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

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Abstract

This paper investigates how bidders in an auction become antagonized over their successful bid. Using data from a large-scale sales campaign on eBay, we show how auction buyers use the platform's feedback system to punish the seller when they discover that the same item is later offered for a lower fixed price. Specifically, we find that i) the probability of receiving unfavorable feedback is four times larger for auction sales than when the same item is sold by the same seller for the fixed price and that ii) this probability is increasing in the auction prices, even though reviewing bidders shaped these prices themselves. By exploiting a temporal variation in how salient the fixed-price offer was for auction buyers, relative to information concerning the transaction they participated in themselves, we show that these effects on feedback are best explained by ex-post reference price shifts.

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

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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 buyers evaluate a transaction (Kahneman et al., 1986; Frey and Pommerehne, 1993; Xia et al., 2004). This is particularly relevant for online markets as their flexible nature allows to vary sales conditions and prices across buyers, either as means of experimentation (Einav et al., 2015) or user-based price discrimination (Mikians et al., 2012; Shiller, 2014). At the same time, they rely crucially on user-written reviews (see Tadelis, 2016). Auctions could, in principle, be a solution. They are easily implemented online and allow differential pricing. They also have the potential to prevent dissatisfied buyers by not taking them as passive price-takers but allowing them, through their bids, to consciously and willingly shape the prices they pay (Chandran and Morwitz, 2005; Hinz et al., 2011). However, the findings presented here 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 buyers who under-utilize competing offers.

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

These findings are hard to reconcile with the fact that the buyers themselves played a crucial part in determining the auction price. By bidding accordingly, they could have easily prevented to pay a price over which they become antagonized. Considering this and the fact that the reviewed item and seller were the same, the feedback difference between the sales mechanisms is also puzzling. To address these findings, an explanation based on ex-post reference price updates is suggested. 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 successful bidders to negatively review a transaction which, had such a shift not occurred, would not have yielded received an unfavorable review.

In line with this reference price explanation, we show that the effect of a higher auction price on adverse feedback is concentrated in the period which immediately follows the auction. During this period, the acquired item had not yet have arrived by post so that buyers could not get new any transaction-specific information (e.g., quality or user experience such as whether trains for which they voucher was used were delayed). However, successful bidders 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 buyers' actual user experience could also start to affect 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. We also that this feedback differential between the sales mechanisms mirrors the 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 feedback differential shrinks to less than a quarter of its initial size. Further evidence comes from showing that the excess amount of unfavorable feedback in auctions relative to fixed-price sales can be explained almost perfectly by what bidders write in their reviews, that is, by comments which refer directly to the seller's pricing policy. It is then shown that competing explanations (such as selection-based arguments, the winner's cure for re-sellers or cooling-off over time) can only account for some of these findings in isolation, but not their ensemble. In contrast, ex-post reference point shifts are in line with all of these results.

2 Related literature

This paper's findings relate to several 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). For auctions specifically, these results also resonate with Einav et al. (2018)'s findings. 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. They 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. Similarly, Bhave and Budish (2017) show that auctions did not persist as a sales mechanism for online markets for event tickets, even though they cleared the market and prevented speculation much more effectively than fixed prices. In line with these observations, this paper presents how sellers suffer *directly* from using an auction when auction buyers under-search and punish sellers for their (perceived) losses.

The direct, negative effect on sellers occurs through unfavorable reviews, left by buyers when they observe a better offer after the auction's end. Thus, instead of reflecting transaction-specific information (such as delayed shipment or a faulty item), reviews are determined by buyers' subjective perceptions of the seller's overall sales strategy. However, once a seller's sales sequence – which a platform can easily observe – rather than harder-to-observe private and transaction-specific information determine feedback, its informational value in the latter dimension diminishes. 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), this paper therefore shows that reviews from disappointed buyers can affect the informativeness of a market platform's reputation system.

The negative feedback analyzed here is a form of customer antagonism, i.e., buyers who convert negative emotions into concrete actions against sellers (see Yi and Baumgartner, 2004). In this regard, the field experiment by Anderson and Simester (2010) is close to this paper. They show that after a mail-order sent out catalogs with randomized discounts, those buyers who had bought the discounted items before, at a higher price, subsequently ceased to order from that mail order.[1] In line with this paper's findings, this effect is most concentrated among the buyers who had previously paid the most, relative to the discount. Besides providing an explanation based on reference price shifts which accommodates these results and those presented here, the present work adds to the empirical literature on customer antagonism along three main dimensions: First, it demonstrates the relevance of customer antagonism in *online* retail, a large and steadily growing market. Second, this is the first study which demonstrates that price-based customer antagonism can also arise in auctions, that is, in a sales mechanism in which buyers have a crucial and active role in the price-setting process. Third, it shows that customer antagonism does not only manifests through demand (e.g., antagonized buyers boycotting a seller) but also through

[1]Similarly, Anderson and Simester (2008) and Leibbrandt (2016) document customer antagonism (in the field and lab, respectively) which is caused by price discrimination. Several theoretical accounts have also explored the constraints which customer antagonism imposes on sellers' pricing strategies (e.g., Rotemberg, 2011; DiTella and Dubra, 2014; Battigalli et al., 2015). However, customer antagonism is not universal. For example, Courty and Pagliero (2010) do not find negative demand effects when internet cafes adjust their prices (in almost real time) to demand during peak hours.

online feedback which is crucial for sellers and for the functioning of sales platforms.[2]

This paper's analysis presents evidence that such antagonism is generated by buyers' ex-post reference price shifts. The fact that these shifts spill over to the reviews of transaction connects these findings to a recent lab experiment by Bushong and Gagnon-Bartsch (2017). They show, in a lab experiment, that negative surprises in outcomes lead subjects to evaluate a transaction and the associated task negatively.[3] The present work presents field evidence for such a mechanism. In another recent and related work, Backus et al. (2017) show that frustrated bidders leave eBay if they fail to obtain an item for which they have been the leading bidder for a long time. This paper differs from these works in a crucial aspect: Instead of being caused by a sudden downward shift in outcomes for a given reference point, the antagonism and frustration presented here is consistent with a reverse channel – a downward shift in reference prices for a given transaction outcome.

