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

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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 in the period considered would decrease from around 1.9 million euros to around 1.3 million euros and the buyers' welfare would increase by the monetary equivalent of around 0.9 million euros.

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

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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 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 about his rivals' non-price characteristics and the buyers' preferences over them

[1] See 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.

is conveyed to each bidder.

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 second 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 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 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 first formal framework where bidders are informed with respect to non-price aspects we derive estimates of the bidders' cost. Based on our second 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 in the second half of 2008 would decrease by 30% from 1.9 million euros to 1.3 million euros. In contrast, buyers would be better off, with a relative utility increase of the monetary equivalent of around 0.9 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 of 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

[2]Interestingly, 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.

7, we perform a counterfactual analysis to determine the impact of non-price information on 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 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. In the second case, which we call no information case, bidders are not informed at all with respect to non-price aspects and thus behave as if they were bidding in a regular open price-only auction. 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 information case and the no 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:

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

The idiosyncratic terms ϵ_j capture the influence of unobservable non-price aspects on the buyer's decision The buyer is assumed to choose the option which maximizes his utility, i.e. the option k for which

$$u_k > u_j \qquad \forall j \neq$$

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,

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

this is equivalent to the statement that the bids $p_1, ..., p_J$ 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

$$p_j = c_j + \frac{P_j}{|\partial P_j / \partial p_j|}. \tag{3}$$

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]

[3] This 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, the average auction duration is quite long, sniping seems not to play a significant role at the auction platform we consider, and bidders are in addition informed via email if they are underbid by a rival.

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

[5] The proof that this statement holds given a weak regularity condition can be found in appendix A.1.

■ **The bidders' behavior in the no information case.** The core assumption in the no information case is that bidders lack information about as well their and their rivals' qualities as the relative importance of price and quality, and that they thus resort to the belief that the buyer bases his decision essentially on their prices. We think our assumption that concealment of non-price information leads bidders to orientate their bidding behavior primarily at prices reasonably captures real-life behavior:

Assume unexperienced bidders taking part in an auction where the only information they have about their rivals is their prices. Let us first consider the extreme case where bidders have no idea about the population their rivals come from. In this case it is hard to think about a reason why they should assume their rivals to be any different from them both in observable and unobservable quality aspects. If bidders have no reason to belief their rivals to be any different from them, than they necessarily also belief that the lowest bid wins the auction. Let us now make the more realistic assumption that bidders have beliefs about the population their rivals come from. As long as they belief the distribution of (observed and unobserved) quality in this population to be concentrated around the mean and not to exhibit long and thick tails, they will on average belief to encounter relatively similar rivals. Consequently, on average bidders should belief differences in prices to be the crucial factor in the buyer's decision. We think that bidders can reasonably be expected to have distributional beliefs of this kind - in fact, bell-shaped distributions which exhibit the described features occur in a large part of economic situations, and former experience with these situations should have shaped bidders' expectations. Thus, we think it is safe to assume that in the case of hidden non-price information bidders primarily orientate their bidding behavior at prices.

We model the no information situation as a limiting case of our model of the bidders' behavior, given by equation systems (1) and (2), where $q_j \to 0$ and $\epsilon_j \to 0$ for all j. In this limiting case, the probabilities P_j degenerate and the bidder with the lowest price p_k wins with probability $P_k \to 1$. In essence this means that the bidders belief the lowest bid to win

the auction. Note that this assumption about the bidders' behavior is not as restrictive and artificial as it might seem: Further down we demonstrate that for our results to hold it is only necessary that bidders belief that the influence of the price on the buyer's decision is sufficiently large relative to non-price aspects.

In consequence, in the no information case we assume bidders to 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 second-lowest costs in the auction. For the rest of the paper, we will assume without loss of generality that the bidders are ordered according to their costs c_j, $c_1 \leq c_2 \leq ... \leq c_J$. With this assumption, bidder j's behavior in the no information case can be expressed as

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

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 buyer and 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.[6] 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 disclosure of non-price information or concealment of non-price 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. $q_1 = 0$).[7] 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 (the 45° line in figure 1). 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 lower line shows the values of q_2 for which the buyer is indifferent between the two information cases, the upper line shows the values of q_2 for which the platform is indifferent.[8] For all combinations of cost difference and quality below the buyer's indifference 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 indifference line of the platform it prefers the no information case. For all other combinations it prefers the information case.

[6]Simulation details can be found in appendix A.2.

[7]Note 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.

[8]We 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.

