Does herding undermine the trust enhancing effect of reputation? An empirical investigation with online-auction data

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Word count: 11143

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Abstract

In today's online markets, the reputation mechanism undergoes its most successful propagation in human history. Online reputation systems substitute informal sanctioning mechanisms at work in close-knit groups and enable complete strangers to trade with each other across large geographic distances. The organizational features of online markets support actors in solving three problems that hamper mutually beneficial market exchange: the value, competition and cooperation problems. However, due to the plethora of trading opportunities available online, actors face a problem of excess, i.e. the difficulty of choosing a trading partner. Imitation of other actors' choices of trading partners (i.e. herding) can solve the problem of excess, but at the same time lead to the neglect of information about these trading partners' trustworthiness. Using a large set of online-auction data ($N \approx 88$k), we investigate whether herding as a strategy for solving the problem of excess undermines the reputation mechanism in solving the cooperation problem. Our analysis shows that although buyers follow others in their decisions of which offers to consider, they do not follow others at any price and refer to sellers' reputations to establish seller trustworthiness. Our results corroborate that reputation systems are viable organizational features that promote mutually beneficial exchanges in anonymous online markets.

Keywords: online markets, cooperation, reputation, trust, herding, excess

1. Introduction

Economic exchange is often embedded in actors' social networks through which information about these actors' deeds and misdeeds is transmitted and selective incentives upheld (Granovetter 1992). In close-knit communities, being a trustworthy and reliable exchange partner is in one's best interest (Hardin 2002); actors are readily informed about each other's past behaviour and sanctions are more effective as they also bear on these actors' other social relations (Buskens and Raub 2013; Giardini and Wittek 2019; Weber [1920] 2002). With economic exchange taking place across longer geographical distances, the mechanisms promoting trust and cooperation in close-knit communities (Cook et al. 2007) have been substituted by more formal institutional arrangements. The organizational features of today's peer-to-peer online markets are a prime example (Diekmann and Przepiorka 2019).

In online markets, thousands of anonymous buyers and sellers trade with each other every day. By means of an electronic rating system, traders comment on each other's behaviour after finished transactions with positive or negative ratings and short texts (Kollock 1999; Resnick et al. 2000; Dellarocas 2003). These ratings are aggregated to form these online traders' reputations. Modern information and communication technologies have reduced the costs of collecting and sharing information to a minimum (e.g., Rifkin 2014), which allows online platforms to leverage the reputation mechanism to promote cooperative market exchanges on an unprecedented scale.

Using a large set of process data obtained from eBay, we investigate how the organization of an online auction market structures market action to promote cooperative market exchanges. Our analysis is guided by Beckert's (2009) argument that social order in markets crucially depends on actors' overcoming three problems which emerge due to the uncertainties inherent in market exchange.

(1) The *value problem* refers to the difficulty of actors to determine and agree on the value of a commodity. It arises because the multiplicity, heterogeneity and complexity of commodities make an immediate assessment of their values difficult.

(2) The *problem of competition* refers to the difficulty of sellers and buyers to generate profit and make a good bargain, respectively. It arises when sellers compete for buyers by reducing prices and buyers compete for commodities by raising their willingness to pay to an extent that undermines their incentive to enter the market in the first place.

(3) The *cooperation problem* refers to the difficulty of actors to establish their exchange partners' intentions to abide by their agreements. It arises because of pecuniary interests and sellers' holding private information about their intentions and quality of their products unknown to buyers.

According to Beckert (2009), these problems are solved when actors form agreeing expectations about the course of action in market exchange (see also Nee 2005). That is, for market exchange to take place, (1) agreement on the value of a commodity must be reached, (2) both parties to the exchange must expect to gain from it, and (3) buyers must expect sellers to be trustworthy while sellers must meet these expectations. However, the abundance of opportunities for market exchange that pour out of the internet suggest a fourth problem actors need to overcome: the *problem of excess* (Abbott 2014), aka *overflow* (Pinch 2012). The problem of excess refers to the difficulty of actors to find and choose a set of potential exchange partners. It is not particular to online markets (see, e.g., Geertz 1978), but is emphasized by the availability of relevant market information online (Graham 2018). It arises because actors face a plethora of online market platforms with each opening access to countless offers of similar commodities. For online market exchange to take place, sellers must choose market platforms and buyers must choose sellers (see also Einav et al. 2016).

Although we discuss throughout our paper how an online market structures market action to solve all four problems, our theoretical and empirical analyses focus on the problems of cooperation and excess (for comprehensive discussions of the value and competition problems see, e.g., Aspers 2009, Beckert 2009, and Einav et al. 2016). In particular, we address the question in how far herding as a strategy of excess avoidance can undermine the trust and cooperation enhancing effect of reputation in an online market.

Our theoretical approach is analytical. We assume boundedly rational yet purposefully acting actors that respond to structural incentives, constrains, and the consequences others' actions can have for their ability to pursue their goals (Coleman 1990, Gintis 2009, Hedström and Bearman 2009). Based on this assumption, we argue that actors at once strive for a bargain and avoid excess when shopping online. They do so by herding on offers that already attracted bids and hence were scrutinized by others. However, we argue that there are also market forces, such as price mechanisms and incentives associated with seller reputations that limit herding. We derive hypotheses from our theoretical argument and test them with a large set of process-produced online-auction data. This is where our empirical contribution lies. Our dataset enables us to identify herding empirically, as it includes the entire bidding process as well as nearly all attributes of an offer a buyer may consider when deciding to place a bid or not. We lay out both our theoretical (Section 2) and empirical argument (Section 4) in three steps:

(i)   First we show how electronic reputation systems employed in online markets structure actors' actions to cope with the problem of cooperation. We argue that the extent to which the reputation mechanism establishes a market structure that shields reputable actors from their less reputable competitors is limited. The reputation mechanism deters fraudulent actors without precluding well intended actors from entering the market and building a good reputation.

(ii)   We then go on demonstrating how the auction mechanism, by which buyers can bid for a commodity offered by a seller, helps actors to cope with the problem of excess. Although the primary function of commodity markets is to handle excess demand or supply, we argue that buyers in online markets face a problem of excess due to cognitive welter, which they solve by herding.

(iii)   Finally, we investigate in how far buyers' need to overcome the problem of excess undermines the reputation mechanisms' efficacy to resolve the cooperation problem. In other words, we test whether herding as a strategy for reducing cognitive welter sidelines hierarchization as a strategy for reducing uncertainty in market exchange.

Previous research shows how herding affects, among others, book sales (Keuschnigg 2012), movie sales (Moretti 2011), song popularity (Salganik et al. 2006), investments in financial assets (Pitluck 2014), microloan granting (Zhang and Liu 2012), and item sales in online auction markets (Dholakia et al. 2002; Simonsohn and Ariely 2008). This previous research focuses either on identifying the effect of herding on product success (Keuschnigg 2012; Moretti 2011; Salganik et al. 2006) or, as we do in this paper, on moderators of individuals' herding behaviour (Dholakia et al. 2002; Pitluck 2014; Simonsohn and Ariely 2008; Zhang and Liu 2012). Our paper goes beyond previous research by showing how the functioning of an online market is affected by the interplay of herding with two other mechanisms: price formation and reputation formation. Moreover, by conceiving herding as a strategy of excess avoidance, our paper contributes to the literature that studies how online market platforms shape the choices of their users (Graham 2018, Pinch 2012). We conclude our paper with a discussion of whether the problem of excess is an inevitable coordination problem that can be found in any market and that needs to be resolved for market exchange to take place.

2. Theory and hypotheses

Today's online market platforms offer ample opportunities to investigate reputation formation as a mechanism of informal social organization (Diekmann et al. 2014; Przepiorka et al. 2017). However, reputation formation, although a significant ingredient, is not the only mechanism promoting cooperative exchanges in online markets; many online markets are purposefully organized in a way that promotes mutually beneficial trade and maximizes the profit of market platform providers (Ahrne et al. 2015). Online market platforms offer different ways to engage in market exchange, impose a certain chronology on actors' moves, and display information about exchange partners in various ways (see also Graham and Henman 2019). It is important to understand the interplay of these market rules and platform design features to understand how they structure market action. In the next two paragraphs we first describe several important features of the market context that we study that are unrelated to aspects of reputation formation and then describe how reputation formation is structured.

In online markets such as eBay, sellers offer their products for sale either in auction or in fixed price format. Sellers can post their offers for a limited time (e.g., 5 days) in which potential buyers can submit bids, if it is an auction, or purchase the item directly, if it is a fixed price offer (Przepiorka 2013). In auctions, at the end of the designated time period, the highest bidder wins the item and is obliged to pay the second highest bid plus a small bid increment (plus shipping costs). If nobody bids on an auction, the offer ends when the time elapses. A fixed price offer ends if a buyer buys the item at the fixed price or when the time elapses. It is a convention that the buyer first sends the money to the seller and, upon receipt of the money, the seller ships the item (Diekmann et al. 2009). Depending on the online market, the provider charges a fee for every offer put online and retains a small fraction of the final price if the item is sold.

After the transaction, the buyer can rate the seller and until May 2008 the seller could rate the buyer by leaving positive, negative or neutral feedback and a short text comment (Bolton et al. 2013; Dellarocas and Wood 2008; Diekmann et al. 2014). These ratings are then aggregated to form actors' reputations in the online market. All actors have the same metrics to assess other actors' reputations: the number of positive ratings, the number of negative ratings, the reputation score (the number of positive ratings minus the number of negative ratings) and the percentage of positive ratings. Typically, this information can be retrieved from every actor's profile page and the latter two metrics are displayed along with sellers' aliases on every offer page. This makes information about actors' reputations costly to fake, unambiguous and comparable across actors (Caprao et al. 2016).

In the next section, we outline how reputation systems employed in online markets structure actors' actions to cope with the problems of competition and cooperation.

(i) Reputation formation

The sequential nature of online market exchange creates trust problems because the seller could keep the buyer's money without sending the merchandise or send back a low quality merchandise (e.g., Akerlof 1970; Güth and Ockenfels 2003; Yamagishi et al. 2009). The feedback system commonly implemented in peer-to-peer online markets mitigates this trust problem by creating incentives for traders' cooperative behaviour (Dellarocas 2003; Kollock 1999; Resnick et al. 2000). It is in a seller's best interest to ship the merchandise the buyer paid for because a negative rating by the buyer may negatively affect the seller's future business. Since actors can rate each other after finished transactions only, building a good reputation from fake ratings is too costly in terms of time and money. Therefore, potential buyers can use information about sellers' reputation to infer these sellers' trustworthiness and

competence, and pay higher prices to trustworthy and competent sellers in exchange for a lower risk of being cheated or in other ways dissatisfied.

Although building a good reputation is costly, the reputation mechanism does not create barriers to market entry for sellers with long-term business interests or honest intentions. New sellers, without a feedback history, have to offer their products at reduced prices. Once these sellers build their reputations for being honest and reliable, they can charge higher prices by which they will be compensated for the initial investment in their reputation (Friedman and Resnick 2001; Przepiorka 2013; Shapiro 1983).[1] In other words, reputation systems in online markets mitigate the cooperation problem by reducing incentives for fraudulent actors to enter the market without aggravating the competition problem.

The above argument suggests that in an online market with a functioning reputation system, sellers' business success in terms of sales and prices will be positively correlated with their reputation. In line with this proposition, it has been shown that sellers with a long record of positive ratings attain higher sales and prices than sellers with a short record or many negative ratings (e.g., Bajari and Hortacsu 2004; Resnick et al. 2006; Diekmann et al. 2014). What is more, several studies show that the correlation between sellers' reputations and their business success is not merely spurious, and that buyers indeed trade off sellers' reputations against the prices these sellers ask for their products (Przepiorka 2013; Resnick et al. 2006; Snijders and Weesie 2009). We thus expect to replicate these previous findings.

> *Hypothesis 1: A seller's number of positive (negative) ratings increases (decreases) the probability of a bid for an item auctioned by the seller.*

> *Hypothesis 2: A seller's number of positive (negative) ratings increases (decreases) the amount of the highest bid for an item auctioned by the seller.*

From the above it follows that in online markets with a reputation system, prices will not only depend on the estimated value of the offered commodity, but also on the properties of the seller, and in particular on the seller's reputation.[2] In the next section, we describe how the auction mechanism structures actors' actions to cope with the value problem and, as a side product, helps them solve the problem of excess.

(ii)   Herding and bargain-hunting

eBay started off as a peer-to-peer market in which collectables and second-hand items could be sold in a convenient way online. In peer-to-peer markets, most items are offered by amateur sellers who may lack the information and knowledge to determine the value of these items. More important, an item's valuation can vary considerably across potential buyers. Under these conditions it is most practical to employ an auction mechanism, by which potential buyers submit bids to determine the value of the item (the working of eBay's auction mechanism is explained in more detail in the online appendix). Hence, the value problem is solved by allowing the group of buyers most interested in an item to bid for it. The auction mechanism ensures moreover that an item is sold to the buyer with the highest valuation. In sum, online "auctions serve as social processes for establishing socially acceptable definitions of value and ownership" (Smith 1989: IX). However, in online peer-to-peer markets, there is an abundance of similar goods that are offered by hundreds of different sellers at the same time; buyers first have to select the offers they want to bid on.

When looking for a particular item, the search result displays a list of items of the same type that are being auctioned. This list typically shows for each item a thumbnail picture, a title, the time left until the auction ends, the highest bid (i.e. current price), and the number of bids that have been submitted. To obtain any information about the seller and detailed information

about the offered item, a buyer has first to click on the item and access the item page. Too many similar offers to choose from present buyers with a problem of cognitive welter (Abbott 2014) or overflow (Graham 2018; Pinch 2012), which they need to solve before they can start bidding. One possibility is for buyers to click through all active offers of one type of item, selecting those with trustworthy sellers promising a bargain. However, given how the reputation mechanism works, buying from a seller with a good reputation and striving for a bargain are opposing wants that buyers have to balance in their search and decision-making process. For example, buyers need to sample a fair number of offers in a short time to find a seller with an acceptable reputation offering the item at a reasonable price. Such a strategy is cognitively demanding, time consuming, and by the time a buyer following this strategy has composed his/her set of offers to bid on, these offers' prices may have changed because other buyers bid on them. An alternative strategy is for buyers to "follow the herd," that is to consider an offer other buyers have considered already (Banerje 1992; Bikhchandani et al. 1992; Simonsohn and Ariely 2008).

We define herding as the imitation of other actors' behaviour.[3] Imitation is a strategy of excess avoidance (Abbott 2014), and imitating others can be beneficial if the imitating actors lack the information on which the imitated actors' behaviour is based (Banerjee 1992; Hedström 1998). In online auction markets, the fact that an item has received a bid from someone else may be perceived by buyers as a sign of the item's quality and the seller's good reputation (e.g. Podolny 2005). Hence, following others may reduce search costs to a minimum. Moreover, once a potential bidder made up their mind and decided to bid for the same item, they too can obtain the information the previous bidders have already and revisit their choice, even before placing a bid. Thus, the more bidders have bid for the same item, the safer may the next bidder feel to assume that the seller and the item have been scrutinized by previous bidders (Bikhchandani et al. 1992). For example, if there are already two bidders

in the auction, the chance that at least one of them checked the attractiveness of the offer is higher than if there was only one. If buyers in online markets indeed use herding as a strategy to cope with the problem of excess, we will observe it in our data.

> *Hypothesis 3: The more buyers have bid for an item, the more likely the item*
>
> *will be bid for by another buyer.*

Following others reduces cognitive welter and search costs, but at the same time, one is competing against other buyers. As a matter of fact, the more bidders join an auction, the less likely is a particular bidder's valuation of the item the highest one, and each bidders' chance of winning it decreases. Larger bidding competition also implies that the highest bidder, who wins the auction, is more likely to pay their reservation price (Simonsohn and Ariely 2008). In other words, buyers face a trade-off between reducing welter and saving search costs by following others, and making a good bargain by looking for items no one has bid on. Thus, if buyers indeed make this trade-off, the herding effect hypothesized in H3 will be hampered and even reversed with an increasing number of bidders.

> *Hypothesis 4: The likelihood of another buyer bidding for an item will first*
>
> *increase and, after reaching a certain point, decrease with the number of*
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> *buyers who bid on the item.*

Hypotheses 3 and 4 are competing hypotheses. While H3 predicts a monotonically increasing relation between the likelihood of another buyer bidding on an item and the number of buyers bidding on it already, H4 predicts an inversely u-shaped relation. The number of existing buyers at which the likelihood of another buyer joining an auction reaches its maximum depends on these buyers' perceptions of sellers' trustworthiness, their valuation of the item, their beliefs about other buyers' valuations of the item and other factors (see, e.g., Bajari and Hortacsu 2003). Since our data does not contain this information, we abstain from making

more precise predictions about the exact turning point of the inverse-u function predicted in H4. However, if buyers exhibit a certain degree of rationality and do not follow others at any price, we expect to find support for H4 rather than for H3 (Simonsohn and Ariely 2008).

Apart from facing larger competition, following others can have other adverse consequences for buyers. If previous bidders have not taken a seller's rating history into account, then blindly bidding on the same item and winning it may be more risky as the seller could be untrustworthy or unreliable. Next, we discuss in how far buyers' need to overcome the problem of excess and, in particular, the herding they engage in as a consequence of that need, could undermine the reputation mechanisms' efficacy to resolve the cooperation problem.

(iii)   Resilience of reputation systems

Herding is known under different names (e.g., social learning) and can lead to so-called success-breeds-success dynamics and growing inequality on the supply side (DiPrete and Eirich 2006; Salganik et al. 2006; van de Rijt et al. 2014). On the demand side, herding can lead to so-called informational cascades, which can occur when actors imitate others' behaviour disregarding their own information about the best course of action (Bikhchandani et al. 1992). In online auctions, informational cascades can occur if new bidders rely on previous bidders' judgements and follow them disregarding the information they can obtain about the seller (Frey and van de Rijt 2016). Buyers handing over responsibility for assessing seller trustworthiness implies that seller reputation will have a smaller bearing on these buyers' decisions to join an auction. As a result, the absolute effect of a seller's reputation on the probability of another bidder joining the auction should decrease with the number of existing bidders.

Hypothesis 5: The more buyers have bid for an item, the smaller will be the absolute effect of the seller's number of positive and negative ratings on the probability of another buyer bidding for the item.

Informational cascades can lead to adverse outcomes because they can reduce the reliability of reputation as a sign of a seller's trustworthiness and competence (Przepiorka and Berger 2017). What is more, untrustworthy sellers anticipating buyers' herd behaviour will induce informational cascades to "play the system." They could auction their items at low starting prices and/or let confederates place bids on their items to attract more bidders and drive up prices. Such behaviour will eventually undermine the reputation mechanism because reputation will become a weaker sign of seller trustworthiness and buyers will rely less on it. A better understanding of how herd behaviour affects reputation systems' effectiveness to identify (un)trustworthy sellers will inform the design of resilient online platforms for social and economic exchange (see, e.g., Helbing 2013 and van de Rijt et al. 2014).

3. Data and methods

The data was collected by means of a spider program on the market platform eBay.de between October 30 and December 31, 2006 (see Przepiorka 2013 for details of the data collection).[4] During the two months, all offers in the category "Foto & Camcorder > Speicherkarten > SD" were collected. This category contained offers of new and used SD (Secure Digital) memory cards, which also differed in their format, memory capacity, and brand. Figure 1 shows a screen shot of an item page where the item was successfully auctioned (i.e. sold). Items were offered for sale by sellers from all over the world and attained an average selling price of about €15. The entire sample contains about 176k valid cases. About 91k cases (52 %) are auctions whereas the reminder of the sample is for fixed

price (22 %) and mixed format offers (26 %). In what follows, only the auctions are considered. The online appendix contains frequency tables and descriptive statistics of all item, offer and seller characteristics that were available online.

[Figure 1]

To test hypothesis H1, we fit a logistic regression model with the binary outcome variable y indicating whether an auction has received at least one bid. To test hypothesis H2, we fit an OLS regression model with the log of the highest bid in EUR as the outcome variable. The logit is fitted based on sold and unsold items whereas the OLS model is fitted based on the subsample of sold items only.[5]

In all our models, a seller's reputation is operationalized by two variables, the log number of positive ratings (+1) and the log number of negative ratings (+1). The log-transformation accounts for the assumption that the absolute effect of the number of ratings on a seller's business success is increasing at a decreasing rate. For example, a seller with 100 positive ratings will be perceived more favourably than a seller with 50 positive ratings whereas a seller with 1100 and a seller with 1050 positive ratings will not make the same level of difference.

To test hypotheses H3 through H5, we model the probability of another bidder joining an auction y', conditional on the number of bidders who already placed a bid in the same auction. For this purpose, we can use a logistic regression model, but we first have to restructure our data to account for the conditionality of the probability of another bidder joining an auction. Thus, for each auction i in our data, we make m_i additional instances,

where m_i is the number of unique bidders, who had joined the auction by the time the auction ended. In the restructured dataset, auctions which received no bids are represented only once, auctions which received bids by one bidder are represented twice, and so on. Only for auctions with $m_i = \max(m)$ we make $m_i - 1$ additional instances, where $\max(m)$ denotes the maximum number of unique bidders who joined an auction. In our data, $\max(m) = 18$. Since conditional on an auction already having 18 bidders the probability of another bidder joining is zero, the auction has only 18 (rather than 19) instances.[6]

In the reshaped data, the binary outcome variable *y'* is one for the m_i first instances of an auction and zero for the last instance. The instances of an auction vary moreover in the number of existing bidders, the time left until the auction ends (in minutes) and the price (i.e. highest bid in EUR) since the last bid was placed. All other variables are constant within-auction. We extract these variables from the so-called bid lists, which are created for all auctions that receive at least one bid (see the online appendix for an illustrative example). Auctions which received no bids are thus represented only once in our data. In these cases, the outcome variable *y'* is zero, the current price corresponds to the starting price, and the time to auction end corresponds to the total auction duration.

Based on the restructured dataset, the probability of another bidder joining an auction conditional on the number of bidders, the time left until the end of the auction, the current price, the seller's reputation and control variables can be estimated using logistic regression. A special variant of this model is also known as continuation ratio model (e.g., Agresti 2010; Guisan and Harrell 2000; O'Connell 2006) and can be conceived as the complement of a discrete time event history model in which the baseline hazard is modelled by the set of $\max(m)$ dummy variables. In all our models we estimate robust standard errors to adjust for same-seller-clusters, rather than same-auction-clusters, for auctions are nested in sellers (e.g., Fitzmaurice et al. 2004; Snijders and Bosker 2012).

Note that in the model we describe above, we conceptualise the effect of the number of existing bidders on the likelihood of attracting a new bidder as an indicator of herding.[7] One could argue that a characteristic of an auction, such as the quality of the item or seller, which is omitted from the model could affect both the number of existing bidders and the likelihood of attracting a new bidder. In that case, the aforementioned effect would be the outcome of crowding, that is, some exogenous aspect of the auction attracting new bidders. With observational data alone, we cannot fully ensure what we observe is not due to crowding but herding. However, we have strong reasons to believe that what we identify is largely due to herding. This is because we have measures of *all* aspects of an auction a potential bidder could see and control for those aspects in our model (see, e.g., Morgan and Winship 2015). Theoretically, there could still be some relevant omitted variables, for instance (higher-order) interactions between the aspects of an auction that are controlled in our models. But the product we focus on is rather standard, so we do not expect such complex interactions. Shortly, our strategy to identify herding relies on extremely tight covariate control (for other studies employing a similar identification strategy, see e.g., Hainmueller et al. 2015).

We restrict the reporting of our results to the variables most relevant to our hypotheses: initial price, current price, number of bidders, selling price, and sellers' reputations. However, keep in mind that all our results are based on analyses in which we also control for over 100 other (mostly dummy) variables. Depending on the model, these include, for instance, the auction duration (5 factors), payment methods and shipping conditions offered by the seller (5 factors), the number of similar items offered for sale at the same time as an auction ends (1 variable), whether an auction ends on the weekend (1 factor), the hour of day at which an auction ends (23 factors), the memory capacity of the cards (8 factors), a seller's country of origin (15 factors), etc.

The online appendix provides a detailed description of all control variables and contains the full versions of the regression tables shown in the Results section. The online appendix also contains alternative model specifications which we estimated to establish the robustness of our main results. We report our main results next and refer to the robustness checks where appropriate.

4. Results

(i)   Reputation formation

The first two models in Table 1 test hypotheses H1 and H2. In the first model (M1), other things being equal, the odds of an auction receiving at least one bid increase by $100 \times [\exp(0.333) - 1] = 40$ %, if a seller's number of positive ratings increases by a factor of 2.7. The odds of an auction receiving at least one bid change by $100 \times [\exp(-0.213) - 1] = -19$ %, if a seller's number of negative ratings increases by a factor of 2.7. These changes in odds correspond to changes of 6.6 percentage points and −4.6 percentage points, respectively, if we take the unconditional selling probability of 0.698 as a reference value.

We obtain corresponding results with model M2, where the log of the selling price (in EUR) is the outcome variable. If a seller's number of positive ratings increases by a factor of 2.7, the highest bid increases by $100 \times [\exp(0.093) - 1] = 9.7$ %. Based on the average selling price of about €15, the change due to the increase in a seller's positive reputation amounts to €1.46. Accordingly, an increase in the number of negative ratings by a factor of 2.7 changes the highest bid by $100 \times [\exp(-0.084) - 1] = -8.1$ % or by -€1.21 at the average selling price. These results provide clear support for our first two hypotheses. There is a substantial premium for sellers' good reputations in terms of the probability of receiving at least one bid

(H1) and in terms of the amount of the highest bid (H2). The reputation premium establishes the main incentive for new traders with long-term business interests and honest intentions to enter the market.[8] Next we look more closely at the auction mechanism and how it structures actors' actions in solving the value problem and the problem of excess.

[Table 1]

(ii)   Herding and bargain-hunting

In model M3 in Table 2, we include the log number of existing bidders (+1) as a linear term. Recall that the analysis is now based on the restructured data and the probability of another bidder joining an auction is the dependent variable. Supporting our third hypothesis (H3), the positive coefficient estimate indicates that the more bidders have joined an auction the larger is the probability that the auction will be joined by yet another bidder. These results are in line with what Simonsohn and Ariely (2008) find based on their analyses of eBay auctions of DVDs. They use a probit model and estimate the herding effect in terms of the number of previous bids rather than bidders (see models 1 and 2 on page 1631 in their paper). In our case, other things kept constant, if an auction with no bidder is joined by one bidder, the odds of the auction being joined by another bidder increase by $100 \times [\exp(1.447 \times \ln(2)) - 1] = 172.6$ %. The change in odds corresponds to a change in probability of 16.5 percentage points, if we take the unconditional selling probability of 0.698 as a reference value. Once the second bidder joins the auction, the odds of the auction being joined by the third bidder increase by $100 \times [\exp(1.447 \times \ln(3/2)) - 1] = 79.8$ %, or 5.6 percentage points in terms of probability if we now take 0.863 as the reference value. The coefficient of the log number of

existing bidders estimated in model M3 suggests that the probability of another bidder joining an auction increases with the number of existing bidders at a decreasing rate. This finding suggests that some buyers are indeed more likely to follow others rather than searching for good offers themselves. However, since with every new bidder joining an auction the price of the auctioned item is increased and the probability that a particular bidder wins the auction decreases, potential buyers face a trade-off between following others to reduce cognitive welter and search costs, and winning an auction at a favourable price. As hypothesized in H4, such a trade-off should be reflected in an inversely u-shaped functional form of the herding effect. That is, the probability of another bidder joining an auction should first increase and start decreasing as from a certain number of existing bidders. We test this hypothesis with models M4 and M5 in Table 2.

[Table 2]

Model M4 contains the log number of existing bidders (+1) and the log number of existing bidders (+1) squared. Model M4 differs from model M3 only by the quadratic term. In line with hypothesis H4 the linear term is positive, the quadratic term is negative, and both coefficient estimates are statistically significant.[9] What is more, the Bayesian information criterion (BIC) of M4 is considerably smaller than the BIC of M3 indicating that the fit of M4 is better than the fit of M3. Based on the coefficient estimates of the log number of existing bidders (b_1) and the log number of existing bidders squared (b_2), we can calculate the number of existing bidders (x) at which the probability of another bidder joining an auction starts decreasing. In order to do this we have to set the first derivative to zero, i.e. $y' = b_1/(x+1) - b_2[2\ln(x+1)/(x+1)] = 0$, and rearrange the equation to get $x = \exp(b_1/2b_2) - 1$. Substituting b_1

and b_2 with the actual coefficient estimates obtained with M4, we get $x = 3.767$. In other words, the probability of another bidder joining increases up to four existing bidders and starts decreasing with four existing bidders. These results are robust across different model specifications and item price categories.[10]

Model M5 tests hypothesis H4 without putting any restrictions on the functional form of the herding effect. The model is estimated with a full set of dummy variables – one for each possible number of existing bidders. The coefficient estimate for '1 existing bidder' indicates that the odds of a new bidder joining an auction is $100 \times [\exp(1.580) − 1] = 385.5$ % higher if the auction has one bidder already, as compared to an auction without bidders. Auctions with two existing bidders attract yet more bidders. The odds of a new bidder joining an auction with two bidders is $100 \times [\exp(2.756 − 1.580) − 1] = 224.1$ % higher than for an auction with only one bidder. Auctions with three existing bidders too tend to attract more bidders than auctions with only two bidders; the odds are $100 \times [\exp(3.043 − 2.756) − 1] = 33.2$ % higher. The herding effect peaks at three existing bidders and starts gradually decreasing thereafter (also see full regression table in the online appendix). Model M5 makes the same prediction with regard to the functional form of the herding effect as M4 and, despite the higher number of degrees of freedom, has a better fit than M4.

Note that in M5, only at 12 existing bidders is the probability of another bidder joining not significantly different from the case of one existing bidder, and only at 17 existing bidders is the probability of another bidder joining not significantly different from the case of zero existing bidders. These comparisons are made under the implicit assumption that everything except for the number of existing bidders stays constant. However, if we want to study a within-auction dynamic, keeping everything but the number of existing bidders constant is not possible, as with every bidder joining an auction the item price increases by at least the minimum bid increment. To demonstrate a within auction dynamic, we construct the

following example based on model M5: we estimate predicted probabilities of another bidder joining and thereby vary the item price along with the number of existing bidders. That is, with every bidder joining the auction we also increase the item price by €0.50, which is the minimum bid increment (see the appendix for an explanation of eBay's auction mechanism). The predicted probabilities are estimated with all other variables held constant either at their modal values or their means. Figure 2 presents the results of this exercise.

[Figure 2]

Figure 2 shows the predicted probability of a new bidder joining an auction conditional on the number of existing bidders *and* the current item price. We observe the largest increase in the predicted probability of another bidder joining when the first bidder joins the auction. Corroborating our results obtained based on model M5, the predicted probability increases up until three existing bidders and starts decreasing as from four existing bidders. These gradual changes in the probability of another bidder joining an auction are now also affected by the gradual increase in item price. At eight existing bidders and an item price of €5.00, the probability of another bidder joining is not significantly different from the probability at zero existing bidders and an auction starting price of €1.00. These results once more support our hypothesis H4. Potential buyers seem to trade off the costs they incur when looking for a trustworthy seller against the likelihood of winning an auction at a good price. Given that the presence of other bidders as well as the item's current price are important determinants of potential buyers' decisions to enter an auction, the question arises in how far herding buyers neglect sellers' reputations. Answering this question is important as the neglect of sellers'

reputations may lead to undermine the reputation systems' efficacy to deter fraudulent sellers from entering the market.

(iii) Resilience of reputation systems

Note first that in models M3 through M5 the coefficient estimates of the log number of positive and negative seller ratings have remained statistically and substantially significant, despite the fact that all these models account for buyers' herd behaviour in one way or another. For example, the coefficient estimate for the log number of positive ratings in model M3 in Table 2 indicates that, everything else equal, the odds of a new bidder joining an auction initiated by a seller with 2.7 times more positive ratings than another seller are $100 \times [\exp(0.131) - 1] = 14.0$ % higher. Correspondingly, the odds of a new bidder joining an auction initiated by a seller with 2.7 times more negative ratings than another seller are $100 \times [\exp(-0.102) - 1] = (-)9.7$ % lower. These results, however, do not tell us whether herding makes buyers more likely to disregard information about sellers' reputations. In order to test hypothesis H5, we include interaction terms of the log number of existing bidders with the log number of positive and the log number of negative seller ratings in model M6 in Table 2.

The coefficient estimate of the interaction term with the log number of positive seller ratings is negative and the coefficient estimate of the interaction term with the log number of negative seller ratings is positive. This suggests that the reputation effect decreases as the log number of existing bidders increases. However, neither interaction term is statistically significant. We do not find support for hypotheses H5 that buyers increasingly disregard information about sellers' reputations when following others in their judgement.[11]

5. Discussion and Conclusions

In online markets, traders provide feedback about their trading partners' conduct after finished transactions, and this information is collected, aggregated and made immediately available to everyone online (Kollock 1999; Resnick et al. 2000; Dellarocas 2003). This centralized information sharing system reduces the necessity for traders to be embedded in offline social networks in order to gain information about potential trading partners (Diekmann et al. 2014). At the same time, it promotes cooperation as only sellers with long-term business interests or honest intentions will find it worthwhile to enter the market and build a good reputation. Our results corroborate that building a good reputation is costly; market entrants have to accept lower prices for their items in order to compensate potential buyers for the risk they take when trading with unknown sellers. However, reputation systems as such do not establish market structures that shield reputable actors from their less reputable competitors (Podolny 1993). For example, established sellers cannot simply reduce prices to drive competitors out of the market as such a strategy would jeopardize their returns on investment in reputation (Shapiro 1983).

In online markets, the search for a particular product produces a long list of offers, which lacks any information about sellers and detailed information about the listed items. Only after clicking on a particular offer can detailed seller and item information be accessed. However, other information, as the number of bids and the highest bid (i.e. current price), is often readily available and can be used to infer something about the seller and the item (Simonsohn and Ariely 2008). In particular, the fact that others have bid on an item already might be a sign of the item's good quality and the seller's trustworthiness and competence (Banerjee 1992; Hedström 1998). Thus, following others in online auctions can be beneficial if it saves search costs and maintains a good chance of winning the auction at a favourable price.

Our results show that buyers indeed follow others in their judgement on which offer to bid, but not at any price. The more buyers have bid on an item, the more likely is the auction joined by another buyer. However, the herding effect increases up to three existing bidders and starts gradually declining with every bidder who joins the auction thereafter. This finding suggests that potential buyers regard it as increasingly unlikely to win an auction at a good price if the number of other bidders increases beyond a certain number.

While this finding shows that herding buyers are aware of the direct costs of their behaviour, it does not reveal in how far these buyers are aware of potential indirect costs of following others. If previous bidders have not taken the seller's rating history into account, then blindly bidding on the same item and winning it may be riskier as the seller could be untrustworthy or unreliable. Moreover, the reputation mechanism could be undermined by sellers with a bad reputation submitting early bids on their own behalf (Helbing 2013; van de Rijt et al. 2014). Fortunately, even after controlling for herding in our statistical analyses, we find a significant and substantial effect of a seller's reputation on the probability of another buyer joining an auction. In other words, even though buyers herd, they do not neglect the information about sellers' reputations that is available to them and place their bids accordingly.

Our paper contributes to the literature on the economic sociology of markets by showing how the set-up of an online market structures market action to help actors cope with three problems that hamper mutually beneficial market exchanges (Beckert 2009): the value problem, the competition problem, and the cooperation problem (see also Nee 2005; Aspers 2009). In the light of the abundance of opportunities for online market exchange, we have suggested to extend this list with the problem of excess (Abbott 2014), that is the difficulty of selecting a set of potential trading partners from among the plethora of offers (see also Einav et al. 2016; Graham 2018, Pinch 2012). Here too, we have shown how actors use a feature of the online market platform to cope with the problem. But is the problem of excess an

inevitable coordination problem that must be resolved in any market, as the other three coordination problems identified by Beckert (2009)?

Markets are diverse and the coordination problems market participants encounter in each case vary in their salience and strength. Rather than being present or absent, we conceive of the three coordination problems described by Beckert (2009) as well as the problem of excess (Abbott 2014) as manifest to various degrees across markets and within markets over time. For example, the value problem may not exist in markets in which prices are determined exogenously (e.g., by the state), or the problem of competition is less severe in monopolies. Our analysis exemplifies how online markets provide technical solutions to mitigate the three coordination problems identified by Beckert (2009): the auction and reputation mechanisms contribute to solving the value and cooperation problems, respectively, without preventing new traders from entering the market (i.e. without aggravating the competition problem). These solutions are inherently (but not entirely) independent of the socio-structural, institutional and cultural embedding of market participants. In fact, the success of online market platforms depends on their overcoming these coordination problems in a generic way to allow market exchanges to take place across geographic, cultural and legal barriers. As a result – *inevitably* – the problem of excess emerges.

In offline markets, habits, convenience and other constraints, which result from actors' embeddedness (Granovetter 1992), preclude these actors from perceiving the problem of excess or simply provide a solution to the problem (although see Geertz 1978). However, the possibility of browsing thousands of similar offers online dissolves actors' proximate embeddedness constraints and makes the problem of excess apparent and gain in strength. In our paper we demonstrate how market participants take advantage of an organizational feature of the online market to cope with the problem: they consider bidding on auctions others have bid on already. However, the auction mechanism, as implemented on eBay at the

time our data was collected, was, in all likelihood, not intended as a solution to the problem of excess. Moreover, platform providers may have sensed that the way in which eBay was designed and used at that time could have unintended consequences of the sort we point out in this paper.

The organizational features of eBay (and other online markets) have changed quite considerably in the last ten years. For example, in 2008, eBay changed its reputation system. Before the change, buyers could rate sellers and sellers could rate buyers alike. This reciprocal rating system was found to lead to an inflation of positive ratings (Bolton et al. 2013). After the change, buyers could rate sellers whereas sellers' possibility to rate buyers was limited (see also Diekmann et al. 2014). More recently, eBay has been transforming its market platform from a peer-to-peer auction site, a global flee market that is, to a B2C market with fewer professional sellers offering consumption goods at a fixed price. Roth (2015) attributes these changes to eBay's need to become faster. While with fixed price offers buyers can purchase the items they want immediately, in auctions they have to wait until the auction ends without knowing whether they will end up wining it. Roth (2015) argues moreover that with a concentration on fewer professional sellers, online market platforms are better able to monitor and enforce these sellers' cooperative business conduct making the market even more secure for buyers.

Markets are endogenous in that their organizational features are adapted in response to market frictions, new technologies, rival platforms, and the behaviours of buyers and sellers (see, e.g., MacKenzie and Millo 2003). This dynamic and endogenous nature of markets limits the generalizability of our findings to other markets (or the same market at a different point in time). However, today's online market platforms offer the possibility to test theories of the interplay of the organization of markets and human behaviour rigorously by means of large sets of process-produced data (Diekmann et al. 2014). In this article, we used such data

to show how the problem of excess accentuated by online auction markets gives rise to herding, and how potentially adverse effects of such herding on the effectiveness of the reputation mechanism to promote cooperation are mitigated by the price mechanism. In this generic form, these findings can be generalized to other product markets in which these three forces (reputation formation among sellers, social influence among buyers, and competition among buyers) are at work. Another potential limitation of our study is that it is based on observational data, which always leaves unanswered the question whether there could be a confounder unaccounted for in the analyses that produces the described effects (e.g., herding in our case). We are confident that this is less of an issue here because in our multiple regression analyses, we account for a comprehensive set of variables a potential buyer could consider in their decision to place a bid in a particular auction. However, future work should test the interplay of the three mechanisms that we describe here (price formation, reputation formation and herding) in well-designed laboratory experiments (see, e.g., Frey and van de Rijt 2016).

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Figure captions

Figure 1: Completed auction of a 1GB SD memory card

Figure 2. Probability of additional bidder joining an auction conditional on the number of

existing bidders and current item price

Tables

Table 1: Regression models of probability of sale and selling price testing hypotheses H1 and H2

	M1 (logit)		M2 (OLS)	
	Coef.	SE	Coef.	SE
Const.	10.405***	1.434	3.322***	0.364
Main explanatory variables				
log(# pos. ratings + 1)	0.333***	0.075	0.093***	0.020
log(# neg. ratings + 1)	-0.213*	0.092	-0.084***	0.019
log(initial price in €)	-1.005***	0.125	0.058***	0.015
... (the full table is shown in the online appendix)				
N_1	88452		61744	
N_2	3248		3051	
pseudo R^2	0.44			
adj. R^2			0.68	
BIC (*df*)	61881 (109)		121275 (108)	

Notes: The table lists coefficient estimates and cluster-robust standard errors (*** $p < 0.001$, ** $p < 0.01$, * $p < 0.05$, for two-sided tests) of logit and OLS regression models. The binary outcome variable of model M1 is one if the auction received at least one bid and is zero otherwise. The outcome variable of model M2 is the log transformed selling price (in EUR) of auctions that received at least one bid. N_1 denotes the number of cases (auctions) and N_2 denotes the number of clusters (sellers).

Table 2: Logit models of probability of additional bidder testing hypotheses H3 through H5

	M3	M4	M5	M6
Constant	2.777**	1.988*	2.207**	2.191*
	(1.003)	(0.857)	(0.855)	(1.038)
Main explanatory variables				
log(# positive ratings + 1)	0.131**	0.144***	0.147***	0.293*
	(0.043)	(0.038)	(0.037)	(0.115)
log(# negative ratings + 1)	-0.102*	-0.116**	-0.115**	-0.311*
	(0.050)	(0.043)	(0.043)	(0.148)
log(current price in €)	-1.154***	-1.009***	-1.023***	-1.161***
	(0.246)	(0.202)	(0.202)	(0.236)
log(# existing bidders + 1)	1.447***	3.742***		1.872***
	(0.085)	(0.201)		(0.330)
× log(# existing bidders + 1)		-1.198***		
		(0.094)		
× log(# positive ratings + 1)				-0.121
				(0.073)
× log(# negative ratings + 1)				0.162
				(0.099)
0 existing bidders (0/1)			ref.	
1 existing bidder (0/1)			1.580***	
			(0.120)	
2 existing bidders (0/1)			2.756***	
			(0.179)	
3 existing bidders (0/1)			3.043***	
			(0.134)	
4 existing bidders (0/1)			2.893***	
			(0.129)	
5 existing bidders (0/1)			2.756***	
			(0.140)	
6 existing bidders (0/1)			2.571***	
			(0.156)	
…				
17 existing bidders (0/1)			1.487	
			(0.930)	
… (*the full table is shown in the online appendix*)				
N_1	356374	356374	356373	356374
N_2	3201	3201	3201	3201
pseudo R^2	0.37	0.39	0.40	0.37
BIC (*df*)	253386 (107)	242600 (108)	241866 (123)	252838 (109)

Notes: The table lists coefficient estimates (*** $p < 0.001$, ** $p < 0.01$, * $p < 0.05$, for two-sided tests) of logit regression models and cluster-robust standard errors in parentheses. The binary outcome variable of all models is one if the auction is joined by a / another bidder and is zero otherwise. N_1 denotes the number of cases (bidder-joins-auction events) and N_2 denotes the number of clusters (sellers).

Endnotes

[1] Note how this is different from the status signaling argument put forward by Podolny (1993): First, Podolny's argument refers to producers and not sellers of a product and construes the main source of uncertainty in the quality of a producer's product rather than in a seller's trustworthiness. Podolny (1993: 830) defines "a producer's status in the market as the perceived quality of that producer's products in relation to the perceived quality of that producer's competitors' products." Moreover, Podolny describes status as being comprised of an opinion-based and a relational component. The opinion-based component can be defined as the regard other market participants have for a given producer and is thus closely related to the notion of reputation we work with in this paper. The relational component is the social ties to other market actors, whose high or low status respectively enhances or diminishes the status of the producer and, more importantly, establishes a constraint to both how the quality of the producer's product is perceived and competition. This relational component is lacking in anonymous online markets. Finally, Podolny argues that status can be conceived as a costly signal because high status producers have lower advertising, transaction and financial costs and thus lower costs of producing high quality products than low status producers (see also Podolny 2005). In contrast, we argue that reputation can be conceived as a costly signal because it is costly to acquire, which deters untrustworthy sellers to enter the market (see also Przepiorka and Berger 2017).

[2] Aspers (2009) calls markets in which commodity prices mainly depend on the standards of their production *standard markets* (e.g., crude oil markets) and markets in which commodity prices depend on the relative status of market actors *status markets* (e.g., fashion markets). Although, as we will show later in this paper, in online markets commodity prices depend on the "rank order" of sellers as per these sellers' reputations, online markets with a reputation system are generally better conceptualised as standard markets. Seller reputations do not create commodity values as such but provide the type of knowledge needed to establish the quality of the commodity and service offered by the seller (Akerlof 1970).

[3] Actors can engage in similar behaviors because of imitation but also because they obtain information from the same sources or face similar socio-structural conditions. If imitation (conscious or unconscious) induces homogeneous behavior it is called herding; if exogenous factors induce homogeneous behavior it is called crowding (Hedström 1998; Pitluck 2014). We will come back to this point in the Data and methods Section.

[4] In an attempt to improve the buyer experience, eBay introduced the so-called "Best Match" algorithm in early 2008 (Netzloff 2008; see also Nash 2008). The Best Match algorithm scores sellers based on information these sellers provide on their profile pages and the offers they poste; sellers with higher scores appear higher up in buyers' search results. It is important to note that our data was collected *before* the introduction of Best Match; it therefore reflects what buyers saw when they searched for a specific product on eBay.de and when they decided which offers to bid for. This makes our data better suited to test our hypotheses than eBay data collected after the Best Match was introduced or any online market data scraped from platforms that use matching algorithms. For a discussion on how website designs and algorithms affect users' choices, see, e.g., Graham and Henman (2019) and Ziewitz (2017).

[5] Unsold items constitute about 30% of the entire sample, and this may be a non-random sample of all items. Fitting the OLS regression based on the sample of sold items only may produce biased and inconsistent estimates. We tackle this problem by also fitting a Heckman selection model (Heckman 1976). Our results are not affected by sample selection. These robustness checks are presented in the online appendix.

[6] Note that sometimes, bidders, after having joined an auction, revise their reservation price (i.e. increase their highest bid) and thus appear more than once on a bid list (a detailed description of eBay's auction mechanism is provided in the online appendix). For our analyses, such behavior is of lesser importance because our unit of analysis is bidders and not bids. That is, we explain why a new bidder joins an auction based on the characteristics of the auction at the moment the new bidder decides to place his or her first bid. In our data, an auction has 3.05 unique bidders and 4.68 bids on average (the median is 3 and 3, respectively). An auction which has received at least one bid has 4.36 unique bidders and 6.70 bids on average (the median is 4 and 6 respectively).

[7] In the herding literature (e.g., Bikhchandani et al. 1992), imitation of previous actors' choices is often assumed to occur in the same situation. In our case, the situation changes as with every bidder joining the auction the item price increases. In our analysis, we control for the current item price to estimate the effect of the number of existing bidders on the likelihood of attracting a new bidder.

[8] One may argue that sellers' number of positive and negative ratings may have an S-shaped association with selling price. That is, for those with very low or very high numbers of ratings

an additional rating has a small effect; for those with moderate number of ratings an additional rating has a large effect. If this was the case, a log transformation of the number of ratings and selling price is not appropriate. We test this by regressing final selling price (without log transforming it) on third-order polynomial specifications for the untransformed number of positive and negative ratings, controlling for the same set of variables as in M2 in Table 1. The third order polynomial terms are insignificant for both positive ($p = 0.883$) and negative ($p = 0.263$) ratings. Moreover, even with the third order specification, the predicted association between reputation and selling price is quadratic (analyses available on request). We thus conclude that log-transforming reputation scores does not distort a potential third order effect. Note that in logistic regressions of the probability of sale, the association between reputation and probability is bound to be S-shaped due to the logit link function.

[9] We also applied Simonsohn's (2018) two-lines approach using the "Robin Hood" algorithm to test the inverse u-shaped relation implied in hypothesis H4. The results corroborate the results reported here and are described in detail in the online appendix.

[10] The inversely u-shaped herding effect remains even if the model is estimated with seller fixed effects. Those fixed effects could only be included with a linear probability specification. Logit/probit specifications did not converge with seller fixed effects. This alternative model specification is described in the online appendix in Table A10. The online appendix also shows that the inversely u-shaped herding effect mainly appears for medium sized and large memory capacities, whereas for small memory sizes the herding effect is monotonically increasing. However, 98% of all auctioned items are of medium or large memory size. Hence, the inverse u-shaped association describes the vast majority of cases. Model estimations using interaction terms with memory size are also reported in Table A10 in the online appendix.

[11] This result does not change even if we estimate the interaction terms of sellers' numbers of positive and negative ratings with the number of existing bidders squared (i.e. based on model M4 rather than M3). These robustness checks are described in more detail in Table A10 in the online appendix.

Figure 1.

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Artikelstandort:	Zürich, Schweiz
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Käufer:	peacemaker9999 (41 ☆)
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Angaben zum Verkäufer

Verkäufer:	detlef6307 (0)
Mitglied:	seit 27.09.06 in Schweiz Angemeldet als privater Verkäufer

- Bewertungskommentare lesen
- Frage an den Verkäufer
- