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Conference Paper

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Beiträge zur Jahrestagung des Vereins für Socialpolitik 2018: Digitale Wirtschaft - Session: Auctions, No. G08-V2

Provided in Cooperation with:
Verein für Socialpolitik / German Economic Association

Suggested Citation: Gesche, Tobias (2018) : Reference Price Shifts and Customer Antagonism: Evidence from Reviews for Online Auctions, Beiträge zur Jahrestagung des Vereins für Socialpolitik 2018: Digitale Wirtschaft - Session: Auctions, No. G08-V2, ZBW - Leibniz-Informationszentrum Wirtschaft, Kiel, Hamburg

This Version is available at:
https://hdl.handle.net/10419/181650

Reference Price Shifts and Customer Antagonism: Evidence from Reviews for Online Auctions

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February 2018

Abstract

Using data from a large-scale sales campaign on eBay, I show that successful auction customers punish the seller through unfavorable public feedback when they later learn discover a cheaper fixed-price offer. The probability of receiving such feedback is four times bigger for auctions than for fixed-price sales of the same item from the same seller. Remarkably, this probability is increasing in the auction price, even though auction customers actively shaped this price themselves. In line with an explanation based on ex-post reference price shifts, this price effect is concentrated in a period during which reference prices were particularly salient because customers information about them, but not about idiosyncratic transaction features (e.g. quality), could change. Consistent with the reference price explanation, the difference in unfavorable feedback between auctions and fixed-price sales is also concentrated in this period and drops to a quarter of its initial size afterwards.

Keywords: customer antagonism, pricing, reference prices, online reputation, eBay

JEL Classification: D44, D91, M31

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I would like to thank to Réné Algesheimer, Björn Bartling, Alessandro Bonatti, Gregory Crawford, Brent Hickman, Michel Maréchal, Frederick Schwerter, and Duncan Simester for helpful comments and discussions. I also thank Andreas Roider for encouragement during the very early stages of this project and acknowledge support by the Swiss National Science Foundation (SNSF Grant #P2ZHP1_171900).

1 Introduction

Pricing is crucial for sellers and policymakers alike for reasons that go beyond the resulting allocations and transfers. Longstanding evidence shows that not only the price itself but also the circumstances under which it is determined affect how customers evaluate a transaction (Kahneman et al., 1986; Frey and Pommerehne, 1993; Xia et al., 2004). Negative feelings about a transaction can even lead to concrete actions against sellers by customers, for example when some are charged different prices than others (Yi and Baumgartner, 2004; Anderson and Simester, 2008, 2010). This is particularly relevant for online markets as their flexible nature allows to vary sales conditions and prices across customers, either as means of experimentation (Einav et al., 2015) or user-based price discrimination (Mikians et al., 2012; Shiller, 2014).[1] Auctions could, in principle, be a solution. They are easily implemented online and allow differential pricing. At the same time, they have the potential to prevent dissatisfied customers who are not passive price-takers but, through their bids, are consciously and willingly determining the prices they pay (Chandran and Morwitz, 2005; Hinz et al., 2011). However, this paper's findings show that when auctions co-exist with fixed-price offers, they cause customer antagonism through features which are typical of online markets – reputation systems and customers' limited perception of competing offers.

Using data from a large-scale online sales campaign, this paper reports on the determinants of post-sale behavior of auction customers towards the seller. During the campaign, the seller first used an auction to sell several thousand units of an item. Two days later, the same seller (a railway company) sold the same item (a voucher for an open-destination rail journey) on the same sales platform (eBay) for a fixed-price. Customers who bought the item via the auction are then found to be four more likely to use the market platform's reputation system to give the seller an unfavorable feedback than customers who bought the item for a fixed-price. Also, the more auction customers paid, the more likely they are to punish the seller through unfavorable feedback.

These results are hard to reconcile with the fact that the customers themselves played a crucial part in determining the auction price. They could have easily prevented to pay a price over which they later become antagonized by bidding accordingly. Similarly, the strong difference in feedback between auctions and fixed-price sales is also puzzling, given that the reviewed product was the same. To explain

[1] A well-known example where this backfired is Amazon's attempt to charge regular customers higher prices than new ones which lead to pronounced criticism when discovered (see Ward, 2000). Turow et al. (2005) provides survey evidence that American internet shoppers are largely unaware of how personal information is used in online retail but that they condemn its use for (differential) pricing when presented with such scenarios. For a review of data-driven differential pricing and its legal challenges, see the recent report by the White House's Council of Economic Advisers (CEA, 2015).

these findings, an explanation based on how reference prices are updated ex-post and how this matters for feedback is provided. The main insight is that a downward-shift in reference prices – as caused by observing a lower fixed-price offer after the auction ended – leads auction customers to negatively review a transaction which, had such a shift not occurred, would not have yielded an unfavorable review.

In line with this reference price explanation, I show that the effect of a higher auction price on adverse feedback is concentrated in the period which immediately follows the auction and during which the obtained item could not have arrived by post. In this period, successful buyers could not get new information related to quality of their recent transaction, e.g. user-experience related to the post-transaction behavior of the seller or whether trains were delayed. However, they could learn through various channels about the fixed-price sale which occurred shortly after the auction had ended. Accordingly, the only new information which could have affected successful bidders' feedback during this initial period was with respect to reference prices. Right afterward, when items started to arrive and customers' actual user experience could also start to determine feedback so that reference prices were less salient, the price effect on feedback drops to zero and stays flat.

Similarly, the higher rate of unfavorable feedback for auctions relative to fixed-price sales can also be linked to reference price shifts. In a first step, it is shown that this feedback difference between the sales mechanism resembles price-effect's temporal variation: In the initial days after the transaction, when there was a pronounced price effect and reference prices were salient, the rate of unfavorable feedback for auctions is about 40 percentage points higher than for reviews referring to the otherwise identical fixed-price sale. For subsequent time periods, during which the price effect diminished and reference prices mattered less, this difference in feedback also shrinks to less than a quarter of its initial size. In an additional analysis it is shown that the excess amount of unfavorable feedback in auctions relative to fixed-price sales can almost perfectly be explained by the incidence of bidder comments which refer to the seller's pricing policy. Together, these resulst show the importance of how ex-post reference point shifts affect customers' evaluation of transactions and their behavior towards the seller.

The findings presented here relate to several branches of the literature, for example to recent findings on pricing in online markets. The observation that buyers and, through their feedback, also sellers experience reference price shifts negatively provides one explanation for why online prices do not change as often as one would expect (Gorodnichenko et al., 2018).[2] In the specific domain of auctions, this

[2]It also explains a recent move by Amazon who recently stopped to show advertisements on smartphones which it had been selling at a discounted price in exchange for the right to shown these adds on the phones' lock-screens. A week after it announced this move, it was reported that Amazon also promised to refund those customers who had previously (and

paper's results resonate with Einav et al. (2018)'s findings on the decline of auctions in online retail. Using a comprehensive dataset from eBay, they show that the share of auctions has decreased from about 65% in 2008 to just over 15% five years later. Similarly, Bhave and Budish (2017) show that auctions did not persist as a sales mechanism in online ticket markets, even though they cleared the market and prevented speculation much more effectively than fixed prices. The authors of these works attribute their results to the search costs which are necessary to make a good deal in an auction, relative to the convenience of fixed-price offers. In line with this explanation, this paper demonstrates how customers' limited search and perception lead them to render deals which they eventually perceive as a loss. In addition, it is shown how sellers are *directly* affected by their customers' (perceived) losses and that this manifests through unfavorable reviews which are unrelated to the idiosyncratic, objective characteristics of the transaction they participated in.

This hostile feedback is a form of customer antagonism, i.e. customers who convert negative emotions into concrete actions against sellers (Yi and Baumgartner, 2004). Several theoretical accounts have explored the constraints which customer antagonism imposes on sellers' differential pricing strategies (Rotemberg, 2011; DiTella and Dubra, 2014; Battigalli et al., 2015). Empirical evidence for this comes from Leibbrandt (2016). He shows in a lab experiment that customers forgo a surplus to avoid buying from price-discriminating sellers and sellers who anticipate this avoid to price-discriminate. Field evidence for customer antagonism can be found in Anderson and Simester (2008). They report that customers stopped ordering at a mail order who charged higher prices for larger cloth sizes, with an effect size twice as large as the pure price effect would imply. A field experiment by Anderson and Simester (2010) shows that even *lowering* prices can lead to similar effects: After another mail-order's sent catalog with randomized discounts, customers who had bought discounted items before, at a higher price, subsequently ceased to order from the mail order. In line with this paper's findings, this effect is most concentrated among the customers who had previously paid the most, relative to the discount.

Besides providing a channel based on reference prices which accommodates these results and those presented here, this paper adds to the empirical literature on customer antagonism along three main dimensions: First, I demonstrate the relevance of customer antagonism in *online* retail, a large and steadily growing market. Second, I show that it not only manifests through customers boycotting a seller but also via attacks on the seller's reputation. This is particularly relevant for online markets which rely crucially on accurate feedback and reputation systems (Dellarocas, 2003; Tadelis, 2016). Third, this is,

willingly) paid a 50$-fee to remove these adds, in order to not "irk" them (see Wycislik-Wilson, 2018).

to my knowledge, the first study which demonstrates that customer antagonism also arises in auctions, i.e. in environments where customers have a crucial and active role in the price-setting process.

This paper's results also relate to a wider literature which examines the effect of reference dependence on the functioning of market mechanisms, for example in the context of contract re-negotiation (Hart and Moore, 2008; Fehr et al., 2011) and bargaining (Herz and Taubinsky, 2017), bidding in auctions (Ariely and Simonson, 2003; Kamins et al., 2004), and relative price perception in posted-offer markets (Simonsohn and Loewenstein, 2006; Weaver and Frederick, 2012; Bordalo et al., 2017). This paper's findings show how reference dependence affects the interplay of auctions and reputation system. The specific form of how it does so relates to previous research which links reference point shifts to harmful, negative emotions. For example, Card and Dahl (2011) report an increase in domestic violence after unexpected losses in football games while Mas (2003) demonstrates that crime reports increase and arrests rates drop after police unions' unexpectedly lost wage arbitrations. However, the hostile behavior documented here occurs in a very different setting, a highly organized virtual market place. Also, the mechanism of how reference dependence causes such actions is different: Instead of being caused by a sudden downward shift in outcomes for a given reference point, the negative actions presented here are caused by a downward shift in reference prices for a given transaction outcome.