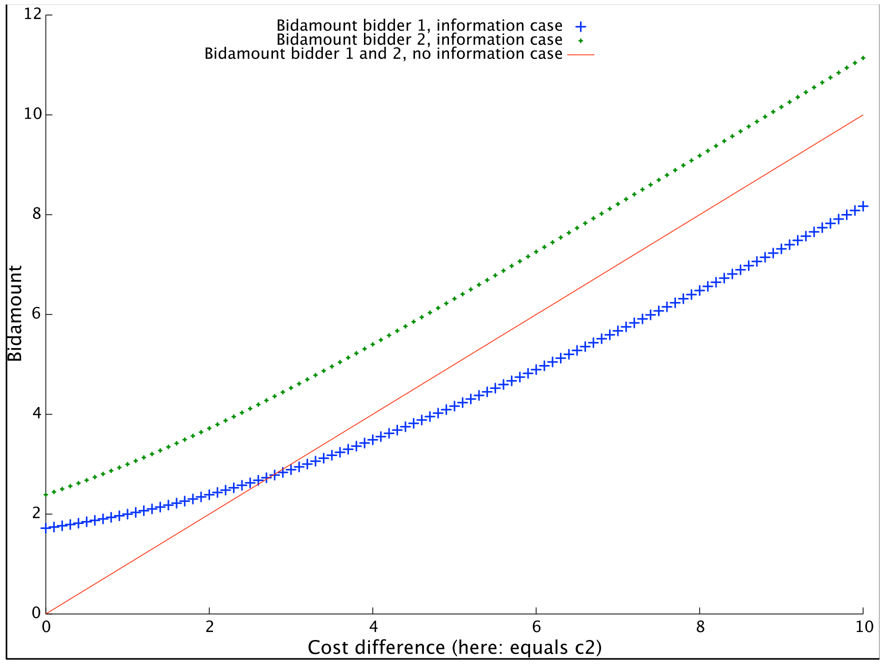

Figure 1: **Bid amounts in dependence on the cost difference.** Bidder 2 is assumed to be of quality 1 in the eyes of the buyer, bidder 1 of quality 0. Bidder 1's costs are normalized to 0. Thus the cost difference equals bidder 2's costs. The two plotted lines show the bid amounts of bidder 1 and 2 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 appendix A.2.

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 case. The reason is that due to the small difference in bidders' costs the stronger bidder cannot force his weaker rival's price down that far that the buyer is better off than in the no information case, where both bidders simply bid c_2. 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, in the information case bidders are aware of their similarity and price competition is relatively fierce. As a result, for small q_2 prices in the information case are so low that in expectation the buyer is better off than in the no information case. The reverse holds true for large values of q_2: In the information case, the stronger bidder is aware of his large advantage relative to his weaker rival, and thus will demand a high markup on his costs c_2. This leads to high prices, making the buyer on average worse off than in the no information case. The indifference line for the buyer, which marks for a given cost

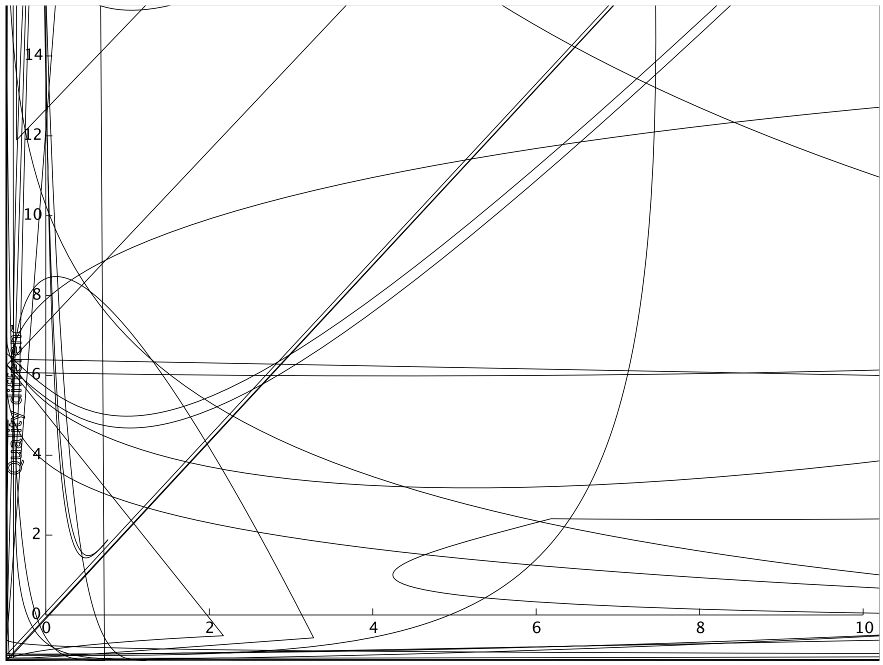

Figure 2: **Indifference lines for the buyer and the auction platform**. The solid line shows for a given difference in costs the difference in bidders' qualities for which the buyer would be indifferent between the no information and the information case. The dashed line shows the respective indifference 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 appendix A.2.

difference the value for which he is indifferent between the two informational arrangements, is increasing with the cost difference, because with an increasing difference in costs the weaker bidder gets more scope for pricing, which partly outweighs the stronger bidder's quality advantage.

Second, reverse statements hold from the perspective of the platform: For small cost differences the platform always prefers the information case over the no information case. From a certain cost difference on, the platform still prefers the information case over the no information case if the difference in bidders' qualities is relatively large compared to that in their costs. If, however, it is the other way round, the platform prefers the no information case over the information case. The intuition here goes similar to that for the buyer's perspective: The platform is interested in contracts being made at high prices. For low cost differences, the stronger bidder cannot force his weaker rival's price down far below

c_2. As a result, the expected platform turnover in the information case, which is a linear combination of the bidders' prices weighted by their winning probabilities, is always higher than that in the no information case, which simply equals c_2. From a certain cost difference on, if the difference between the bidders' qualities is low awareness about that fact spurs price competition, which leads to low prices making the platform on average worse off than in the information case. In contrast, if the difference in qualities is large and the stronger bidder is aware of his considerable advantage, he will demand a high markup on his costs, the prices will be high, and the platform is better off in the information case. The increase of the indifference line is again explained by the fact that the low quality bidder gets more pricing leeway with an increasing difference in costs, which makes the bidders more similar in terms of strength for a larger range of quality difference.

