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ORIGINAL ARTICLE

The value of a good reputation online: an application to art auctions

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Abstract Using a unique dataset of art auctions on eBay, we conduct an empirical analysis of the value of a seller's online reputation. Several aspects distinguish our work from most existing research. We analyze a heterogeneous panel data consisting of a large number of observations over a large period of time, including significant variation in reputation across and within sellers. The panel structure of our dataset allows us to employ fixed effects techniques to control for observed and unobserved differences across auctions. Our results point to a highly significant, and sizable, impact of a negative reputation on the behavior of market participants and on market outcomes. Negative feedback is associated with a significant reduction in the number of bidders and a reduction in the probability of sale; negative feedback is also associated with a significant reduction in sale price. Consistent with previous research, the impact of additional positive feedback on market outcomes for the seasoned sellers in our sample is not statistically significant.

keywords Art auctions · Internet markets · Reputation

1 Introduction

Tens of thousands of works of art are available for sale by auction daily on eBay. The winner of a successful auction has to pay the winning price and trust that the seller will deliver the product as agreed, at a later date. The buyer and the seller also have the opportunity to rate their level of satisfaction with the transaction (positive, neutral and negative). This information is readily available on eBay to future potential buyers. Reputation mechanisms like this one can increase the level of trust among market participants and can result in significant welfare gains (Ben-Ner and

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Putterman 2003). Resnick et al. (2000) also highlight the importance of this type of feedback mechanism in alleviating the "lemons' market" problem (Akerlof 1970) that would result if there was no clear distinction of quality across different sellers (see also Houser and Wooders 2005). Bolton et al. (2004) experimentally observe that a feedback mechanism induces substantial improvements in transaction efficiency. Brown and Morgan (2006), Li and Xiao (2010) contribute ideas to the design of a more robust feedback system.[1]

Several studies have analyzed the impact of a seller's eBay reputation on the final auction price using cross-sectional techniques. In many of these studies, a negative reputation, or negative feedback, seems to have the effect of reducing the final auction price, but there are significant differences across studies on the magnitude and significance of the effect. Cross-sectional studies rely on variation in feedback rating across auctions from many different sellers, potentially a different seller per auction, in order to identify the impact of the feedback rating on market outcomes. Thus, differences in presentation, auction design and other seller- and auction-specific characteristics that are difficult to measure, or that are part of the unobserved heterogeneity, are potentially present in these studies. In contrast, the identification strategy pursued in this paper takes advantage of within-seller's variation in feedback ratings that should be less vulnerable to bias as a result of potential correlation between observed reputation measures and unobserved sellers' specific effects.[2]

Our analysis indicates that, when unobserved seller heterogeneity is controlled for, negative feedback is associated with a significant and sizeable reduction in the auction's final price. A negative feedback is also associated with a significant reduction in the number of bidders and a reduction in the probability of sale. Consistent with previous research, the impact of additional positive feedback on market outcomes for the seasoned sellers in our sample is not statistically significant. We also consider the impact of past negative feedback on the likelihood of future negative feedback. Our results suggest that the probability of receiving a negative feedback varies across artists but that receiving a negative feedback has no significant impact on future feedback dynamics. We also observe that artists respond to a negative feedback with a significant increase in the auction's opening bid.

There is a substantial literature on the effect of positive and negative feedback on market outcomes on eBay using cross-sectional techniques. Bajari and Hortacsu (2003) find that a negative reputation has a significant negative impact on the number of bidders but does not significantly impact the final auction price. Lucking-Reiley et al. (2007) find that negative feedback has a statistically significant effect on price but that positive feedback does not. They estimate that a one percent increase in positive feedback increases sale price by only 0.03%, while a one

[1] Other relevant papers include Ben-Ner and Putterman (2003), Ba et al. (2003), Bolton and Ockenfels (2010) and Dellarocas (2002, 2007) who surveys the theoretical and empirical literature. See also Bajari and Hortacsu (2004) for a survey on Internet auctions.

[2] As a potential weakness of our approach, consider a scenario suggested by a referee in which in response to negative feedback artists systematically reduce the quality of their work in a way that is not captured by the fixed effects and control variables in our sample. This kind of behavior will bias our estimates of the impact of negative feedback on auctions' outcomes.

percent increase in negative feedback reduces the sale price by a 0.11%, a much larger effect. McDonald and Slawson (2002) report that a high reputation seller (90th percentile of eBay rating) receives a 5% higher price than a low reputation seller (10th percentile) and gets more bids. Similarly, Dewan and Hsu (2001) report that a higher net score increases the final auction price. Melnik and Alm (2002) estimate that the impact of negative feedback is significant but very small in magnitude, and the same holds for the impact of the overall rating. Eaton (2002) finds no robust statistically significant relation between negative feedback and the probability of sale and price of sold items. Ba and Pavlov (2002) using field experiments observed that willingness to pay increased with a sellers' positive feedback. Houser and Wooders (2005) estimate that a 10% increase in positive feedback increases price by 0.17% and a 10% increase in negative feedback reduces it by 0.24%, a relatively small effect. They conclude that seller's reputation has an economically and statistically significant effect on price. Livingston (2005) focuses his attention on the number of positive feedbacks rather than on the impact of a negative reputation. His analysis suggests that sellers are strongly rewarded for the first few positive feedback ratings, but additional positive feedback has a small impact. Perhaps surprisingly, when the author considers the impact of negative and neutral feedback on bidding behavior, he reports the associated coefficient to be of the same sign as that associated with positive feedback.

