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Information Disclosure in Open Non-Binding Procurement Auctions: an Empirical Study

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Information Disclosure in Open Non-Binding Procurement Auctions

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Abstract. We study non-binding procurement auctions where both price and non-price characteristics of bidders matter for being awarded a contract. The outcome of such auctions critically depends on how information is distributed among bidders during the bidding process. As we show theoretically, whether it is in the buyer's interest to disclose or to conceal non-price information depends on the precise relationship between bidders' procurement cost and their qualities. We empirically study the impact of a change in the information structure using data from a large European online procurement platform. In a counterfactual analysis we analyze the reduction of non-price information available to the bidders. We find that on average bidders' price quotes would increase by 5%, auction turnover would increase by 8%, and buyers' welfare would be reduced by 8%.

Keywords: Procurement, Non-Binding Auctions, Supply Chain Management

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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-price 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. That is, bidders can be provided with different levels of information regarding the buyers preferences over both the price and the non-price characteristics of the offers.

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' valuations of bidders' non-price characteristics. We find that concealing all non-price information on average leads to an increase of bidders' price quotes by 5%, an increase of auction turnover by 8%, and a reduction of buyers' welfare by 8%.

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

[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.

fully informed both about the non-price characteristics of their rivals and about the buyers' preferences over their own and their rivals' non-price characteristics. In the second case, all quality information is concealed from the bidders. We show that whether or not it is beneficial for buyers to reveal quality information depends on characteristics of the market considered, namely the relationship between the differences in the bidders' costs and that in their qualities.

Our empirical analysis 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 all quality information is publicly available to bidders, and we can show that bidders' observed behavior is indeed in line with our model for the case of disclosed quality information. Based on this framework we conduct a counterfactual analysis and determine the impact of concealing quality information from the bidders. That is, we first derive estimates of the bidders' costs based on the current setting and then determine counterfactual auction outcomes for the case of concealed non-price information. We find that if non-price information was not available to the bidders, on average their price quotes would increase by 5%, expected auction turnover would increase by 8%, and expected buyers' welfare would be reduced by the monetary equivalent of 8%. Our analysis thus shows that the decision whether or not to reveal quality information to the bidders has an economically significant impact on auction outcomes.

Our work adds to a relatively new strand of literature which analyzes non-binding auctions. We are especially interested in the effect of different information structures in this auction format. There already are some theoretical papers which analyze the conditions under which it is beneficial for the buyer in non-binding auctions to inform bidders about their qualities. Gal-Or et al. (2007) show that under simultaneous bid submission the buyer is better off when he discloses quality information to the bidders. Extensions such as the inclusion of 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 costs 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 non-binding 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, we find that buyers would be worse off if all information with respect to non-price characteristics was concealed.

Wan and Beil (2012) and Wan et al. (2012) analyze a related but slightly different problem, they study auctions where bidders in order to win the auction additionally have to meet certain quality standards. Those articles explore theoretically and experimentally under which conditions it is optimal to provide information with respect to the screening among bidders either prior or after bidding has taken place.

Our work in general contributes to the literature which analyzes efficient ways to procure contracts when the buyer's valuation of an offer depends on additional dimensions besides price. Scoring auctions (where binding scoring rules take price and non-price characteristics into account) have already received significant attention in the literature and by now are quite well understood. Asker and Cantillon (2008, 2010) show 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. Practical implementability of scoring auctions through

[2] 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.

iterative process is analyzed for example in Bichler and Kalagnanam (2005) or Parkes and Kalagnanam (2005).

In practice non-binding auctions have established as a prominent format to take price and non-price characteristics into account. Several articles compare the performance of this format as compared to scoring 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.

2 Theory

■ **Framework.** We consider an open and non-binding procurement situation where a buyer wants to procure some contract among J participating firms. Each firm has some cost c_j for providing the service. For a certain period of time $t \in [0, T]$ bidding firms can continuously submit publically observable prices. We denote the vector of final prices quoted at the end of the submission period by each firm by $\mathbf{p} = (p_1, ..., p_J)$. Once price submission has finished the buyer can freely choose to award the contract to some firm j at price p_j.

For the buyer's decision not only the final price p_j quoted by firm j matters but also its non-price characteristics which result in a certain quality relevant for the buyer which we denote by q_j.[3] The way firms' qualities and prices influence the buyer's decision is established

[3] In more formal terms the quality of some firm j, q_j, is some function g of that firm's non-price characteristics, $\mathbf{A}_j$, and the respective preferences $\boldsymbol{\alpha}$ of the buyer, that is $q_j = g(\boldsymbol{\alpha}, \mathbf{A}_j)$. For our theoretical analysis it is not necessary to define quality at this level, but the definition will come in handy for our empirical analysis.

in detail in expression (1).

Before the selling process starts we assume that nature draws the vector of qualities assigned to the firms, $\mathbf{q} = (q_1, ..., q_J)$. After the draw we assume that the buyer is informed about the firms' qualities $\mathbf{q}$. With respect to the information firms receive about their qualities we differentiate between two cases: In the first case, which we call *information case (IC)*, in addition also all firms are informed about $\mathbf{q}$, that is in the information case $\mathbf{q}$ is common knowledge. In the other case, which we call *no information case (NIC)*, $\mathbf{q}$ remains concealed from the firms, that is in the no information case the buyer knows each firm's quality but the firms know neither their own nor their rivals' qualities.

We assume that the buyer can choose among J firms and an outside option. He receives a certain amount of utility u_j when he chooses firm j. This amount of utility depends on the price p_j put forward by this firm and the firm's exogenous quality q_j. We model the utility a buyer receives from a certain firm as being linearly dependent on the price p_j, the firm's quality q_j, and an error term ϵ_j. With that, the buyer's decision process is given as

$$\begin{aligned} \max_{j\in\{0,1,\dots,J\}} \quad & u_j, \quad \text{where} \\ u_0 &= \epsilon_0 \\ u_1 &= -p_1 + q_1 + \epsilon_1 \\ &\vdots \\ u_J &= -p_J + q_J + \epsilon_J \end{aligned} \tag{1}$$

As for the behavior of the buyer and that of the firms only differences in both qualities and utilities matter, we can assume without loss of generality that the utility the buyer derives from the outside option equals zero. The error terms ϵ_j capture uncertainty in the buyer's decision due to unobserved influences unrelated to price or the observed quality aspects.[4] We assume the ϵ_j to follow a symmetric distribution with mean zero. When making his

[4]For example the buyer might be influenced in his decision by his (unobserved) taste regarding for example the username firm j chooses at a bidding platform.

decision, the realizations of the ϵ_j are known to the buyer, but they remain concealed from the firms while bidding. The buyer is assumed to choose the option which maximizes his utility, i.e. the option k for which

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

Our research interest lies in the implications of availability of quality information to the firms in open and non-binding auctions. In order to develop an understanding of the mechanisms at play we look at two polar cases of information structures: In the first case, the *information case (IC)*, firms are assumed to have full information about both their own quality and their rivals' qualities. In the second case, the *no information case (NIC)*, firms are assumed to have no information at all with respect to their own and their rivals' qualities.

■ **Information case:** In the information case we assume that every firm j has full information about its own quality q_j, its rivals' qualities q_k, and the prices p_k its rivals put forward. We also assume that firms are fully informed about the way the buyer makes his decision - that is, the firms perceive the buyer to decide according to maximization problem (1). In contrast to the buyer, who knows the realizations of the ϵ_j when making his decision, from the firms' perspectives the ϵ_j are random. We assume that the unobservables ϵ_j follow some distribution, and that the firms know the distribution the ϵ_j are drawn from. In consequence, given some bid p_j of its own, firm j can derive all winning probabilities $P_k(\mathbf{p}, \mathbf{q})$, $k \in \{0,1,...,J\}$, which are functions of all firms' final price bids $\mathbf{p} = (p_1,...,p_J)$ and all firms' qualities $\mathbf{q}$. We assume that the winning probability P_k of each firm k is log concave in its final price quote.[5] Expected profits π_j of firm j are given by

$$\pi_j = P_j(\mathbf{p}, \mathbf{q})(p_j - c_j).$$

We can now determine the Nash equilibrium in final prices $\mathbf{p} = (p_1,...,p_J)$ submitted by the firms at the end of each bidding period where each firm chooses its final price bid as a

[5] Notice that the Logit framework referred to from section 4 onwards satisfies this assumption.

best reply to all other firms' final price bids. As usual for the price setting market game, the equilibrium can be characterized by the first order conditions of each firm with respect to the final price bid submitted.[6] This is summarized in the subsequent proposition.