The observation that the indifference line of the platform is not aligned with that of the buyer can be explained by the fact that the platform cares only about the turnover created in an auction, regardless of which quality the buyer chooses in expectation, while the buyer also cares about the quality he chooses in expectation. Thus, for a given cost difference the quality differences where the buyer respectively the platform are indifferent between the information and the no information case in general differ. Note also that whether the buyer's indifference line runs above or below that of the platform depends on the given model specifications.

Based on the results of our comparison of information structures, we can make the following observation:

Observation. *Whether the buyer in an open non-binding auction prefers to disclose non-price information to the bidders or to keep it concealed depends on the relationship between the difference in the bidders' costs and the difference in the bidders' qualities.*

The central intuition is that from the buyer's point of view the informational arrangement which creates the highest competitive pressure is the preferable one. If the difference in bidders' qualities is small and the difference in their costs high, then it is beneficial to

disclose non-price information in order to make the bidders aware of their similarity in terms of quality which in turn spurs price competition. If, however, the difference in bidders' costs is small and that in their qualities is high, then non-price information should be concealed from them to keep the predominance of the strong bidder(s) hidden. From the point of view of the platform it is in general the other way round: As the platform makes money out of the turnover created in an auction, it prefers the informational arrangement which hinders price competition.

4 Data

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. To be more precise, in the overview of an auction besides price two non-price characteristics of a bidder's rivals are particularly highlighted: the number of positive ratings and the number of negative ratings this rival got from buyers of former auctions he won. These characteristics will play an important role in our further analysis. 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 like the bidders' ratings, licenses, etc.

In the following, we concentrate on data from auctions on painting and wallpapering jobs. For 2,126 auctions we have collected information about cost factors of the jobs offered (like for example the area to paint, whether paint is provided by the buyer, and so on). In addition, for every auction we have information about the number and the identities of the

	Mean	SD	Median	Min	Max
Nbr. of bidders per auction	7.83	4.38	7	2	26
Bid amount	559.33	514.03	400	48	18,830
Startprice	508.30	386.65	400	100	2000
Nbr. of auction participations per bidder	3.73	9.04	1	1	170
Auctions per buyer	1.01	0.10	1	1	2
Auction duration (days)	8.47	6.85	5.98	0.05	65.95
Last bid placement (hours till auction end)	24.28	55.50	3.98	0	610.27
Share of auctions with last bid submission less than one hour before auction end:	31%				
Nbr. of auctions	1,928				
Nbr. of bidders	2,670				
Nbr. of buyers	1,907				

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

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). All the auctions considered took place during the second half of 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. In addition, as in the following we want to study whether bidders react to their competitors' qualities, we use only auctions in which at least two bidders participate. We are left with 1,928 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 all of the 1,928 auctions the buyer in the end decided for one of the participating bidders.

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.[9] 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.[10]

■ **Econometric model.** 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 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 denoting the buyer's preferences over these characteristics, the quality q_{nj} of bidder j in auction n is given by $\mathbf{A}_{nj}$. 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

[9]We 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.

[10]The 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.

formulated as[11]

$$
\begin{aligned}
u_{n0} &= \varsigma s_n + \epsilon_{n0} && (\equiv v_{n0} + \epsilon_{n0}) \\
u_{n1} &= \rho p_{n1} + \quad \mathbf{A}_{n1} + \epsilon_{n1} && (\equiv v_{n1} + \epsilon_{n1}) \\
&\vdots \\
u_{nJ_n} &= \rho p_{nJ_n} + \quad \mathbf{A}_{nJ_n} + \epsilon_{nJ_n} && (\equiv v_{nJ_n} + \epsilon_{nJ_n}).
\end{aligned}
\tag{4}
$$

The idiosyncratic terms ϵ_{nj} capture unobserved non-price aspects. The buyer is assumed to choose the alternative which offers him the highest utility. By assuming the idiosyncratic 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 $\{\varsigma, \rho, \quad\}$ can be obtained by maximizing the likelihood

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

■ **Estimation results.** We estimated our model on all auctions from the painting and wallpapering category with an announced startprice of at most 2000 EUR and which were conducted during the second half of 2008. Table 2 shows the results. The first column displays the coefficient estimates $\{\hat{\rho}, \hat{\ }\}$, the second column the respective average marginal

[11]Note 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. In addition, note that in all auctions for which we have cost information available the outside option is never chosen. Thus for our estimation results it makes no difference whether we account for the outside option or not. However, further down we will extend our analysis also on auctions for which no cost information is available. In that larger sample, the outside option is sometimes chosen. For this extension of our analysis, we assume that the value of the outside option depends linearly on the startprice s_n announced by the buyer.

Covariates in buyer's utility fct.	Coefficient estimates	Average marginal effects
Bid amount (EUR)	-.011 (.0004)	-.0009 (.00006)
Nbr. of positive ratings	.016 (.001)	.0013 (.0001)
Nbr. of negative ratings	-.108 (.014)	-.0086 (.0012)
Controls:		
Distance (km)	-.006	-.0005
Trade License	.298	.0238
In craftsmen register	.293	.0234
Registered at platform	-.066	-.0053
Master craftsman company	.136	.0108
Senior journeyman company	.073	.0058
Engineer	-.118	-.0094
Technician	1.042	.0830
Other certifications	.025	.0020
Nbr. of employees	-.012	-.0009
Nbr. of observations	17,028	
Nbr. of auctions	1,928	

Table 2: **Results of the estimation of the logit discrete choice model.** The estimates are based on data from 1,928 auctions. The startprice set in all these auctions is less than 2,000 EUR. In all these auctions we observed 17,028 bids (on average, a buyer made his decision among eight bids, the outside option included). Standard errors are reported in parentheses. Significance niveaus are reported by stars: ***: 1%, **: 5%, *: 10%.

effects. Besides some controls, a buyer's decision seems to be strongly influenced by the bidders' prices and the ways they have been rated by former buyers: a price reduction of 10 EUR highers a bidder's winning probability by around 1%, 10 positive ratings higher it by about 1.3%, and 10 negative ratings lower it by about 9%. For comparison: the average bid amount is about 560 EUR, the average number of positive ratings is 21, and the average number of negative ratings is 2.