In our view, the findings from the current cross-sectional literature suggest that the first few positive feedback ratings matter quite a bit but matter less beyond these few initial positive feedbacks and that a negative reputation seems to have the effect of reducing the final auction price, but that there are significant differences across studies on the magnitude of this effect. Bajari and Hortacsu (2004) review the existing evidence from the cross-sectional literature and conclude: "We believe that these results are likely to significantly understate the returns from having a good reputation. Since getting positive feedback requires effort on the part of sellers, it appears that sellers are making efforts to avoid negative feedback…" Our analysis indicates that a negative eBay reputation has a significant impact on market outcomes, large enough to be consistent with their observation.

One possible reason why previous studies have not pursued a panel-data strategy may be because negative feedback is rare. The probability of a bad feedback in our data is 0.00026, and this figure is comparable with other studies (Melnik and Alm 2002; Bajari and Hortacsu 2003). Thus, to be able to conduct a panel-data analysis with sufficient variation in feedback ratings, we need data on a large sample of auctions, from a relatively large number of sellers, over a large period of time. In this paper, we consider auctions posted over a period of 4 months in 2001 and again in 2004. We analyze a panel dataset of 4,514 art auctions from 42 different artists who post their own work for sale on eBay regularly, and this represents about ten times as many observations as are common in the cross-sectional literature in this area. Our data include significant variation in reputation across and within sellers, as well as significant variation in other relevant characteristics, such as style (e.g., abstract, cubist), medium (e.g., acrylic, oil), ground (e.g., stretch canvas, cardboard) and size.

The paper proceeds as follows. In Sect. 2, we analyze research findings from papers closely related to our analysis. In Sect. 3, we describe the data to be used in the paper. In Sect. 4, we present the empirical analysis and describe results. Section 5 concludes.

2 Related literature

Similar to our study, Cabral and Hortacsu (2005) use panel data to analyze the impact of eBay's reputation rating. Their paper considers data on homogeneous goods, and for the most part, the focus is on market outcomes other than the ones considered in this paper. In particular, they consider the impact of feedback on sales growth, the frequency of future negative feedback and sellers' exit from the market. They also find that negative feedback has a significant and sizeable effect on market outcomes. Unlike Cabral and Hortacsu (2005), we consider the impact of a seller's feedback on the opening bid, the number of bidders, the probability of sale and the final sale price. Like Cabral and Hortacsu (2005), we also analyze the impact of a negative feedback on feedback dynamics; our analysis contributes to a better understanding of the feedback dynamics process.

Resnick et al. (2006) overcome some of the potential omitted variables problems in the cross-sectional literature by means of randomized controlled field experiments. In particular, they study the effect of reputation on the sale price of vintage postcards and consider two different experimental designs. In their primary experiment, a highly experienced seller posts matched pairs of auction lots under his real identity and under newly created sellers' identities. This design allows the researchers the opportunity to measure the effect of positive feedback on auction outcomes. They observe that the market rewards the seller who has accumulated a large number of positive feedbacks. In particular, they find that buyers are willing to pay 8.1% more for lots sold by the seller who has accumulated a large number of positive feedbacks when compared with newly created sellers' identities. In a second experiment, the researchers compared results for new sellers with one or two negative feedbacks with results for new sellers without negative feedback. The researchers employ fictitious buyers with zero feedback of their own to assign negative feedback to their fictitious sellers along with a negative comment of the form 'item's condition was worse than described' or 'item not as described.' The fictitious sellers considered in this experiment had between 5 and 17 feedbacks. In this second experiment, the researchers find no impact of negative feedback.

The experimental approach considered by Resnick et al. contributes significantly to a better understanding of the impact of feedbacks on market outcomes but has its own limitations. As the authors indicate, they cannot rule out that the measured differences in willingness to pay observed in the first experiment may be due to the effect of repeated interactions of the high reputation seller with specific buyers rather than the effect of the public reputation embodied in the sellers' feedback. Several factors may also contribute to the lack of negative feedback effect found in the second experiment. The researchers point to the small sample size as a potential problem. It is also possible that the negative comment posted by the fictitious buyer (i.e., the authors themselves) was not sufficiently informative. Furthermore, the fictitious buyers had zero feedback at the time of posting the negative feedback. Potential buyers may discount negative feedback from buyers with zero feedback of their own (i.e., the market may treat these buyers as inexperienced and untrustworthy), and they may also discount the two negative feedbacks because they were both posted within a minute of each other. The authors refer to these aspects of the experimental design as experimenter's error. Another possible explanation suggested by the authors is that the market treats new sellers as untrustworthy but does not distinguish among feedback profiles of new sellers. These remarks highlight the possibility of a potential impact of the experimental design on the market outcomes and on some of the final conclusions of the study.

Unlike Resnick et al., we observe that negative feedback has a significant negative effect on market outcomes. The fact that all the sellers in our sample have an established reputation may contribute to explain the observed differential impact of negative feedback. Also, unlike Resnick et al., the negative feedback ratings in our sample are generated from the natural market exchange process rather than being part of the experimental design, and for that reason, they are not subject to potential experimental design error and are representative of the feedback process in this market. Certainly, both econometric modeling and experimental analysis have limitations; we view both approaches as complementary.