Finally, this works connects to previous research which shows that online auction buyers often bid more than what is necessary to obtain the same item via a fixed-price sale when both are simultaneously available (see Ariely and Simonson, 2003; Malmendier and Lee, 2011). This could be due to buyers who know their valuation but bid too high (as it has been well established for second-price auctions in the lab where bidders' valuations can be tightly controlled; for an overview see Kagel, 1995). Alternatively, the vast differentiation of online markets (Brynjolfsson et al., 2011) can cause buyers to under-search and rely on heuristic rules so that lower-priced offers are not considered.[4] In this regard, there is some discussion on whether such behavior ought to be called "over-bidding," as this expression is typically associated with only the behavior described first (see Schneider, 2016; Malmendier, 2016). However, the fact that bidders act under cognitive limitations – either in their bidding process or in their perception and use of alternative, cheaper offers – is undisputed. This paper confirms this notion. Importantly, it also indicates a channel through which such a loss does not only harm the buyer who misses a better offer but also sellers and the degree to which online reviews display objective transaction characteristics.

[2] An long literature covers the importance of online feedback for sales and the functioning of online market places (see Melnik and Alm, 2002; Livingston, 2005; Houser and Wooders, 2006; Resnick et al., 2006; Anderson and Magruder, 2012).

[3] Similar spill-overs are documented in Card and Dahl (2011) who report an increase in domestic violence after unexpected losses in football games and in Mas (2003) who demonstrates that crime reports increase and arrests rates drop after police unions' unexpectedly lost wage arbitrations. In a wider sense, this work also relates to others which show how, via different mechanisms, reference dependence affects the functioning of economic exchange systems in the context of bargaining (Herz and Taubinsky, 2017), auction bidding (Ariely and Simonson, 2003; Kamins et al., 2004) or posted-offer markets (Simonsohn and Loewenstein, 2006; Weaver and Frederick, 2012).

[4] Examples of buyers' reliance on heuristics and salient cues in online markets rather than doing a thorough search include the use of prominent digits of used cars' odometers (Lacetera et al., 2012) and their registration years (Englmaier et al., 2016) rather than absolute mileage and age differences, and the neglect of extra fees (Hossain and Morgan, 2006).

3 Description of the online sale

3.1 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 ("ebay.de"), conducted a sales campaign for rail tickets. Starting from August 1 and going until August 10, on each of these days a special offer started to be available. Beginning on the respective days, each of these special offers were available for purchase on a dedicated eBay-page over the next 24 hours. Of particular relevance for this paper are the offers which started on 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, buyers had to fill in their departure and arrival stations; its specific use was therefore up to the client. At the time of the sale on eBay, the railway operated a webpage from which the railway company's "regular" price (i.e., the price without a voucher) for a given itineraries could be easily retrieved. Buyer could therefore have different valuations for the voucher, depending how they intended to use it and the opportunity cost of obtaining the ticket elsewhere. When the campaign was conducted, prices for all itineraries covered by the vouchers were capped by 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€.[5] buyers 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 always take-it-or-leave-it offer for that price. 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.[6]

[5] More precisely, in eBay's "proxy"-auction, a bidder can submit a bidding cap. Starting from an initial price, eBay then 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).

[6] For both, the auction and the buy-it-now sales, the final sale price was subject to an additional shipping fee of 2.50€. 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. Also note ticket purchases are excluded from the EU-rule which normally guarantees consumers the right to return online purchases for a full refund within 14 days after the purchase.

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 also has a seller profile which was publicly accessible. It displays, for a limited time, for each of the reviews a seller received the following associated 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 buyer's account is also displayed next to this buyer's account name. Note that at the time of the sales campaign, feedback from sellers for buyers – in contrast to feedback from buyers for sellers – could only be positive or not be given at all. This rule regarding had been introduced earlier to prevent buyers and sellers from exchanging feedback in a reciprocal manner (see Bolton et al., 2013).

In 2008, the review history of a seller on eBay.de was publicly accessible. One could therefore access the individual reviews which a given seller seller had received, including all the associated data (see above). Starting from August 1, these review data were copied for 40 consecutive days from the review page of the seller which sold the vouchers. This paper looks, for reasons which will later become clear, on data covering multiples of six days after the initial offer date. This means that in the following, data for auction reviews left in the 36 days from August 1 are used. The data for reviews referring to the fixed-price sale are those left in the 36 days starting from August 3.[7]

3.2 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 reviews referring to the fixed-price. This difference corresponds approximately to one standard deviation in the distribution of auction prices.

The table also displays the reviewing buyer's own feedback score, abbreviated by "Buyer's Score". It increases with each positive rating a buyer has received in a previous transaction.[8] In general, eBay members typically receive positive feedback in more than 98% of all transactions (the median share is

[7] 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.

[8] 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 for the price paid, the reviewing buyer's own feedback score, and the feedback left by the buyer 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 buyers hid their feedback scores; buyer's feedback score-statistics omit these observations (see footnote 8).

100%, see Bolton et al., 2013; Nosko and Tadelis, 2015). This high share of positive reviews among eBay members allows to take a reviewing buyer's feedback as an approximation of this buyer's eBay-experience, even though it is actually a lower bound on the number of prior transaction by the reviewing buyer. As these scores are strongly dispersed, they are put into four categories which are defined by whether a buyer's feedback score is weakly less than 10 or whether it surpasses the thresholds of 10, 100, or 1000, respectively. Although to some degree arbitrary, the first category can be thought of belonging to relatively inexperienced eBay-members while the second and third category contain experienced and very experienced members, respectively. 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, the buyers who write reviews buyers are fairly experienced: For both sales mechanisms, just 11% of them had a feedback score of less than ten while only around 3% of the reviews were supposedly written by professionals with at least 1000 transactions; the rest lies in between.[9]

Finally, the table displays the feedback received by seller from buyer. 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% if the voucher was sold in an auction.