Bidders who become antagonized because they experience an unexpected, ex-post downward shift in reference prices could, in principle, have known about the fixed-price offer. This links this work to preceding ones which deal with cognitive constraints in online markets. Such markets are easier searchable but also more vast and differentiated than offline ones so that the net effect on search depth and information usage can be negative (Brynjolfsson et al., 2011). In consequence, online customers frequently rely on salient cues such as prominent digits of used cars' odometers (Lacetera et al., 2012) and differences in cars' first registration years rather than absolute age differences (Englmaier et al., 2016). They also often neglect extra fees (Hossain and Morgan, 2006) or, in auctions, herd with other bidders (Simonsohn and Ariely, 2008). In particular, Ariely and Simonson (2003) and Malmendier and Lee (2011) show that customers in online auctions do often bid more than what is necessary to obtain the same item via a fixed-price sale. While there is some discussion whether this is due to limited attention or too high search costs and whether this ought to be called over-bidding (Schneider, 2016; Malmendier, 2016), the fact that alternative, cheaper offers are left unused is undisputed. This paper confirms these results. Importantly, it also indicates a channel through which such a loss does not only harm the customer who misses a better offer but also the seller if the customer finds out later.

2 Description of the online sale

2.1 Context of the study

In early August 2008, a large German railway company, in cooperation with the German branch of the internet auction and sales platform eBay, conducted a sales campaign for rail tickets. Starting from August 1 and going until August 10, every day a special offer was available for purchase on a dedicated eBay-page. Of particular relevance for this paper are the offers of August 1 and 3. On these two days, the offered item was the same. It was a voucher for a return trip, second class on all domestic trains (except night trains) operated by the railway company. After its sale and payment via money transfer, the paper voucher was shipped by post. In order to use it, customers had to fill in their departure and arrival stations; its specific use was therefore up to the client. At the time of the sale, the railway company had a fixed tariff system in which only the itinerary, but not the specific timing determined the price of a regular ticket. Customers could therefore easily know the voucher's value for them, e.g. via price quotes provided on the railway company's website. This resulted in different valuations for the voucher, depending how customers intended to use it and the opportunity cost of obtaining the ticket elsewhere. When the campaign was conducted, the regular price of the itineraries covered by the voucher reached up to 230.00€.

While the vouchers sold on August 1 and 3 were the same, the sales mechanism differed between the two days. On August 1, vouchers were sold via auctions. The auction format was always eBay's standard incremental auction which is a slightly modified, open-bid second-price auction, starting from a price of 1.00€.[3] Customers could therefore influence the final price through their bid, which was also an upper cap on the price they had to pay in case that their bid was the highest. In contrast, vouchers sold on August 3 were offered for a fixed-price of 66.00€. In this sale, buyers could not influence the price; it was a take-it-or-leave-it offer. Except for these differences in the sale mechanism, all the procedures and transactions characteristics, e.g. payment options, the seller, the sale platform, shipping procedures, and shipping costs were the same.[4]

[3] More precisely, in eBays "proxy"-auction, a bidder can submit a bidding cap. Starting from an initial price, eBay than raises the price to the second-highest cap plus an increment as long as this does not exceed the highest cap. The increment depends on the price and is 1.00€ or less for the auctions reported here. This so-determined price is displayed and bidders can re-can raise their bidding cap if they do so before the fixed ending time of the auction. The winner then has to pay the final price. More information on eBay's sales mechanisms can be found in Hasker and Sickles (2010).

[4] For both, the auction and the buy-it-now sales, the final sale price was subject to an additional shipping fee of 2.50€. Also, in both cases the voucher came with an additional 10.00€-discount coupon which could be applied for later regular ticket purchases in the webstore of the railway company.

eBay allows and encourages its members to mutually review their transactions. Part of such a review is that buyers can rate sellers along several dimensions and give an overall feedback rating which is either "negative", "neutral" or "positive". The seller's feedback score, which is the sum of positive overall feedbacks minus the sum of negative overall feedback (neutral feedback counts zero), is prominently displayed beside a seller's account name. Each seller has also a publicly accessible seller profile. It displays, for a limited time, for each of the reviews which the seller got the following information: The review's overall rating, which is either positive, neutral or negative, the time when the review was left, the offer to which the review refers, the username of the buyer who left the review, and a short text comment written by the reviewing buyer. For each review, the feedback score of the reviewing customer's account is also displayed next to this customer's account name. Note that in contrast to feedback from buyers for sellers, feedback from sellers for buyers can only be positive or not be given at all, a rule which eBay had previously introduced to prevent that buyers and sellers exchange feedback in a reciprocal manner (see Bolton et al., 2013).[5]

Starting from August 1, I obtained the reviews and associated data for the two offers from the seller's review page for forty consecutive days. This paper looks, for reasons which will later become clear, on data covering multiples of six days after the initial auction data. This means that in the following, I will use data from reviews for the auction which were left in the 36 days from August 1 and, for comparison, data from reviews for the fixed-price sale left from August 3 on over the following 36 days.[6]

2.2 Data description

Table 1 below shows the summary statistics for the data which were obtained from the reviews displayed on the seller's profile page. For reviews which refer to the auction the price is, on average, 13.09€ higher than for the fixed-price. The reviewing buyer's own feedback score, later abbreviated by "Buyer's Score", increases with each positive rating a buyer has received in a previous transaction.[7] In general, eBay members have a very high rate of positive feedback scores, with an average over 98% and a median rate of 100% (see Bolton et al., 2013; Nosko and Tadelis, 2015). Therefore, a reviewing buyer's feedback score can be taken as an approximation of this buyer's eBay-experience, even though it is actually a lower bound on the number of prior transaction in which the reviewing buyer has been

[5] Until May 2008, sellers could give buyers not only positive or no feedback but also negative or neutral feedback.

[6] All crucial results remain unaffected when the additional four days of observations for the auction reviews and the additional two days for the fixed-price reviews are used.

[7] eBay allows, but discourages, its member to conceal their feedback score as long as they only act as buyers. Here, this applies to less than 0.8% of the observations. These observations are omitted for all analysis involving the buyer's score.

Table 1. Descriptive statistics by sales mechanism

	AUCTION mean (s.d.)	FIXED PRICE mean (s.d.)
Price	79.09 (13.64)	66.00 (0.00)
Reviewing buyer's feedback score	207.99 (504.10)	182.79 (628.18)
≤ 10	11.1%	11.3%
≤ 100 (and >10)	43.8%	47.0%
≤ 1000 (and >100)	41.8%	39.3%
> 1000	3.3%	2.4%
Feedback given for the seller	0.79 (0.57)	0.95 (0.20)
$+1$: positive	86.4%	96.6%
± 0: neutral	5.8%	1.7%
-1: negative	7.8%	1.7%
Observations	3,575	15,175

Notes: Descriptive statistics of the price paid, the reviewing customer's own feedback score, and the feedback left by the customer in a review, grouped by reviews for auctions and fixed-price sales. 25 (0.7%) of the auction and 131 (0.9%) of the fixed-price customers hid their feedback scores; buyer's feedback score-statistics omit these observations (see footnote 7).

involved before. As these scores are strongly dispersed, I created four categories, defined by whether the score is weakly less than 10 or whether it surpasses the thresholds of 10, 100, or 1000. Although to some degree arbitrary, the first category for a buyer's feedback score can be thought of belonging to relatively inexperienced eBay-members. The second and third categories then contain experienced and very experienced members. Those in excess of at least 1000 prior transactions are very likely to be professional sellers themselves who acted as buyers in this transaction. Generally speaking, buyers are fairly experienced: For both sales mechanisms, just around 11% of buyers had a feedback score of ten or less while only around 3% of the buyers were supposedly professionals with at least 1000 transactions; the rest lies in between.

Finally, the table displays the feedback which the seller received from buyers for the transaction of the voucher. The average feedback score is 0.79 if it was for an auction as compared to an average score of 0.95 when the same voucher was obtained from the same seller for a fixed-price. Viewed differently, while the share of 96.6% positive reviews for the fixed-price sale is slightly lower but not too far away from eBay's average of 98%, this share is drastically smaller, at a level of 86.4% when the voucher was sold in an auction.

2.3 First findings

To explore the differences in the feedback between the two sales mechanisms in more detail and to control for differences in the reviewing customers' experience, I estimate the following regression model:

$$\Pr[f_i \leq 0 \mid \mathbf{x}_i] = \Phi\Big(\alpha + \beta \cdot Auction_i + \sum\nolimits_{s=1}^{3} \delta_s \cdot \mathbb{1}[Buyer's\ Score_i > 10^s]\Big) \tag{1}$$

The dependent variable in the above equation indicates whether the feedback f_i left by a buyer for transaction i is non-positive (i.e. negative or neutral). This reflects that positive feedback is the overwhelming norm on eBay with several studies concluding that any other feedback, including neutral feedback, is considered to be a bad evaluation (see Dellarocas and Wood, 2008; Cabral and Hortaçsu, 2010; Bolton et al., 2013; Cabral and Li, 2015; Nosko and Tadelis, 2015). The main independent variable, $Auction_i$ is a dummy which equals one if review i refers to an auction. The three dummies for whether $Buyer's\ Score_i$ surpasses the respective power-of-ten-threshold (but not the next-highest) indicate a lower bound on the number of the reviewing buyer's hitherto transactions and therefore measure this buyer's experience. In this way, they capture previous research's findings that socially motivated behavior such as such as giving feedback is moderated by market participants' experience and their own reputational stakes (see List, 2003, 2006). Unobserved idiosyncratic features of the transaction which affect feedback, for example user experience, are captured by an error term encapsulated in the standard normal distribution's cumulative distribution function Φ ($\mathbf{x}_i$ summarizes the independent variables).

Table 2 presents the marginal effects one obtains when model (1) is estimated by Probit.[8] The estimates in the first column reflect the previously indicated difference of 10.2 percentage points in the share of non-positive feedback between the sales mechanisms and shows that it is significant. In consequence, the rate of such feedback for auctions is about four times as large as the corresponding rate of 3.4% for the fixed price sale. The results in the second column show that this result remains unchanged when one controls for buyer experience via their own feedback scores. A potential confounder is that some customers bought multiple vouchers. This allowed them to issue multiple reviews and this may have disproportionately affected reviews for one of the sales mechanisms. The analysis was therefore repeated using only the first review which each distinct buyer left. Columns 3 and 4 present the corresponding results. They do not differ in any meaningful way from the previous results when the

[8] This and the following regressions were also estimated as Poisson-models and as linear probability models via OLS. The qualitative results and, within reasonable bounds, the quantitative results remain always unchanged.