Proposition 1. *In the information case there exists a unique Nash equilibrium in final price quotes. It is characterized by*

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

Proof. Existence and uniqueness of the equilibrium have already been shown in the literature, compare Caplin and Nalebuff (1991) and Mizuno (2003). □

■ **No information case:** In the no information case we assume that firms do know that given a certain draw of qualities $\mathbf{q}$ the buyer makes his decision according to the maximization problem given by (1), but that they do not know which qualities $\mathbf{q}$ were actually drawn, that is they neither know the qualities of their rivals nor their own quality. In addition, firms are assumed not to have more information about their own quality than about their rivals' qualities.[7] (Of course, they also do not know the realizations of the ϵ_j.). In addition, we assume that firms have symmetric beliefs about the distribution of quality in the population, and that they believe the draws of the qualities $q_1, ..., q_J$ to be independent from each other. We assume the q_j to follow a symmetric distribution. Then, from the point of view of the firms the buyer decides as if he had the following decision problem:

[6]The current framework relies on the standard assumptions underlying Bertrand competition, where firms' costs are common knowledge. Notice, however, that the same result would obtain in the limit of alternating myopically best responses of firms without common knowledge of cost, e.g. compare Fudenberg and Levine (1998). Experimental evidence that players significantly underestimate their rivals' rationality can be found for example in Weizsaecker (2003).

[7]We make this assumption for two reasons: First, if we assumed that each bidder had more information about his own quality than his rivals, bidders would in essence play a signaling game, and this would render the theoretical analysis intractable. Second, with regard to our later application, we think this assumption is a sensible approximation of a bidder's information state if information about the buyer's preferences $\boldsymbol{\alpha}$ and his rivals' non-price characteristics $\mathbf{A}_j$ are concealed from him: Of course the bidder is still informed about his own non-price characteristics, but without sufficiently detailed information about the buyer's preferences he cannot transform this information into meaningful information about his own (relative) quality. (Remember that a bidder's quality q_j is some function of that bidder's non-price characteristics $\mathbf{A}_j$ and the buyer's respective preferences $\boldsymbol{\alpha}$.)

$$\begin{aligned} \max_{j\in\{0,1,...,J\}} \quad u_j, & \quad \text{where} \\ u_0 &= \epsilon_0 \\ u_1 &= -p_1 + \tilde{\epsilon}_1 \\ &\vdots \\ u_J &= -p_J + \tilde{\epsilon}_J \end{aligned} \tag{3}$$

where $\tilde{\epsilon_j} = q_j + \epsilon_j$. This means in the no information case firms behave as if the buyer made his decision based only on their prices p_j and error terms $\tilde{\epsilon}_j$.

Under the assumption that firms know the distribution of the ϵ_j and the distribution of the q_j they can derive the distribution of the $\tilde{\epsilon}_j = q_j + \epsilon_j$ and thus their winning probabilities. Therefore, given some bid p_j of its own, firm j can derive beliefs about all winning probabilities $\tilde{P}_k$, $k \in \{0, 1, ..., J\}$. We assume that the winning probability $\tilde{P}_k$ of each firm k is log concave in its final price quote.[8] Expected profit $\tilde{\pi}_j$ of firm j is then given by

$$\tilde{\pi}_j = \tilde{P}_j(\mathbf{p}) \cdot (p_j - c_j)\,. \tag{4}$$

We obtain the Nash equilibrium in final price quotes, in the no information case those are based on the winning probabilities $\tilde{P}_k$, however.

Proposition 2. *In the no information case there exists a unique Nash equilibrium in final price quotes. It is characterized by*

$$p_j + \frac{\tilde{P}_j}{\partial \tilde{P}_j / \partial p_j} - c_j = 0, \quad \forall j \in \{1, ..., J\}. \tag{5}$$

Proof. Existence and uniqueness of the equilibrium have already been shown in the literature, compare Caplin and Nalebuff (1991) and Mizuno (2003). □

■ **Comparing both information regimes:** We are interested in whether the buyer prefers to disclose or to conceal quality information. This decision clearly has to be taken

[8] Notice that the Logit framework referred to from section 4 onwards satisfies this assumption.

prior to knowing the precise number and identity of the participating firms and their quality. The buyer then will prefer the information structure which gives him the highest expected utility. As we summarize in the subsequent theorem neither information regime dominates the other.

Proposition 3. *There is no information structure which dominates the other.*

Proof. See appendix A.1. □

The central intuition is that from the buyer's point of view the informational arrangement which creates the highest competitive pressure among firms is the preferable one. Which information regime creates more competitive pressure as perceived by the firms depends on the specific situation considered, as we show. First, consider for example a situation where firms have similar production cost but very different qualities. A regime which conceals non-price information suggests tough competition and induces more aggressive bidding. Second, consider a situation where firms have quite different production cost but quality differences are such as to compensate for those differences (i.e. the more expensive producer also has higher quality). In this case the full revelation of non-price information induces more aggressive bidding. In the subsequent section we find a detailed illustration of those tradeoffs.

□ **Illustration of tradeoffs and model mechanics:** For every standard assumption about the distribution of the ϵ_j (normal or type I extreme value) the winning probabilities P_j either cannot be expressed in closed form or contain exponential terms which lead to transcendental equations. Thus, for any standard assumption about the distribution of the ϵ_j the first order conditions (2) cannot be solved analytically. The same holds for the $\tilde{\epsilon}_j$ and the $\tilde{P}_j$.

In order to nevertheless gain further insights into the mechanics of our model we make use of the fact that the winning probabilities of the bidding firms can be approximated by a first order series approximation. Details regarding the approximation are given in appendix A.2. Using this approximation, we analyze bidding in an auction where the buyer can only choose among two firms.[9] We assume that firm 1 is of low quality and low costs, while firm 2 is of high quality and high costs (i.e. $q_1 < q_2$ and $c_1 < c_2$). Firm one's perception of its winning probability in the information case, P_1, and its perception of its winning probability in the no information case, $\tilde{P}_1$, are given as

$$P_1(\mathbf{p}, \mathbf{q}) = \frac{1}{2} + \frac{1}{a}(p_1 - p_2 + q_1 - q_2), \tag{6}$$

$$\tilde{P}_1(\mathbf{p}) = \frac{1}{2} + \frac{1}{\tilde{a}}(p_1 - p_2). \tag{7}$$

The coefficients a and $\tilde{a}$ depend on the variances of ϵ_j and $\tilde{\epsilon}_j$. It holds that $0 < a \leq \tilde{a} < 1$. The winning probabilities of firm two are simply $P_2 = 1 - P_1$ and $\tilde{P}_2 = 1 - \tilde{P}_1$.

Relationship between the firms' equilibrium bids: By making use of the first order conditions established in theorems 1 and 2 we can derive equilibrium bids in either case.[10] We directly turn towards the comparison of equilibrium bids for either information regime:

$$p_1^* = \tilde{p}_1^* - \frac{1}{3}(q_2 - q_1) - \frac{1}{2}(\tilde{a} - a), \tag{8}$$

$$p_2^* = \tilde{p}_2^* + \frac{1}{3}(q_2 - q_1) - \frac{1}{2}(\tilde{a} - a). \tag{9}$$

The intuition behind expressions (8) and (9) is straightforward: The first term added to $\tilde{p}_2^*$ respectively subtracted from $\tilde{p}_1^*$ captures that in case of disclosed quality information firms become aware of firm two's competitive advantage in terms of quality: The net competitive pressure on the low-quality firm (firm one) increases, while that on the high-quality firm (firm two) decreases. The last term in expressions (8) and (9) captures that in case of concealed quality information firms perceive the buyer's decision to be more random and thus add an additional uncertainty markup on their costs.

[9] This means we implicitly assume that the value of the outside option is so low that the upper limit to the prices of firm 1 and 2 is above the equilibrium prices. The outside option simply leads to upper limits for the prices of firm 1 and 2. Thus its explicit treatment would only make our analysis more complicated without delivering further insights.

[10] Those are given as follows: $p_1^* = \frac{1}{3}(2c_1 + c_2) - \frac{1}{3}(q_2 - q_1) + \frac{a}{2}$ and $p_2^* = \frac{1}{3}(c_1 + 2c_2) + \frac{1}{3}(q_2 - q_1) + \frac{a}{2}$ for the information case, $\tilde{p}_1^* = \frac{1}{3}(2c_1 + c_2) + \frac{\tilde{a}}{2}$ and $\tilde{p}_2^* = \frac{1}{3}(c_1 + 2c_2) + \frac{\tilde{a}}{2}$ for the no information case.