■ **Discussion of estimation results.** Our results hinge on the assumption that the error terms ϵ_{nj} in equation system (4) are neither correlated with the prices p_{nj} nor with the bidders' attributes $\mathbf{A}_{nj}$. In other words, for our estimation results to be consistent there must be no unobserved factors which influence the buyers' utilities in a way systematically

connected to our observables. However, as we analyze auctions conducted on an online marketplace and as we were provided with very detailed recordings of these auctions, we are pretty sure that we are able to control for all factors which have a systematic influence on the buyers' utilities: our data contains exactly the amount of information about the bidders the buyers have available when making their decisions. Thus there should be no influences on the buyers' utilities which are both unobserved and in some way systematically connected to the bidders' attributes, and the idiosyncratic terms ϵ_{nj} should simply reflect differences among the buyers' in their tastes regarding the bidders' attributes. Consequently, it should hold that the ϵ_{nj} are uncorrelated with the bidders' attributes $\mathbf{A}_{nj}$ and their prices p_{nj}, which implies consistency of our estimation results.

The important take away here 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 A.1). 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 $c_{n1} \leq ... \leq c_{nJ_n}$ the bid amount of bidder j in auction n is given by

$$p_{nj} = \begin{cases} c_{n2} & \text{if } j = 1, \\ c_{nj} & \text{otherwise,} \end{cases} \tag{5}$$

while in the information case it is given by

$$p_{nj} = c_{nj} + \frac{P_{nj}}{|\partial P_{nj} / \partial p_{nj}|} \equiv c_{nj} + \hat{\tau}_{nj}. \tag{6}$$

Bidder j's markup $\hat{\tau}_{nj}$ 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

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

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 $\hat{\tau}$ as

$$\hat{\tau}_{nj} = \mu_j + \beta S_{nj} + \vartheta_{nj}. \tag{7}$$

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 (5) and (6)). 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:

$$c_{nj} = a_j + \quad \mathbf{K}_{nj} + \nu_{nj} \tag{8}$$

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

$$\begin{aligned} p_{nj} &= c_{nj} + \hat{\tau}_{nj} \\ &= a_j + \mathbf{K}_{nj} + \nu_{nj} + \mu_j + \beta S_{nj} + \vartheta_{nj} \\ &= \mathbf{K}_{nj} + \beta S_{nj} + a_j + \mu_j + \vartheta_{nj} + \nu_{nj}. \end{aligned} \tag{9}$$

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 (9) 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 $\hat{a}_j \equiv a_j + \mu_j$ and $\epsilon_{nj} \equiv \vartheta_{nj} + \nu_{nj}$ and arrive at

$$p_{nj} = \mathbf{K}_{nj} + \beta S_{nj} + \hat{a}_j + \epsilon_{nj}. \tag{10}$$

Equation (10) 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 $\hat{a}_j$, and an error term ϵ_{nj}. The unobserved bidder specific constant $\hat{a}_j$ 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 (7) and the error term ν_{nj} from the costs equation (8). 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 (10) by mean-differencing (i.e. employing a fixed effects estimator), and by that getting rid of the individual specific and unobserved constants

$\hat{a}_j$. 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 (10) 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 (10) by a fixed effects estimator, we have to restrict our sample to bidders which are observed in at least two auctions. In addition, we do not use observations where a bidder put forward the lowest bid in an auction. We do this because if bidders had no information regarding the buyers' quality preferences, bidders who put forward the lowest bid do not orientate their bid amounts at their own costs but at that of the competitors with the second lowest costs, and our identification strategy no longer works. This leaves us with a sample of 936 bidders, taking part in 1,469 auctions (the mean number of auction participations is 10.18, the median number is 6). In 22.6% 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, we control

Dependent variable: Bid amount of bidder j in auction n	(1)	(2)	(3)	(4)
Strong rival (dummy)	-88.86	-93.29	-92.77	-97.34
	(16.62)	(19.61)	(16.72)	(19.86)
Controls:				
Area to paint (m^2)	1.80	1.82	1.79	1.82
Area to paper (m^2)	1.53	1.40	1.54	1.40
Paper removal (m^2)	2.72	2.84	2.80	2.92
Cleaning (dummy)	85.23	65.64	92.35	71.90
Reparation (dummy)	36.77	53.36	36.95	53.42
Priming (dummy)	129.89	132.48	129.84	131.87
Nbr. of windows	9.40	9.57	10.06	10.27
Nbr. of window frames	36.52	33.58	34.84	31.78
Nbr. of doors	51.20	50.36	52.28	51.41
Nbr. of door frames	19.13	20.55	18.46	19.95
Nbr. of radiators	91.50	91.95	91.48	91.83
Paint by contractor (dummy)	25.10	13.58	25.57	14.19
Varnish by contractor (dummy)	128.58	117.43	129.17	117.35
Distance (km)	1.19	1.14	1.25	1.20
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	0.295	0.303	0.289	0.298
N	8,353	8,353	8,353	8,353

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 936 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-R^2 are close to the overall R^2. Significance niveaus are reported by stars: ***: 1%, **: 5%, *: 10%.