3 Data and descriptive analysis

An auction on eBay includes a description of the item being auctioned, including pictures. When posting a new auction, sellers can choose several auction characteristics (e.g., the opening bid). Buyers can browse through thousands of auctions posted every day. Auctions are organized by categories and subcategories, which simplifies the buyer's search. Buyers can also use a powerful search engine and are also able to request additional information about an auction from the seller anonymously via e-mail. Potential buyers can participate in an active auction at any time over the duration of the auction. The highest bidder at the end of the auction wins the item at a price equal to the second highest bid.

3.1 The data

Between July and November of 2001 and again between August and December of 2004, we collected data on all auctions from a group of "self-representing" artists. This group is composed of artists who sell their own artwork through eBay, without representation. Paintings are the most popular form of artwork, but other forms of artwork, like collages, ceramic tiles or sculptures, are also common. In our analysis, we use data on original paintings only. The sample includes 42 artists chosen from a group of artists who posted at least 25 paintings for sale in 2001 and who continued to sell on eBay until the end of 2004. The dataset employed in our analysis includes 4,514 auctions, with 2,245 auctions from 2001 and 2269 auctions from 2004. The data included auctions posted between mid-July and mid-November 2001 and between mid-August and mid-December 2004.

For each auction, we collected four different kinds of information: object-specific characteristics, other auction characteristics, bidding history and artist reputation. Characteristics specific to the object being auctioned include information on the height, width, style (abstract, pop, whimsical, etc.), medium (acrylic, oil, etc.) and ground (stretch canvas, paper, wood, etc.). Other auction characteristics include the opening bid, the shipping and handling fees, availability of a variety of payment methods, the final number of bidders and the selling price. Most artists accept a variety of payment methods including credit cards and other forms of online payment. Six sellers in our sample accepted only checks or money orders initially, although by 2004 all the artists accepted credit cards and other forms of online payment.

For several years now, eBay has been using a simple form of advertising, or as they call it, "Featured Plus!" (FP). This type of advertising works as follows: at the time of listing the item on eBay, sellers are given the option of incurring an extra fee in return for having their product listed first when buyers search for specific items, or when buyers browse a specific category, like "art/paintings/abstract" . This type of advertising is not cheap; the cost is $19.99 per auction or about 40% of the average sale price of a standard auction. In our data, we also record the FP status of an auction and take it into account when we conduct the econometric analysis.

At the end of each market transaction, the buyer and the seller in each particular auction have a chance to rate their level of satisfaction with the transaction (positive, neutral and negative). We collect data on the type of feedback received by the seller in all previous transactions, which is readily available from eBay. We use these data to define several measures of feedback history: one represents the number of unique buyers prior to the current auction, which could be interpreted as a measure of the artist's customer base on eBay, another one measures the number of negative feedback ratings received, and a third one represents the feedback rating as reported on eBay, which is equal to the number of positive feedbacks divided by the number of positive and negative feedbacks from unique users; neutral feedback does not count. Each of these variables can be interpreted by potential buyers as measures of a seller's reputation.

In addition to quantitative reputation measures, eBay also offers users the opportunity to comment on their level of satisfaction with a particular transaction. Recent research by Xiao and Houser (2005) highlights the importance of written feedback in promoting the efficiency of online auctions (see also Masclet et al. 2003). I reviewed the comments associated with all the negative feedback received by the sellers in the dataset; this includes all feedbacks received by the artist until January 2005. This review indicated that all the negative feedbacks received by the artists in my sample relate to problems with the shipping process and none of the negative feedbacks relates to the quality of the product being sold. Examples of negative feedback include "No accurate address to send payment to and will not respond to emails" or "No response from seller unable to complete transaction". Positive feedback usually complements specific aspects of the artwork. Examples of this type of feedback are "original and beautiful work", "Charming painting well packed! Professional. Thank you A++++". As a referee pointed out, these messages may convey relevant information that goes beyond the feedback rating. However, it is inherently difficult to quantify this information, and for this reason, we follow the same approach as other researchers in the related literature and treat feedback as a purely quantitative variable.

Several characteristics of these data make them unique. First, the data collected comprise all eBay transactions for a specific group of sellers for a long period of time, while the data collected by other researchers usually represent only a narrow snapshot of market activity from a cross-section of sellers. Second, by nature, the intrinsic value of artwork is uncertain, especially in the case of less well-known artists. In contrast, much of the data collected by other researchers refer to homogeneous items or items whose market value can be determined with accuracy, like coins or stamps, which lessens the value of auctions as a selling, price-finding mechanism. Third, the panel structure of our data allows us to control for combinations of sellers' fixed effects and other forms of fixed effects, like medium, ground and Feature Plus! status. In contrast, most of the existing econometric research has been conducted using cross-sectional analysis, the exception being Cabral and Hortacsu (2005).

3.2 Descriptive statistics

We report sample descriptive statistics in Tables 1, 2. In Table 1, we divide auctions by year and according to their "Feature Plus!" status. FP auctions are significantly different from other auctions. In particular, the average size of a FP painting is more than twice that of a painting in a standard auction. Canals-Cerda (2006) shows that FP status has a significant impact on auction outcomes, including the number of bidders, the sale probability and the final sale price. This impact is also reflected in Table 1. In our empirical analysis, we control for FP status as part of our fixed effects strategy, and this allows us to compare paintings from the same artist with similar characteristics and with the same FP status.

Bid values in Table 1 are measured in real 2004 dollars. The sale price of paintings ranges from as little as \$0.01 to as much as \$1441.41. The average probability of sale for standard auctions is 62% in 2001 and 48% in 2004, or 95 and 87%, respectively, for FP auctions. The average selling price is about \$48 for the first group of auctions and \$224 for the second group. Differences in the sale price between both groups of auctions are partly due to differences in the characteristics of objects being auctioned, like size, medium or ground. There are also significant differences in the number of bidders and bids received. FP auctions with at least one bidder receive bids from more than five bidders on average, or more than double the number of bidders in standard auctions.

Table 2 presents detailed information about the range of variation of several measures of reputation available in our sample. Like eBay, we only count unique buyers. That is, only the first positive feedback from a buyer counts, and only the first negative feedback counts. The variables listed include the eBay rating and the overall number of feedback ratings from unique buyers divided by category: positive, negative and neutral. As with existing research, negative feedbacks are rare

Table 1 Descriptive statistics for auction specific characteristics

	2001				2004			
	Mean	SD	Min.	Max.	Mean	SD	Min.	Max.
Standard auctions								
Open bid	33.88	31.75	0.01	436.75	47.81	65.94	3	595.55
Sale price**	46.11	45.25	2.23	426.02	49.80	58.01	3.01	595.55
# Square feet	2.06	2.34	0.01	20.25	1.95	2.40	0.02	24
# Bidders*	2.56	1.82	1	13	2.35	1.62	1	10
# Bids*	4.25	4.20	1	38	3.75	4.11	1	29
# Auctions	2,226				1,758			
% Sold	0.620				0.484			
Feature Plus! auctions								
Open bid	40.92	51.96	0.01	235.10	69.92	75.48	6.6	595.55
Sale price**	225.00	159.82	40.08	697.62	222.91	132.05	21.10	1441.41
# Square feet	5.69	3.43	0.29	12	5.40	3.09	0.44	24
# Bidders*	6.28	3.41	1	14	5.26	2.71	1	17
# Bids*	15.44	13.03	1	52	12.27	8.22	1	47
Auctions	19				511			
% Sold	0.947				0.873			

* For auctions with at least one bidder

** For sold auctions

in our sample. In particular, the average eBay rating across auctions is 99.9% in 2001 and 99.78% in 2004. About 87% of auctions in 2001 and about 52% of auctions in 2004 are associated with a zero negative feedback rating. The maximum number of negative feedbacks for an artist in our sample is eight. In 2001, 36 artists have a perfect eBay rating in our sample, and 27 have a perfect rating in 2004. The lowest eBay rating is 98.04 in 2001 and 94.32 in 2004. Most of the artists in our sample have ample experience selling on eBay. The average number of unique feedback responses in 2004 is 512. The feedback history for the artists in our sample was constructed from the overall feedback history received by January 2005. These data overlap with our auctions' data. The total feedback received by the artists in our sample was 30,305, including 50 negative and 55 neutral. Thus, the average frequency of a negative feedback is 0.16%. The total feedback received from unique buyers was 17,844, including 39 negative and 55 neutral, and the average frequency of negative feedback from a unique buyer is 0.22%.

4 Empirical models and estimation results

In this section, we analyze the impact of the feedback history on several outcomes of interest, including the probability of sale, the number of bidders and the second highest bid, as well as the likelihood of future negative feedbacks and the artists'

Table 2 Feedback information

Auctions	2001				2004			
	Mean	SD	Min.	Max.	Mean	SD	Min.	Max.
Ebay rating	99.90	0.307	98.04	100	99.78	0.342	94.32	100
Positive	137.33	120.74	0	576	508.85	260.78	39	1650
Negative	0.234	0.676	0	4	1.39	2.06	0	8
Neutral	0.164	0.427	0	2	2.14	2.40	0	9
Auctions by # of negative feedback								
Negative feedback	0	1	2	4	0	1 or 2	3 or 5	7 or 8
Frequency	1946	128	143	28	1189	669	278	133
% Frequency	86.68	5.70	6.37	1.25	52.40	29.48	12.26	5.86
Artists								
Max. negative #	0	1	2	4	0	1	2.3	5.8
Frequency	36	4	1	1	27	7	2.3	2,1
% Frequency	0.86	0.10	0.02	0.02	0.64	0.17	0.12	0.07

Feedback	Overall	Positive	Negative	Neutral
All feedbacks	30,305	30,199	50	55
% Frequency	100	99.65	0.165	0.181
Unique buyers	17,827	17,733	39	55
% Frequency	100	99.47	0.219	0.309

response to negative feedback. The type of eBay auctions that we consider are ascending-bid, second-price, auctions subject to some specific rules. The seller of the object being auctioned sets the opening bid, s_0. Bids are submitted electronically. New bids arrive sequentially at any time during the length of the auction. The price of the auction at any point in time is set at the current second highest bid, which based on auction theory should equal the second highest bidder's maximum willingness to pay. The number of active bidders at any point during the auction is public information. Any new bid has to surpass the current second highest bid by a minimum increment in order to be recorded.[3]

Given the heterogeneous nature of the data employed in our analysis, we divide the data into groups along several different dimensions: artist, medium, ground and Feature Plus! status. More precisely, all paintings from a particular artist, using a particular medium (e.g., oil), on a particular ground (e.g., canvas), and for a specific Feature Plus! status will be assigned to a specific fixed effect group. These data segmentation skim along with the use of fixed effects (FE) techniques allow us to identify the average effect of explanatory variables (e.g., measures of feedback) from variation in the data within relatively homogeneous groups, after controlling for FE differences across groups.

[3] In eBay, the value of the minimum increment varies with s_0. The minimum increment is \$0.05 for bids under \$1.00 dollar and increases up to \$100.00 for bids above \$5000.00.

Table 3 FE Log-linear regression models for the number of bidders

	Model 1		Model 2		Model 3		Model 4	
	Coef.	*T*-val	Coef.	*T*-val	Coef.	*T*-val	Coef.	*T*-val
Feedback								
# Neg. feedback	−0.0912	−5.51	−0.0272	−3.11				
# Fbk//100	0.0000	0.00	0.0550	9.06	−0.0137	−0.95	0.0539	9.60
SD eBay Fbk.					0.1418	4.02	0.0915	8.03
Dimension								
Square-Feet	0.0162	1.57	0.0474	4.60	0.0180	1.74	0.0493	4.82
Square-Feet^2	−0.0005	−0.81	−0.0021	−3.40	−0.0005	−0.90	−0.0022	−3.60
Others								
Shipping cost	−0.0016	−1.05	−0.0079	−5.59	−0.0017	−1.12	−0.0078	−5.53
M. payment	0.1522	1.31	−0.2976	−3.66	0.2226	1.90	−0.4274	−5.19
Style	Yes		Yes		Yes		Yes	
Year and month	Yes		Yes		Yes		Yes	
Artist F.E.	Yes		No		Yes		No	
R-sq	0.5519		0.3227		0.5504		0.3310	
# Obs.	4,514		4,514		4,514		4,514	

Fixed effects include control for artist specific effects, medium, ground and Feature Plus! Status. eBay feedback has been standardized. Models that do not include artist specific fixed effects still include other types of fixed effects

All econometric models considered share a common structure. The endogenous outcome of interest, y_{ij} associated with auction i from group j is represented as a function of four components: measures of an artist's feedback rating, Z_{ij}, observed exogenous explanatory variables, X_{ij}, a group-specific fixed effect, δ_j, representing group-specific unobserved heterogeneity, and a residual component, ε_{ij}, representing other sources of random variation unobserved by the econometrician. Analytically, we consider models of the form

$$y_{ij} = \beta_0 + \delta_j + \gamma Z_{ij} + \beta X_{ij} + \varepsilon_{ij} \tag{1}$$

that are estimated using group-specific fixed effect (FE) techniques appropriate for each specification.[4] The results from our econometric analysis are presented in Tables 2, 3, 4, 5, 6 and are discussed in the next subsections.

4.1 Buyers' response to an increase in a seller's negative feedback rate

In this subsection, we analyze the impact of an increase in an artist's negative feedback rating on the behavior of bidders. In particular, we consider the impact on the number of bidders, the probability of sale and the second highest bid—and indirectly on prices. Overall, we observe that the response of bidders to an increase

[4] Style is included in X_{ij} rather than in the group FE definition because, by eBay's policy, each auction can be associated with up to three different styles, and, as a result, we have a very large number of possible style combinations.

Table 4 Conditional logit models for the sale probability

	Model 1		Model 2		Model 3		Model 4	
	Coef.	*T*-val	Coef.	*T*-val	Coef.	*T*-val	Coef.	*T*-val
Feedback								
# Neg. feedback	0.8471	−1.56	0.9016	−3.05				
# Fbk//100	0.9366	−0.90	1.1346	5.20	0.9238	−1.11	1.1362	5.70
Std. eBay Fbk.					1.3578	1.78	1.5002	8.32
Dimension								
Square-feet	0.9239	−1.58	1.0278	0.72	0.9288	−1.48	1.0297	0.76
Square-feet^2	1.0042	1.46	0.9991	−0.38	1.0040	1.39	0.9990	−0.42
Other								
Shipping cost	0.9977	−0.33	0.9831	−3.09	0.9975	−0.35	0.9838	−2.98
M. payment	1.3780	0.30	0.4848	−2.23	1.5012	0.37	0.2048	−3.87
Style	Yes		Yes		Yes		Yes	
Year and month	Yes		Yes		Yes		Yes	
Artist F.E.	Yes		No		Yes		No	
LLF	−1923.11		−2582.85		−1922.84		−2549.24	
# Obs.	4,514		4,514		4,514		4,514	

Fixed effects include control for artist specific effects, medium, ground and Feature Plus! Status. eBay feedback has been standardized. Models that do not include artist specific fixed effects still include other types of fixed effects. Coefficient parameters are reported as odds ratios

in an artist's negative feedback rating is large in magnitude, has the expected sign and is statistically significant in most cases. We investigate the significance of specific econometric model assumptions on results and highlight the importance of controlling for sellers' specific fixed effects.

4.1.1 The impact of feedback on the number of bidders and the sale probability

The arrival of potential bidders to an auction is a complex function of artist and artwork characteristics, opening bid, bidders' arrival process and bidders' bidding behavior. A structural analysis of this process has been conducted in Canals-Cerda and Pearcy (2005) and is not the objective of this study. In Table 3, we present results from log-linear regression models of the number of bidders, plus one, as a function of characteristics of the artwork being auctioned and artist feedback measures. The table presents results for models estimated using a fixed effects strategy to control for artist-, medium- and ground-specific effects, as well as Feature Plus! status, and these results are presented as models one and three. Also, for the purpose of analyzing the impact of artists' specific fixed effects, the table also presents results for the same model specifications without including artists' fixed effects, and these results are presented as models two and four. All estimated models have significant explanatory power, as indicated by R-square values around 0.55 for models with artists' fixed effects, and R-square values around 0.33 for models that do not control for artists' fixed effects. Looking at the models with

Table 5 Honore's FE models for the log-second highest bid

	Model 1		Model 2		Model 3		Model 4	
	Coef.	*T*-val	Coef.	*T*-val	Coef.	*T*-val	Coef.	*T*-val
Feedback								
# Neg. feedback	−0.0475	2.12	0.0220	1.29				
# Fbk//100	−0.0062	0.25	0.0426	4.10	−0.0071	0.28	0.0487	5.19
Std. eBay Fbk.					0.1542	1.61	0.0143	0.61
Dimension								
Square-feet	0.1507	6.34	0.2099	10.87	0.1515	6.30	0.2097	10.90
Square-feet^2	−0.0046	1.81	−0.0088	5.56	−0.0046	1.82	−0.0088	5.64
Other								
Shipping cost	0.0229	4.45	0.0065	2.23	0.0229	4.30	0.0067	2.30
M. payment	0.4568	2.05	0.5741	4.50	0.5206	2.28	0.5743	4.57
Style	Yes		Yes		Yes		Yes	
Year and month	Yes		Yes		Yes		Yes	
Artist F.E.	Yes		No		Yes		No	
LLF	−22,138		−171,881		−22,149		−172,071	
# Obs.	4,514		4,514		4,514		4,514	

Fixed effects include control for artist specific effects, medium, ground and Feature Plus! Status. eBay feedback has been standardized. Models that do not include artist specific fixed effects still include other types of fixed effects

Table 6 The dynamics of negative feedback

	Logit models				Conditional logit models			
	Model 1		Model 2		Model 3		Model 4	
	Coef.	T-val	Coef.	T-val	Coef.	T-val	Coef.	T-val
# Neg. feedback	1.4127	4.65	1.3993	4.58	1.0587	0.50	1.0835	0.62
# feedbks/100			0.9192	−1.57			1.0818	0.36
Artist F.E.	No		No		Yes		Yes	
Pseudo *R*-sq	0.0274		0.0294		0.0099		0.0099	
# Obs.	17,827		17,827		17,827		17,827	

Fixed effects include control for artist specific effects. eBay feedback has been standardized. Coefficient parameters are reported as odds ratios

artists' fixed effects, we observe that size is not an important determinant of number of bidders. The overall number of feedback responses received does not have a significant effect either. In contrast, from model one, we observe that the average effect of an additional negative feedback is a 9% reduction in the number of bidders, and the effect is highly significant. We observe similar results in model three when we use the standardized eBay feedback measure instead. In that case, an increase in eBay's feedback increases the number of bidders significantly; in particular, a one-unit increase in this reputation measure increases the number of bidders by 14%.

The results are substantially different in models two and four that do not control for fixed effects. In particular, the impact of reputation is significantly reduced, from 9% in model one to 2.7% in model two and from 14% in model three to 9% in model four, while the impact of other characteristics is significantly enhanced.

In Table 4, we present results from fixed effects conditional logit models for the probability of sale. For ease of interpretation, the impact of explanatory variables is reported as odd ratios, which are independent of any specific value of the explanatory variables in the logit family, and t-values are also reported accordingly.[5] Looking at model one, with artists' fixed effects, the results suggest that an increase in size reduces the odds of sale, although the effect is not significant at the usual significance rate. An increase in negative feedback results in a reduction in the odds of sale of about fifteen percent, per negative feedback, but again this impact is not significant. The results for model three, using the standardized eBay feedback measure instead, accept a similar interpretation. That is, an increase in eBay feedback increases the odds of sale accordingly, but the effect is again insignificant. Interestingly, the effects of negative feedback are significant for the models that do not include controls for artists' specific fixed effects. One possible interpretation of this result is that the models that control for artists specific fixed effects are in some form explaining away useful identifying variation. Alternatively, one can also entertain the possibility that the result is biased due to the lack of controls for artists' specific fixed effects.

4.1.2 *The impact on the second highest bid*

As indicated in Sect. 3, the final auction price is the result of a combination of sellers and buyers' choices. However, we can measure the impact of sellers' feedback on buyers' willingness to pay by concentrating our attention on the second highest bid. The second highest bid is only observed in auctions with two or more bidders. Otherwise, the opening bid, for auctions with a single bidder or with no bidders, represents an upper bound to the second highest bid. Thus, it is appropriate in this framework to employ censored regression techniques to analyze the impact of a seller's feedback on the final auction price. Formally, consistent with Eq. (1), consider a log-linear specification for the second highest bid, where the second highest bid, $\bar{v}_{ij}$, is observed when $\bar{v}_{ij} \geq s_{0,it}$, with $s_{0,ij}$ representing the opening bid. Thus, consider $y_{it} = \ln \bar{v}_{ij}$ and $c_{it} = \ln s_{0,it}$ representing the censoring threshold. We observe $\mathrm{Max}(y_{it}, c_{it})$, or after a transformation, $y^*_{it} = y_{it} - c_{it} = \beta_0 + \delta_j - c_{it} + \gamma Z_{ij} + \beta X_{ij} + \varepsilon_{ij}$, the equivalent expression $\mathrm{Max}(y^*_{it}, 0)$. We estimate these fixed effects censored regression models using semiparametric estimation techniques developed in Honore (1992) and surveyed in Arellano and Honore (2001) and use