Relationship between the buyer's expected utilities: In appendix A.2 we use results from Small and Rosen (1981) to derive the expected utility of the buyer in the information case, EU, and that in the no information case, $\widetilde{\text{EU}}$. Again we directly turn towards the comparison of the expected utilities for either information regime:

$$\begin{aligned} \text{EU} - \widetilde{\text{EU}} \quad = \quad & \frac{1}{3a}(q_2 - q_1)\left[(c_2 - c_1) - 2(q_2 - q_1)\right] \\ & + \frac{1}{4}(2a\tilde{a} + \tilde{a}^2 - 3a^2) \\ & + (\frac{\tilde{a}}{2a} - \frac{1}{2})(c_2 + c_1 - q_2 - q_1) \end{aligned} \tag{10}$$

Equation (10) shows that the net change in the expected utility of the buyer depends on three factors: The first term captures the tradeoff between the competitive advantage of the low-cost firm and that of the high-quality firm. If the difference in costs is small but that in qualities is very high, disclosure of quality information weakens competition because firms become aware of the high-quality firm's large net advantage. If in contrast the difference in costs is very high and that in qualities small, disclosure of quality information strengthens competition as it mitigates the net advantage of the low-cost firm. The second term captures that in the no information case firms perceive the decision of the buyer to be more random. In the no information case they thus demand an uncertainty markup on their prices which in turn decreases buyer's welfare. The third term weighs the effect of uncertainty on buyer's welfare (term two) against that of quality information (term one). The weight of either effect depends on how strong relative to costs firms' pricing decisions are influenced by quality information. The smaller the influence of quality information, the more the effect of uncertainty outweighs that of quality information.

The graphs in figure 1 illustrate how the buyer's preferences regarding the information structure change as a function of the auction parameters, namely the firms' costs, their qualities, and the difference between the variance of the ϵ_j and that of the $\tilde{\epsilon}_j$. The parameter sizes used for this simulation exercise resemble typical parameter sizes from our applica-

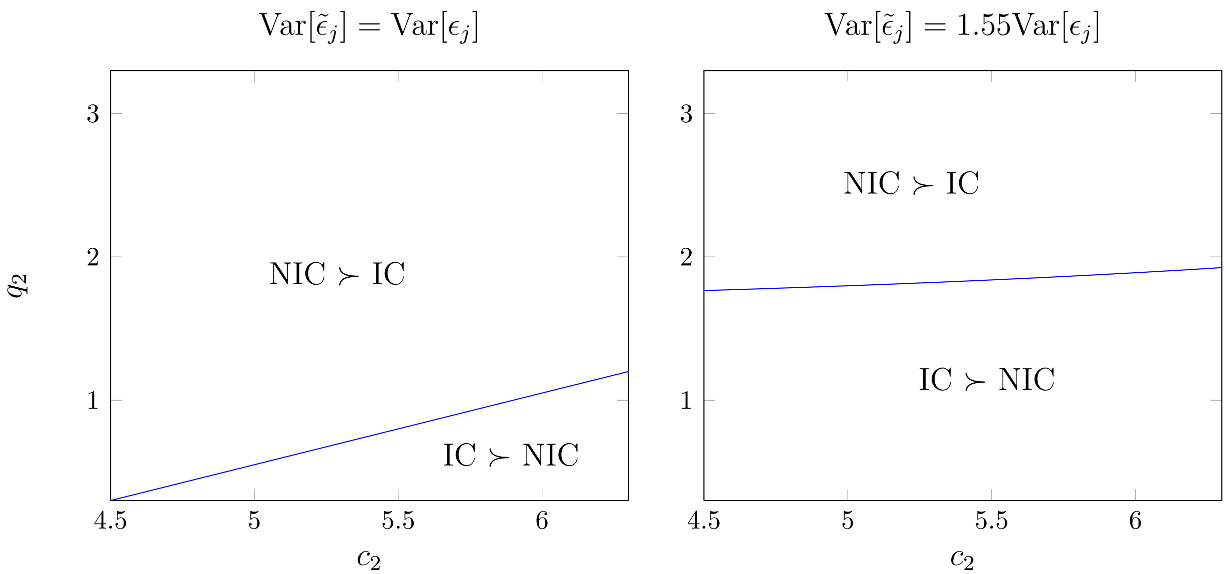

Figure 1: **Preferences of the buyer regarding the information structure as a function of the auction parameters.** The graphs show the indifference line of the buyer. The indifference line of the buyer represents the parameter set at which the buyer is indifferent between both information structures. We assumed that $c_1 = 4.5$ and $q_1 = 0.3$. These parameters sizes resemble typical parameter sizes from our application. For all q_2-c_2-combinations above the indifference lines the buyer prefers the no information case over the information case, for all combinations below he prefers the information case over the no information case. For the left graph we assumed that in the no information case firms do not perceive the buyer's decision to be more random than in the information case. For the right graph we assumed that the firms' perception of uncertainty in the no information case equals that in our data (which in technical terms means that $\text{Var}[\tilde{\epsilon}_j] = 1.55\text{Var}[\epsilon_j]$). For the parameter space depicted our approximation is good (see appendix A.2).

tion.[11] The important take-away is that which information structure to choose for a certain application is not clear ex ante but depends on the specific situation analyzed.

3 Data

We have available an extensive dataset from a popular European online procurement platform. On this platform private customers tender jobs ranging from construction over general repair and renovation to teaching. Jobs are awarded through an open non binding auction.

The exact procedure is as follows: A private customer (respectively buyer) posts a de-

[11] The average quality in our data is 0.3 (as a lookahead to section 4 this equals the average value of $\boldsymbol{\alpha}\mathbf{A}_j$). The average (estimated) costs are 450 euros. In "utility-units" this is 4.5 (which equals the average value of ρc_j). For our simulation we set $q_1 = 0.3$ and $c_1 = 4.5$.

	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%				
Percentage of his rivals a certain bidder encounters at least twice	0.12	0.15	0	0	1
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 costs information and information about bidders' characteristics available.

scription of the job he wants to be procured. This description is entered into a free-text field and usually contains job details like for example the area to be painted or whether or not cleaning is required, the job site, a price expectation (termed startprice in the following) and an announcement of the time span during which tradesmen (respectively bidders) can put forward quotes. All this information is available to all tradesmen registered at the platform. During the defined time span all tradesmen who are interested can publically announce prices for which they are willing to procure the job offered. Announced prices can be changed at any point during the auction. The current price quote of each bidder and all his non-price characteristics are publicly observable on the website. The non-price characteristics include the number of positive and negative ratings the bidder received so far, his home location, qualifications like the possession of certain degrees and his area of expertise. Highlighted among the non-price characteristics are a bidder's ratings. At the end of the auction the buyer is free to award the job to one of the bidders or to withdraw his offer. In case of an award the platform obtains a certain percentage of the successful bid as commission.

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

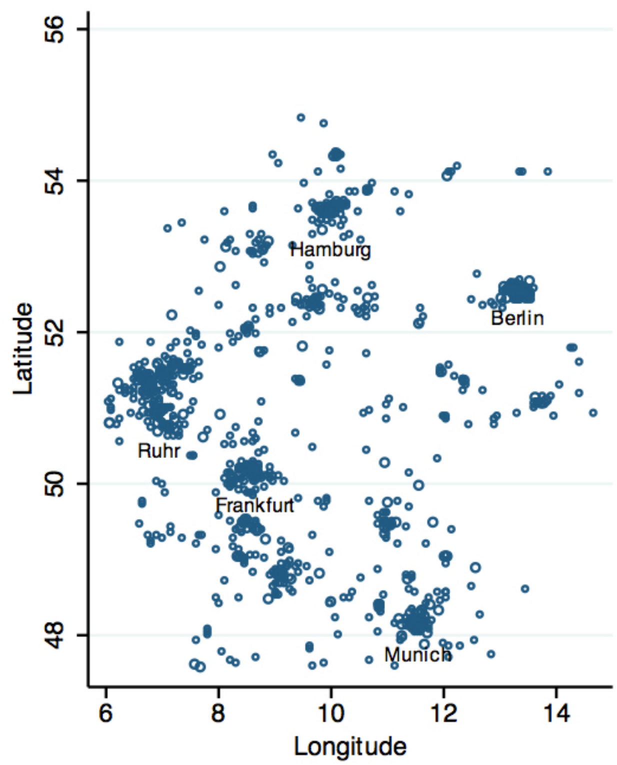

Figure 2: **Spatial distribution of auctions**. The spatial distribution of the 1,928 auctions which were conducted in the 2nd half of 2008 and for which we have collected costs information is displayed.

addition, for every auction 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 final 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.

When posting a job offer, every buyer also sets a so called startprice. The startprice is set for purely informational reasons, it neither puts any restriction on bids submitted nor on the award decision taken by the potential buyer. In 3% of the auctions under consideration a startprice of more than 2000 EUR is set. A major part of these auctions aims at procuring jobs with special requirements, e.g. the use of scaffolding. As there is not enough information in the data to sufficiently control for special costs elements like that, for the following analysis we drop all auctions with startprices of more than 2000 EUR. In addition, as in order to confirm whether bidders' pricing behavior is in line with our information case framework we study bidders' reactions to competitors' qualities (see appendix A.3), we use only auctions in which at least two bidders participate. We are left with 1,928 auctions. Descriptive statistics for these auctions are given in table 1. Figure 2 shows the spatial distribution of these.