[9] If one looks on the feedback score per reviewing buyer (instead of the reviewing buyer's feedback per review), results look similar with average/median feedback scores of 208.94 (180.50) and 81 (74) for auctions (fixed-price) sales, respectively.

3.3 First findings

The above statistics show that auctions have a 10.2 percentage points higher chance of receiving either negative or neutral feedback than fixed price sales. Note that giving positive feedback is the overwhelming norm on eBay and that several studies conclude 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). Given this and the fact that except for the sales format, auction and fixed-price sales were identical, the observed difference in feedback between the sales mechanisms and the size of this feedback differential is remarkable.

One possibility is that the difference in feedback is driven by differences in the reviewing buyers' market experience. For example, socially motivated behavior – to which giving unconditional feedback belongs – has been shown to be moderated by market participants' experience and their own reputational stakes (see List, 2003, 2006). Another potential driver for the feedback differential is that some buyers could buy multiple vouchers. This allowed them to issue multiple reviews which may have disproportionately affected reviews for one of the sales mechanisms. A particularly relevant instance of such a channel would be buyers who bought multiple vouchers in the auction with the aim of reselling them. This reselling-motive would bring in a common-value element and (strategic) uncertainty into their, otherwise private and independent, valuations. Such valuations can affect bidding in the auction and bidders' subsequent evaluation (i.e., if such bidders later realize they suffered from the "winner's curse;" see Thaler, 1988; Kagel and Levin, 1986), which then manifest in their multiple reviews.

To examine these possibilities, a probit regression was run using the data from the auction and fixed sale reviews.[10] The dependent variable was a dummy indicating whether a transaction received a non-positive (i.e., neutral or negative) review. The main independent variable is a dummy which equals one if the given review refers to an auction sale and zero if it refers to a fixed price sale. Its coefficient therefore measures the feedback differential between these sales mechanisms. To control for the effect of the reviewing buyer's reputation and market place experience, additional independent variables indicate to which category, as displayed in Table 1, the buyer's feedback score belongs. In order to deal with the case of multiple reviews by the same buyers affecting feedback disproportionately, the analysis was also repeated using only the first review from each distinct buyer. The full results are portrayed in Table B.1

[10] 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. There is also virtually no change in the result when instead of dropping multiple reviews from the same buyer and only using the first ones, controls for the number of reviews left by the reviewing buyer are added.

in Appendix B. They paint a clear picture and show that inclusion of these controls and the exclusion of multiple reviews do not change the observed feedback differential:

Finding 1. *There is a negative feedback differential between sales mechanisms. Auctions are significantly more likely to receive non-positive feedback than fixed-price sales, at a magnitude of 10 ppt ($p<0.01$).*

Of course, there can still be some unobserved heterogeneity and selection with respect to buyer characteristics For example, high-valuation buyers may have deliberately selected into the auction to pre-empt a later fixed-price market. Table 1 shows that in fact, auction customers paid a price which was about 13€ higher than the fixed price.[11] However, it is not entirely clear how this selection would cause the observed feedback differential. While the observation of higher prices paid in the auction is, at first sight, consistent with higher valuations, this would also imply that such buyers can also enjoy higher net rents. Also, by bidding accordingly, they could auction buyers could limit the price they had to paid so that they could always prevent negative rents. Deliberate selection into the auction should therefore not lead to the observed feedback differential.

More generally, any process which assumes that participation and bidding in the second-price auction is the result of deliberate and anticipating behavior also implies that the eventual price reflects such considerations. It should enable a successful bidder to enjoy a, at least weakly, larger rent than the next-best perceived option. In consequence, a higher auction price should not trigger unfavorable, complaining feedback. To check whether this holds, the data from (only) the auction reviews was used to regress an indicator for non-positive feedback on the auction price. As before in the analysis of the feedback differential, this regression was also performed with additional controls for the reviewing buyer's experience and by repeating it with only using first reviews from each buyer being used. If the price paid in the auction is the result of high-valuation bidders who deliberately select into the auction, it should, if at all, affect feedback in a positive manner. The results – which are independent of whether one controls for the buyer's feedback score and/or whether multiple reviews by the same seller are excluded (see Table B.2 in Appendix B) – do, however, indicate the opposite:

Finding 2. *There is a negative price effect within auctions. For each 10€ paid more than the fixed price offer, the chance to receive non-positive feedback increases significantly, by about 2.2 ppt ($p<0.01$).*

[11] Only very few reviews referred to auctions which ended in a price below the fixed price. This limits the possibility to check whether auctions ending below the fixed price lead to better feedback. However, all of these reviews (9 out of 3,575; 0.25%) were positive. This provides some first evidence in the direction of such an effect. Note that this also supports the notion that it was not primarily the use of an auction format per se which yielded unfavorable reviews but rather a reference-price effect. Further, more substantiated support for this notion is provided in Subsections 4.3 and 4.4.

4 Reference price shifts

The data and findings described above raise several questions. 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? This sections first shows how ex-post reference price shifts provide an answer to these questions. It then provides empirical evidence which is in line with this channel.

4.1 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 buyer whose bid exceeded the later-offered fixed price but not the bidder'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 buyers 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 fails. 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 the auction price and a successful bidder's reference price becomes negative once the latter is updated with the observed, lower fixed-price offer. 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 buyer or that the acquired item provided insufficient quality – absent the new reference price, the buyer would not have given an unfavorable review.

Reference price shifts can also explain the negative price effect: The larger the price a buyer 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 have 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.[12] Advertisements for the sales campaign were however focused on the respective day's special offer (and, in the case of web banners, 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 them 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. In consequence, buyers who had obtained a ticket in the auction and were initially not aware of the subsequent fixed-price offer could learn about it after they had won an auction. The following subsection provides evidence in line with this reasoning and show how it can be used to relate reference price shifts to feedback-giving.

