals exactly c_2). For high cost differences, however, the situation resembles that examined in Katok and Wambach (2011). When the cost difference between bidder 1 and bidder 2 is high and bidder 2 bids aggressive, bidder 1 has the possibility to lower his bid such far that he keeps a fairly high winning probability, which in turn lowers bidder two's expected utility. Bidder 2 is aware of that, and therefore he will refrain from bidding aggressive. Thus, for high cost differences in the information case both bidder 1 and bidder 2 bid high relative to their costs. As a consequence, for high cost differences the expected turnover of the platform is always higher in the information case.

The main point to take away is that what information structure the buyer (respectively the platform) prefers depends on the relationship between the model parameters, namely between the difference in the bidders' costs and the difference in the bidders' qualities. Accordingly, for the following analysis of the information structure of a large European online procurement platform we will use our theoretical framework to structurally estimate unknown quality and cost parameters. These estimates then allow us to perform counterfactual simulations and to determine the effects of availability of quality information on the buyers' welfare and the turnovers of the platform.

4 Data and framework for empirical analysis

For our study of the impact of different information structures we use an extensive dataset from a popular European online marketplace for contractors. The exact procedure on this platform is as follows: Buyers post descriptions of their job offers. After a buyer posted a job, contractors have a certain amount of time to (potentially repeatedly) announce the price for which they would be willing to do the job. At every point of this process, each bidder knows his rivals' prices and non-price characteristics. At the end of the bidding process the buyer is free to give the job to one of the participating bidders or to withdraw his offer. For his decision the buyer has available information about each contractors' prices and non-price characteristics.

In the following, we concentrate on data from auctions on painting and wallpapering jobs. Altogether, we have data on 45,329 auctions, covering the years 2006 to 2008. For all of these auctions, we have information about the number and the identities of the participating bidders, the prices put forward, the bidder's non-price characteristics and the choice of the potential buyer (including whether or not he chose to withdraw his job offer). For 3,433 of these 45,329 auctions, we have in addition collected information about cost factors of the jobs offered (like for example the area to paint, whether paint is provided by the buyer, and

	Mean	SD	Median	Min	Max
Nbr. of bidders per auction	7.19	4.39	7	1	28
Bid amount	583.74	529.29	440	35	18,830
Startprice	523.95	396.73	400	100	2000
Nbr. of auction participations per bidder	3.93	11.35	1	1	275
Auctions per buyer	1.02	0.13	1	1	3
Auction duration (days)	9.44	7.55	8.91	0.01	92.25
Last bid placement (hours till auction end)	35.13	87.66	5.90	0	1994.44
Nbr. of auctions	3,326				
Nbr. of bidders	3,669				
Nbr. of buyers	3,274				

Table 1: **Descriptive statistics** for auctions with both cost information and information about bidders' characteristics available. The announced startprice is less or equal than 2000 EUR.

so on). All the auctions for which we collected cost factors took place during the year 2008.

With posting a job offer, every buyer also sets a startprice. The startprice is set purely for informational reasons. It is non-binding in the sense that contractors are free to bid over it and the buyer in his final decision is not bound in any way to his announcement. In 3% of the auctions under consideration a startprice of more than 2000 EUR is set. A major part of these auctions is about jobs with special requirements, e.g. the use of scaffolding. As there is not enough information in the data to sufficiently control for special cost elements like that, for the following analysis we drop all auctions with startprices of more than 2000 EUR. We are left with 3,326 auctions for which cost information and information about bidders' non-price characteristics are available. Descriptive statistics for these auctions are given in table 1.

In the following we use the data to analyze the impact of availability of quality information to the bidders. The structure of our analysis is as follows: As a first step we analyze the buyers' preferences. Based on the results of this preparatory step, we examine whether

bidders are aware of their rivals’ qualities, i.e. their rivals’ non-price characteristics and the buyers’ respective preferences. In concrete terms, we look whether bidders orientate their behavior at their costs only or also at their qualities. Finally, based on the insights gained and the theoretical framework developed in section 2, we perform a counterfactual analysis to estimate the effects of a change in the platform’s information structure.

5 Estimation of the buyers’ preferences

A bidder’s quality is determined by the bidder’s non-price characteristics and the buyers’ respective preferences. In this section we elicit the buyers’ preferences using a logit discrete choice model: For a given auction n we model the buyer’s decision as a discrete choice among the participating bidders and an outside option. We do not observe the value of the buyer’s outside option, but we assume that the startprice s_n a buyer announces can be used as a valid proxy.⁸ The buyer is assumed to base his decision among the bidders on the prices put forward and the non-monetary characteristics of each bidder. Bidders’ non-monetary characteristics comprise binary characteristics, indicating for example the possession of a german ”Meister” degree, discrete characteristics like number of positive ratings and number of negative ratings, and a continuous measure for the distance between bidder j ’s home and the job site.⁹

We estimate the buyers’ preferences along the lines of the model we developed in section 2: a buyer’s utility from choosing an alternative is assumed to be linearly dependent on that alternative’s price p_{nj} , its quality q_{nj} and an idiosyncratic error term ϵ_{nj} . We assume that a

⁸We do not argue that the startprice equals the value of the buyer’s outside option. We are aware that a buyer’s announcement of the startprice will be influenced by strategic considerations. However, as the level of the bids put forward is highly correlated with the level of the announced startprice, and as it seems reasonable to believe that this fact is known to the buyer, the announced startprice should contain information about the price expectation of the buyer. This price expectation should be formed relative to the buyer’s outside option, and thus the announced startprice should be a valid proxy for the value of the outside option.