Table 2. Differences in feedback between auction and fixed-price reviews

	(1)	(2)	(3)	(4)
Dependent variable:	$y_i = 1$: Negative or neutral feedback			
Auction	0.102***	0.102***	0.100***	0.100***
	(0.008)	(0.008)	(0.008)	(0.007)
Buyer's Score >10		-0.018**		-0.015***
		(0.007)		(0.006)
Buyer's Score >100		-0.015**		-0.012*
		(0.008)		(0.006)
Buyer's Score >1000		-0.004		0.002
		(0.014)		(0.013)
First reviews only	no	no	yes	yes
Observations	18,750	18,594	15,857	15,721

Notes: Average marginal effects of Probit estimates obtained from regressing a dummy for negative or neutral feedback on a dummy for whether the review was for the auction and dummies for the reviewing buyers' own feedback score. Columns 1 & 2 use all reviews and report standard errors clustered on the buyer level. Columns 3 & 4 only use the first review each buyer posted and report robust standard errors. Significance levels: *** p<0.01, ** p<0.05, * p<0.1

whole sample is used. Taken for themselves, the controls for the buyer score indicate that intermediately experienced buyers are significantly less likely to give non-positive feedback than inexperienced buyers, the omitted category. In contrast, buyers with at least 1000 prior transactions do not differ significantly from inexperienced ones in their propensity to give non-positive feedback. However, the magnitude of these pure experience effects is relatively small, compared to the adverse effect of selling via the auction.

The above shows that transactions for the same exchanged item, the same seller, and on the same sales platform receive much more unfavorable feedback when based on an auction as opposed to a subsequent fixed-price sale. In principle, there might be some unobserved heterogeneity on the buyer side which could cause these findings. However, it is not entirely clear how this would cause the documented pattern. If high-valuation customers deliberately selected into the auction, for example to pre-empt a later fixed-price market, their high valuation and control over the price should also have enabled them to realize higher net gains. While the observation of higher prices paid in the auction is, at first sight, consistent with higher valuations, the finding that auctions receive worse feedback than fixed-price sales is inconsistent with the notion that deliberative selection caused these differences.

A selection-based argument also implies that not just participation in the auction but also its eventual auction price is the deliberate consequence of the buyer's bidding behavior. In consequence, it should not

trigger unfavorable feedback. To check whether this holds, a regression model similar to (1) is estimated for the auction data. The only difference is that instead of the $Auction_i$-dummy, $\Delta_{10}Price_i$ is included as the key independent variable. This variable measures the effect of the price paid in the auction on the probability of getting non-positive feedback. To make the interpretation of the corresponding coefficient easier, it is not the absolute price paid in the auction but the difference to the fixed price of 66€, divided by 10. Thus, the point estimate refers to the change in the probability of leaving a non-positive feedback associated with a change in the price difference to the fixed price by 10€.

Table 3 reports the marginal effects obtained from estimating this model by Probit. If selection motives were driving the differences in customer feedback between the sales mechanisms and the price paid in the auction is the deliberate product of auction customers' bidding behavior and indicative of their higher valuation, it should, if at all, affect feedback in a positive manner. However, the results indicate the opposite: The higher the price paid in the auction, the more likely is that a review entails a non-positive feedback for the transaction. On average, for each 10€ paid more in the auction than for the fixed-price offer, the probability of non-positive feedback rises by about 2.3 percentage points, independently of whether controls are added or whether multiple reviews from the same customer are used or not.

Table 3. Price effects in feedback for auction reviews

	(1)	(2)	(3)	(4)
Dependent variable:	$y_i = 1$: Negative or neutral feedback			
Δ_{10}Price	0.022***	0.022***	0.023***	0.023***
	(0.005)	(0.005)	(0.005)	(0.005)
Buyer's Score >10		-0.036		-0.034
		(0.029)		(0.025)
Buyer's Score >100		-0.045		-0.040
		(0.029)		(0.025)
Buyer's Score >1000		0.011		0.035
		(0.052)		(0.050)
First reviews only	no	no	yes	yes
Observations	3,575	3,550	2,283	2,265

Notes: Average marginal effects of Probit estimates obtained from regressing an indicator for negative or neutral feedback on the difference between the auction price and the fixed-price divided by 10 and dummies for the reviewing buyers' own feedback score. Columns 1 & 2 use all reviews and report standard errors clustered on the buyer level. Columns 3 & 4 only use the first review each buyer posted and report robust standard errors. Significance levels: *** p<0.01, ** p<0.05, * p<0.1

3 Reference price shifts

The findings presented above raise several question. Given that the both, the seller and the sold item were identical across the different sales mechanisms, why is feedback for auction sales so much worse than for fixed-price offers? Even more puzzling, why do higher auction prices lead to unfavorable reviews, given that bidders could have easily avoided to pay a price with which they are not satisfied? In this section, I will show how reference price shifts provide an answer to these questions.

3.1 Sources and consequences of ex-post reference price shifts

To see how reference price effects can explain the observed patterns, consider a successful bidder, e.g. a customer whose bid exceeded the later-offered fixed price but not the buyer's valuation. In itself, this does not provide a reason to be unsatisfied, because the buyer can still realize a positive surplus. In fact, reference-dependence can even be an additional source of utility as it captures the extra joy of making a bargain (i.e. the positive difference between a buyer's reference price such as an itinerary's regular price and the price paid in the auction). However, there is numerous evidence which shows that customers also consider the prices paid by others as reference points (see Shafir et al., 1997; Ariely and Simonson, 2003; Simonsohn and Loewenstein, 2006; Amir et al., 2008; Weaver and Frederick, 2012).

If a buyer evaluates a transaction based on non-idiosyncratic features such as prices offered to others, the above reasoning does not go through anymore. In this case, observing a fixed-price lower than the auction price reverts the previously perceived extra-utility from making a bargain. Instead, the difference between a buyer's reference price and the auction price becomes negative once the lower fixed-price offer is incorporated in a new reference price. In consequence, what felt like a bargain before is now evaluated as a loss. To the degree that this experience also affects reviews, successful bidders will then rate auctions worse than otherwise identical fixed-price sales. Note that this does not mean that the auction has a negative economic net value to the customer or that the acquired item provided insufficient quality – absent the new reference price, the customer would not have given an unfavorable review. Reference price shifts can also explain the negative price effect: The larger the price a customer paid in the auction, the larger is the distance to the new, decreased reference price and therefore the experienced loss. In consequence, bidders can become antagonized over the auction price, even if they had ex-ante been satisfied with it and explicitly agreed to pay this price (see Appendix A for a formal model which captures this reasoning).

In the context under consideration here, there are several reasons why such an ex-post reference

point shift could occur for successful bidders in the auction. Even though the whole sequence of the sales campaign's offers was fixed before-hand, it was relatively hidden and listed as such only on the seller's eBay page but not on the pages displaying the actual auctions. The advertisement for the sales campaign (for example via banners on eBay and other web pages) was however focused on the respective day's special offer and lead directly to the corresponding sales pages on eBay, bypassing any listing of upcoming offers. While this limited ex-ante information about the fixed-price offers, successful bidders could learn about it ex-post, after the auction had ended, through several channels:

First, successful bidders received a confirmation email which listed the obtained item and the final price, together with further information regarding the payment and shipping procedures. Right below this essential information, the confirmation email also contained a list of the seller's upcoming sales. For those who obtained the voucher in the auction on August 1, this confirmation email did therefore feature a salient advertisement for the fixed-price sale following two days later. Second, the accompanying advertisement campaign continued to advertise the respective day's special offer, including the advertisement for the fixed-price sale on August 3. Third, several news pages started to report on the rather particular sequence of sales mechanisms after the auction had ended. Customers who had obtained a ticket in the auction and were initially not aware of the subsequent fixed-price offer might thus have learned about it *after* they had won an auction. In the following, I will provide evidence in line with this reasoning and show how it can be used to relate reference price shifts to feedback-giving.

3.2 Identifying reference price shifts

In order to test the explanation proposed above, a variable which indicates whether a customer's reference price shifted would be ideal. However, this requires knowing what customers *perceive* – which is generally hard to measure, in particular so for observational field data. However, a variable which indicates whether other factors were more salient relative to reference prices and changes therein serves essentially the same purpose in identifying a reference price-induced effect on customer feedback. To obtain such an indicator, I will exploit the specific time structure of the sales campaign and when information regarding the fixed-price offer arrived, relative to other information.

After the auction, successful bidders could learn through several channels about the fixed-price offer. Information with regard to reference prices could therefore change quickly after the auction and lead them to revise their reference prices. In contrast, transaction-specific information regarding their acquisition, e.g. experiences during the associated train ride or whether the voucher was actually sent by

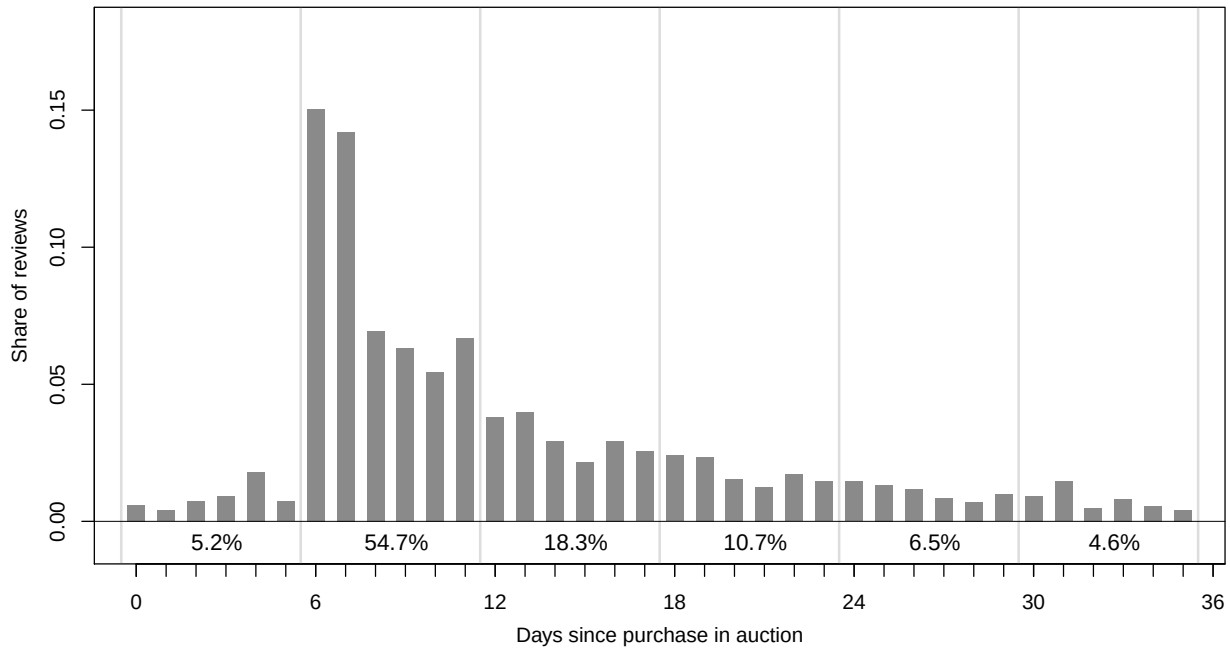
the seller, remained constant for a while. This is due to the fact that the shipment of the paper voucher took time and was initiated only after the customer's money transfer had arrived on the seller's account. Successful bidders could therefore not get any new information regarding quality, seller behavior or other idiosyncratic transaction features, relative to those they had at the day of the transaction, before the voucher had arrived by post. In contrast, a buyer's reference price could be affected in this time period through the information regarding the fixed-price offer.