4 Counterfactual analysis

The goal of our counterfactual analysis is to determine the impact of availability of quality information on the aggregate welfare of the buyers. In the market setting of our data information about bidders' non-price characteristics is publicly available and bidders can infer information about the preferences of the buyers form observing the buyers' former decisions. Thus the observed market outcome should be well described by our information case model. We verify this assumption by testing empirically whether bidders' observed behavior is in line with the predictions of the information case model. In particular, we employ a reduced form model to analyze bidders' reactions to quality shocks. Details regarding this analysis can be found in appendix A.3. As implied by our information case model, we find that bidders react to the appearance of an high-quality rival with drastic price reductions. This finding confirms our assumption that our information case model describes actual bidders' behavior well.

The first step in our counterfactual analysis is to elicit information about the bidders' qualities by estimating the buyers' preferences from their observed decisions. Together with our model for the bidders' behavior in the information case we use the information about bidders' qualities gained to derive estimates of the bidders' costs. We then use these costs estimates together with our model for the bidders' behavior in the counterfactual no information case to see what would happen to buyers' welfare if quality information was concealed from the bidders.[12]

[12] Note that in practice concealment of quality information can easily be achieved through two channels: First, making information about a bidder's non-price characteristics exclusively available to the buyers but not to his rivals. And second, undertaking measures which make it more difficult for bidders to assess the quality of their own non-price characteristics, such as offering predefined input masks for job descriptions which do not directly foresee to convey quality preferences of buyers.

■ **Estimation of the buyers' preferences.** We elicit the buyers' preferences using a logit discrete choice model: For a given auction n we model the decision of the buyer of that auction as a discrete choice among all the participating bidders and an outside option. The buyer is assumed to base his decision among the bidders on the prices put forward and the non-price characteristics of each bidder. Bidders' non-price characteristics comprise binary characteristics, indicating for example the possession of certain degrees, discrete characteristics like number of positive ratings and number of negative ratings, and a continuous measure for the distance between bidder j's home location and the job site.[13]

□ **Econometric model.** We estimate the buyers' preferences along the lines of the model we developed in section 2: a certain buyer's utility from choosing an alternative is assumed to be linearly dependent on the price p_{nj} of that alternative, its quality q_{nj} and an error term ϵ_{nj}. A bidder's quality is defined as some function of that bidder's non-price characteristics and the buyer's respective preferences. 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-price characteristics of bidder j in auction n, and $\boldsymbol{\alpha}$ denoting the preferences of the buyer over these characteristics, the quality q_{nj} of bidder j in auction n is given by $\boldsymbol{\alpha}\mathbf{A}_{nj}$.[14] With ρ denoting the price elasticity of the buyer in auction n, the utility he derives one each of the J_n participating bidders can explicitly be

[13]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.

[14]For simplicity we are assuming that each buyer has the same preferences $\boldsymbol{\alpha}$. We could replace this assumption by assuming that the preferences $\boldsymbol{\alpha}$ of the buyers follow a normal distribution and accordingly estimate a mixed logit model. However, this more involved approach does not deliver significantly different results.

formulated as[15]

$$
\begin{aligned}
u_{n1} &= \rho p_{n1} + \boldsymbol{\alpha}\mathbf{A}_{n1} + \epsilon_{n1} \\
&\vdots \\
u_{nJ_n} &= \rho p_{nJ_n} + \boldsymbol{\alpha}\mathbf{A}_{nJ_n} + \epsilon_{nJ_n}.
\end{aligned}
\tag{11}
$$

The error terms ϵ_{nj} capture unobserved influences on the buyer's decision unrelated to bidders' prices or their observed qualities. The buyer is assumed to choose the alternative which offers him the highest utility. By assuming the error terms ϵ_{nj} to be independently, identically type I extreme value distributed we obtain the standard logit model: The choice probabilities are given as

$$
P_{nj} = \frac{e^{\rho p_{nj} + \boldsymbol{\alpha}\mathbf{A}_{nj}}}{\sum_{k=1}^{J_n} e^{\rho p_{nk} + \boldsymbol{\alpha}\mathbf{A}_{nk}}}.
$$

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

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

□ **Estimation results.** We estimated our model on all auctions from the painting and wallpapering category with an announced startprice of at most 2000 EUR, which were conducted during the second half of 2008, and for which we have costs information available. Table 2 shows the results. The first column displays the coefficient estimates $\{\hat{\rho}, \hat{\boldsymbol{\alpha}}\}$, the second column the respective average marginal effects. Besides by some controls, a buyer's decision seems to be strongly influenced by the bidders' prices and the way bidders have been rated by former buyers: on average a price reduction of 10 EUR leads to an increase

[15] Note that we did not include intercepts in the utility specifications for the bidders 1 to J_n. As only differences in utilities matter for the buyers' decisions, that does not put any restrictions on our discrete choice model. We also did not include an outside option into our model. The reason is that in our dataset the outside option is never chosen and we thus do not have variation in our data from which to draw meaningful information about the value of the outside option.

Covariates in buyer's utility fct.	Coefficient estimates	Average marginal effects
Bid amount (EUR)	-.011*** (.0004)	-.0010*** (.00006)
Nbr. of positive ratings	.016*** (.001)	.0014*** (.0001)
Nbr. of negative ratings	-.108*** (.014)	-.0097*** (.0012)
Controls:		
Nbr. of employees	-.012	-.0011
Distance (km)	-.006***	-.0005***
Trade License	.292***	.0263***
Master craftsman company	.138	.0124
Senior journeyman company	.077	.0070
Other certifications	.024	.0021
In craftsmen register	.290***	.0261***
Nbr. of observations	15,100	
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 15,100 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%.

of the bidder's winning probability of around 1%, 10 positive ratings lead to an increase of about 1.3%, and 10 negative ratings reduce 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.

Our results hinge on the assumption that the error terms ϵ_{nj} in (11) 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 convinced 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. Thus, 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.

■ **Estimation of bidders' costs.** Our goal is to calculate the change in buyers' welfare if quality information were concealed from the bidders. To calculate the change in buyers' welfare we need information about bidders' counterfactual prices. If we had information about bidders costs c_{nj} we could calculate bidders' counterfactual prices employing our no information case model.[16] We do not have explicit cost information, but as observed bidders' behavior is in line with our model for the case of disclosed quality information (compare appendix A.3) we can use this model to derive estimates of the bidders' costs c_{nj} from the observed prices p_{nj}:

The basic assumption in our model for the case of disclosed quality information is that in each auction bidders are informed about each other's qualities. As a bidder's quality is given as a function of that bidder's non-price attributes and the buyer's preferences over these attributes, that implies that bidders are informed about both each other's non-price attributes and the respective preferences of the buyer. In our data we have available information about each bidder's non-price attributes, and we make the assumption that in each auction bidders meet a representative buyer whose preferences (ρ, α) equal our preference estimates $(\hat{\rho}, \hat{\alpha})$ (compare table 2).

Our assumption that bidders' behavior can be described by our model for the information case implies that the observed bids p_{nj} are equilibrium bids which for every auction n solve

[16]We have available information about the cost factors of each auction, but we do not have information about each bidders' opportunity costs. We think for our application opportunity costs can be expected to be quite heterogeneous, as bidders are very diverse (the spectrum ranges from private persons to professionals from medium-sized firms). Thus, without information on opportunity costs we do not have sufficient information on bidders' costs c_{nj}.

the bidders' first order conditions

$$p_{nj} + \frac{P_{nj}}{\partial P_{nj}/\partial p_{nj}} - c_{nj} = 0, \quad \forall j \in \{1, ..., J_n\}. \tag{12}$$

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

$$\hat{P}_{nj} = \frac{e^{\hat{\rho} p_{nj} + \hat{\boldsymbol{\alpha}} \mathbf{A}_{nj}}}{\sum_{k=1}^{J_n} e^{\hat{\rho} p_{nk} + \hat{\boldsymbol{\alpha}} \mathbf{A}_{nk}}} \tag{13}$$

With these, the first order conditions (12) can be solved directly for estimates $\widehat{c}_{nj}$ of the bidders' costs c_{nj}.