⁹The distance measure is constructed from the buyer’s and the bidders’ zip-codes. As such it is only approximate. However, given the assumption that also the buyers can in general be expected to base their decision on a rough distance estimate and not an exact calculation, it should suffice to capture the respective part of the buyers’ decisions.

bidder's quality q_{nj} depends linearly on that bidder's characteristics and the preferences of the buyer over this characteristics. With \mathbf{A}_{nj} subsuming the non-monetary characteristics of bidder j in auction n , and $\boldsymbol{\alpha}$ denoting the buyer's preferences over these characteristics, the quality q_{nj} of bidder j in auction n is given by $\boldsymbol{\alpha}\mathbf{A}_{nj}$. With ρ denoting the price elasticity of the buyer, the utility he derives from either his outside option (indexed by 0) or one of the J_n participating bidders can explicitly be formulated as¹⁰

$$\begin{aligned} u_{n0} &= \varsigma s_n + \epsilon_{n0} \quad (\equiv v_{n0} + \epsilon_{n0}) \\ u_{n1} &= \rho p_{n1} + \boldsymbol{\alpha}\mathbf{A}_{n1} + \epsilon_{n1} \quad (\equiv v_{n1} + \epsilon_{n1}) \\ &\vdots \\ u_{nJ_n} &= \rho p_{nJ_n} + \boldsymbol{\alpha}\mathbf{A}_{nJ_n} + \epsilon_{nJ_n} \quad (\equiv v_{nJ_n} + \epsilon_{nJ_n}). \end{aligned}$$

The buyer is assumed to choose the alternative which offers him the highest utility. By assuming the idiosyncratic error terms ϵ_{nj} to be independently, identically type I extreme value distributed, we obtain the standard multinomial logit model: The choice probabilities are given as

$$P_{nj} = \frac{e^{v_{nj}}}{\sum_{k=0}^{J_n} e^{v_{nk}}},$$

and estimates of the model parameters $\{\varsigma, \rho, \boldsymbol{\alpha}\}$ can be obtained by maximizing the likelihood

$$L = \prod_{n=1}^N \prod_{j=0}^{J_n} (P_{nj})^{y_{nj}}, \quad y_{nj} = \begin{cases} 1 & \text{if alternative } j \text{ is chosen in auction } n, \\ 0 & \text{otherwise.} \end{cases}$$

We estimated our model first on all auctions from the painting and wallpapering category

¹⁰Note that we did not include intercepts in the utility specifications for the bidders 1 to J_n . This does not mean that we impose strong restrictions on our discrete choice model. As just differences in utility matter, this specification only implies that the constant part of utility is the same for bidders 1 to J_n and normalized to zero, and that the normalized utility of the outside option is linear in the startprice of the auction.

Covariates in buyer's utility fct.	Coefficient estimates	
	All auctions with startprice \leq 2000EUR	Subset of auctions with startprice \leq 2000EUR for which cost information is available
Bid amount (EUR)	-.005*** (.00006)	-.010*** (.0003)
Nbr. of Positive Ratings	.009*** (.0005)	.016*** (.001)
Nbr. of Negative Ratings	-.039*** (.004)	-.111*** (.012)
Startprice (EUR)	-.003*** (.00005)	-.011 (1.342)
Distance (km)	-.002*** (.0001)	-.005*** (.0006)
Nbr. of Employees	-.070*** (.012)	-.050 (.036)
Registered at Platform	-.092* (.056)	-.137 (.155)
Verified as Professional	-.847*** (.036)	24.153 (788.619)
Master Craftsman Company	.163*** (.030)	.136 (.083)
Senior Journeyman Company	.008 (.024)	.004 (.068)
Engineer	-.151** (.060)	-.203 (.140)
Technician	.226 (.169)	.890* (.539)
Freelancer	.345 (.324)	-.160 (1.093)
Trade License	.123*** (.017)	.225*** (.055)
Craft Card	-.113*** (.023)	.034 (.063)
In Craftsmen Register	.091*** (.016)	.295*** (.048)
Other Certifications	.024 (.019)	-.008 (.052)
Liability Insurance	.129*** (.033)	.122 (.098)
N	311,332	26,863

Table 2: **Results of the estimation of the logit discrete choice model.** The estimates are based on 311,332 observations (all auctions with startprice \leq 2,000EUR) respectively 26,863 observations (subset of auctions with startprice \leq 2,000EUR for which cost information is available). Standard errors are reported in parentheses. Significance niveaus are reported by stars: ***: 1%, **: 5%, *: 10%.

with an announced startprice of at most 2000 EUR and then on the subset of these auctions for which cost information is available. Table 2 shows the results. In the larger sample, besides price and some other characteristics, especially the way a bidder has been rated by former buyers strongly influences the actual buyer's decision: 10 positive ratings higher a bidder's winning probability by nearly 1%, 10 negative ratings lower it by about 3%. In the considerably smaller sample of auctions for which cost information is available, the way a bidder is rated seems to have an even stronger influence on the buyer's decision.

The important take away for the following section is that the way a bidder is rated obviously strongly influences the buyer's decision: everything else equal, the higher the difference between positive and negative ratings, the more likely a bidder is to be chosen. This finding holds both in our large and our small sample of auctions, and additionally it is robust against different utility specifications, like the use of logarithmized ratings or startprice-normalized bid amounts.

6 Analysis of the information structure

Bidders have available information about their rivals' prices and non-price characteristics. However, buyers do not explicitly state their preferences over bidders' non-price characteristics and thus bidders are not explicitly informed about their qualities. The question we want to answer in this section is whether bidders do have (implicit) information about buyers' preferences and thus are able to orientate their behavior at their qualities.

■ **Econometric model.** In section 2 we developed a theoretical framework for the case where bidders are informed about their qualities, and another for the case where bidders are not informed about their qualities. We make use of contrasting implications of these two frameworks regarding bidders' behavior when faced by a strong rival to identify whether bidders are aware of their qualities: If bidders have no information about their qualities, they will orientate their bidding behavior at their costs only. So, *ceteris paribus* bidders'

should show no reaction to the appearance of a strong rival. If in contrast bidders do have information about their qualities, it can be shown that

$$\frac{\partial p_{nj}}{\partial q_{nk}} < 0$$

holds (see appendix). I.e., if *ceteris paribus* an auction participant is replaced by one with a higher quality, the bidding behavior of the other bidders should become more aggressive, meaning that they should lower their bids.