To determine this initial time period during which only reference prices but not the user experience could change, the buyer comments for auctions were checked manually for statements which indicate that a voucher had arrived. The first such statement dates on August 7. Reassuringly, this coincides with the timing of the first such comment in a review for the fixed-price sale. This suggests that the seller dealt with the after-sale logistics for these identical items in the same way. Therefore, in the first six days from the day of the auction, no voucher and no new transaction-specific information reached successful bidders.

Figure 1 provides further evidence for this conclusion. It displays the temporal pattern of when reviews for the auction were left. In the first six days from August 1, the day of the auction offer, relatively few reviews occur. During each of these initial six days, less than 2%, together 5.2%, of all the 3,575 reviews for auctions were left. Six days after the auction, on August 7, the daily rate suddenly spikes to almost 15% and remains relatively high for all days in the second six-day-bin which accommodates 52.4% of all auction reviews. This is consistent with the notion that, starting from August 7, customers got the voucher and that from this date on, uncertainty regarding the user experience resolved and provided an additional and major trigger for customers to write a review. From day 6 after the auction (August 7) on, new information regarding the customers' idiosyncratic transaction did therefore affect feedback, in addition to the information regarding the fixed-price sale. In contrast, this transaction-specific information was absent during the initial six days so that reference point shifts were relatively more salient in this period.

The relative importance of reference point shifts in the first six days from the auction date is also confirmed by an analysis of the text comments which sellers left with their reviews. Those comments which refer explicitly to the seller's sales and pricing strategy, that is first selling via an auction and then via a fixed-price, were marked. As a first evidence regarding the negative feelings this triggered, it is worthwhile to note that most of these comments were written in a hostile and complaining manner. More important for a strategy which identifies the relative importance of reference price-induced effects

Figure 1. Timing of auction reviews



Notes: *Grey bars*=Share of total reviews for auctions on a given day. *Percentage numbers*=Share of reviews per six-day-bin (bin of six consecutive days, separated by vertical lines).

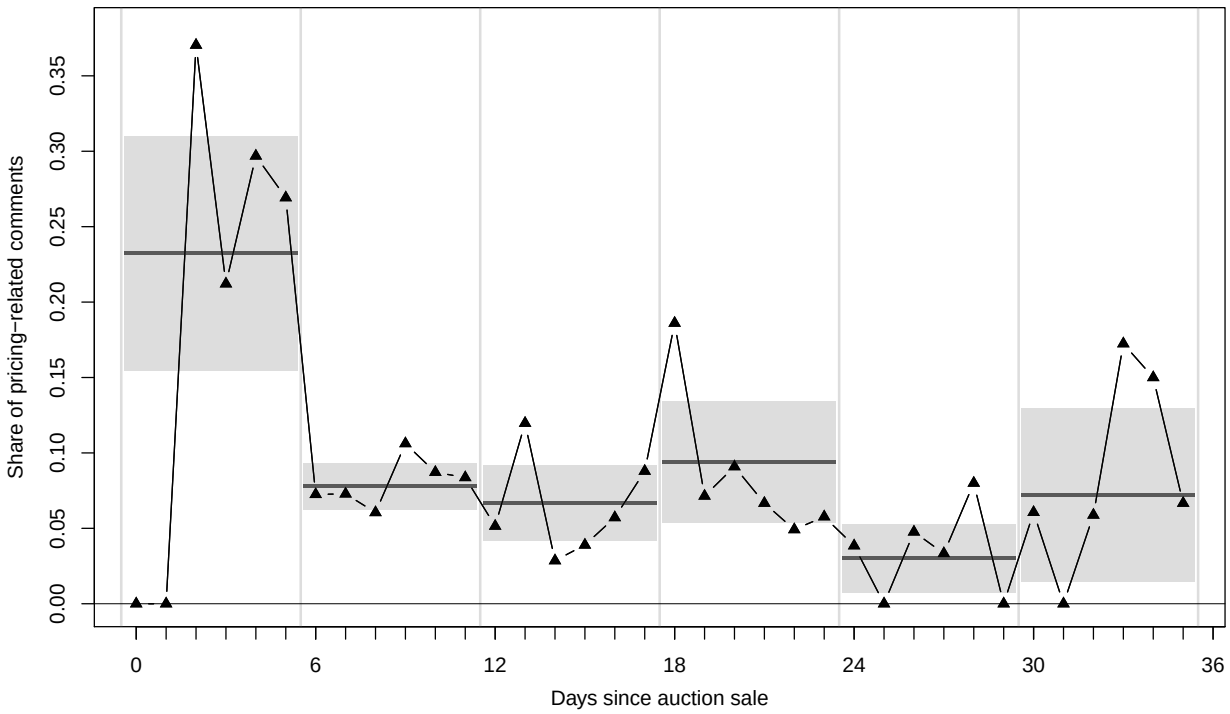
is, however, the timing of these comments. The triangles in Figure 2 display the share of reviews with such pricing-related comments among all auction reviews left on a given day. On the day of the auction and the day thereafter (day 0 and 1), no such comments are observed. Then, on the second day after the auction when the fixed-price sale took place (day 2), the share of daily reviews which contains such comments jumps to more than 36% and stays high for the next three days (days 3 – 5). A week after the auction, on day 6, when the vouchers started to arrive by post, the share of such comments falls sharply and stays relatively low. This corresponds exactly to the proposed pattern of how the salience of reference price-related information relative to other information behaves over time and how this affects customers' perceptions and their corresponding feedback.

The visual impression regarding the timing of pricing-related comments can also be confirmed statistically. For this, the binary variable which indicates a comment referring to the sellers' pricing strategy is used as the dependent variable in a regression. The independent variables are five dummies which allow identifying each of the six-day-bins covering the data's 36 days. The conditional means obtained from these estimates are depicted as horizontal, grey lines within each of the six-day-bins in Figure 2. The grey rectangles indicate the associated 95%-confidence intervals around these conditional means. These

results show that the share of price-related comments, which is around 23% during the first six-day-bin, is significantly lower by 14 to 20 percentage points for each of the following five six-day-bins ($p<0.01$, see Table 6 in Appendix B for the results of this and further regressions controlling for additional factors).

Overall, these findings are highly consistent with the notion that for the first six days, the news of the fixed-price offer and the associated reference price shift were a stronger determinant of reviews than in the following days. They also conform with typical models of salience (as, for example, in Bordalo et al., 2013): In the first six-day-bin, the salience of price is relatively high as, upon learning about the fixed-price offer, a bidder's price norm decreases. This makes a higher price paid in the auction stick out more. In contrast, the salience of quality such as user experience is low in this period as it corresponds to the reference level, i.e. the quality expectations customers had at the time of the transaction. Once the voucher arrives, new information in this dimension can start to enter customers' perceptions. This then increases the salience of quality or user experience relative to reference prices and is reflected in feedback and the associated comments.

Figure 2. Timing of pricing-related comments in auctions



Notes: *Black triangles*=Share of auction reviews on a given day in which the comment refers to the seller's pricing strategy. *Grey rectangles and horizontal lines*=95%-confidence interval and point estimates of coefficients indicating the probability that such a comment occurs within each bin of six days.

3.3 De-composing price effects

The preceding results show that in the first six days after the auction, reference price shifts were particularly salient and strong drivers of feedback. In line with this, the negative effect of the auction price on feedback should, if caused by a shift in the reference price, be more pronounced in these first six days than in later periods. To test this, I estimated a regression model where the price effect is measured separately for the initial six days and the sample's five remaining six-day-bins. That is, the following Probit-model is fitted with data which refer to the auction sale:

$$\begin{aligned}\Pr[f_i < 0 \mid \mathbf{x}_i] = \Phi\Big(&\alpha + \beta_1 \cdot \Delta_{10}Price_i + \sum\nolimits_{t=2}^{6} \beta_t \cdot \Delta_{10}Price_i \times SixDayBin\#t_i \\ &+ \sum\nolimits_{t=2}^{6} \gamma_t \cdot SixDayBin\#t_i + \sum\nolimits_{s=1}^{3} \delta_s \cdot \mathbb{1}[Buyer's\ Score_i > 10^s] + \epsilon_i\Big)\end{aligned} \tag{2}$$

The dependent variable is, as in the preceding regressions, whether a review entails non-positive feedback. Also as before, it features indicators controlling for the reviewing customer's own feedback scores as control variables and the price difference to the fixed-price offer as an independent variable. The regression model also includes five dummies denoted by $SixDayBin\#t_i$. Their values indicate during which bin of six consecutive days, starting from the auction date a review was left. As the first six-day-bin is the omitted category, the coefficient β_1 measures the price-slope in this period. The coefficients on the terms which interact the price with one of the six-day-bin-indicators (β_2 through β_6) therefore capture the differences between the first period's price slope and those of later six-day-bins. They are the main variables of interest for testing the following prediction: As reference price shifts are relatively less salient in later six-day-bins than in the first one, the corresponding price-slopes should also be less pronounced. Accordingly, the price slope during the first six days, given by $\hat{\beta}_1$, should have a larger value than the slope estimates $\hat{\beta}_1 + \hat{\beta}_t$ for later six-day-bins. The corresponding values of $\hat{\beta}_t$ are therefore predicted to be negative if reference price shifts are driving the price effect.