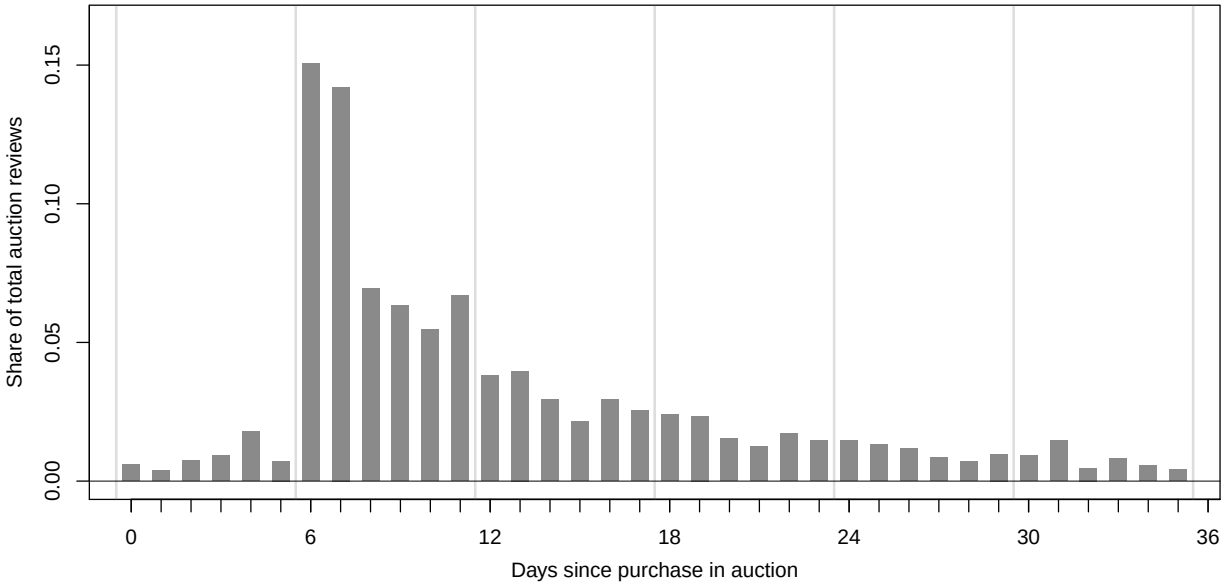
4.2 Identifying reference price shifts

In order to test the explanation proposed above, a variable which indicates whether a successful bidder's reference price shifted would be ideal. However, this requires knowledge over what such buyers *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 buyer feedback. To obtain such an indicator, one can 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 shortly after the auction and lead

[12] Unlike as in Backus et al. (2014), the titles for different listing of the same item were always the same.

Figure 1. Timing of auction reviews



Notes: Histogram of when auction reviews were left; bins of six consecutive days separated by vertical lines.

buyers to revise their reference prices. In contrast, transaction-specific information regarding their recent 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 buyer's money transfer had arrived on the seller's account. Before the voucher had arrived by post, buyers 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. In contrast, information regarding the fixed-price offer could affect a successful bidder's reference price in this time period.

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 without it, 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,

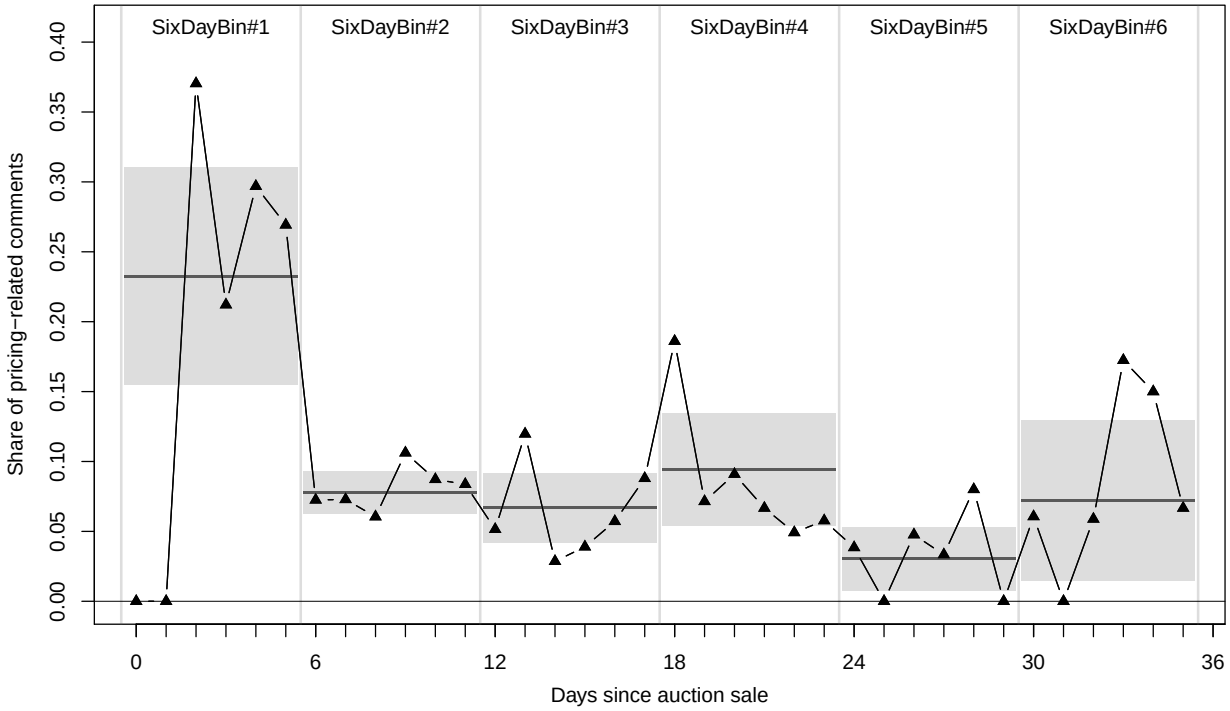
relatively few reviews occur. Less than 2% daily, in total 5.2% of all the 3,575 auction reviews were left between day 0 and 5 from the action date. On August 7, the day following the initial six days, the daily rate suddenly spikes to almost 15% and remains relatively high for all days in the second six-day-bin which accommodates 52.4% of all auction reviews. This is consistent with the notion that, starting from this day on, the arrival of the voucher and its possible use afterwards resolved uncertainty regarding the user experience and provided trigger for buyers to review their transaction. Thus, from day 6 after the auction on, new information regarding the buyers' idiosyncratic transaction could affect feedback, in addition to the information regarding the fixed-price sale. This information was absent during the initial six days so that reference price 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 successful bidders left with their reviews. Those comments which refer explicitly to the seller's sales and pricing strategy, i.e., first selling via an auction and then via a fixed price, were marked. As a first evidence regarding the negative feelings this sales strategy 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 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).[13] A week after the auction, on day 6, when the vouchers started to arrive by post, the share of such comments falls and stays relatively low. This corresponds exactly to the proposed pattern of how the salience of information which affects reference prices, relative to other, idiosyncratic information behaves over time and how this affects buyers' 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;