We now use the theoretical frameworks developed in section 2 to develop an econometric model which allows us to identify the reaction of the bidders to the appearance of a strong rival: In the no information case under the assumption $c_{n1} \leq \dots \leq c_{nJ_n}$ the bid amount of bidder j in auction n is given by

$$p_{nj} = \begin{cases} c_{n2} & \text{if } j = 1, \\ c_{nj} & \text{otherwise,} \end{cases} \quad (4)$$

while in the information case it is given by

$$p_{nj} = c_{nj} + \frac{P_{nj}}{|\partial P_{nj} / \partial p_{nj}|} \equiv c_{nj} + \tilde{\tau}_{nj}. \quad (5)$$

Bidder j 's markup $\tilde{\tau}_{nj}$ on his costs c_{nj} depends on the relationship of bidder j 's quality to the other bidders' qualities and thus in the end on the relationship of bidder j 's non-monetary characteristics \mathbf{A}_{nj} to the other bidders' non-monetary characteristics $\mathbf{A}_{n,-j}$.

Let the binary variable S_{nj} indicate whether bidder j has to face a strong rival in auction n . For the sake of exposition we assume that a strong rival is distinguished by the possession of a certain characteristic s . We know from our theoretical considerations that if bidder j has information about the buyers' preferences, *ceteris paribus* he should lower his bid if one of his rivals is replaced by a stronger one. We can model this behavior in terms of the

markup as

$$\tilde{\tau}_{nj} = \tau_{nj} + \beta S_{nj},$$

with $\beta < 0$. Here, τ_{nj} is the markup of bidder j in auction n if he would not have to face a strong rival, i.e. if ceteris paribus the strong rival was deprived of his characteristic s .

We cannot simply repeat each auction, replace one of bidder j 's rivals by a stronger one, and look whether this has an effect on bidder j 's behavior ($\beta \neq 0$) or not ($\beta = 0$). Thus, for estimation purposes we have to work with further assumptions. The first assumption is in fact hardly more than an interpretation of τ_{nj} : We interpret τ_{nj} as the strength of bidder j relative to his rivals in auction n who are (where applicable) deprived of the characteristic s , and simply state that τ_{nj} has some kind of distribution with mean μ_j and variance σ_τ^2 . We then can write $\tilde{\tau}$ as

$$\tilde{\tau}_{nj} = \mu_j + \beta S_{nj} + \vartheta_{nj}. \quad (6)$$

μ_j can be interpreted as the strength of bidder j relative to the whole population of not strong rivals (rivals without s), ϑ_{nj} as the deviation from μ_j such that $\tau_{nj} = \mu_j + \vartheta_{nj}$. ϑ_{nj} is assumed to have mean zero and variance σ_τ^2 .

Besides (possibly) by his relative quality, bidder j 's bid in auction n is determined by his costs c_{nj} (compare equations (4) and (5)). We do not know the exact costs c_{nj} of bidder j in auction n . However, for every auction we observe cost factors like the area to be painted, whether paint is provided by the buyer, and so on. We subsume those cost factors in \mathbf{K}_{nj} and assume that bidder j 's costs c_{nj} are linearly dependent on them:

$$c_{nj} = a_j + \boldsymbol{\xi} \mathbf{K}_{nj} + \nu_{nj} \quad (7)$$

a_j denotes bidder specific constant cost components and can be interpreted as the opportunity costs of bidder j (i.e. as proxy for the otherwise workload and order situation of bidder j). ν_{nj} is an idiosyncratic error term with mean zero and variance σ_ν^2

With these assumptions we can express bidder j 's bid as

$$\begin{aligned}
p_{nj} &= c_{nj} + \tilde{\tau}_{nj} \\
&= a_j + \boldsymbol{\xi}\mathbf{K}_{nj} + \nu_{nj} + \mu_j + \beta S_{nj} + \vartheta_{nj} \\
&= \boldsymbol{\xi}\mathbf{K}_{nj} + \beta S_{nj} + a_j + \mu_j + \vartheta_{nj} + \nu_{nj}.
\end{aligned} \tag{8}$$

Note that from here on we exclude bidder-auction pairs nj from our analysis if bidder j announced the lowest price in auction n . Thus, expression (8) captures both the case where bidders are informed about their qualities and the case where bidders are not informed about their qualities (in the latter case μ_j , β and ϑ_{nj} would simply equal zero). We define $\tilde{a}_j \equiv a_j + \mu_j$ and $\epsilon_{nj} \equiv \vartheta_{nj} + \nu_{nj}$ and arrive at

$$p_{nj} = \boldsymbol{\xi}\mathbf{K}_{nj} + \beta S_{nj} + \tilde{a}_j + \epsilon_{nj}. \tag{9}$$

Equation (9) relates the bid amount bidder j puts forward in auction n to the observed cost elements \mathbf{K}_{nj} , an indicator for the presence of a strong bidder, S_{nj} , a bidder specific constant \tilde{a}_j , and an error term ϵ_{nj} . The unobserved bidder specific constant \tilde{a}_j essentially captures both the opportunity costs of bidder j and the average quality of bidder j relative to the whole population of not strong rivals (rivals without s). The error term ϵ_{nj} consists of the error term ϑ_{nj} from the markup equation (6) and the error term ν_{nj} from the costs equation (7). Thus it captures unobserved influences on bidder j 's markup (respectively his relative strength) and costs in auction n .

■ **Identification strategy.** We restrict our analysis to data on bidders which are observed in several auctions. In doing so, we loose some estimation efficiency, but as the number of observations available remains quite high, that does not matter much. What we gain is the possibility to estimate equation (9) by mean-differencing (i.e. employing a fixed effects estimator), and by that getting rid of the individual specific and unobserved constants

\tilde{a}_j . The assumption which has to hold for our estimates to be consistent is that the ϵ_{nj} are mean-independent from the observable cost elements \mathbf{K}_{nj} and the strong rival indicator S_{nj} . As we will discuss in more detail below, this assumption is likely to hold in our case.