■ **Counterfactual Simulation.** Our counterfactual assumption is that quality information is concealed from the bidders. In this case the bidders' subjective perception of the buyers' decision process in a certain auction n is

$$\begin{aligned} \max_{j \in \{1,...,J_n\}} \quad & u_{nj}, \quad \text{where} \\ u_{nj} \quad = \quad & -p_{nj} + \tilde{\epsilon}_{nj} \qquad \text{for } j \in \{1, ..., J_n\}. \end{aligned} \tag{14}$$

The $\tilde{\epsilon}_{nj}$ are given as the sum of the error terms ϵ_{nj} and the (unobserved) quality-draws q_{nj}, that is $\tilde{\epsilon}_{nj} = q_{nj} + \epsilon_{nj}$. Thus, the distribution of the $\tilde{\epsilon}_{nj}$ results from the convolution of the density of the ϵ_{nj} with the bidders' belief about the density of the quality distribution.

For reasons of computational feasibility we make the assumption that the error terms $\tilde{\epsilon}_{nj} = q_{nj} + \epsilon_{nj}$ follow a type I extreme value distribution.[17] In order to derive plausible counterfactual estimates we assume that bidders' beliefs about the moments of the quality distribution coincide with the empirical moments of the quality distribution. This implies

[17]Note that our results are not driven by specific assumptions about the distributions of the ϵ_{nj} and the $\tilde{\epsilon}_{nj}$. As long as these distributions are continuous, single-peaked and have no fat tails, our qualitative results hold. What is of relevance for our results is just the relationship between the variance of the ϵ_j and the variance of the $\tilde{\epsilon}_j$.

	Mean	*SD*	*Median*
Actual bidamounts (p_{nj})	559 €	514 €	400 €
Estimated costs ($\hat{c}_{nj}$)	450 €	518 €	304 €
Counterfactual bidamounts ($\hat{p}_{nj}$)	586 €	512 €	435 €

Table 3: **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.

that the bidders' beliefs about the moments of the distribution of the error terms $\tilde{\epsilon}_{nj}$ coincide with the empirical moments of the $\tilde{\epsilon}_{nj}$. We can get information about the empirical moments of the $\tilde{\epsilon}_{nj}$ by simply running a logit estimation with only the bidders' prices included as covariates. We get that $\mathrm{Var}[\tilde{\epsilon}_{nj}] = 1.55\,\mathrm{Var}[\epsilon_{nj}]$.[18] We now can formulate the bidders' first order conditions in the no information case as

$$\hat{p}_{nj} + \frac{\hat{P}_{nj}}{\partial \hat{P}_{nj}/\partial \hat{p}_{nj}} - \hat{c}_{nj} = 0, \quad j \in \{1, ..., J_n\}, \tag{15}$$

where

$$\hat{P}_{nj} = \frac{e^{\frac{1}{\sqrt{1.55}}\hat{\rho}\hat{p}_{nj}}}{e^{\frac{1}{\sqrt{1.55}}\hat{v}_{n0}} + \sum_{k=1}^{J_n} e^{\frac{1}{\sqrt{1.55}}\hat{\rho}\hat{p}_{nk}}}. \tag{16}$$

We solve conditions (15) numerically for estimates $\hat{p}_{nj}$ of bidders' equilibrium prices in the no information case.

With estimates $\hat{p}_{nj}$ of the counterfactual bids we can calculate the counterfactual aggregate utility of the buyers: Following Small and Rosen (1981), for type I extreme value distributed error terms ϵ_j the change in expected utility of the buyer in an auction n can be

[18] We get information about the relationship between the variance of the ϵ_j and that of the $\tilde{\epsilon}_j$ by comparing the price coefficient from the logit estimation with only the prices included as covariates to the price coefficient of the logit estimation with also bidders' non-price characteristics included as covariates.

	Actual (Information case)		**Counterfactual** (No information case)
Average price quotes	559 €	$\xrightarrow{+5\%}$	586 €
Average buyer's utility (monetary equivalent, normalized)	0 €	$\xrightarrow{-8\%}$	-34 €
Average auction turnover	425 €	$\xrightarrow{+8\%}$	462 €

Table 4: **Results of counterfactual analysis, related to outcome of one representative auction.** 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.

calculated as

$$\Delta\text{EU}_n = \text{EU}_n - \widetilde{\text{EU}}_n = \ln\left(\sum_{j=1}^{J_n} e^{\hat{\rho}p_{nj}+\hat{\boldsymbol{\alpha}}\mathbf{A}_{nj}}\right) - \ln\left(\sum_{j=1}^{J_n} e^{\hat{\rho}\hat{p}_{nj}+\hat{\boldsymbol{\alpha}}\mathbf{A}_{nj}}\right)$$

The change in buyers' aggregate utility if quality information was concealed is then simply given as

$$\Delta\text{EU}_{total} = \sum_{n=1}^{N} \Delta\text{EU}_n \tag{17}$$

Division by $\hat{\rho}$ delivers the monetary equivalents of the utility values.

We used data from all auctions from the painting and wallpapering category which were performed during the second half of 2008 and for which we have information about the cost factors available to compute the aggregate welfare of the buyers and the total platform turnover for the counterfactual case of concealed quality information. As we find, in case quality information was concealed, on average bidders final price quotes increase by 5% (compare table 3). The expected counterfactual turnover in all auctions considered increases from 820,000 euros to 890,000 euros (i.e. an increase of 8%). Using formula (17), we also find that the aggregate utility of the buyers decreases by the monetary equivalent of around 65,000 euros, which corresponds to 8% of total auction turnover.

■ **Discussion.** Our counterfactual results were derived using our theoretical frameworks for the case of disclosed and the case of concealed quality information, and the assumption that bidders' actual behavior can be described by the model for the case of disclosed quality information. Before we discuss the general assumptions underlying both our frameworks, let us address our assumption that our information case model describes actual bidders' behavior. We already mentioned that in our application information about bidders' non-price characteristics is publicly available, and that bidders can derive information about the buyers' preferences from observations of buyers' former decisions. Thus, bidders should possess quality information. However, the fact that bidders possess quality information does not mean that they necessarily incorporate this information in their pricing decisions. In order to test whether bidders actually do incorporate quality information in their pricing decisions we therefore employed a reduced form model to identify the bidders' reaction to a quality shock. Details are given in appendix A.3. We found that bidders react to the appearance of an in terms of quality very strong rival by an average price reduction of about 90 euros, which is quite drastic given an average bidamount of 560 euros. This behavior is in line with the implications of our model for the case of disclosed quality information. For this reason we are convinced that our information case model is suited to describe actual bidders' behavior.

Let us turn now to the general assumptions underlying both our theoretical frameworks. Our frameworks abstract from inter-auction dynamics. For the development of our frameworks we assumed that both buyers and bidders do not behave strategically across auctions. We think this assumption is reasonable for our application: First, as during the time period considered each buyer on average auctions off only one contract we can exclude strategic inter-auction behavior of buyers. Second, as the probability of repeated encounters between bidders is quite low (around 12%, see table 1), it should be reasonable to assume that if at all phenomenons like tacit collusion play a negligible role. We also do not think that explicit collusion in a given auction plays a role: For once, bidders are not able to communicate with each other on the online platform. Then, as shown on the map in figure 2, most auctions are procuring jobs in large cities/metropolitan areas. There, in contrast to rural areas, bidders should not know about the whole pool of potential rivals, what makes interactions between them apart from that on the platform quite unlikely. Thus, interaction among bidders participating in a certain auction and between these bidders and the buyer should be restricted to happen during this auction.

A slightly different concern might be that some bidders behave strategically across auctions due to capacity constraints, e.g. Jofre-Bonet and Pesendorfer (2000). However, most auctions are about smaller jobs which should take about one to three days to complete (as shown in table 1, the median startprice set is around 500 euros), and in the time span we consider (half a year) the average number of auction participations is around four. Thus, we do not think that capacity constraints do play a major role here. To summarize, we think that modeling each auction in an isolated manner is a reasonable approach for our application.

We further made the assumption that a bidding equilibrium emerges in each auction. In particular, this assumption implies that dynamic phenomenons like sniping do not occur in our application. Given the numbers in table 1 this assumption seems to be justified: On average the last bid is placed well before the end of an auction, meaning that sniping seems to play no role in our data. Thus, the assumption that in each auction in our application an equilibrium is achieved should be justified.