[13] This also supports the notion that it was the otherwise identical fixed-price offer on day 2 which affected bidders' reviews and not any of the other offers which took play over the nine days following the auction (see also Figure 3).

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.

the grey rectangles indicate the associated 95%-confidence intervals around these conditional means. These results show that the share of pricing-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 ($p<0.001$, full reression results in Table B.3 in Appendix B).

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, it is incorporated in a bidder's price norm which therefore decreases. This makes a higher price paid in the auction stick out more. In contrast, the salience of quality or user experience is low in this period as it corresponds to the reference level, i.e., the expectations buyers had at the time of the transaction. Once the voucher arrives, new information in this dimension can start to enter buyers' perceptions. This then increases the salience of quality or user experience relative to prices, as reflected through a lower share of pricing-related comments in the later six-day-bins.

4.3 Linking the price effect to reference price shifts

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, the following Probit-model was fitted with data of reviews which refer to the auction sale. It allows to measure the price effect separately for the initial six days and the sample's five remaining six-day-bins:

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

In the above specification, the dependent variable is whether the review for a transaction entails non-positive feedback (i.e, if feedback is negative or neutral: $f_i \in \{-1, 0\}$). The function Φ captures the cdf of the error term, $\mathbf{x}_i$ summarizes the independent variables for transaction i. The main independent variable is $\Delta_{10}Price_i$, the difference in the auction price to the 66€ fixed price, divided by 10. Additional independent variables control for whether the reviewing buyer's feedback score $Buyer'sScore_i$ surpasses a power-of-ten threshold but not the next highest. If this were the only variables, this regression setup would be the one which lead to Finding 2 above, the 2.2 percentage points-increase in non-positive feedback for each 10€ paid about the fixed price (measured via the estimate for β_1).

However, the regression model also includes five dummies denoted by $SixDayBin\#t_i$ and their interaction with $\Delta_{10}Price_i$. Their values indicate during which bin of six consecutive days, starting from the auction date, a review was left and allow to de-compose the price effect over the sample's duration. As the first six-day-bin is the reference category, the coefficient β_1 now measures the price-slope in only 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, estimated by $\hat{\beta}_1$, should – if triggered by a reference price effect – have a larger value than the slope estimates $\hat{\beta}_1 + \hat{\beta}_t$ for the later six-day-bins. Thus, the estimates for β_t should be negative.

Note that the above reasoning does not predict a gradually decreasing price effect over time. It

Table 2. Price effects for auctions reviews de-composed 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 during which reference prices were particularly salient. The next five rows present the difference of that slope to the respective price slopes estimated for the subsequent six-day-bins (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

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 during 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 would not impose a hazard with respect to a false positive. By the same reasoning, a potential situation where the size of variations 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 decrease the potential for confirming this prediction. However, it does not create a danger of erroneously detecting reference price-induced variation in the price effect.

With this in mind, one can look at Table 2. It shows the marginal effects obtained from the Probit-estimates of model (1). 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 than the 2.2 percentage point price effect which was previously estimated over the whole sample's 36 days (see Finding 2 and Table B.2). The model's interaction terms allow 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 rows in Table 2 show these differences 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.[14] 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.

4.4 Linking the feedback differential to reference price shifts

The above results show how the negative effect of the auction price on reviews is concentrated in the initial period after the auction. This is in line with an explanation based on reference price shifts as

[14] One estimated price-slope for one six-day-bin which is marginally significant (p=0.086) in (only) one specification.

they were most salient in this period. In the following, it will be shown that the same reference price-explanation is also able to organize the feedback differential 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 (1) is estimated, using the combined data from reviews for the auction and the fixed-price sale. Besides this, the main difference is that instead of the $\Delta_{10}Price_i$-variable, an $Auction_i$-dummy which indicates whether review i refers to an auction (and therefore measures the feedback differential between the 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.[15] The regression model therefore allows to de-compose the feedback differential between auctions and fixed-price sales along the timing of when these differences occur, similar as in the analysis of the price effect above.

The resulting estimates are presented in Table 3 and reflect the temporal pattern observed in the preceding analysis of 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 the otherwise identical fixed-price sale (which, during the first six days of the fixed-price sale, has a magnitude of about 3%). This difference decreases significantly, by about 27 to 39 percentage points, i.e, to a quarter and less of its initial size, in subsequent six-day-bins.