Put together, our estimation strategy is to use data on bidders which are repeatedly observed and to estimate equation (9) by employing a fixed effects estimator. The bidders' information state is identified by β , the coefficient on the strong rival indicator: Our theory predicts that if bidders are not informed about the buyer's preferences over their non-monetary characteristics, β should equal zero. If, however, bidders are informed about the buyer's preferences, β should be negative and significantly different from zero.

■ **Estimation.** We define that a given bidder j encounters a strong rival in auction n if at least one of the other bidders in auction n has a difference of positive and negative ratings of at least 90:

$$S_{nj} = \begin{cases} 1 & \text{if encounter with a strong rival,} \\ 0 & \text{otherwise.} \end{cases}$$

As we want to estimate equation (9) by a fixed effects estimator, we have to restrict our sample to bidders which are observed in at least two auctions. In addition, we include in our sample only bidders which have a difference of positive and negative ratings of less than 90. There is some (quite small) efficiency loss due to this restriction, but it simplifies the determination of encounters with strong rivals a lot. This leaves us with a sample of 1,448 bidders, taking part in 2,547 auctions (the mean number of auction participations is 9.6, the median number is 5). In 18.9% of these auctions a bidder with a ratings difference of at least 90 takes part.

Table 3 shows our estimation results. The first column exhibits our base specification. As the number of bidders in an auction might have an influence on a single bidders' behavior, in column two we add dummies to control for auction size. In column three,

Dependent variable: Bid amount of bidder j in auction n	(1)	(2)	(3)	(4)
Strong Rival (Dummy)	-61.12*** (13.41)	-60.97*** (14.53)	-63.64*** (13.56)	-63.82*** (14.76)
<i>Controls:</i>				
Area to paint (m ²)	1.88***	1.91***	1.88***	1.91***
Area to paper (m ²)	2.09***	2.00***	2.10***	2.00***
Paper removal (m ²)	2.72***	2.81***	2.73***	2.82***
Cleaning (Dummy)	76.24***	68.37**	78.50***	70.42**
Reparation (Dummy)	66.12***	77.90***	66.00***	
Priming (Dummy)	138.92***	139.28***	138.52***	138.82***
Nbr. of windows	32.43***	32.43***	32.44***	
Nbr. of window frames	113.40***	132.81***	113.53***	132.81***
Nbr. of doors	53.38***	52.62***	53.84***	53.06***
Nbr. of door frames	29.11***	30.56***	28.91***	
Nbr. of radiators	7.25	5.46	7.28	5.54
Paint by contractor (Dummy)	8.33	-.03	9.00	.57
Varnish by contractor (Dummy)	361.21***	353.14***	360.81***	352.58***
Distance (km)	1.06***	1.03***	1.10***	1.08***
Dummies for nbr. of bidders		X		X
Dummies for region			X	X
Dummies for startprice interval				
Bidder FE's	X	X	X	X
R ²	0.344	0.3512	0.347	0.354
N	13,909	13,909	13,909	13,909

Table 3: **Identification of the bidders' reaction to a strong rival; results of fixed effects estimation.** Dependent variable is bid amount. Covariates are a dummy indicating the appearance of strong rival (a rival with a difference between positive and negative ratings of at least 90) and cost controls. The panel consists of 1,448 bidders who on average take part in 10 auctions each. Cluster-robust standard errors are reported in parentheses. For all results: both within- and between-R² are close to the overall R². Significance niveaus are reported by stars: ***: 1%, **: 5%, *: 10%.

we control for regional influences by adding region dummies.¹¹ Column four shows the results for the specification with both size and region dummies. The coefficients on the cost factors do not vary much between the specifications, and they are of reasonable size: A professional craftsman in Germany charges on average 5 to 6 EUR per painted square meter. This includes the painting, the paint, masking and travel. The average area to be painted in our data set is 163.7 m², the average travel distance 44.7 km. Together with our estimation results in table 3 this implies that the average price per square meter painted, including paint and travel, is about 3 EUR on the auction platform. Given that most of the bidders on the platform are non-professionals,¹² this number seems to be plausible. In all four specifications the coefficient on the strong rival indicator S_{nj} is highly significant and strongly negative, meaning that bidders bid more competitive if they encounter a strong rival: they lower their bids by around 60 EUR, which is a quite strong reduction if one considers that the average bid amount in our sample is about 580 EUR.

■ **Discussion of estimation results.** Our estimation results suggest that bidders react to the appearance of a strong rival by lowering their bids. However, as mentioned during the derivation of equation (9) above, the coefficient at the strong rival indicator S_{nj} , β , can only be interpreted as the direct causal effect of the appearance of a strong rival on bidder j 's bidding behavior if the unobserved part of equation (9), ϵ_{nj} , is mean independent from the observables \mathbf{K}_{nj} and S_{nj} . ϵ_{nj} equals $\vartheta_{nj} + \nu_{nj}$ and thus captures two unobserved influences on bidder j 's bid: One, ϑ_{nj} , stems from the composition of auction n in terms of the qualities of bidder j 's rivals, the other, ν_{nj} , stems from bidder j 's cost components.

It could be that ϑ_{nj} , the term capturing unobserved quality effects, is correlated with the strong rival indicator S_{nj} . Then bidder j would not directly react to the large difference in positive and negative ratings which characterizes a strong rival, but to some other attributes typical for either the strong rival or for participants in an auction with a strong rival. In

¹¹We define auctions to be from the same region when the first digit of their zip code is identical.

¹²85% of the bidders in our sample are neither master craftsmen nor senior journeymen.

this case we would still be able to determine whether bidder j has quality information: If bidder j did not have quality information at all, *ceteris paribus* he should not react to the appearance of a strong rival, whatever quality aspect that might proxy for. So: possible correlation between the covariates and ϑ_{nj} does not fundamentally hinder us to identify whether bidders have quality information - it could only lead us to wrong conclusions about what kind of quality aspects bidders directly react to. However, as we know from our logit estimations that the ratings difference has a strong influence on the buyer's decision and as the difference in a bidder's ratings is not strongly correlated with any other of his characteristics or the bidder composition of the auction, we are pretty sure that we identify the direct reaction of the bidders to their rivals' difference in positive and negative ratings.