[5] Given $\mathrm{Odds}(x)$ representing the ratio of the probability of outcome one over the probability of outcome zero, it can be easily shown that $\mathrm{Odds}(x_{-i}, x_i + 1)/\mathrm{Odds}(x) = \exp(\beta_i)$, with this ratio representing the change in odds of sale as a result of a unit increase in x_i. When results are reported as odds ratio, the t value corresponds to the null hypothesis of odds ratio equal to one, or no change in odds.

the bootstrap method with 100 repetitions to generate t values.[6] The basic idea of the estimation technique is to "define pairs of 'residuals' that depend on the individual specific effect in exactly the same way. Intuitively, this implies that differencing the residuals will eliminate the fixed effects" (Arellano and Honore 2001). A detailed description of the approach can be found in these references.

Estimation results are presented in Table 5. Looking across model specifications, we observe that size is a significant determinant of value. In particular, for models with artists' specific fixed effects, a one square foot increase in size is associated with a 15% increase in the second highest bid, and this effect is statistically significant. A one-unit increase in negative feedback is associated with an average loss in value of 4.7%, in the model that controls for artists' fixed effects, or with a gain of 2.2% in the model that does not control for artists' fixed effects, but the effect is only significant in the first case. The impact of the eBay feedback is analyzed in models three and four, and the associated coefficient in this case has the expected positive sigh and is large in magnitude when artists' specific fixed effects are included. A one standard deviation increase in eBay reputation results in an average gain in value of 15%, although the effect is not statistically significant. With regard to this result, observe that two sellers with the same number of negative feedback will have different eBay feedback ratings unless their overall number of feedback is the same. Thus, one possible interpretation of the non-significant result is that the standardized eBay feedback rating represents a noisy measure of reputation and as such the associated impact is not estimated accurately. In contrast with this last result, in the model without artists' specific fixed effects, the estimated gain from an increase in eBay reputation is practically negligible.

Thus, the reputation effects estimated in models that do not include artists' specific fixed effects are at odds with any sensible interpretation of how a feedback mechanism should work and are also at odds with our findings from the models that control for artists' fixed effects, but are consistent with some reported results in the cross-sectional literature (Livingston 2005; Table 7). We can only speculate as to how unobserved seller effects may lead to biased results in model specifications that do not take into account artists' fixed effects. One referee suggested that the number of negative feedback is often strongly positively correlated with the number of positive ratings, making it difficult to disentangle the effects of positive and negative ratings in cross-sectional studies; a similar argument was presented in Resnick et al. (2006). It may also be the case that low-quality sellers may be more prone to leave the eBay marketplace when they receive a negative feedback. This could lead to a positive correlation between unobserved seller characteristics that contribute positively to higher prices and a negative feedback rating. A version of this second argument can be found in Brown and Morgan (2006) who suggest that the feedback mechanism imposes significant switching costs to good-quality sellers for transferring to a competing market or for changing their online identity.[7] Alternatively, it may also be the case than artists that produce high-quality artwork

[6] We use the same approach described in Stata manual v.9 "bootstrap—Bootstrap sampling and estimation".

[7] This account is also consistent with results in Cabral and Hortacsu (2005).

Table 7 FE Log-linear regression models for the opening bid

	Model 1		Model 2		Model 3		Model 4	
	Coef.	*T*-val	Coef.	*T*-val	Coef.	*T*-val	Coef.	*T*-val
Feedback								
# Neg. feedback	0.2143	13.69	0.0343	3.75				
# Feedbks/100	−0.0084	−0.60	−0.067	−10.54	0.0279	2.03	−0.061	−10.29
Std. eBay Fbk.					−0.227	−6.70	−0.045	−3.76
Dimension								
Square-feet	0.1963	20.11	0.1520	14.09	0.1929	19.44	0.1509	13.99
Square-feet^2	−0.007	−12.9	−0.005	−7.75	−0.007	−12.54	−0.005	−7.61
Other								
Shipping cost	0.0172	12.14	0.0237	16.00	0.0173	11.99	0.0238	16.02
M. payment	0.6718	6.12	1.2225	14.35	0.5571	4.94	1.2888	14.85
Style	Yes		Yes		Yes		Yes	
Year and month	Yes		Yes		Yes		Yes	
Artist F.E.	Yes		No		Yes		No	
R-sq	0.7327		0.5048		0.7237		0.5048	
# Obs.	4,514		4,514		4,14		4,514	

Fixed effects include control for artist specific effects, medium, ground and Feature Plus! Status. eBay feedback has been standardized. Models that do not include artist specific fixed effects still include other types of fixed effects

may be less concerned with other aspects of online transactions that may nevertheless be valued by buyers, like good packaging and prompt delivery, and this can also generate a positive correlation between unobserved seller characteristics that contribute positively to prices and a negative feedback rating. This last scenario is consistent with the type of confounding unobserved seller-specific heterogeneity that Resnick et al. (2006) and other authors have in mind when they refer to omitted variable bias.

4.2 Feedback dynamics

Our objective in this subsection is to ascertain the impact of past negative feedback on the likelihood of future negative feedback. Understanding how feedback is generated can help us better understand the impact of negative feedback on market outcomes.