Note that the above reasoning does not predict a gradually decreasing price effect over time. It rather stipulates a sharp decline in the price effect's magnitude after six days and no further change thereafter. Also, the prediction's test does not rely on any manually coded variable such as the dummy which indicates pricing-related comments. Rather, this variable was used to identify the six-day-bins in which reference prices were particularly salient, meaning that it was used to derive the above prediction. Its test will however be based on "hard" data stored in eBay's database (the auction's final price and the date when a review for it was left). Any imprecision or subjective wiggle room in the manual coding of

pricing-related comments would thus negatively affect the reasoning which leads to the above prediction. In consequence, such errors would make it harder to confirm the prediction but do not impose a hazard with respect to a false positive. By the same reasoning, a potential situation where the size of variation in reference prices relative to variations in other information is large not only in the first six days – as assumed in deriving the above prediction – but also in any of the later periods would also increase the potential for a false negative. However, it does not create any problem with regards to erroneously detecting reference price-induced variation in the price effect.

With this in mind, one can look at Table 4 which shows the marginal effects obtained from the Probit-estimates of model (2). The non-interacted price effect in the first line is strong and significant. It corresponds to an increase of around 12 percentage points in the probability of non-positive feedback for each 10€ paid above the fixed-price if the review was left in the first six days from the day of the auction. The effect in this six-day-bin is much stronger, by a factor larger than five, than the average price effect which was previously estimated over the whole sample's 36 days (see Table 3 above). The interaction term allows to estimate a separate price slope for the subsequent six-day-bins and compute the difference to the initial bin's slope. The second to sixth row in Table 4 show these differences, which therefore correspond to the model's interaction terms, and draw a clear pattern: All the differences are consistently estimated to be significantly negative at a magnitude similar to the initial period's price effect. In fact, none of the implied price slopes for the later six-day-bins is significantly different from zero at conventional significance levels. These findings can therefore be summarized by saying that the price effect is entirely concentrated in the initial period when reference prices were most salient.

Note that the observed pattern of the price effect does not indicate a decreasing effect over time. It rather shows that after the first six days, the price-slope sharply decreases and stays roughly constant at a level close to zero over the sample's remaining days. This pattern is inconsistent with an alternative explanation based on the notion that negative emotions "cool off" over time (e.g. Bosman et al., 2001; Lee, 2013; Oechssler et al., 2017). Such an effect would predict a gradually decreasing price-slope which would correspond to increasingly negative coefficients for higher-numbered interaction terms. Such a pattern is, however, not observed. This finding is also inconsistent with the notion that having paid a higher price is in itself a trigger of unfavorable reviews. Apart from the conceptual problem that, through their bid, auction buyers could have easily prevented to pay a price which they consider so bad that it triggers negative feedback, there is no reason why such a pure price effect should apply only in the first six days but not later.

Table 4. Price effects in feedback for auctions reviews over six-day-bins

	(1)	(2)	(3)	(4)
Dependent variable:	$y_i = 1$: Negative or neutral feedback			
Δ_{10}Price	0.125***	0.125***	0.116***	0.116***
	(0.024)	(0.024)	(0.027)	(0.027)
Δ_{10}Price×SixDayBin#2	-0.117***	-0.116***	-0.108***	-0.108***
	(0.025)	(0.025)	(0.028)	(0.027)
Δ_{10}Price×SixDayBin#3	-0.117***	-0.119***	-0.110***	-0.109***
	(0.025)	(0.026)	(0.029)	(0.029)
Δ_{10}Price×SixDayBin#4	-0.105***	-0.105***	-0.096***	-0.096***
	(0.031)	(0.031)	(0.032)	(0.035)
Δ_{10}Price×SixDayBin#5	-0.130***	-0.129***	-0.152***	-0.151***
	(0.029)	(0.029)	(0.035)	(0.035)
Δ_{10}Price×SixDayBin#6	-0.092***	-0.098***	-0.076***	-0.081**
	(0.035)	(0.035)	(0.023)	(0.036)
SixDayBin#2	-0.107**	-0.105*	-0.131**	-0.126**
	(0.054)	(0.054)	(0.058)	(0.057)
SixDayBin#3	-0.118**	-0.116**	-0.129**	-0.128**
	(0.056)	(0.056)	(0.060)	(0.059)
SixDayBin#4	-0.078	-0.075	-0.076	-0.072
	(0.062)	(0.061)	(0.065)	(0.065)
SixDayBin#5	-0.129**	-0.128**	-0.092	-0.090
	(0.061)	(0.061)	(0.072)	(0.071)
SixDayBin#6	-0.075	-0.069	-0.136**	-0.125*
	(0.073)	(0.074)	(0.066)	(0.066)
Buyer's Score >10		-0.031		-0.031
		(0.028)		(0.024)
Buyer's Score >100		-0.047		-0.039
		(0.028)		(0.024)
Buyer's Score >1000		0.002		0.028
		(0.051)		(0.050)
First reviews only	no	no	yes	yes
Observations	3,575	3,550	2,283	2,265

Notes: Average marginal effects of Probit estimates obtained from regressing a dummy for non-positive feedback on the difference between the auction price and the fixed-price divided by 10, a dummy for the six-day-bin since the auction data, its interaction with the price variable, and dummies for the reviewing buyers' own feedback score. The first row reports the estimated price-slope for the first six-day-bin, the next five rows the difference of that slope to the subsequent six-day-bins' estimated price slopes (which are all not significantly different from zero). Columns 1 & 2 use all reviews and report standard errors clustered on the buyer level. Columns 3 & 4 only use the first review each buyer posted and report robust standard errors. Significance levels: *** p<0.01, ** p<0.05, * p<0.1

Another alternative explanation, based on the notion that the negative price effect could be caused by customers who had a negative user experience and therefore lower net utility if they paid a higher price, cannot account for these findings either. The price effect should then be concentrated in the period after the voucher arrived and not vice versa. In contrast, the findings are highly consistent with a reference price effect: The auction price affects reviews in precisely the period during which comments regarding the pricing of the auction are frequent and information regarding a lower reference price sale is particularly salient, compared to other information. As soon as the voucher and with it other, transaction-related information started to arrive and the reference price channel diminished in relative importance, the auction price effect ceased to determine feedback.

3.4 De-composing auction effects

The above results show how the negative effect of the auction price on reviews is concentrated in the initial period after the auction during which reference price shifts were most salient. In the following, it will be shown that the same reference price-explanation is also able to organize the feedback differences between sales mechanisms, that is between the auction and the fixed-price sale. To do so, a model similar to the interaction model displayed in equation (2) is estimated, using the combined data from reviews for the auction and the fixed-price sale. The main difference is that the model does not feature the $\Delta_{10}Price_i$-variable. Instead, the $Auction_i$-dummy, which measures effects between sales mechanisms, is included. This variable is fully interacted with the set of dummies indicating in which six-day-bin, counted from the respective transaction date, a review is left.[9] The regression model therefore allows to de-compose differences along the timing of when these differences occur, similar as in the analysis of the price effect above.

The corresponding estimates are presented in Table 5 and reflect those on the price effect: In the first six-day-bin, when reference price shifts were particularly salient and the negative price effect within auctions was pronounced, the feedback difference between the sales mechanisms is also particularly strong. During this period, the rate of non-positive feedback in auctions is about 41 percentage points higher than the corresponding rate for otherwise identical fixed-price sale (the rate of non-positive feedback during the first six days of the fixed price sale, the baseline, has a magnitude of about 3%). This difference decreases significantly to a quarter and less of its initial size (by about 27 to 39 percentage

[9] In consequence, the dates defining the six-day-bins for the fixed-price sale are lagged by two days relative to those for the auction. Any of the following remain unchanged if based on estimation results for which six-day-bins are defined relative to the auction's transaction for both sales mechanisms.

Table 5. Feedback differences between auction and fixed-price reviews de-composed over six-day-bins

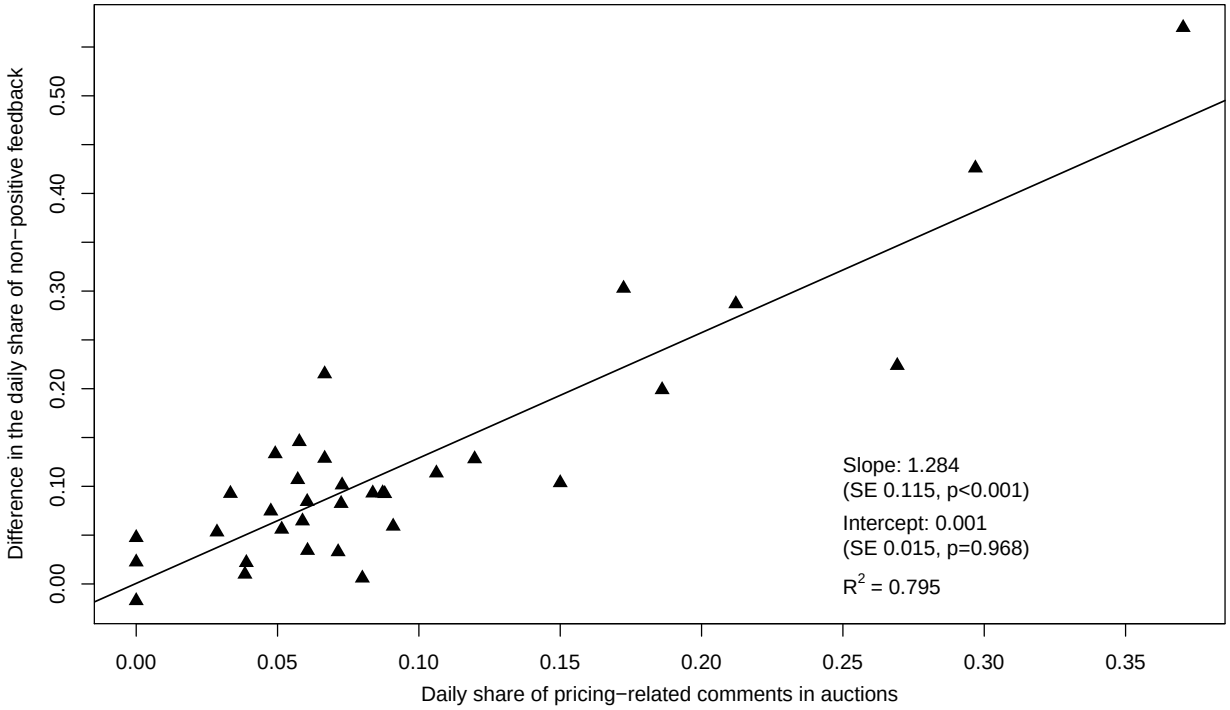
	(1)	(2)	(3)	(4)
Dependent variable:		$y_i = 1$: Negative or neutral feedback		
Auction	0.410***	0.405***	0.410***	0.403***
	(0.046)	(0.046)	(0.043)	(0.043)
Auction×SixDayBin#2	-0.315***	-0.310***	-0.326***	-0.319***
	(0.047)	(0.047)	(0.044)	(0.044)
Auction×SixDayBin#3	-0.337***	-0.334***	-0.335***	-0.331***
	(0.048)	(0.048)	(0.046)	(0.046)
Auction×SixDayBin#4	-0.293***	-0.286***	-0.276***	-0.268***
	(0.053)	(0.053)	(0.050)	(0.050)
Auction×SixDayBin#5	-0.391***	-0.386***	-0.375***	-0.369***
	(0.051)	(0.051)	(0.050)	(0.050)
Auction×SixDayBin#6	-0.288***	-0.290***	-0.327***	-0.325***
	(0.064)	(0.064)	(0.055)	(0.055)
SixDayBin#2	-0.013***	-0.013***	-0.010**	-0.010**
	(0.004)	(0.004)	(0.004)	(0.004)
SixDayBin#3	0.001	-0.001	0.000	0.00
	(0.005)	(0.005)	(0.005)	(0.005)
SixDayBin#4	0.011*	0.011*	0.013**	0.013**
	(0.006)	(0.006)	(0.006)	(0.006)
SixDayBin#5	0.025***	0.025***	0.026***	0.025
	(0.008)	(0.008)	(0.008)	(0.008)
SixDayBin#6	0.025**	0.026***	0.026***	0.027***
	(0.010)	(0.010)	(0.009)	(0.009)
Buyer's Score >10		-0.017**		-0.014**
		(0.007)		(0.006)
Buyer's Score >100		-0.014**		-0.010*
		(0.007)		(0.006)
Buyer's Score >1000		-0.004		0.004
		(0.014)		(0.013)
First reviews only	no	no	yes	yes
Observations	18,750	18,594	15,857	15,721