In contrast, possibly problematic for the identification of the bidders' information state is correlation between the covariates and ν_{nj} , the unobserved part of equation (9) which stems from the bidders' cost components. If the unobserved deviation in bidders' costs from their expected value is systematically connected to the appearance of a strong rival, significance of β would no longer indicate that bidders are informed about the buyer's preferences. Assume for example that there is a characteristic of the jobs offered which is unobserved by us as researchers but observed by the bidders and which signals a reduction in costs. If strong bidders select themselves mainly into auctions with this unobserved characteristic, both in the case of informed and uninformed bidders we would observe a downward deviation of bids which would be correlated with the appearance of a strong rival and which could not be explained by the observable cost characteristics. This systematic downward deviation would be observed both in the case of informed and not informed bidders: in the case of informed bidders it would be caused by both lower costs and a strategic reaction to the presence of a strong rival, in the case of not informed bidders it would solely be caused by lower costs. So, in this case a downward deviation of bids which occurs systematically with the appearance of a strong bidder no longer necessarily indicates a strategic reaction - the presence of a strong rival could simply proxy for lower costs.

Dependent variable: Bid amount of bidder j in auction n	(1)	(2)	(3)
Strong Rival (Dummy)	-73.09*** (9.29)	-46.29*** (10.35)	-129.41*** (28.03)
<i>Controls:</i>			
Area to paint (m ²)	.59***	.65***	2.06***
Area to paper (m ²)	.84***	.82***	2.25***
Paper removal (m ²)	1.02***	.85**	.61
Cleaning (Dummy)	-59.22**	-44.13*	191.50***
Reparation (Dummy)	45.89***	45.82***	-99.92***
Priming (Dummy)	66.26***	49.08***	171.82***
Nbr. of windows	7.65	3.12	99.14*
Nbr. of window frames	51.59	81.63**	-19.13
Nbr. of doors	31.74***	29.89***	26.61
Nbr. of door frames	18.51**	19.05**	53.94***
Nbr. of radiators	-2.69	-5.85	-31.68***
Paint by contractor (Dummy)	13.56**	17.27***	2.10
Varnish by contractor (Dummy)	299.67***	283.84***	518.13*
Distance (km)	.44***	.44***	.49**
Dummies for nbr. of bidders		X	X
Dummies for region		X	X
Dummies for startprice interval	X	X	
Bidder FE's	X	X	X
R ²	0.545	0.555	0.425
N	13,909	13,909	3,027

Table 4: **Identification of the bidders' reaction to a strong rival; robustness checks.** Dependent variable is bid amount. Covariates are a dummy indicating the appearance of strong rival (a rival with a difference between positive and negative ratings of at least 90) and cost controls. The results in columns 2 and 3 are from the whole panel (1,448 bidders taking part on average in 10 auctions each). Note that due to high correlations between startprice and cost factors the coefficients on the cost factors in columns 2 and 3 are no longer clearly identified. Column 1 shows estimation results for a panel which includes only auctions with at least 15 participants. For all results: both within- and between-R² are close to the overall R². Cluster-robust standard errors are reported in parentheses. Significance niveaus are reported by stars: ***: 1%, **: 5%, *: 10%.

However, there are two reasons why we do not think that correlation of this kind plays a role: First, we collected our data by extracting the cost information from the job offers as they were available to the bidders. It is quite unlikely that we systematically missed a factor which is observable to the bidders and which indicates lower costs. Second, even if we missed a factor of this kind, it should be known to the buyers. Before an auction starts, the buyers announce a startprice. This startprice is announced for informational purposes, and it should be reasonable to assume that besides at strategic considerations buyers orientate the level of the announced startprice also at the costs of their job. So, if there is a cost factor which is unobserved by us as researchers but known to the buyers and bidders, this cost factor should be reflected in the level of the startprice. As can be seen from table 5, auctions in which a strong rival appears actually do systematically differ from auctions in which there is no strong rival in terms of the startprice. However, auctions in which a strong rival appears do not have a lower, but a higher startprice, indicating that strong rivals select themselves into auctions which seem to be quite valuable relative to the observable cost elements. This kind of selection should work against the hypothetical effect of the appearance of a strong rival in the case of informed bidders. As we are still able to observe more competitive bidding when a strong rival appears, we are quite certain that the coefficient on S_{nj} identifies strategic bidding behavior. In addition, if we control for different startprice intervals in the estimation of equation (9), the coefficient on S_{nj} stays highly significant and negative (see columns 1 and 2 of table 4).¹³

To summarize, our results strongly indicate that bidders seem to be informed about the preferences of the buyers over their non-monetary characteristics and thus their qualities, and that they behave accordingly. If a strong rival appears, the bidding behavior becomes far more competitive. This effect is quite strong: column 3 of table 4 shows the results of the estimation of equation (9) on the subset of auctions with at least 15 participating

¹³Note that after the introduction of dummies for startprice intervals the coefficients on the cost factors are in general no longer clearly identified, as the correlation between the startprice and job characteristics like for example the area to be painted is very high.

	Startprice			
	Obs	Mean	SE	[95% Conf. Interval]
Subset of auctions without strong rival ($S_{nj} = 0$)	2,065	513.62	8.97	[496.03, 531.21]
Subset of auctions with strong rival ($S_{nj} = 1$)	482	562.29	17.14	[528.60, 595.97]
p-value of two-sample t test: 0.0121				

Table 5: **Comparison of startprice distribution** for subset of auctions with a strong rival and for subset of auctions with no strong rival. The whole set of auctions is comprised of all auctions used for the estimations in columns 1 to 4 and 6 to 7 in table 3.

bidders. Although in most cases only one strong rival appears among at least 15 auction participants,¹⁴ the impact is still quite drastic, with an average reduction of the bid amounts by 120 EUR (for comparison: the mean bid amount in this subsample is around 650 EUR). Moreover, the competitive effect of the appearance of a strong rival is highly significant and robust against several controls.