These findings establish a direct link, via the precise timing (before and after the first six days) and the precise manner (a sudden drop, rather than a gradual shift), which connects the within-auction price effect and the feedback differential between auction and fixed-price reviews. Both of these results therefore mirror the salience and importance of reference price effects in determining online feedback. Further support in line with this comes from the comments which buyers actually wrote in their feedback. Figure 3 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 (i.e., the same rate of pricing-related comments as depicted in Figure 2). The units of observation are 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 a non-positive feedback for the auction and if this was the only source of the feedback differential between the sales mechanisms (i.e., an extra non-positive comment would be

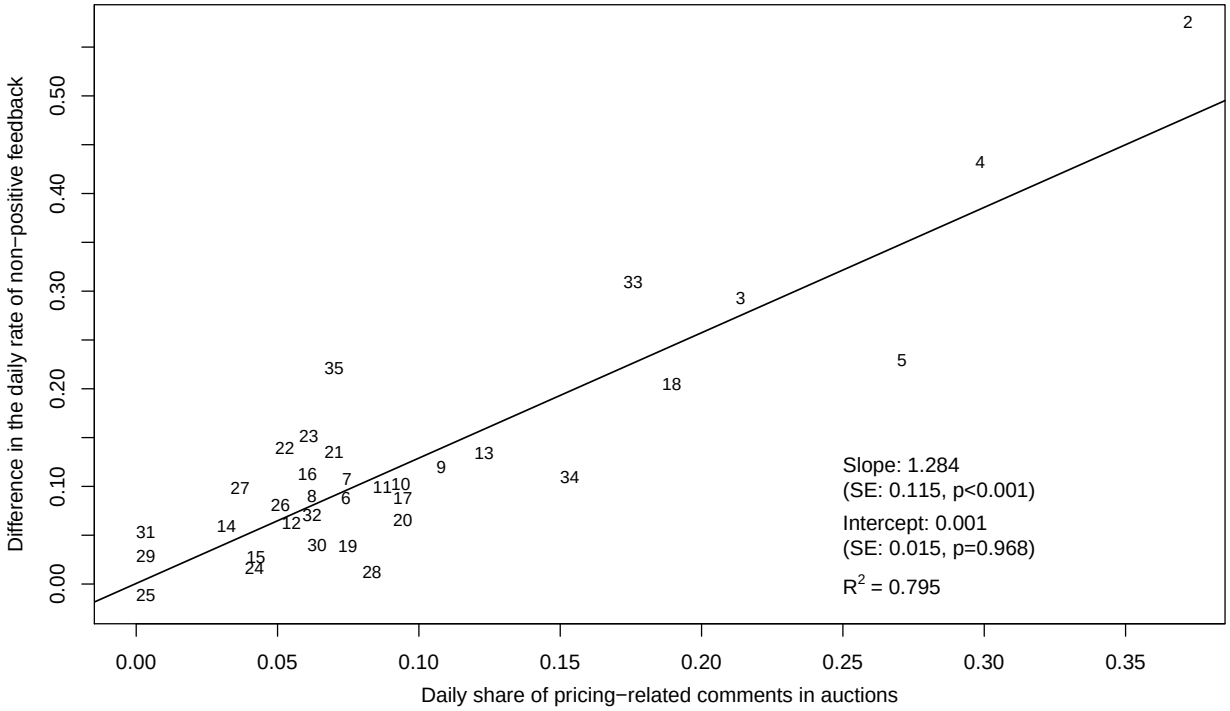
[15] In consequence, the dates defining the six-day-bins for the fixed-price sale in the regression are lagged by two days relative to those for the auction. Any of the following conclusions remain unchanged if they are based on estimation results for which six-day-bins are defined relative to the auction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

Table 3. Feedback differences between auction and fixed-price sales 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

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 difference in the rate of non-positive feedback between auctions and fixed-price sales for the first six-day-bin during which reference prices were particularly salient. The next five rows show how this initial auction-effect differs from those estimated for each of the respective subsequent six-day-bins. 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

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



Notes: *Numbers*=Data points, the number indicates days since the auction sale.* *Vertical axis*=Difference in the daily rate of non-positive feedback between auctions and 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. *: The data points "10" and "17" are slightly shifted for illustrative purposes; their actual position would (almost) overlap with the data point "11".

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 a correlation coefficient of 0.891 ($p<0.001$). This corresponds to an explanatory power/R^2 of 0.795.

These findings are also confirmed by the results of a simple OLS-regression in which the differences in the daily rate of non-positive feedback between the sales mechanisms is regressed on the daily rates of pricing-related comments and a constant: The resulting regression line, depicted in Figure 3, has a significantly positive slope. For each percentage point more in the daily share of pricing-related comments, the difference in that day's share of non-positive feedback between auctions and fixed-price sales changes, on average, by 1.284 percentage points. The associated intercept is estimated to be essentially zero so that the regression has the same explanatory power as the correlation coefficient. Thus, pricing-related comments within auctions explain almost four fifths of the variations in the feedback differential between auctions and fixed-price sales. Also note that the data points in the figure are portrayed by

numbers which correspond to the number of days passed since the auction sale. Consistent with the preceding findings, the observations with the largest share of pricing-related comments and, therefore, the strongest effect on the feedback differential ("2", "3", "4", and "5") are the ones from the first six-day-bin, when reference prices where most salient.

5 Discussion

The results in the above section de-compose Finding 1, the feedback differential between sales mechanisms and Finding 2, the negative price effect on feedback within auctions, along the timing when feedback was written. They show a clear temporal variation: The differential between reviews for auction and reviews for fixed price sales are much stronger in the first six days than in any other period. The same applies for the negative the price effect within auction reviews. These effects do therefore reflect the temporal pattern in the salience of reference prices from the fixed price sale. In addition, pricing-related comments within auction reviews have considerable explanatory power for the feedback differential between the sale mechanisms. Together, these results are in line with the notion that ex-post reference price shifts were, at least to a substantial degree, the triggers of customer antagonism in auctions and the negative online reviews associated with it.

With regards to alternative explanations for the observed pattern of unfavorable reviews, first note that all results remain virtually unchanged when multiple reviews from the same buyer are dropped. This speaks against the notion that antagonism originates from buyers who aimed to re-sell the vouchers and thus participated in a common-value auction. Under the reasonable assumption that it are especially such buyers who buy multiple vouchers, one would except less pronounced antagonism effects when multiple reviews are dropped. This is not observed. Likewise, one would also expect that re-sellers have more experience than other buyers. However, the results do not change when controls for the buyer's experience and standing in the marketplace are included. The invariance of the results to these controls suggests that such buyers are not driving the observed feedback patterns.