Average marginal effects of Probit estimates obtained from regressing a dummy for negative or neutral feedback on a dummy for whether the review was for the auction, a dummy for the six-day-bin since the auction data, its interaction with the price variable, and dummies for the reviewing buyers' own feedback score. The first row reports the estimated price-slope for the first six-day-bin, the next five rows the difference of that slope to the subsequent six-day-bins' estimated price slopes (which are all not significantly different from zero). Columns 1 & 2 use all reviews and report standard errors clustered on the buyer level. Columns 3 & 4 only use the first review each buyer posted and report robust standard errors. Significance levels: *** p<0.01, ** p<0.05, * p<0.1

points) in subsequent six-day-bins. These findings establish a direct link between the precise timing (before and after the first six days) and manner (a sudden drop, rather than a gradual shift) of the price effect's variations within auctions reviews to the variation of feedback differences between auction and fixed-price reviews. Both of these results therefore mirror the salience of reference price effects.

Further support for this conclusion comes from Figure 3. It plots the difference in the daily rates of non-positive feedback between auctions and fixed-price sales over the daily rates of pricing-related comments in auction reviews (the same data as displayed in Figure 2). The units of observation are therefore the 34 days starting from August 3 in which feedback for both, the auction and the fixed-price sale, could be left. If every pricing-related comment resulted in non-positive feedback for the auction and this were the only source of differences for such feedback between the sales mechanism, i.e. an extra non-positive comment would be issued if and only if such a comment occurred, then these two measures would co-vary perfectly. In reality, the two daily rates are indeed strongly and significantly correlated, with

Figure 3. Feedback differences between auction and fixed-price sales over pricing-related comments



Notes: *Vertical axis*=Difference of the daily rate of non-positive feedback for auctions minus the difference in the daily rate of non-positive feedback for fixed-price sales (for each of the sample's 34 days with feedback data for both sales mechanisms. *Horizontal axis*=Daily rate of pricing-related feedback for auctions. *Line*=Result of an OLS-regression of feedback differences on pricing-related comments and a constant.

a correlation coefficient of 0.891 ($p<0.001$). This corresponds to an explanatory power/R^2 of 0.795.[10] These results are also confirmed by the results of a simple OLS-regression in which the differences in the feedback rates are regressed on the rates of pricing-related comments and a constant: The resulting line, depicted in the figure, has a significantly positive slope, an almost zero intercept and therefore the same explanatory power. Pricing-related comments in auctions do therefore explain more than three quarters of the variations in the feedback-differences between auctions and fixed-price sales.

The above findings reveal two main insights: First, the variations in feedback within one sales mechanism (the auction) are mirrored in feedback differentials between two sales mechanism (the auction and the fixed-price sale). This reflection of within-variations in between-variation is inconsistent with the notion that unobserved heterogeneity caused feedback differences between the two sales mechanisms. Second, the fact that the temporal pattern of both, within- and between-effects follow the salience of reference prices indicates their relevance in determining feedback. This notion is also confirmed by the finding that pricing-related comments have considerable explanatory power for the differences in feedback between sales mechanisms. Together, these results provide multiple evidence for the notion that reference price effects were, at least to a considerable degree, the triggers of feedback and feedback differences between the auction and the fixed-price sales.

4 Discussion & Conclusion

This paper shows how ex-post reference price shifts can adversely affect customer behavior. This manifests through unfavorable public feedback which successful bidders are more likely to give for an auction than for an otherwise identical fixed-price sale. Such feedback is also more likely to be left the higher the auction price is, even though antagonized bidders shaped this price themselves. The result presented here show that these effects are caused by successful bidders who learn, after they have won the auction, about the fact that the same item was later sold for a lower, fixed-price. This information is not relevant for assessing the objective value of the idiosyncratic transactions in which the auction customers had participated in. However, it can shift their reference prices downwards and thereby negatively affect how they assess their transaction retrospectively. This then causes, moderated by their social preferences, a negative effect on the seller's reputation.

Before the consequences of these findings are discussed, recall that they are based on reviews which

[10] The same impression can also be obtained from Figure 4 in Appendix B which presents the two measures as co-varying and almost overlapping time-series.

were left voluntarily by customers. For them, the outcome of the transaction they participated in and their motivation to give feedback was important enough that they considered it worthwhile to give feedback which reflects their assessment. As having obtained the object is a necessary but not a sufficient condition for giving feedback, the point estimates presented here should be taken with some caution and as representative of those customers, not the entire population. However, the main results regarding the difference in feedback across sales mechanisms, the price effect, and how they are moderated by the salience of reference prices are all based on relative effect sizes within the sample of feedback-giving customers. The point estimates are therefore less important. Also, only these feedback-giving customers' assessments materialize into concrete, observable actions which affect the seller's feedback score. As such feedback scores and ratings crucially affects sales records (see Melnik and Alm, 2002; Livingston, 2005; Houser and Wooders, 2006; Resnick et al., 2006; Anderson and Magruder, 2012) this study's findings have several implications:

First, this paper documents an unintended consequence of pricing patterns which are not uncommon in online markets. Einav et al. (2015) show that auction and fixed-price offers for the same retail goods are often available within close temporal succession. However, auction customers often end up paying more than necessary for alternative fixed-price offers available to them (Ariely and Simonson, 2003; Malmendier and Lee, 2011). Similar patterns can also occur when reverse auctions are used alongside fixed-price offers to sell unused capacities, for example in the travel and hotel industry (the most prominent example being Priceline, see Wang et al., 2009; Gardner, 2012). Sequential sales where auctions precede fixed-price sales might, at first sight, also seem appealing to sellers in various other situations. For example, first selling via an auction can help a monopolist to construct a demand curve from the observed bids. Based on this, it can then compute a profit-maximizing price for subsequent fixed-price sales. The same sequential sales strategy, though less motivated by profit-seeking concerns, can also be employed to prevent (ticket-)scalping (Courty, 2003; Roth, 2007; Leslie and Sorensen, 2014; Bhave and Budish, 2017). First selling via an auction and then selling a potential remainder for a lower, fixed-price reverts and destroys the business model of scalpers. I show that the use of such pricing strategies comes with the caveat of potentially causing antagonism among those customers who have the highest valuation for a seller's product.

The second implication relates to the first. Sellers can often exploit inattentive and under-searching customers, for example by deliberately using overly complicated pricing rules (Grubb, 2015), preventing price comparisons (Ellison and Fisher Ellison, 2009) or shrouding fees (Brown et al., 2010). This paper's

results show that customers punish the seller when they realize that they missed a better deal. As long as the costs of such antagonism are not factored into the seller's trade-off regarding the use of obfuscating sales strategies they can, eventually, backfire.

Third, the adverse reactions by customers which are documented here do not only matter for buyers and sellers but also for market platforms. If auction customers punish the seller for their perceived losses, sellers stop demanding this sales format, in line with the findings by Bhave and Budish (2017) and Einav et al. (2018). In addition, the way how this punishment of sellers occurs does not only lead to less demand for auctions but also harms the functioning of reputation systems more generally. These systems are usually considered as a way to give market participants some credible punishment threat in order to prevent fraudulent behavior and to ensure sufficient quality. This is particular relevant in rather anonymous online situations where traditional mouth-to-mouth reputation cannot fulfill this rule (see Dellarocas, 2003; Bolton et al., 2004; Jin and Kato, 2006; Cabral and Hortaçsu, 2010; for a recent review of the topic see Tadelis, 2016). This paper's results show how a reference price shift, i.e. a purely psychological process, leads customers to rate a seller unfavorably. Feedback does therefore not reflect objectively negative elements of an idiosyncratic transaction such as a delayed shipment or a faulty item. It rather represents the customer's subjective negative experience, caused by ex-post observing another offer. However, once feelings about a seller's overall sales sequence rather than objective and transaction-specific facts determine feedback, its informational value in the latter dimension diminishes.[11] In consequence, reviews from antagonizing customers can, similar to the problems created by omitted reviews (Dellarocas and Wood, 2008; Nosko and Tadelis, 2015) or fake reviews (Anderson and Simester, 2014; Mayzlin et al., 2014; Luca and Zervas, 2016), create negative externalities from single transactions on the overall quality and informativeness of a market platform's reputation system.