Finally notice that the framework we consider is purely static, it clearly does not consider entry or exit of buyers or bidders. Especially for business models in the very dynamic online markets those aspects are of crucial importance, however. Very often rapid growth is much more important than instantaneous profits.[19] A formal consideration of the dynamic aspects

[19]The prototypic example of a company engaged in online markets which focuses its strategy on long-run growth but not short-run profits is Amazon. In a recent interview for HBR IdeaCast from Harvard Business Review Jeff Bezos, CEO of Amazon.com, states: "Percentage margins are not one of the things we are seeking to optimize. It's the absolute dollar-free cash flow per share that you want to maximize, [...]" And later on: "[W]e believe by keeping our prices very, very low, we earn trust with customers over time, and that that actually does maximize free cash flow over the long term." (Source: Interview with Jeff Bezos,

such as the long run profitability of firm growth in a specific sector by far exceeds the bounds of our structural analysis. Nevertheless our analysis can crucially contribute to questions arising in this broader context. The current information regime on the platform seems to especially benefit buyers since they face lower bids as compared to the counterfactual situation where all non-price information is concealed. If the most challenging task to achieve the long run growth objectives of the online platform indeed is to attract as many buyers as possible, then the current information regime seems to be the right approach to implement those objectives.

5 Concluding remarks

Non-binding reverse auctions are establishing as one of the most prominent tools for electronic procurement activities both for firms and government organizations. Whereas in non-binding auctions typically no structure is imposed on the buyer's decision process, important design questions arise, however, with respect to the information regime throughout the bidding process. We added to the understanding of this auction format by analyzing the effects of different designs of the information structure of an open non-binding auction.

After establishing a formal framework we first observed that the buyers prefer that informational arrangement which creates higher competitive pressure among bidders. As we show, which of the informational regimes indeed induces more competitive pressure crucially depends on the precise situation considered. Thus, from a theory point of view none of the regimes dominates.

To obtain further insights on the impact of the information regimes in non-binding auctions for real market situations we then conduct an empirical analysis based on an extensive data set from a large European online procurement platform. The informational setup on this platform is such that bidders are informed about each others' qualities. Building on our formal framework, we perform a counterfactual welfare analysis to assess the consequences

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of concealing non-price information from the bidders. As we find on average this leads to an increase of bidders' prices by 5%, an increase in auction turnover by 8%, and a decrease in buyers' welfare by 8%.

The final policy recommendation implied by those results clearly depends very much on the final objectives of the online platform. Consider for example the rather plausible case where the crucially important objective is not given by the maximization of short run turnover but the long run growth of the company which can mainly be achieved through the attraction of large amounts of buyers posting their procurement inquiries. Then our results clearly show that the current information regime to reveal all non-price information is the one to best implement this objective.

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A Appendix

A.1 Proof of proposition 2:

As the firms' first order conditions given in propositions 1 and 2 are transcendental given any standard assumption about the distribution of the error terms ϵ_i, it is impossible to derive closed form solutions for the equilibrium prices in both the information and the no information case. In order to demonstrate that no information structure weakly dominates the other we thus resort to the use of numerical simulations.

We look at an auction with two bidding firms. The costs of the firms are $\mathbf{c} = (c_1, c_2) = (0, 1)$. We make the assumption that the error terms ϵ_i are iid type I extreme value distributed, and that the distribution of quality $f(q_j)$ is discrete: q_1 shall be drawn with probability 0.1, q_2 with probability 0.9.

Then for $\mathbf{q} = (q_1, q_2) = (0, 1)$ we get $\mathrm{EU} - \widetilde{\mathrm{EU}} = 0.75$. Thus, for these parameter values the buyer prefers the information case over the no information case. In contrast, for $\mathbf{q} = (0, 3)$ we get $\mathrm{EU} - \widetilde{\mathrm{EU}} = -0.34$. With these parameter values the buyer prefers the no information case over the information case.

A.2 First order series approximation:

■ **Derivation of analytical results using a first order series approximation:** If we assume the error terms ϵ_j to follow a symmetric distribution, the first order Taylor approximation of the cumulative distribution function of $\epsilon_2 - \epsilon_1$ around zero is given by

$$F_{\epsilon_2 - \epsilon_1}(x) \approx \frac{1}{2} + \frac{1}{a}x. \tag{A1}$$

$\frac{1}{a}$ equals the first derivative of $F_{\epsilon_2 - \epsilon_1}$ at zero. Note that in general the quality of this approximation is good for values close to zero and worsens for values of x far from zero. A further discussion of this issue can be found below.

$\tilde{\epsilon}_j$ is defined as $\tilde{\epsilon}_j = \epsilon_j + q_j$. If also the q_j follow a symmetric distribution the first order Taylor approximation of $F_{\tilde{\epsilon}_2 - \tilde{\epsilon}_1}$ around zero is given by

$$F_{\tilde{\epsilon}_2 - \tilde{\epsilon}_1}(x) \approx \frac{1}{2} + \frac{1}{\tilde{a}}x. \tag{A2}$$

$\frac{1}{\tilde{a}}$ equals the first derivative of $F_{\tilde{\epsilon}_2 - \tilde{\epsilon}_1}$ at zero. The variance of the distribution of $\tilde{\epsilon}_j$ is at least equal to $\max\{\mathrm{Var}(\epsilon_j), \mathrm{Var}(q_j)\}$ (as $\tilde{\epsilon}_j = \epsilon_j + q_j$). Therefore, the variance of $\tilde{\epsilon}_2 - \tilde{\epsilon}_1$ is at least as large as the variance of $\epsilon_2 - \epsilon_1$. Thus, as the derivative of the cdf of a symmetrically distributed random variable at zero decreases with the variance of the random variable, it holds that $0 < a \leq \tilde{a} < 1$. Note that if $\mathrm{Var}(q_j) = 0$ then $\tilde{a} = a$.

The firms' winning probabilities in the information case are

$$\begin{aligned} P_1(\mathbf{p}, \mathbf{q}) &= P(\epsilon_2 - \epsilon_1 \leq p_2 - q_2 - p_1 + q_1), \\ P_2(\mathbf{p}, \mathbf{q}) &= P(\epsilon_2 - \epsilon_1 > p_2 - q_2 - p_1 + q_1). \end{aligned}$$

If the P_j in the first order conditions given in proposition 1 are expressed using the approximation (A1), it is straightforward to solve these systems after the equilibrium prices $\mathbf{p}^*$:

$$\begin{aligned} p_1^* &= \frac{1}{3}(2c_1 + c_2) - \frac{1}{3}(q_2 - q_1) + \frac{a}{2}, \\ p_2^* &= \frac{1}{3}(c_1 + 2c_2) + \frac{1}{3}(q_2 - q_1) + \frac{a}{2}. \end{aligned}$$

The firms' winning probabilities in the no information case are

$$\begin{aligned} \tilde{P}_1(\mathbf{p}, \mathbf{q}) &= P(\tilde{\epsilon}_2 - \tilde{\epsilon}_1 \leq \tilde{p}_2 - \tilde{p}_1), \\ \tilde{P}_2(\mathbf{p}, \mathbf{q}) &= P(\tilde{\epsilon}_2 - \tilde{\epsilon}_1 > \tilde{p}_2 - \tilde{p}_1). \end{aligned}$$

Using the first order conditions in proposition 2 and the approximation (A2), it follows that the equilibrium prices in the no information case are given as

$$\begin{aligned} \tilde{p}_1^* &= \frac{1}{3}(2c_1 + c_2) + \frac{\tilde{a}}{2}, \\ \tilde{p}_2^* &= \frac{1}{3}(c_1 + 2c_2) + \frac{\tilde{a}}{2}. \end{aligned}$$

From simply comparing (p_1^*, p_2^*) to $(\tilde{p}_1^*, \tilde{p}_2^*)$, it follows that

$$\begin{aligned} p_1^* &= \tilde{p}_1^* - \frac{1}{3}(q_2 - q_1) - \frac{\tilde{a} - a}{2}, \\ p_2^* &= \tilde{p}_2^* + \frac{1}{3}(q_2 - q_1) - \frac{\tilde{a} - a}{2}. \end{aligned}$$

According to Small and Rosen (1981) the change in the buyer's expected utility from a change in the information structure can be computed as

$$\Delta\text{EU} = \text{EU} - \widetilde{\text{EU}} = \int_{(\widetilde{W}_1, \widetilde{W}_2)}^{(W_1, W_2)} \left\{ P_1(W_1, W_2) \mathrm{d}W_1 + [1 - P_1(W_1, W_2)] \mathrm{d}W_2 \right\},$$

where $W_1 = q_1 - p_1$, $W_2 = q_2 - p_2$, $(\widetilde{W}_1, \widetilde{W}_2) = (q_1 - \tilde{p}_1^*, q_2 - \tilde{p}_2^*)$, $(W_1, W_2) = (q_1 - p_1^*, q_2 - p_2^*)$ and $P_1(W_1, W_2) = \frac{1}{2} + a(W_1 - W_2)$. Some algebra delivers

$$\begin{aligned} \text{EU} - \widetilde{\text{EU}} = {} & \frac{1}{3a}(q_2 - q_1)\left[(c_2 - c_1) - 2(q_2 - q_1)\right] \\ & + \frac{1}{4}(2a\tilde{a} + \tilde{a}^2 - 3a^2) \\ & + (\frac{\tilde{a}}{2a} - \frac{1}{2})(c_2 + c_1 - q_2 - q_1), \end{aligned}$$

as stated in the main body of the text.