The above results reveal further insights which speak to alternative explanations. First, the temporal variations in feedback within one sales mechanism (the auction, shown in Table 2) are mirrored in the temporal variations of feedback differentials between two sales mechanisms (between the auction and the fixed-price sale, shown in Table 3). This fact is inconsistent with the notion that some sort of customer selection along an unobserved variable drives the results. If this were the case, the temporal pattern which organizes the differences *between* sales mechanism – and which is therefore caused by

such unobserved selection – should not be exactly the same temporal pattern which organizes the price effect *within* one sales mechanism (the auction), thus, when selection has already taken place.

Also note that the observed temporal patterns do not indicate a gradually decreasing effect over time. The results do rather show that right after the first six days, both the feedback differential and the price effect both sharply decrease and then stay roughly constant at a low level over the sample's remaining days. This observation is inconsistent with an alternative explanation arguing that negative emotions "cool off" over time (e.g. Bosman et al., 2001; Lee, 2013; Oechssler et al., 2017). Such an explanation would predict a gradually decreasing price-slope and feedback differentials (i.e., negative coefficients which decrease for higher-numbered interaction terms). This is, however, not observed.

The concentration of the price effect in only the first six-day-bin 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 in later periods. This finding also speaks against the notion that the negative price effect could be caused by buyers who had a negative user experience and therefore lower net utility if they paid a higher price. The price effect should then be concentrated in the period *after* the voucher had arrived, when such user experience could materialize. This is, however, the opposite of what is observed.

Overall, reference price shifts which occur ex-post, after the transaction is concluded, are the explanation which is most consistent with the observed feedback patterns. However, it is important to note that there are two aspects of such a mechanism which are not examined here: First, while the proposed reference price-channel is in line with the present findings and those by Anderson and Simester (2010), the data comes from a field setting where the seller choose its. Consequently, it is not clear whether the resulting antagonism is outcome-based and triggered by the reference price shifts alone or whether, in addition, it also requires that buyers perceive the seller to treat them (intentionally) unfairly.[16] Second, there are only 9 out of 3,575 observations where the auction price was below the fixed price. Also, there are no observations in which a fixed-price sale of the vouchers preceded the auction. Thus, the question of whether an ex-post reference price *increase*, as opposed to the decrease studied here, would trigger

[16]Not that pure payoff-based preferences against the seller do not provide an explanation. They would predict a negative price effect in all periods, not only the first six days. Also note that while there is evidence that bidder behavior in auctions is influenced by the competing bidders' payoffs (Bartling and Netzer, 2016), empirical results speak against such an effect by the seller's payoff (Bartling et al., 2017).

a perceived gain and with it, better feedback cannot be answered. However, if such a positive effect existed, a reference price explanation would suggest that it is likely be less strong than the negative one presented here. This is because perceived gains – as opposed to perceived losses – are not amplified by loss aversion.

6 Conclusion

This paper provides evidence that ex-post reference price shifts can adversely affect buyer behavior in an auction context. This manifests through unfavorable public feedback which buyers 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 the antagonized buyers were successful bidders in an auction and shaped this price themselves. As such feedback scores and ratings crucially affects transactions and the platform hosting them (see the references in Footnote 2), this study's findings have several implications:

From a marketing and pricing point of view, this paper documents an unintended consequence of pricing strategies 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 buyers 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 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). Also, sequential pricing strategies where auctions precede fixed-price sales might, at first sight, be sometimes appealing to sellers. 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.[17] This paper shows that the use of such a pricing strategies comes with the caveat of causing antagonism among those buyers who bid the most and therefore have the highest valuation for a seller's product.

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

[17] 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.

presented here show that even for a participatory sales format such as an auction, obfuscating sales strategies can, eventually, backfire.

Third, the behavior documented here also matters for market design, specifically for the sales formats offered by online market platforms and the feedback systems used by them. The aim of such feedback systems is to ensure quality and to prevent fraud by providing a reputational incentive to behave accordingly (see Dellarocas, 2003; Bolton et al., 2004; Jin and Kato, 2006; Cabral and Hortaçsu, 2010; Tadelis, 2016). If auction buyers punish the seller directly for their *perceived* losses and not actual losses, sellers have an additional reason to stop using this sales format. In addition, this paper shows evidence that a reference price shift, i.e., a purely psychological and subjective process, affects buyer feedback. If the aim of feedback systems is to measure objective quality, the present results indicate that reference price shifts can decrease the "objectiveness" and, therefore, the informational value of feedback scores.[18]

[18]eBay has tried to prevent such feedback 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).

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For Online Publication

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

Online Appendix

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

The following presents a simple model which formalizes the reasoning presented in section 4.1. The model combines reciprocal with reference-dependent preferences to explain the feedback differences between auctions and fixed-price sales and the negative effect of the auction price on feedback. It describes how a buyer ("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 buyer's rational purchase decision, subsequent changes in her reference point affect the buyer's actions.

Consider a buyer 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 buyer. In a later period $t \in \{1, 2, ...\}$ the buyer 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 (such as the seller's refusal to ship the item) or the item's quality. A buyer's valuation at the transaction date her expectation over user experience, 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 buyer 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 buyer 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 $r_0(p) \in [p, \bar{p}]$.