[11] In fact, eBay has tried to prevent this by making it clear that before buyers give a *"neutral or negative feedback, they should contact the seller and try to resolve problems"* and that such feedback should be *"fair and objective"* (eBay.de's feedback rules, retrieved and translated from http://pages.ebay.de/help/feedback/howitworks.html at 09.02.2009).

Appendix A: A model of reference-dependent feedback-giving

The following presents a simple model which formalizes the reasoning presented in section 3.1. The model combines reciprocal with reference-dependent preferences to explain the puzzling feedback differences between auctions and fixed-price sales and the negative effect of the auction price on feedback. It describes how a customer ("she") evaluates her purchases and how this influences her behavior towards the seller ("he"). It takes an ex-post perspective by looking at how, given a customer's rational purchase decision, subsequent changes in her reference point affect the customer's actions.

Consider a customer who has obtained an item in period $t = 0$ for a price p. At the time of the purchase, the item has expected value v for the customer. In a later period $t \in \{1, 2, ...\}$ the customer may then get new information about the item which she did not have initially. This information is denoted by the term $e_t \in \mathbb{R}$ and represents (positive or negative) user experience, for example regarding moral hazard in the seller's post-transaction behavior (e.g. the seller's refusal to ship the item) or the item's quality. A customer's valuation at the transaction date reflects this expectation, thus $e_0 = 0$ can always be assumed. At some later period $\tau > 0$, user experience realizes. The net utility of the transaction as experienced by the customer in period t is then given by $u_t = v - p + \epsilon_t$ with $\epsilon_t = 0$ if $t < \tau$ and $\epsilon_t = e_\tau$ for $t \geq \tau$.

How the customer assesses the transaction is not only dependent on her net utility u_t but also how this compares to the reference utility $u_t^r = v - r_t$ of buying the item elsewhere at price r_t. This additional reference-dependent utility is given by $\mu(u_t - u_t^r) = \mu(r_t - p + \epsilon_t)$ where $\mu \geq 0$ scales this utility in relation to the base net utility u_t. Changes in the reference-dependent utility occur either through user experience ($e_t \neq 0$) and/or through an update in the reference price ($r_t \neq p$). The initial reference price is some convex combination between the transaction price and the (not chosen) outside option of obtaining the same item elsewhere at a price $\bar{p} \geq p$. It is therefore given by the function r_0 which is increasing in p and has an image $r_0(p) \geq p$.

Asymmetric reference-dependence is captured by scaling the reference-dependent utility of losses relative to gains with $\lambda > 0$. Loss aversion then corresponds to assuming $\lambda > 1$, a parameter range which is also possible here. This would amplify the main effects which will be derived in the following but it is not a necessary assumption. Assuming additivity, a customer's assessment of the transaction at time t is then given by the following expression:[12]

[12] This linear form of reference-dependent utility has been used Köszegi and Rabin (2006) to illustrate applications of reference-dependent utility and in related works that followed (e.g. Heidhues and Köszegi, 2008, 2014). In particular,

$$A_t(\epsilon_t, r_t, v, p) = v - p + \epsilon_t + \mu \cdot \big(\max\{r_t - p + \epsilon_t, 0\} + \lambda \cdot \min\{r_t - p + \epsilon_t, 0\} \big) \tag{3}$$

Customers are allowed to take an action x which is either in favor of or against the seller, based on this assessment. In the context of this paper, these actions are giving favorable or unfavorable (online) feedback. Therefore, this action will be referred to as "feedback" in the following; the results however apply to any other action with similar consequences. Feedback is denoted by $x_n \in X$ where X is a discrete, finite and ordered subset of $\mathbb{R}$. There is also the possibility that no feedback is given, meaning that no action for or against the seller is taken by the customer. As a convention, an index and value of zero is assigned to this case, therefore $x_0 = 0$ denotes "no feedback". Negative elements x_n of X with $n \in \mathbb{Z}_-$ then represent an unfavorable (worse than none) feedback while positive elements with $n \in \mathbb{Z}_+$ represent favorable (better than none) feedback. Accordingly, higher positive (negative) values of the index n denote more favorable (less unfavorable) feedback. "Actual feedback" $x_n \neq x_0$ can only be given once for each transaction and it is assumed that there is always at least one kind of favorable and unfavorable feedback, besides the possibility of giving no feedback (i.e. that $\{x_{-1}, x_0, x_1\} \subseteq X$ holds).[13]

Giving feedback has both, gains and costs to customers. In the context of online feedback, costs of giving feedback can derive, for example, from the time and effort of having to log in to the respective site, searching the respective option and writing a comment. These costs of giving feedback x_n are captured by $c(x_n)$ which is the image of a twice continuously differentiable function $c : \mathbb{R} \to \mathbb{R}_0^+$, evaluated at $x_n \in X \subset \mathbb{R}$.[14] Giving no feedback does not create any costs so that $c(0) = 0$ holds. I also assume that c is strictly convex. Therefore, all "actual" feedback ($x_n \neq 0$) is costly and giving more extreme feedback is more costly, for example because more elaborate wording has to be used or because a customer inherently rations stronger feedback. Note that c does not need to be symmetric

Lange and Ratan (2010) and Ahmad (2015) use a linear model to study how, given reference-dependent preferences, optimal bids in auctions are determined ex-ante. Note that (3) can also be understood as a special case of a more general compound function $\mathcal{A}_t(\{e_k, r_k, v, p\}_{k=0}^t) \equiv \sum_{k=0}^t \alpha_k A_k(e_k, r_k, v, p)$ with time-period specific weights α_k which also takes into account past assessments and which is evaluated at period t. As this analysis will only be interested in the effects which involve contemporary changes, i.e. $\partial \mathcal{A}_t(\{\epsilon_k, r_k, v, p\}_{k=0}^t)/\partial x_t = \alpha_t \cdot \partial A_t(\epsilon_t, r_t, v, p)/\partial z_t$ with $z_t \in \{\epsilon_t, r_t\}$, it is sufficient to focus on the current period t and normalize its weight to one.

[13] In terms of the model, eBay's feedback system is therefore represented by $X = \{x_{-2}, x_{-1}, x_0, x_1\}$ with successive elements referring to negative/neutral/no/positive feedback, respectively (see section 2.3 on why "neutral" feedback is considered to be unfavorable). Note that the values of the variable $f \in \{-1, 0, 1\}$ used to designate negative, neutral or positive feedback in the main text do not necessarily reflect the associated values of x_n.

[14] This means that only the values of c over X will be relevant. However, defining these costs via a continuous function over the real space simplifies the subsequent exposition.

around its minimum. Thus, the costs of giving favorable and unfavorable feedback can grow at different rates, consistent with the findings by Dellarocas and Wood (2008) and Nosko and Tadelis (2015).

A customer also gets utility from giving feedback, for example through a reciprocity-motive in which punishing (rewarding) a seller for a negatively (positively) assessed transaction yields additional utility. Such additional utility of feedback is captured by the term $\psi \cdot (x_n \cdot A_t)$. The variable $\psi > 0$ therefore represents a customer's preference for giving the seller feedback which reflects her assessment relative to the costs of giving feedback.[15] Accordingly, a customer's utility of providing feedback f_n, given her current assessment A_t, is given by

$$U_t\big(x_n|\psi, A_t\big) = A_t(\epsilon_t, r_t, v, p) \cdot \big(1 + \psi x_n\big) - c\big(x_n\big). \tag{4}$$

A customer chooses her feedback so that it maximizes the above expression. It is therefore denoted by $x_t^* \equiv \arg\max_{x_n \in X} U_t\big(x_n|\psi, A_t\big)$ holds. Customers are assumed to be myopic regarding when to issue a non-zero feedback or, equivalently, they take current perceptions as indicative of future realizations.[16] Therefore, once $x_t^* \neq 0$ holds, customers issue the feedback which reflects their contemporary assessment of the transaction. Before and after, they do not issue feedback. Assuming that the motivation to give feedback, as measured by ψ, is heterogeneously distributed across customers according to the strictly increasing c.d.f. $\Psi(z) \equiv \Pr[\psi \leq z]$, one then gets the following:

Proposition 1. *Given an assessment $A_t = A_t(\epsilon_t, r_t, v, p)$, it holds that the probability $\Pr[f_t^* \leq x_n|A_t]$ of observing feedback less or equal than some non-maximal feedback score $x_n < \max\{X\}$*

a) is positive and strictly decreasing in A_t for $A_t \neq 0$ and $A_t \cdot x_n > 0$,

b) equals one and is invariant in A_t for $A_t \leq 0 \leq x_n$,

c) equals zero and is invariant in A_t for $A_t \geq 0 > x_n$.

d) is strictly positive for any A_t in a non-empty interval around zero if $x_n = 0$.

Proof: see end of this appendix.

Case d) implies that the customer's assessment has to have a sufficiently large (positive or negative) magnitude in order for any actual feedback $x_n \neq$ to be issued. Case c) shows that no unfavorable

[15] Besides reciprocal motives, this formulation also captures complementary altruistic utility of contributing informative feedback to the public good which unconditional feedback effectively constitutes (Avery et al., 1999; Bolton et al., 2004)

[16] This would correspond to $\mathrm{E}[z_\tau] = z_t$ for each $\tau > t$ and $z_t \in \{e_t, r_t\}$ and is consistent with findings that current reference points reflect expectations (see Ericson and Fuster, 2011; Gill and Prowse, 2012; Bartling et al., 2015).

feedback will be issued when the customer's assessment is non-negative. Conversely, case b) implies that no favorable feedback will be issued when the customer's assessment is non-positive.[17] Case a) covers feedback which has the same sign as the underlying assessment and shows that more favorable (unfavorable) feedback is more likely for higher, positive (lower, negative) assessments. Feedback therefore varies with the underlying assessment but only if both are equally signed. In consequence, the comparative statics of $A_t = A_t(e_t, r_t, v, p)$ carry over to equally-signed feedback. For unfavorable feedback, this means the following:

Corollary 1. *The probability of observing unfavorable feedback $x_n < 0$ is*

i) zero and price-insensitive if the assessment is positive $\left(\frac{\partial \Pr[x_t^* < 0 | A_t(\epsilon_t, r_t, v, p) > 0]}{\partial p} = 0\right)$,

ii) positive and price-sensitive if the assessment is negative $\left(\frac{\partial \Pr[x_t^* < 0 | A_t(\epsilon_t, r_t, v, p) < 0]}{\partial p} > 0\right)$.

Case i) covers situations when there is a positive assessment. A customer will then not issue unfavorable feedback. Accordingly, the price effect with respect to this event is zero. Note that this does not mean that feedback is unaffected by prices. As long as the underlying assessment is positive, a higher price may lead to less pronounced positive positive or even omitted feedback – it is however never negative as this would require a negative assessment. Case ii) is relevant when the customer's assessment is negative. In this situation, a higher price paid leads to a lower, negative overall assessment and thereby increases the chance that unfavorable feedback of some given magnitude, as opposed to no feedback at all, is issued.

In order to perceived as such, the outside option has to be at least as good as not buying the good at all, which has a normalized assessment value of zero. In consequence, if the item and not the outside option was obtained, $A_0 \geq 0$ has to hold. Given the above assumptions on e_0 and r_0, this means that in a posted offer market, every customer who bought an item did so at a price p such that $v - p + \mu\left(r_0(p) - p\right) \geq 0$ holds. Similarly, in a first- or second-price auctions, a customer's bid is always an upper ceiling on the realized price such that the above condition can also be ensured to hold. In consequence, part i) of the above corollary applies. A negative feedback and a price effect as described in part ii) therefore requires a change in the buyer's assessment *after* the transaction is concluded.

Such an ex-post change can be either due to sufficiently negative experience $e_t < 0$ or due to the downward revision of a customer's reference price such that $r_t - p < 0$ is sufficiently low. The

[17] To see this note that case b) implies $\Pr[x_t^* \leq 0 | A_t \leq 0] = 1$ and, therefore, $\Pr[x_t^* > 0 | A_t \leq 0] = 0$.

comparison of two sales mechanisms with otherwise identical, idiosyncratic features means that for both mechanisms, the same level of ϵ_t is observed. Differences in feedback between these mechanisms, as documented in Table 2, can therefore not be caused by user experience or quality but by reference point shifts which are different across sales mechanisms. It is also not consistent with the finding that the difference decreases after the voucher had arrived, i.e. when user experience could materialize (see Table 5) The price effect as documented in Table 3 can, when viewed as an isolated finding, be explained as a consequence of negative user experience. However, only a reference price shift can explain this finding together with the above described findings on feedback differences between the sales mechanisms and the fact that the price effect is also concentrated in exactly the period when reference prices were particularly salient (see Table 4).

Proof of Proposition 1

The unrestricted optimum, given by $\tilde{x}_t^* \equiv \arg\max_{x_t \in \mathbb{R}} U_t\big(x_n|\psi, A_t\big)$ with $A_t = A_t(e_t, r_t, v, p)$ has to solve $A_t\psi = c'(f_t^*)$. Strict convexity of $c \in \mathcal{C}^2$ with a minimum at zero ensures that this is the only optimum and that c' is strictly increasing. Therefore, c is invertible and $\tilde{f}_t^* = c'^{-1}(A_t\psi)$ holds. Also, as $\tilde{x}_t^*$ is a maximum, $U''(\tilde{x}_t^*|\psi, A_t) = -c''(\tilde{x}_t^*) < 0 = U'(\tilde{x}_t^*|\psi, A_t)$ applies. In consequence, $U'(\tilde{x}|\psi, A_t) \gtreqless 0$ holds for any $\tilde{x} \in \mathbb{R}$ such that $\tilde{x} \lesseqgtr \tilde{x}_t^*$. For any $x_n \in X$, the loss $U(x_n|\psi, A_t) - U(\tilde{x}_t^*|\psi, A_t) < 0$ is therefore strictly increasing in $|x_n - \tilde{x}_t^*|$. The restricted optimum $x_t^* = \arg\max_{x_t \in X} U_t\big(x_n|\psi, A_t\big)$, is thus uniquely defined and one of the two elements in X closest to the unrestricted solution $\tilde{x}_t^*$. For $x_t^* \leq x_n$ to apply, it then has to hold that $\tilde{x_t}^* \leq \lambda_n \cdot x_n + (1-\lambda_n) \cdot x_{n+1}$ with $\lambda_n \in (0,1)$ determined by the specific cost function c and the distance $x_{n+1} - x_n$. For any $x_n < \max\{X\}$, it then holds that

$$
\begin{aligned}
\Pr[x_t^* \leq x_n] &= \Pr\left[\tilde{x}_t^* \leq \lambda_n \cdot x_n + (1-\lambda_n) \cdot x_{n+1}\right] \\
&= \Pr\left[c'^{-1}(A_t\psi) \leq \lambda_n \cdot x_n + (1-\lambda_n) \cdot x_{n+1}\right] \\
&= \begin{cases}
\Psi\Big(\frac{c'(\lambda_n \cdot x_n + (1-\lambda_n) \cdot x_{n+1})}{A_t}\Big) & \text{if } A_t > 0, \\
1 & \text{if } A_t = 0 \text{ and } x_n \geq 0, \\
0 & \text{if } A_t = 0 \text{ and } x_n < 0, \\
1 - \Psi\Big(\frac{c'(\lambda_n \cdot x_n + (1-\lambda_n) \cdot x_{n+1})}{A_t}\Big) & \text{if } A_t < 0.
\end{cases}
\end{aligned}
$$

The proposition is then a direct consequence from the above and the assumptions on Ψ. □

Appendix B: Further results

To verify that comments relating to the seller's pricing strategy were issued more often during the first six days from the auction on, the following Probit-model was estimated using the auction data:

$$\Pr[CommentPricing_i = 1] = \Phi\Big(\alpha + \sum_{t=2}^{6} \beta_t \cdot SixDayBin\#t_i + \sum_{s=1}^{3} \gamma_s \cdot \mathbb{1}[Buyer'sScore_i > 10^s]\Big)$$

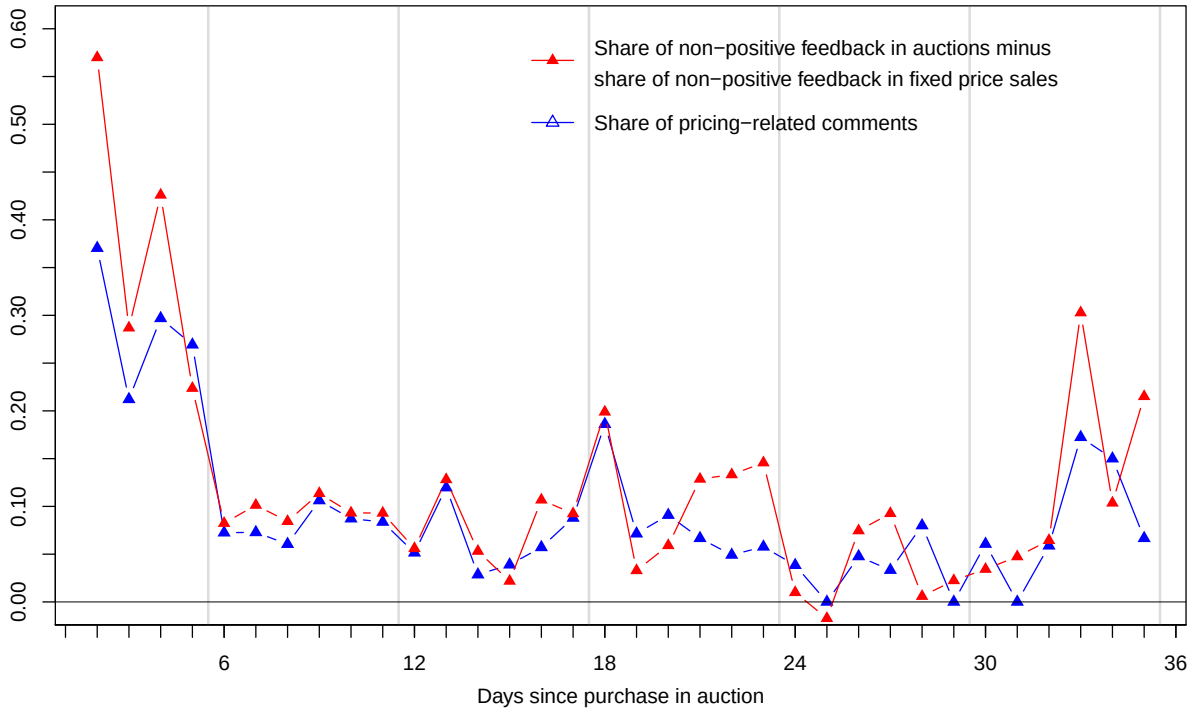
The dependent variable is a manually coded dummy which indicates whether a comment refers to the pricing strategy of the seller (selling first via an auction and then via a fixed-price), the remaining variables are the same as in the main text. Table 6 reports marginal effects relative to the first six days, the baseline. Figure 2 in the main text depicts the implied conditional expectations from column (1).

Table 6. Pricing-related comments in reviews over six-day-bins

	(1)	(2)	(3)	(4)
Dependent variable:	$y_i = 1$: Comment referring to the seller's pricing strategy			
SixDayBin#2	-0.155***	-0.149***	-0.132***	-0.124***
	(0.040)	(0.040)	(0.036)	(0.035)
SixDayBin#3	-0.165***	-0.159***	-0.136***	-0.130***
	(0.042)	(0.041)	(0.037)	(0.037)
SixDayBin#4	-0.138***	-0.132***	-0.107***	-0.100**
	(0.045)	(0.044)	(0.041)	(0.040)
SixDayBin#5	-0.202***	-0.196***	-0.171***	-0.165***
	(0.041)	(0.041)	(0.039)	(0.038)
SixDayBin#6	-0.160***	-0.148***	-0.153***	-0.141***
	(0.049)	(0.050)	(0.042)	(0.042)
Buyer's Score >10		-0.023		-0.018
		(0.022)		(0.020)
Buyer's Score >100		-0.033		-0.024
		(0.021)		(0.020)
Buyer's Score >1000		0.067		0.080*
		(0.048)		(0.047)
First reviews only	no	no	yes	yes
Observations	3,575	3,550	2,283	2,265

Notes: Average marginal effects of Probit estimates obtained from regressing a dummy for comments which refer to the seller's sales strategy on dummies for the six-day-bin when the review was written and the buyers' own feedback score. Columns 1 & 2 use all collected reviews for the auction and report standard errors clustered on the buyer level. Columns 3 & 4use only the first review which buyer posted for the auction and report robust standard errors.

Figure 4. Feedback differences and pricing-related comments over time



Notes: *Red triangles*=Difference of the daily rate of non-positive feedback for auctions minus the daily rate of non-positive feedback for fixed-price sales (for each of the sample's 34 days with feedback data for both sales mechanisms). *Blue triangles*=Daily rate of pricing-related feedback for auctions.

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