In order to analyze feedback dynamics in our data, we estimate logit models with controls for lagged feedback and past sales, as well as conditional logit models to account for artists' fixed effects. The models are estimated using feedback data from unique buyers (this includes the first positive, negative and neutral feedback received from a buyer, when applicable), which are the exact same data used by eBay to generate its feedback ratings. The effect of past negative feedback on future feedback is identified from variation in feedback histories over the 17,827 feedback events from unique buyers in the logit model, and from within-artists' variation in feedback histories in the conditional logit model.

Estimation results are presented in Table 6, with coefficient parameters reported as odd ratios as in prior tables. Negative feedback is rare and, as a result, difficult to predict. Thus, it is not surprising to observe very small R-square values associated with all models. Interestingly, the estimated coefficients from simple logit models and fixed effects conditional logit models lead to different interpretations. Estimation results from the logit model suggest that an additional negative feedback increases the odds of receiving negative feedback from a future sale by 41%, although this probability is still very small. This measured effect is highly significant. In contrast, estimation results from conditional logit models suggest that a one-unit increase in the number of negative feedbacks has an insignificant effect on the odds of receiving a negative feedback in a future sale. Thus, the effect disappears once we control for artists' specific fixed effects in a conditional logit framework.

As was pointed out by a referee, negative feedback is very rare and there is little variation in the number of negative feedbacks from observation to observation. Thus, we should be cautions not to draw any definitive conclusion from these results.[8] With this caveat, we interpret these results as being consistent with a scenario in which some artists have a higher latent probability of receiving a negative feedback than others, irrespective of their feedback rating, but receiving a negative feedback at a particular point plays no significant role in the future feedback dynamics process.

4.3 Artists' response to negative feedback

In this subsection, we consider the impact of feedback on the auctions' opening bid set by the artist. We always observe the auction's opening bid, irrespective of the final outcome. Thus, we can analyze this variable by means of simple panel-data linear regression techniques. In Table 7, we present estimation results from several log-linear regression model specifications of the minimum acceptable opening bid, which is set by the artist, as a function of feedback history and other characteristics specific to the artwork being auctioned. All estimated models have significant explanatory power, as indicated by their R-square values. The size of the artwork and the availability of multiple forms of payment are important determinant of the open bid.[9] Looking at the results from the models that control for artists' fixed effects, we observe that the overall number of feedback responses received does not have a significant effect on the opening bid, while the number of negative feedback responses received is associated with a significant increase in the opening bid.

The results from these models suggest that a one-unit increase in negative feedback increases the minimum opening bid by about 21%, other things the same.

[8] Cabral and Hortacsu (2005) consider several models of buyers and sellers' behavior and find that it is not easy to empirically distinguish between theories.

[9] We should be careful not to give a general interpretation to the "multiple forms of payment" effect as there are only a few artists in our sample that do not offer multiple forms of payment across all the auctions.

This result is highly significant. Similar results are observed when we use a standardized eBay feedback measure instead of the number of negative feedbacks. In this case, a higher eBay feedback value decreases the opening bid significantly, which is consistent with the previous result. One possible interpretation of this finding is that it measures the response of the artist to an anticipated or perceived decrease in the number of potential bidders. How can this be the case? As we have shown, receiving a negative feedback results in a decrease in the arrival of bidders. As a result, the likelihood of attracting a single bidder in an auction increases with respect to the probability of attracting more than one bidder. Thus, in auctions with a single bidder, the artist may extract higher rents from the buyer if the opening bid is higher, as long as it is not higher than the buyer's maximum willingness to pay. For comparison purposes, we also consider models that do not include artists' fixed effects and observe a significant reduction in the magnitude of the coefficients associated with different measures of reputation.

5 Conclusions

Most existing studies of the impact of reputation on market outcomes on eBay have been conducted using cross-sectional statistical techniques and have produced a range of different results. In our view, the current cross-sectional literature suggests that the first few positive feedback ratings on eBay matter quite a bit but matter less beyond these few initial positive feedbacks and that a negative reputation seems to have the effect of reducing the final auction price, although there are significant differences across studies on the magnitude of this effect.

Taking advantage of a unique dataset of art auctions on eBay, we use panel-data techniques and within-seller's variation over time in reputation measures to identify the impact of reputation on market outcomes. Consistent with the evidence from cross-sectional studies, the impact of additional positive feedback on the seasoned sellers in our sample has no significant effect on market outcomes. Furthermore, our results point to a large and statistically significant impact of negative feedback on the behavior of buyers and sellers and on market outcomes. We observe that an increase in an artist's negative feedback rating has the expected effect, is large in magnitude and is statistically significant in most cases. In particular, an additional negative feedback results in a 9% reduction in the number of bidders on average, and the effect is highly significant. A one-unit increase in negative feedback is associated with a 4.7% average reduction in value, when we control for artists' fixed effects, or with a 2.2% gain in value when we do not control for artists' fixed effects, but the effect is only significant in the first case. Also, a one-unit increase in negative feedback has an insignificant effect on the odds of receiving a negative feedback in the future. After receiving a negative feedback, artists in our sample significantly increase the opening bid in future auctions. A one-unit increase in negative feedback increases the minimum opening bid by about 21%. For comparison purposes, we also consider models that do not include artists' fixed effects and observe a significant reduction in the magnitude of the coefficients associated with different measures of reputation or even a change in the sign of the coefficient as indicated above. Thus, including controls for artists' specific fixed effects has a significant impact in the magnitude and interpretation of the effect of negative feedback on this market. Overall, we interpret our results as evidence that the feedback rating has a significant impact on market outcomes.

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