7 Counterfactual analysis

In this section we perform a counterfactual analysis to determine the impact of availability of quality information on buyers welfare and profits of the platform.¹⁵ Based on our results from section 6, we assume that bidders are informed about the buyers' preferences over their non-monetary characteristics and thus their qualities, and that respectively their strategic behavior can be described by the model we developed for the information case in section 2. We use these assumptions to derive the buyers' welfare and the platform turnovers in the counterfactual case of uninformed bidders.

■ **Estimation of bidders' costs.** To calculate the counterfactual buyers' welfare and

¹⁴There are 231 auctions with at least 15 participating bidders. In 58% of those auctions no strong rival appears, in 30% there appears one, in 10% there appear two, and in 2% there appear three.

¹⁵Remember that in section 3 we demonstrated that whether revelation of quality information is preferred by the buyers respectively the platform depends on the distributions of bidders costs and qualities.

the platform turnovers, we need to know the counterfactual bid amounts. If bidders do not have information about their qualities, they will base their bidding behavior solely on their costs c_{nj} . We do not observe the costs c_{nj} of the bidders, but we can derive an estimate \widehat{c}_{nj} from our assumptions that bidders are informed and that their behavior can be described by our model for the information case: these assumptions imply that the observed bids p_{nj} are equilibrium bids which solve the bidders' first order conditions

$$p_{nj} + \frac{P_{nj}}{\partial P_{nj} / \partial p_{nj}} - c_{nj} = 0, \quad \forall n \in \{1, \dots, N\}, j \in \{1, \dots, J_n\}. \quad (10)$$

Besides on the bid amounts p_{nj} and the bidders characteristics \mathbf{A}_{nj} , the winning probabilities P_{nj} depend on the preferences $\{\varsigma, \rho, \boldsymbol{\alpha}\}$ of the buyer. By inserting our estimates $\{\widehat{\varsigma}, \widehat{\rho}, \widehat{\boldsymbol{\alpha}}\}$ (compare table 2), we directly arrive at estimates \widehat{P}_{nj} for the winning probabilities:

$$\widehat{P}_{nj} = \frac{e^{\widehat{\rho}p_{nj} + \widehat{\boldsymbol{\alpha}}\mathbf{A}_{nj}}}{e^{\widehat{\varsigma}s_n} + \sum_{k=1}^{J_n} e^{\widehat{\rho}p_{nk} + \widehat{\boldsymbol{\alpha}}\mathbf{A}_{nk}}}$$

With these, the first order conditions (10) can simply be solved after an estimate \widehat{c}_{nj} of the bidders' costs c_{nj} .

■ **Counterfactual Simulation.** Given the counterfactual case that bidders are not informed about their qualities, under the assumption $\widehat{c}_{n1} \leq \dots \leq \widehat{c}_{nJ_n}$ their counterfactual bids \tilde{p}_{nj} are given by

$$\tilde{p}_{nj} = \begin{cases} \widehat{c}_{n2} & \text{if } j = 1, \\ \widehat{c}_{nj} & \text{otherwise.} \end{cases}$$

The counterfactual winning probabilities \tilde{P}_{nj} can simply be calculated as

$$\tilde{P}_{nj} = \frac{e^{\widehat{\rho}\tilde{p}_{nj} + \widehat{\boldsymbol{\alpha}}\mathbf{A}_{nj}}}{e^{\widehat{\varsigma}v_{n0}} + \sum_{k=1}^{J_n} e^{\widehat{\rho}\tilde{p}_{nk} + \widehat{\boldsymbol{\alpha}}\mathbf{A}_{nk}}}.$$

The calculation of the platform turnovers and the buyers' welfare and their counterfac-

	Actual (Information case)	Actual, in expectation (Information case)	Counterfactual, in expectation (No information case)
Platform turnover	9,848,065 EUR	10,313,873 EUR	6,914,780 EUR
Aggregate utility buyers (monetary equivalent, normalized)	635,200 EUR	0 EUR	2,685,600 EUR

Table 6: **Results of counterfactual analysis.** The results are based on data from 42,246 auctions with on average 6.5 participating bidders. The outside option was actually chosen in 20,119 auctions.

tuals is now straightforward: to calculate the actual platform turnovers, we simply add up the bid amounts p_{nj} of the bidders which were chosen in the end. For comparison with the counterfactual case, we also compute the actual expected platform turnovers by multiplying the bidders' bid amounts p_{nj} with their estimated winning probabilities \hat{P}_{nj} and adding the results up. The counterfactual expected platform turnovers are computed in the same way by multiplying the bidders' counterfactual bid amounts \tilde{p}_{nj} with their counterfactual winning probabilities \tilde{P}_{nj} and adding up. The buyers' welfare is compared analogously: To calculate the actual total utility, we take the observed bids p_{nj} and characteristics \mathbf{A}_{nj} , calculate the utility the buyers get in expectation from the bidders chosen using the preference estimates $\{\hat{\varsigma}, \hat{\rho}, \hat{\alpha}\}$, and then add these up. The actual expected utility is calculated by multiplying the utility the buyer gets in expectation from a bidder by this bidder's winning probability \hat{P}_{nj} and adding up, the counterfactual expected utility is calculated by multiplying the counterfactual utility the buyer gets in expectation from a bidder by this bidder's counterfactual winning probability \tilde{P}_{nj} and adding up. Division by $\hat{\rho}$ delivers the monetary equivalent of the utility values. Table 6 presents the results of these exercises.

The figures in table 6 show what would happen both to the platform turnovers and the buyers' aggregate utility if the platform changed its information policy. In the counterfactual

case where quality information was concealed from the bidders - which could in our application simply be achieved by making information about the bidders non-price characteristics exclusively accessible to the buyers - the expected platform turnovers would decrease by around 3 million euros to about 7 million euros. On the other hand, the expected aggregate utility of the buyers would increase by the monetary equivalent of around 2.7 million euros. Thus, our empirical analysis demonstrates that while it is favorable for the procurement platform to keep quality information publicly available, buyers would be better off if quality information was concealed from the bidders.

8 Concluding remarks

Non-binding reverse auctions establish themselves as the most prominent tool for the electronic procurement activities of both firms and government organizations. We added to the understanding of this auction format by analyzing the effect of different designs with respect to the information structure of an open non-binding auction. Our analysis is based on an extensive data set from a large European online procurement platform. We found strong evidence that bidders are aware of their rivals' qualities, i.e. their rivals' characteristics and the buyers' preferences over those non-price characteristics. Building on formal frameworks for the cases where bidders do respectively do not information about their relative quality, we performed a counterfactual analysis. Our results suggest that the effect of a change in the platform's information structure would be quite strong: if information about their qualities was concealed from the bidders, according to our estimates platform turnovers would decrease by around 3 million euros, whereas the buyers' welfare would increase by the monetary equivalent of around 2.7 million euros. For comparison: actual platform turnovers for the time span considered are around 10 million euros.

There are two main points to take away from our analysis: First, the choice of a certain information structure has a large impact on buyers' welfare and turnovers of the auction

platform. Our counterfactual welfare estimates show that the expected effects of a change in the information structure of an auction platform can be quite significant. Second, without knowledge about the parameters of a specific auction there is no clear-cut ex-ante advice regarding the design of its information structure - the optimal information structure depends on the relationship between bidders' costs and qualities. The empirical framework proposed in our article can be used to analyze open non-binding auctions and render them in a more efficient way.

In this article, we analyzed the consequences of different information structures regarding bidders' qualities, i.e. bidders' non-price characteristics and the respective buyers' preferences. A maintained assumption was that bidders at all times are fully informed about their rivals' prices. Obviously, the designer of an open non-binding auction can not only decide whether or not to keep quality information secret, but also whether or not to conceal prices. The effect of hidden prices on the auction outcome is analyzed in a companion paper.

References

- Asker, J. and E. Cantillon (2008). Properties of scoring auctions. *RAND Journal of Economics* 39, 69–85.
- Asker, J. and E. Cantillon (2010). Procurement when price and quality matter. *RAND Journal of Economics* 41, 1–34.
- Athey, S. and J. Levin (2001). Information and competition in U.S. Forest Service timber auctions. *Journal of Political Economy* 109, 375–417.
- Branco, F. (1997). The design of multidimensional auctions. *RAND Journal of Economics* 28, 63–81.
- Che, Y.-K. (1993). Design competition through multidimensional auctions. *RAND Journal of Economics* 24, 668–680.
- Chen-Ritzo, C.-H., T. P. Harrison, A. M. Kwasnica, and D. J. Thomas (2005). Better, faster, cheaper: An experimental analysis of a multiattribute reverse auction mechanism with restricted information feedback. *Management Science* 51, 1753–1762.
- Colucci, D., N. Doni, and V. Valori (2011). Information disclosure in procurement auctions with horizontally differentiated suppliers. Working Paper.
- Doni, N. and D. Menicucci (2010). A note on informational disclosure in procurement auctions. *Economics Letters* 108, 307–310.
- Engelbrecht-Wiggans, R., E. Haruvy, and E. Katok (2007). A comparison of buyer-determined and price-based multiattribute mechanisms. *Marketing Science* 26, 629–641.
- Gal-Or, E., M. Gal-Or, and A. Dukes (2007). Optimal information revelation in procurement schemes. *RAND Journal of Economics* 38, 400–418.

- Haruvy, E. and E. Katok (2010). Increasing revenue by decreasing information in procurement. Working Paper.
- Jap, S. D. (2002). Online reverse auctions: Issues, themes and prospects for the future. *Journal of the Academy of Marketing Science* 30, 506–525.
- Jap, S. D. (2003). An exploratory study of the introduction of online reverse auctions. *Journal of Marketing* 67, 96–107.
- Jap, S. D. and E. Haruvy (2008). Interorganizational relationships and bidding behavior in industrial online reverse auctions. *Journal of Marketing Research* 45, 550–561.
- Katok, E. and A. Wambach (2011). Collusion in dynamic buyer-determined reverse auctions. Working Paper.
- Kostamis, D., D. R. Beil, and I. Duenyas (2009). Total-cost procurement auctions: Impact of suppliers' cost adjustments on auction format choice. *Management Science* 55, 1985–1999.
- Lewis, G. and P. Bajari (2011). Procurement contracting with time incentives: Theory and evidence. *The Quarterly Journal of Economics* 126, 1173–1211.
- Rezende, L. (2009). Biased procurement auctions. *Economic Theory* 38, 169–185.

Appendix

Proof of $\frac{\partial p_j}{\partial q_k} < 0$:

The probabilities P_j can be directly derived from equation system (1) as

$$\begin{aligned} P_j &= \Pr(q_j - p_j + \epsilon_j > q_k - p_k + \epsilon_k, \quad \forall k \neq j) \\ &= \Pr(\epsilon_j - \epsilon_k > q_k - p_k - (q_j - p_j), \quad \forall k \neq j) \\ &= \Pr(\epsilon_j - \epsilon_k > v_k - v_j, \quad \forall k \neq j). \end{aligned}$$

I.e., P_j is in essence a cumulative distribution. From the explicit formulation of P_j it is clear that

$$\begin{aligned} \frac{\partial P_j}{\partial v_j} &> 0, \\ \frac{\partial P_j}{\partial v_k} &< 0, \quad \forall k \neq j, \end{aligned}$$

and

$$\begin{aligned} \frac{\partial P_j}{\partial p_j} &= -\frac{\partial P_j}{\partial v_j} \\ \frac{\partial P_j}{\partial q_k} &= \frac{\partial P_j}{\partial v_k} \\ \frac{\partial^2 P_j}{(\partial p_j)^2} &= \frac{\partial^2 P_j}{(\partial v_j)^2} \\ \frac{\partial^2 P_j}{\partial p_j \partial q_k} &= -\frac{\partial^2 P_j}{\partial v_j \partial v_k}. \end{aligned}$$

Starting from the first order conditions

$$p_j + \frac{P_j}{\partial P_j / \partial p_j} - c_j = 0, \quad \forall j \in \{1, \dots, J\},$$

the implicit function theorem and a little algebra deliver us

$$\begin{aligned}
\frac{\partial p_j}{\partial q_k} &= -\frac{\frac{\partial(\frac{P_j}{\partial P_j/\partial p_j})}{\partial q_k}}{\frac{\partial(p_j + \frac{P_j}{\partial P_j/\partial p_j})}{\partial p_j}} \\
&= -\frac{\frac{\partial P_j}{\partial q_k} \frac{\partial P_j}{\partial p_j} - \frac{\partial^2 P_j}{\partial q_k \partial p_j} P_j}{2\left(\frac{\partial P_j}{\partial p_j}\right)^2 - \frac{\partial^2 P_j}{(\partial p_j)^2} P_j} \\
&= -\frac{-\frac{\partial P_j}{\partial v_k} \frac{\partial P_j}{\partial v_j} + \frac{\partial^2 P_j}{\partial v_k \partial v_j} P_j}{2\left(\frac{\partial P_j}{\partial v_j}\right)^2 - \frac{\partial^2 P_j}{(\partial v_j)^2} P_j}
\end{aligned}$$

The numerator is obviously larger than zero. For $\frac{\partial p_j}{\partial q_k} < 0$ to be true, the regularity condition

$$2\left(\frac{\partial P_j}{\partial v_j}\right)^2 - \frac{\partial^2 P_j}{(\partial v_j)^2} P_j > 0$$

has to hold. It is easy to verify that this condition holds at least for most of the common cumulative distribution functions, for example the uniform, the normal and the type I extreme value distribution. (Note that if the ϵ_j in equation system (1) are assumed to be uniformly, normally or type I extreme value distributed, the P_j equal the cumulative uniform, normal or type I extreme value distribution, respectively.)

Simulation Details:

We assume that there are two bidders participating at the auction, that these two bidders have costs $c_1 = 0$ and $c_2 \geq 0$, and that they differ with respect to their exogenous quality, $q_1 = 0$ and $q_2 > 0$. The utilities the buyers receive from the bidders in expectation are given as

$$\begin{aligned}
E[u_1] &= -p_1 \\
E[u_2] &= -p_2 + q_2.
\end{aligned}$$

In the no information case each bidder bids c_2 ($p_1^{NI} = c_2$ and $p_2^{NI} = c_2$). Thus, under the assumption that the error terms in (1) follow a type I extreme value distribution and are iid among the buyers, the choice probabilities are

$$\begin{aligned}
P_1^{NI} &= \frac{e^{-c_2}}{e^{-c_2} + e^{-c_2+q_2}}, \\
P_2^{NI} &= \frac{e^{-c_2+q_2}}{e^{-c_2} + e^{-c_2+q_2}}.
\end{aligned}$$

The expected utility buyers get from their choice in the no information case is

$$P_1^{NI} E[u_1]^{NI} + P_2^{NI} E[u_2]^{NI} = P_1^{NI}(-c_2) + P_2^{NI}(-c_2 + q_2).$$

The expected turnover on the platform in the no information case is simply c_2 .

In the information case the bids p_1^I and p_2^I are given by the first order conditions

$$p_1^I = \frac{P_1^I}{|\partial P_1^I / \partial p_1^I|}$$

$$p_2^I = c_2 + \frac{P_2^I}{|\partial P_2^I / \partial p_2^I|}$$

With the adequate expressions for P_1^I and P_2^I ,

$$P_1^I = \frac{e^{-p_1^I}}{e^{-p_1^I} + e^{-p_2^I + q_2}},$$

$$P_2^I = \frac{e^{-p_2^I + q_2}}{e^{-p_1^I} + e^{-p_2^I + q_2}},$$

and the use of a little algebra the first order conditions can be formulated as

$$p_1^I = e^{p_2^I - p_1^I - q_2} + 1 \quad (11)$$

$$p_2^I = c_2 + e^{p_1^I - p_2^I + q_2} + 1. \quad (12)$$

Conditions (11) and (12) determine the bids p_1^I and p_2^I as functions of c_2 , and q_2 . Given p_1^I and p_2^I , in the information case the buyer chooses bidder 1 with probability P_1^I and bidder 2 with probability P_2^I . The expected utility buyers get from their choice in the information case is

$$P_1^I E[u_1]^I + P_2^I E[u_2]^I = P_1^I(-p_1^I) + P_2^I(-p_2^I + q_2).$$

The expected turnover on the platform in the information case is

$$P_1^I p_1^I + P_2^I p_2^I$$

Figure 1 results when we set $q_2 = 1$ and numerically solve the equation system given by (11) and (12) after p_1^I and p_2^I for different values of c_2 .

Figure 2 shows the values of q_2 at which the buyers are indifferent between the two information structures (solid line), respectively at which the platform is indifferent between the two information structures (separated line). The condition for indifference of the buyers is given by

$$P_1^{NI}(-c_2) + P_2^{NI}(-c_2 + q_2) = P_1^I(-p_1^I) + P_2^I(-p_2^I + q_2), \quad (13)$$

that for indifference of the platform is given by

$$c_2 = P_1^I p_1^I + P_2^I p_2^I. \quad (14)$$

The indifference line for the buyers result when, given different values of c_2 , equations (11), (12) and (13) are simultaneously solved for p_1^I , p_2^I and q_2 . Analogue, the indifference line for the platform results when, given different values of c_2 , equations (11), (12) and (14) are simultaneously solved for p_1^I , p_2^I and q_2 .