■ **Discussion of the quality of the series approximation:** In discrete choice models the error terms ϵ_j are commonly assumed to follow either a type I extreme value or a standard normal distribution.

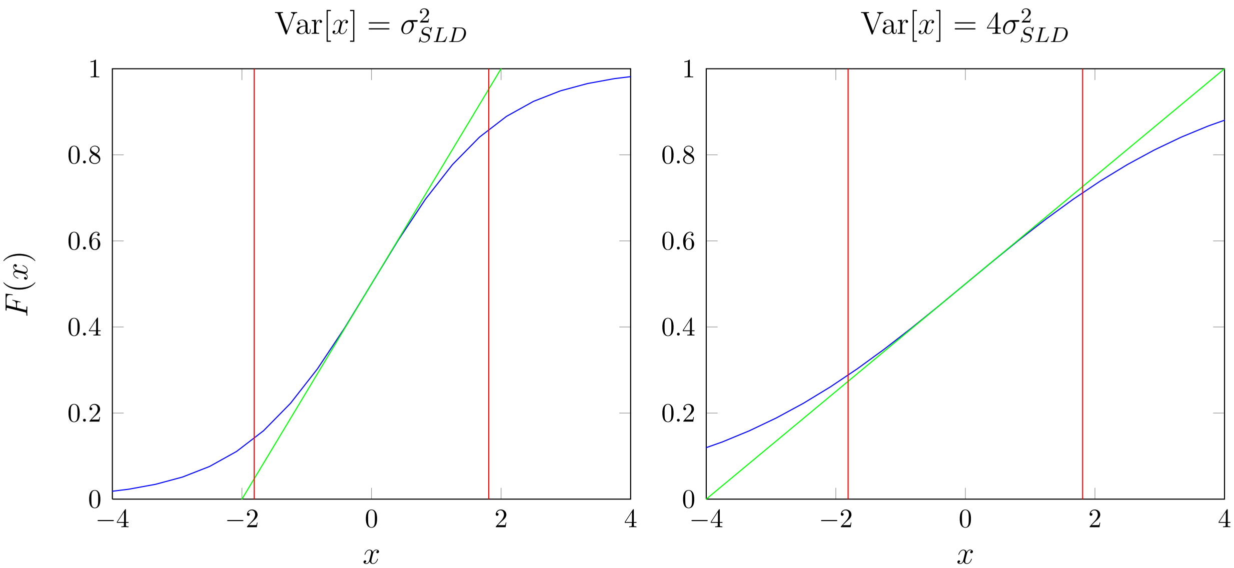

Figure 3: **Graph of a standard logistic distribution (variance equals σ^2_{SLD}) and a logistic distribution with variance of $4\sigma^2_{SLD}$.** The left graph depicts a standard logistic distribution and its first order approximation around zero. The vertical lines indicate a deviation of plus/minus one standard deviation from zero. The right graph depicts a logistic distribution with variance four times as large as that of a standard logistic distribution and its first order series approximation around zero. The vertical lines in each graph indicate a deviation of plus/minus one standard deviation of the standard logistic distribution from zero.

We exemplarily discuss the quality of the first order series approximation for the assumption that the ϵ_j and the $\tilde{\epsilon}_j$ follow a type I extreme value distribution. (As $\tilde{\epsilon}_j$ is defined as $\tilde{\epsilon}_j = q_j + \epsilon_j$ it holds that $\text{Var}[\tilde{\epsilon}_j] \geq \text{Var}[\epsilon_j]$.) This assumption implies that the difference $\epsilon_2 - \epsilon_1$ follows a standard logistic distribution and the difference $\tilde{\epsilon}_2 - \tilde{\epsilon}_1$ follows a logistic distribution with a larger variance.

The linear approximation of the cumulative distribution of a standard logistic distribution is given as

$$F_{\epsilon_2 - \epsilon_1}(x) = \frac{1}{2} + \frac{1}{4}x. \tag{A3}$$

The left graph in figure 3 exemplarily depicts the cumulative distribution function of a standard logistic distribution and the linear approximation of it around zero. Obviously, a linear approximation is not suited to capture the tail behavior of the cdf, but for intermediate values of x the course of the linear approximation is close to that of the cdf. At $x = 0$, the course of the linear approximation is exactly equal to that of the cdf. With the distance from $x = 0$ increasing, the course of the linear approximation begins to deviate from that of the cdf.

In general, a linear approximation around $x = 0$ captures that a cdf of the kind we consider is strictly increasing in x. What our first order approximation does not capture is that the curvature of the cdf is changing in x. That is the magnitude of changes in the firms' (perceived) winning probabilities caused by changes in the firms' prices depends on the values of the prices before the change, which is not captured by our linear approximation.

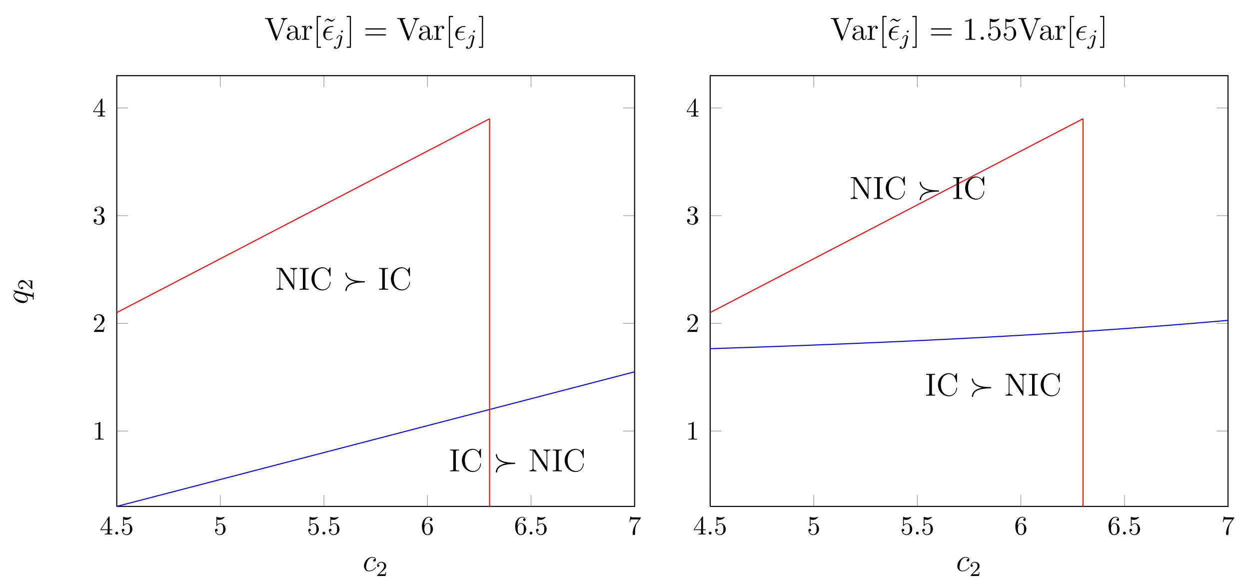

Figure 4: The red lines in all three graphs confine the parameter space for which our approximation is good. The blue lines in the first and the second graph depict the indifference lines for the buyers. For parameter values above the indifference line the buyer prefers the no information case, for parameter values below the indifference line the buyer prefers the information case. For the computation of the first indifference line we assumed $a = 4$ and $\tilde{a} = 4$, for that of the second $a = 4$ and $\tilde{a} = 4$. For both indifference lines we assumed $c_1 = 0$ and $q_1 = 0$.

However, for x values close to zero also the magnitude in changes is captured quite well. For example in figure 3 it is shown that if x deviates up to about one standard deviation from zero, the linear approximation captures also the curvature of the cdf quite well.

What does this mean with respect to our comparative results? We compare the case of disclosed quality information to that of concealed quality information. At the core of our results lies a qualitative comparison of the behavior of the firms in the case of disclosed quality information to that in the case of concealed quality information. The behavior of the firms is determined by the first order conditions given in propositions 1 and 2, and these conditions in turn dependent on the P_j respectively $\tilde{P}_j$ and their first derivatives. If quality information is disclosed, the winning probabilities P_j of the firms are determined by the cdf of $\epsilon_1 - \epsilon_2$, if quality information is concealed the perceived winning probabilities $\tilde{P}_j$ of the firms are determined by the cdf of $\tilde{\epsilon}_1 - \tilde{\epsilon}_2$. Thus, we are able to make correct qualitative comparisons between the case of disclosed and that of concealed quality information as long as our approximations to the cdf of $\epsilon_1 - \epsilon_2$ respectively to that of $\tilde{\epsilon}_1 - \tilde{\epsilon}_2$ preserve qualitative relationships between these cdfs as they are relevant in the firms' first order conditions. Concretely, that means as long as our model parameters are such that the arguments of P_j and $\tilde{P}_j$ in equilibrium, $(p_1^* - p_2^*) - (q_1 - q_2)$ and $\tilde{p}_1^* - \tilde{p}_2^*$, are in an area where the qualitative relationships between the levels and between the first derivates of the cdfs of $\epsilon_1 - \epsilon_2$ and $\tilde{\epsilon}_1 - \tilde{\epsilon}_2$ are preserved, we are able to draw meaningful qualitative conclusions.