for regional influences by adding region dummies.[12] 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 painting, paint, cleaning and travel. The average area to be painted in our data set is 138.3 m^2, the average travel distance 45.0 km (one-way). Together with our estimation results in table 3 this implies that the average price per square meter painted, including

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

paint and travel, is about 3 to 4 EUR on the auction platform. Given that most of the bidders on the platform are non-professionals,[13] 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 90 EUR, which is a quite strong reduction if one considers that the average bid amount in our sample is about 550 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 (10) 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 (10), 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 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:

It might be that either strong bidders select themselves into certain kinds of auctions, or that certain types of bidders select themselves into auctions where a strong bidder is

[13]78% of the bidders in our sample are neither master craftsmen nor senior journeymen.

present. In effect, that would lead to a correlation between the appearance of a strong bidder and the auction composition (measured by the error component δ_{nj} which reflects the average strength of bidder j in auction n). To be sure that we actually capture the bidders reaction to the appearance of a strong rival, in column 1 of table 4 we control for the bidder composition of the different auctions. We do so by taking the averages over the attributes of all not extraordinarily strong bidders (bidders with a difference of positive and negative ratings of less than 90) and using these averages as further controls in our fixed effects regression. As can be seen, controlling for the auction composition does not change our results. In addition a large difference in positive and negative ratings is not correlated with any other of a strong bidder's attributes. Also, besides the prices put forward the most prominent information auction participants are given is their rivals' ratings. Thus, we are pretty sure we are capturing the bidders' reaction 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 (10) 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 their qualities, i.e. the buyers' preferences regarding their attributes. 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

Dependent variable: Bid amount of bidder j in auction n	(1)	(2)
Strong rival (dummy)	-97.81 (19.66)	-60.57 (14.00)
Controls:		
Area to paint (m^2)	1.69	.63
Area to paper (m^2)	1.41	.13
Paper removal (m^2)	2.54	1.37
Cleaning (dummy)	62.98	-48.90
Reparation (dummy)	37.65	31.37
Priming (dummy)	120.27	25.59
Nbr. of windows	12.76	.92
Nbr. of window frames	27.73	-85.65
Nbr. of doors	46.96	38.14
Nbr. of door frames	19.17	14.60
Nbr. of radiators	84.65	30.77
Paint by contractor (dummy)	17.70	28.91
Varnish by contractor (dummy)	104.87	137.02
Distance (km)	.78	.57
Dummies for nbr. of bidders	X	X
Dummies for region	X	X
Controls for bidder composition	X	
Dummies for startprice interval		X
Bidder FE's	X	X
R^2	0.340	0.501
N	8,353	8,353

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 panel consists of 936 bidders who on average take part in 10 auctions each. Column 1 shows results of the fixed effects regression where controls for the bidder composition of the auctions were added. Column 2 shows results of the fixed effects regression with dummies for different startprice intervals added. Note that these dummies are highly correlated with the cost factors. Thus the coefficients on the cost factors in column 2 are no longer clearly identified. For all results: both within- and between-R^2 are close to the overall R^2. Cluster-robust standard errors are reported in parentheses. Significance niveaus are reported by stars: ***: 1%, **: 5%, *: 10%.

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.

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

	Startprice			
	Obs	Mean	SE	[95% Conf. Interval]
Subset of auctions without strong rival ($S_{nj} = 0$)	1,137	486.15	11.76	[463.08, 509.22]
Subset of auctions with strong rival ($S_{nj} = 1$)	332	544.42	20.16	[504.77, 584.08]
	p-value of two-sample t test: 0.0128			

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 in table 3.

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 (10), the coefficient on S_{nj} stays highly significant and negative (see column 2 of table 4).[14]

To summarize, our results strongly indicate that bidders seem to be informed about the

[14]Note 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.

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. 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. 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 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

$$p_{nj} + \frac{P_{nj}}{\partial P_{nj} / \partial p_{nj}} - c_{nj} = 0, \quad \forall n \in \{1, ..., N\},\ j \in \{1, ..., J_n\}. \tag{11}$$

Besides on the bid amounts p_{nj} and the bidders characteristics $\mathbf{A}_{nj}$, the winning probabilities P_{nj} depend on the preferences $\{\varsigma, \rho, \quad \}$ of the buyer. By inserting our estimates $\{\hat{\varsigma}, \hat{\rho}, \hat{\ } \}$

(compare table 2), we directly arrive at estimates $\hat{P}_{nj}$ for the winning probabilities:

$$\hat{P}_{nj} = \frac{e^{\hat{\rho} p_{nj} + \hat{\boldsymbol{\alpha}} \mathbf{A}_{nj}}}{e^{\hat{\varsigma} s_n} + \sum_{k=1}^{J_n} e^{\hat{\rho} p_{nk} + \hat{\boldsymbol{\alpha}} \mathbf{A}_{nk}}} \tag{12}$$

With these, the first order conditions (11) can simply be solved after an estimate $\widehat{c}_{nj}$ of the bidders' costs c_{nj}.[15]

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

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

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

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

Table 6 gives summary statistics describing the distributions of the actual bidamounts p_{nj}, the estimated costs $\hat{c}_{nj}$ and the counterfactual bidamounts $\hat{p}_{nj}$.