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 buyer's assessment of the transaction at time t is then given by the following expression:[1]

[1]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, Lange

$$A_t(\epsilon_t, r_t, v, p) = v - p + \epsilon_t + \mu \cdot \big(\max\{r_t - p + \epsilon_t, 0\} + \lambda \cdot \min\{r_t - p + \epsilon_t, 0\} \big) \tag{1}$$

buyers 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, this action is 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 buyer. 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. It is also 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).[2]

Giving feedback has both, gains and costs to buyers. 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 $x_n \in X \subset \mathbb{R}$.[3] Giving no feedback does not create any costs, i.e., $c(0) = 0$ holds. The function c is also assumed to be 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 buyer inherently rations stronger feedback. Note that c does not need to be symmetric

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 (1) 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. This would also take into account past assessments when they are evaluated at period t. However, this paper's analysis will be only interested in the effects of 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 therefore sufficient to focus on the current period t and normalize its weight to one.

[2]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 3.3 on why "neutral" feedback is considered to be unfavorable). Note that the values of the variable $f \in \{-1, 0, 1\}$ which is used to designate negative, neutral or positive feedback in the main text do not necessarily reflect the associated values of x_n.

[3]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 buyer 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 buyer's preference for giving the seller feedback which reflects her assessment relative to the costs of giving feedback.[4] Accordingly, a buyer's utility of providing feedback f_n, given her current assessment A_t, can be expressed by

$$U_t\big(x_n|\psi, A_t\big) = A_t(\epsilon_t, r_t, v, p) \cdot \big(1 + \psi x_n\big) - c\big(x_n\big). \tag{2}$$

A buyer chooses her feedback so that it maximizes the above expression. It is therefore denoted by $x_t^* \equiv \arg\max_{x_n \in X} U_t\big(x_n|\psi, A_t\big)$. buyers are assumed to be myopic regarding when to issue a non-zero feedback or, equivalently, they take current perceptions as indicative of future realizations.[5] Therefore, once $x_t^* \neq 0$ holds, buyers 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 buyers 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 buyer'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

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

[5] 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 buyer's assessment is non-negative. Conversely, case b) implies that no favorable feedback will be issued when the buyer's assessment is non-positive.[6] 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 buyer 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 in such a situation in which the buyer's assessment is negative. A higher price paid then 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 be perceived as such, a buyer's 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 buyer who bought an item did so at a price p such that $v - p + \mu\left(r_0(p) - p\right) \geq 0$ held. Similarly, in a first- or second-price auctions, a buyer's bid is always an upper ceiling on the realized price such this 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 was concluded.[7]

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

[7] This also separates this theory from typical accounts of "regret aversion" in an auction context which arise from anticipated regret, i.e. before a transaction is concluded (for an overview on the topic, see Engelbrecht-Wiggans and Katok, 2007). Of course, regret is eventually experienced ex post, when the transaction is concluded but then, its root cause is the (unexpected) shift in reference prices.

Such an ex-post change can be either due to sufficiently negative experience $e_t < 0$ or due to the downward revision of a buyer's reference price such that $r_t - p < 0$ is sufficiently low. The 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 B.1, can therefore not be caused by user experience or quality. This is also inconsistent with the finding that the difference decreases after the voucher had arrived, i.e., when user experience could materialize (see Table 3). Ex-post reference point shifts – which are different across sales mechanisms – do however provide an explanation to the feedback differences and their exact timing. The price effect as documented in Table B.2 can be explained as a consequence of negative user experience, but only as an isolated finding. However, only a reference price shift can explain this finding together i) with the above described findings on feedback differences between the sales mechanisms, ii) the fact that the price effect is also concentrated in exactly the period when reference prices were particularly salient, and iii) further evidence presented in this paper (see Table 2 and Table B.3).

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 the function $c \in \mathcal{C}^2$ 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. $\square$

Appendix B: Further data analysis and results

Table B.1. Feedback differential 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

Table B.2. 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 for both tables: Average marginal effects of Probit estimates obtained from regressing an indicator for negative or neutral feedback on a dummy for whether the review was for the auction (in Table B.1) or the difference between the auction price and the fixed price divided by 10 (in Table B.2) and dummies for the reviewing buyers' own feedback score. (The underlying model is therefore regression model (1) without the interactions and, in case of Table B.1, with a auction-dummy instead of the $\Delta_{10}Price_i$-term.) 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

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 B.3 reports marginal effects relative to the first six days, the baseline. Figure 2 in the main text depicts the implied conditional expectations from the first column of table B.3.

Table B.3. 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 & 4 use only the first review which buyer posted for the auction and report robust standard errors. Significance levels: *** p<0.01, ** p<0.05, * p<0.1

To investigate whether the feedback difference between auctions and fixed-price sales was moderated by the reviewing buyers' experiences, the following model was estimated:

$$\Pr[f_i \leq 0 \mid \mathbf{x}_i] = \Phi\Big(\alpha + \beta_1 \cdot Auction_i + \sum\nolimits_{s=1}^{3} \delta_s \cdot \mathbb{1}[Buyer's\ Score_i > 10^s \\ + \sum\nolimits_{s=1}^{3} \delta_s \cdot Auction_i \times \mathbb{1}[Buyer's\ Score_i > 10^s\Big)$$

Table B.4 below presents the corresponding marginal effects (and differences therein) one obtains when the model is estimated by Probit.

Table B.4. Differences in feedback between auction and fixed-price reviews (continued)

	(1)	(2)
Dependent variable:	$y_i = 1$: Negative or neutral feedback	
Auction	0.120***	0.117***
	(0.027)	(0.023)
Auction×Buyer's Score >10	-0.017	-0.019
	(0.029)	(0.026)
Auction×Buyer's Score >100	-0.028	-0.025
	(0.029)	(0.026)
Auction×Buyer's Score >1000	0.020	0.038
	(0.052)	(0.051)
Buyer's Score >10	-0.015**	-0.012**
	(0.006)	(0.00)
Buyer's Score >100	-0.010*	-0.008
	(0.006)	(0.006)
Buyer's Score >1000	-0.009	-0.005
	(0.012)	(0.012)
First reviews only	no	yes
Observations	18,594	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 and the interaction of these variables. Columns 1 uses all reviews and report standard errors clustered on the buyer level. Columns 2 only uses the first review each buyer posted and report robust standard errors. Significance levels: *** p<0.01, ** p<0.05, * p<0.1