As the cumulative distribution function of a logistic distribution becomes less steep around zero with increasing variance (see the right graph in figure 3), the range in which the first order series approximation is reasonably good widens with increasing variance. Thus a first order series approximation preserves the qualitative relationships between the levels and between the first derivates of the cdf of a standard logistic distribution and the cdf of a logistic distribution with higher variance if the argument of the distribution functions lies in between around plus/minus one standard deviation (σ_{SLD}) of the standard logistic distribution. σ_{SLD} is equal to 1.81. It is easy to show that both in the information case and the no information case the arguments of the cumulative distribution functions lie in between +/- σ_{SLD} if $|c_2 - c_1| \leq \sigma_{SLD}$ and $|(q_2 - q_1) - (c_2 - c_1)| \leq \sigma_{SLD}$.

Note that all the qualitative results we derive hold within parameter ranges for which our approximation is good. This can be seen from the graphs in figure 4. The red lines in each graph constrain the area of parameter values for which our approximation is good. The two left graphs demonstrate that our finding that the buyer's preferences with respect to the information structure depend on the specific parameters of a given auction holds within the set of parameters for which our approximation is good and also for different β. The graph on the right demonstrates that also our finding that the influence of higher uncertainty in the no information case is unclear ex ante holds within the set of parameters for which our approximation is good. Thus, all our qualitative findings are not simply artifacts of our approximation.

A.3 Analysis of the information state of the bidders

In section 2 we proposed two models to describe bidders' behavior in open non-binding auctions. Here we use a reduced form model to very that observed bidders' behavior is indeed in line with the predictions of our information case model. In particular, we exploit contrasting testable predictions of both the information case and the no information case framework: If bidders behave according to our information case model, they should react to changes in the quality composition of an auction. In particular, they should show a strong reaction to the appearance of a high quality opponent. In contrast, if bidders behave according to our no information case model they should not exhibit changed bidding behavior as a reaction to different qualities of rivals.

□ **Econometric model.** We test for these contrasting implications by using the following simple reduced form model of the bidders' pricing behavior:

$$p_{nj} = \boldsymbol{\xi}\mathbf{K}_{nj} + \beta S_{nj} + a_j + \nu_{nj}. \tag{A4}$$

This reduced form model describes the bidders' pricing behavior along the lines of our theoretical frameworks from section 2. Basically we assume that the price bidder j puts forward in auction n depends on his costs c_{nj} and, in case of disclosed quality information, on his quality relative to that of his rivals. We assume the costs c_{nj} to depend on the observable cost factors $\mathbf{K}_{nj}$ and on unobserved factors which capture essentially bidder j's opportunity costs for the job offered in auction n and his efficiency. How bidder j fares in terms of quality relative to his rivals in auction n is assumed to depend on bidder j's strength in terms of quality relative to the whole population of bidders and an unobserved auction-specific deviation. Both bidder j's efficiency and his overall strength in terms of quality are captured in the bidder specific constant a_j. The error terms ν_j capture bidder j's opportunity costs for the job offered in auction n and the auction-specific deviation to this overall strength.

The binary variable S_{nj} indicates whether bidder j has to face a rival bidder who is strong in terms of quality. We know from our theoretical considerations that if ceteris paribus a rival of bidder j is replaced by one who is stronger in terms of quality, if quality information is disclosed bidder j should react with a decrease in his price. In contrast, if quality information is concealed, bidder j should show no reaction. That means we expect $\beta < 0$ if bidders behave according to our information case model, and $\beta = 0$ otherwise.

□ **Identification strategy.** We restrict our analysis to 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 (A4) by mean-differencing (that is, employing a fixed effects estimator), and by that we get 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 costs 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.

□ **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:[20]

$$S_{nj} = \begin{cases} 1 & \text{if encounter with bidder with (no. of pos. ratings - no. of neg. ratings)} \geq 90, \\ 0 & \text{otherwise.} \end{cases}$$

As we want to estimate equation (A4) by a fixed effects estimator, we have to restrict our sample to bidders which are observed in at least two auctions. This leaves us with a sample of 941 bidders, taking part in 1,498 auctions (the mean number of auction participations is 10, the median number is 6). In 22.2% of these auctions a bidder with a ratings difference of at least 90 takes part.

Table 5 shows our estimation results. The first column displays our base specification. In column two we add dummies to control for auction size and region dummies to control for regional influences.[21] The coefficients on the costs factors do not vary much between the specifications, and they are of reasonable size: A professional tradesman 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 5 this implies that the average price per square meter painted, including 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,[22] this number seems to be plausible. In both 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

[20]For comparison the mean difference of positive and negative ratings in our sample is 5.8. 1% of the bidders in our sample have a ratings difference of at least 90.

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

[22]78% of the bidders in our sample are neither master craftsmen nor senior journeymen.

Dependent variable: Bid amount of bidder j in auction n	(1)	(2)	(3)	(4)
Strong rival (dummy)	-82.85***	-91.57***	-93.79***	-59.96***
	(14.89)	(17.73)	(17.77)	(12.60)
Controls:				
Area to paint (m^2)	1.72***	1.74***	1.61***	.59***
Area to paper (m^2)	1.41***	1.28***	1.29***	.05
Paper removal (m^2)	2.72***	2.89***	2.54***	1.38***
Cleaning (dummy)	77.63***	64.08**	54.01*	-46.38
Reparation (dummy)	40.60***	56.39***	42.30***	29.65***
Priming (dummy)	124.60***	125.44***	114.41***	21.80
No. of windows	10.41	11.00	13.39	1.93
No. of window frames	34.31	25.40	19.41	-81.33***
No. of doors	45.78***	46.23***	42.22***	34.45***
No. of door frames	17.72***	18.56***	18.21***	13.31***
Nbr. of radiators	85.33***	85.58***	78.91***	27.62***
Paint by contractor (dummy)	25.99**	14.97	18.89*	27.37***
Varnish by contractor (dummy)	125.58*	116.82	102.01	123.63
Distance (km)	1.15***	1.17***	.76***	.52***
Dummies for nbr. of bidders		X	X	X
Dummies for region		X	X	X
Controls for bidder composition			X	
Dummies for startprice interval				X
Bidder FE's	X	X	X	X
R^2	0.292	0.300	0.341	0.508
N	9,546	9,546	9,546	9,546

Table 5: **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 costs controls. The panel consists of 941 bidders who on average take part in 10 auctions each. Column 4 shows results of the fixed effects regression with dummies for different startprice intervals added. Note that these dummies are highly correlated with the costs factors. Thus the coefficients on the costs factors in column 4 are no longer clearly identified. 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%.

to the appearance of a strong rival by lowering their bids. This verifies our assumption that bidders behave according to our information case model. However, as mentioned during the derivation of equation (A4) 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 (A4), ν_{nj}, is mean independent from the observables $\mathbf{K}_{nj}$ and S_{nj}. ν_{nj} captures two unobserved influences on bidder j's bid: One stems from the composition of auction n in terms of the qualities of bidder j's rivals, the other stems from bidder j's costs components.

It might be that either strong bidders select themselves into certain auctions, or that certain types of bidders select themselves into auctions where a strong bidder is present. In effect, that would lead to a correlation between the appearance of a strong bidder and the auction-specific composition in terms of bidders' qualities. To be sure that we actually capture the bidders reaction to the appearance of a strong rival, in column 3 of table 5 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' differences in positive and negative ratings.

In contrast, possibly problematic for the identification of the bidders' information state is correlation between the covariates and the unobserved part of equation ($A4$) which stems from bidders' costs 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. However, there are two reasons why we do not think that the appearance of a strong rival is correlated with unobserved cost factors: First, we collected our data by extracting the costs 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 a deviation in 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 costs factor which is unobserved by us as researchers but known to the buyers and bidders, this costs factor should be reflected in the level of the startprice. 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 costs 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 (A4), the coefficient on S_{nj} stays highly significant and negative (see column 4 of table 5).[23]

[23] Note that after the introduction of dummies for startprice intervals the coefficients on the costs 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.