The calculation of the platform turnovers and the buyers' welfare and their counterfactuals 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

[15] As the prices p_{nj} put forward by the bidders appear in the arguments of the exponential functions in formula 12, the cost estimates $\hat{c}_{nj}$ are quite sensitive to price outliers. As a result for 3% of the bidders in our sample we get negative cost estimates $\hat{c}_{nj}$. A small part of these negative cost estimates is of high absolute value. In order to being able to present meaningful summary statistics for our cost estimates, we assume that $c_{nj} \geq 0$. Note that this assumption has no noticeable effect on our counterfactual bid amounts, platform turnovers and buyers' utilities.

	Mean	*SD*	*Median*	*Min*	*Max*
Actual bidamounts (p_{nj})	559.33	514.03	400	48	18,830
Estimated costs ($\hat{c}_{nj}$)	449.60	517.66	304.30	0	18,739
	(10.41)				
Counterfactual bidamounts ($\hat{p}_{nj}$)	460.89	518.73	307.88	0	18,739
	(10.51)				

Table 6: **Estimated costs and counterfactual bidamounts.** The results are based on data from 1,928 auctions with on average 7.8 participating bidders. All auctions were conducted during the second half of 2008. Bootstrapped standard errors for the mean of the estimated costs and the mean of the counterfactual bidamounts are given in parentheses.

by multiplying the bidders' counterfactual bid amounts $\hat{p}_{nj}$ with their counterfactual winning probabilities $\hat{P}_{nj}$ 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 $\{\hat{\varsigma}, \hat{\rho}, \hat{\ }\}$, 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 $\hat{P}_{nj}$ and adding up. Division by $\hat{\rho}$ delivers the monetary equivalent of the utility values. Table 7 presents the results of these exercises.

The figures in the upper half of table 7 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 170,000 euros to about 650,000 euros. On the other hand, the expected aggregate utility of the buyers would increase by the monetary equivalent of around 180,000 euros.

For our analysis so far we have only used auctions which were conducted in the second half of 2008 and for which we had manually collected information about cost factors from the

	Actual (Information case)	**Actual** in expectation (Information case)	**Counterfactual** in expectation (No information case)
Set of auctions for which cost information is available: (1,928 auctions)			
Platform turnover	820,777	820,778	650,197
			(16,222)
Relative change			− 170,581
Aggregate utility buyers			
(monetary equivalent, normalized)	0	0	177,029
Relative change			+ 177,029
Auctions without cost information included: (7,725 auctions)			
Platform turnover	1,912,901	1,912,901	1,336,435
			(31,216)
Relative change			− 576,466
Aggregate utility buyers			
(monetary equivalent, normalized)	0	0	871,932
			(36,396)
Relative change			+ 871,932

Table 7: **Results of counterfactual analysis.** The results are based on data from auctions conducted in the second half of 2008. The upper half of the table shows counterfactual platform turnovers and buyers' utilities for the set of auctions for which cost information is available (1,928 auctions with on average 7.8 participants). The lower half of the table shows counterfactual platform turnovers and buyers' utilities for all auctions conducted in the second half of 2008 (now also auctions for which cost information is not available are included; altogether we have 7,725 auctions with on average 7.1 participants). All numbers are in euros. Bootstrapped standard errors for the counterfactual platform turnovers and the counterfactual aggregate utility of the buyers are given in parentheses.

job descriptions posted by the buyers. These auctions are part of a larger sample of auctions for which we have information about the participating bidders, the bids put forward, and the buyers' decisions. As we did not use a certain systematic procedure when collecting cost information for a subset of auctions, it is reasonable to assume that this subset is a random selection from that larger auction sample. Accordingly, the finding that bidders are informed about their qualities should transfer to all auctions conducted in the second half of 2008.

The figures in the lower half of table 7 show the results when our counterfactual analysis is done on all auctions conducted in the second half of 2008. Like for the smaller sample of auctions for which cost information is available, when quality information was hidden from the bidders total expected platform turnovers in the second half of 2008 would decrease by

around 0.6 million euros to about 1.3 million euros, while the expected aggregate utility of the buyers would rise by the monetary equivalent of around 0.9 million euros.

■ **Discussion and Robustness Checks.** When we first take a look at the estimation results as they are given, it is noticeable that for the total set of auctions conducted during the second half of 2008 the drop in platform turnovers is significantly smaller than the increase in the buyers' aggregate utility. At first sight this might seem kind of odd, as in our case concealment of non-price information seems to lead to higher competitive pressure, which in turn leads to lower prices. As the bidders' non-price characteristics are exogenously given, one might guess that the gain in bidders' utility should be equal to the loss in platform turnovers, as both result from a decrease in bidders' prices.

However, this reasoning only goes through if the existence of the buyers' outside option is neglected. In contrast to the subset of auctions with cost information available, where the outside option is never chosen in the actual case and where accordingly the increase in buyers' aggregate utility equals the decrease in platform turnovers, in the total set of auctions the actual share of auctions where the outside option is chosen is 43%. With the concealment of non-price information resulting in decreased prices, now in in some of these auctions buyers are better off when choosing one of the participating bidders instead of the outside auction - the expected share of auctions where the outside option is chosen decreases to 27% in the no information scenario. This creates turnover in auctions where there formerly has been none, leading to a decrease in platform turnovers weaker than the increase in buyers' aggregate utility.

After discussing the estimation results per se let us now take a look at their reliability: For the derivation of our counterfactual results given in table 7 we made certain assumptions about the counterfactual bidder behavior. We assumed that without the availability of non-price information bidders resort to the belief that the lowest bid wins the auction. In section 2 we showed that this assumption can be interpreted as a limiting case of our model describing the actual bidder behavior, and we stated that for our results to hold it would

be already sufficient if the influence of the price on the buyers decision was large relative to non-price aspects. To back up this statement and to show that our results are not driven by our simplifying assumption about the bidders' counterfactual behavior, we repeated our counterfactual analysis, thereby replacing the strong assumption that bidders belief that the lowest bid wins by the weaker assumption that bidders only belief the price being relatively more important for the buyer's decision than non-price aspects.

In concrete terms, first exactly like in our counterfactual analysis above we used our model for the actual bidder behavior, given by equation system (11), to derive estimates for the bidders' costs $\hat{c}_{nj}$. We then used these cost estimates to numerically solve equation system (11) for each auction n after estimates $\hat{p}_{nj}$ of the counterfactual prices, while in doing so scaling up the price coefficient by different factors and setting the coefficients of the non-price attributes to zero. Table 8, which can be found in appendix A.3, shows the results of this exercise. It can be seen that if we replace our assumption that bidders belief the lowest bid to win by the somewhat weaker assumption that bidders belief the price dominating non-price aspects in the buyers' decision processes, our results get even more pronounced, with the platform turnovers decreasing stronger and the aggregate buyers' utility increasing more. The reason for these more pronounced results is that under the counterfactual assumption that bidders belief the lowest bid to win, the bidder with the lowest costs bids exactly the second lowest costs. If bidders only belief the buyers' decision processes to be dominated by price with a small remaining uncertainty due to non-price aspects, then the bidder with the lowest costs also bids above his costs but now less than the second lowest costs, while all the other bidders bid nearly their costs. This on average renders the prices smaller and thus the results more pronounced than in the case where bidders belief the lowest price to win. Put together, relaxing our counterfactual assumption that bidders belief the lowest bid to win the auction would simply lead to stronger results.

Besides our assumptions about counterfactual bidder behavior another crucial point in the derivation of our counterfactual results given in table 7 is the estimation of the bidders'

costs $\hat{c}_{nj}$. The estimation of the bidders' costs hinges on assumptions about the bidders' beliefs regarding the buyers' choice processes. We do not know the actual beliefs of the bidders regarding the buyers' choice process. However, we think it is reasonable to assume that the bidders' beliefs do not differ significantly from what is actually going on: the auctions we consider are about procuring quite standard craftsmen jobs, namely painting and wallpapering. Most people have experience with this kind of jobs, either because they once did these themselves or because they once hired a contractor. Thus it seems quite natural to assume that bidders have a good sense of how in expectation buyers value their non-price attributes relative to their prices, and we therefore made the assumption that bidders are fully informed in terms of our model of a buyer's choice process developed in section 2. In concrete terms this means that we derived our counterfactual results in table 7 under the assumption that the bidders' beliefs about the buyers' preferences correspond to our estimation results in table 2.[16]

To be sure that our results are not driven by our assumption that in terms of our model in the information case bidders are fully informed about the buyers' preferences, we conducted robustness checks by deriving the changes in platform turnovers and aggregate buyers' utility under different assumptions regarding the bidder beliefs. Concretely, we scaled the preference coefficients given in table 2 by different factors, used these scaled coefficients to derive the bidders' costs, and then computed the counterfactual platform turnovers and buyer utilities. The results are given in table 9, which can be found in appendix A.3. It seems that the figures in table 7 are quite robust against scaling of the preference coefficients. Even if the bidders' beliefs about the buyers' preferences would deviate by a factor of 100, the reduction in platform turnovers respectively the increase in the aggregate utility of the buyers would merely be more pronounced.

[16]Note that this also means that we assume the bidders to belief a buyer's utility u_{nj} from the choice of a certain bidder j to be linearly dependent on the price p_{nj}, the bidder's attributes $\mathbf{A}_{nj}$ and an idiosyncratic term ϵ_{nj}. Clearly, one could think of other, possibly nonlinear relationships between u_{nj}, p_{nj}, $\mathbf{A}_{nj}$ and ϵ_{nj}, but we think the assumption of a linear relationship is quite likely to resemble the actual bidder beliefs.

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 have information about non-price aspects, 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 0.6 million euros, whereas the buyers' welfare would increase by the monetary equivalent of around 0.5 million euros. For comparison: actual platform turnovers for the time span considered are around 1.9 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.

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A Appendix

A.1 Proof of $\frac{\partial p_j}{\partial q_k} < 0$:

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

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

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

$$\frac{\partial P_j}{\partial v_j} > 0, \qquad \frac{\partial P_j}{\partial v_k} < 0, \quad \forall k \neq j,$$

and

$$\frac{\partial P_j}{\partial p_j} = -\frac{\partial P_j}{\partial v_j}, \quad \frac{\partial P_j}{\partial q_k} = \frac{\partial P_j}{\partial v_k}, \quad \frac{\partial^2 P_j}{(\partial p_j)^2} = \frac{\partial^2 P_j}{(\partial v_j)^2}, \quad \frac{\partial^2 P_j}{\partial p_j \partial q_k} = -\frac{\partial^2 P_j}{\partial v_j \partial v_k}.$$

Starting from the first order conditions

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

the implicit function theorem and a little algebra deliver us

$$\frac{\partial p_j}{\partial q_k} = -\frac{\frac{\partial(\frac{P_j}{\partial P_j/\partial p_j})}{\partial q_k}}{\frac{\partial(p_j + \frac{P_j}{\partial P_j/\partial p_j})}{\partial p_j}} = -\frac{-\frac{\partial P_j}{\partial v_k}\frac{\partial P_j}{\partial v_j} + \frac{\partial^2 P_j}{\partial v_k \partial v_j} P_j}{2(\frac{\partial P_j}{\partial v_j})^2 - \frac{\partial^2 P_j}{(\partial v_j)^2} P_j}$$

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

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

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.)

A.2 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

$$\mathrm{E}[u_1] = -p_1, \quad \mathrm{E}[u_2] = -p_2 + q_2.$$

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

$$P_1^{NI} = \frac{e^{-c_2}}{e^{-c_2} + e^{-c_2+q_2}}, \quad P_2^{NI} = \frac{e^{-c_2+q_2}}{e^{-c_2} + e^{-c_2+q_2}}.$$

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

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

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

$$p_1^I = \frac{P_1^I}{|\partial P_1^I/\partial p_1^I|}, \quad p_2^I = c_2 + \frac{P_2^I}{|\partial P_2^I/\partial p_2^I|}.$$

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

$$P_1^I = \frac{e^{-p_1^I}}{e^{-p_1^I} + e^{-p_2^I+q_2}}, \quad P_2^I = \frac{e^{-p_2^I+q_2}}{e^{-p_1^I} + e^{-p_2^I+q_2}},$$

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

$$p_1^I = e^{p_2^I - p_1^I - q_2} + 1 \tag{A1}$$

$$p_2^I = c_2 + e^{p_1^I - p_2^I + q_2} + 1. \tag{A2}$$

Conditions (A1) and (A2) 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

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

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 (A1) and (A2) 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

$$P_1^{NI}(-c_2) + P_2^{NI}(-c_2 + q_2) = P_1^I(-p_1^I) + P_2^I(-p_2^I + q_2), \tag{A3}$$

that for indifference of the platform is given by

$$c_2 = P_1^I p_1^I + P_2^I p_2^I. \tag{A4}$$

The indifference line for the buyers result when, given different values of c_2, equations (A1), (A2) and (A3) 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 (A1), (A2) and (A4) are simultaneously solved for p_1^I, p_2^I and q_2.

A.3 Robustness Checks:

	Platform turnover (in expectation)	**Aggregate utility buyers** (in expectation; monetary equivalent, normalized)	**Mean bidamount**
Set of auctions for which cost information is available: (1,928 auctions)			
Actual values (Information case)	820,778	0	559.3 (Avg. costs: 449.6)
Counterfactual values (No information case; given are changes relative to information case)			
Price only	− 170,581	+ 177,029	460.9
Price dominant, $\hat{\rho} \times 10$	− 268,350	+ 274,701	461.7
Price dominant, $\hat{\rho} \times 100$	− 315,646	+ 322,357	450.5

Table 8: **Robustness check, assumption about counterfactual bidder behavior.** The results are based on data from auctions conducted in the second half of 2008 for which cost information is available (1,928 auctions with on average 7.8 participants). The table shows results of the counterfactual analysis under different assumptions about the bidders counterfactual behavior: Bidders belief that the lowest price wins ("Price only"), Bidders belief that the buyers' decision processes are dominated by prices ("Price dominant, $\hat{\rho} \times 10$" and "Price dominant, $\hat{\rho} \times 100$"). All numbers are in euros.

	Subset of auctions with cost information available (1,928 auctions)		Whole set of auctions (7,725 auctions)	
	Platform turnover (in expectation)	**Aggregate utility buyers** (in expectation; monetary equivalent, normalized)	**Platform turnover** (in expectation)	**Aggregate utility buyers** (in expectation; monetary equivalent, normalized)
Actual values (Information case)	820,778	0	1,912,901	0
Counterfactual values (No information case; given are changes relative to information case)				
$(\hat{\rho}, \hat{\ }) \times 1$	− 170,581	+ 177,029	− 576,466	+ 871,932
$(\hat{\rho}, \hat{\ }) \times 2$	− 173,379	+ 173,973	− 517,807	+ 788,827
$(\hat{\rho}, \hat{\ }) \times 0.5$	− 163,151	+ 168,188	− 581,941	+ 911,354
$\hat{\rho} \times 2, \hat{\ } \times 0.5$	− 175,476	+ 170,284	− 525,101	+ 793,945
$\hat{\rho} \times 0.5, \hat{\ } \times 2$	− 165,226	+ 179,067	− 577,267	+ 912,212
$(\hat{\rho}, \hat{\ }) \times 10$	− 163,040	+ 163,740	− 480,357	+ 743,935
$(\hat{\rho}, \hat{\ }) \times 0.1$	− 157,717	+ 161,551	− 576,732	+ 915,750
$\hat{\rho} \times 10, \hat{\ } \times 0.1$	− 165,054	+ 157,805	− 480,242	+ 743,771
$\hat{\rho} \times 0.1, \hat{\ } \times 10$	− 184,764	+ 215,543	− 558,763	+ 925,352
$(\hat{\rho}, \hat{\ }) \times 100$	− 429,569	+ 309,945	− 578,340	+ 835,310
$(\hat{\rho}, \hat{\ }) \times 0.01$	− 156,007	+ 159,590	− 575,411	+ 913,539

Table 9: **Robustness check, actual bidder beliefs about buyers' preferences.** The results are based on data from auctions conducted in the second half of 2008. The left part of the table shows counterfactual platform turnovers and buyers' utilities for the subset of auctions for which cost information is available (1,928 auctions with on average 7.8 participants), the right part shows counterfactual platform turnovers and buyers' utilities for the whole set of auctions (7,725 auctions with on average 7.1 participants). All numbers are in euros. The coefficients used to derive estimates of the bidders' costs in our counterfactual analysis in section 7 are modified as indicated to account for different possible beliefs of the bidders about the buyers' preferences.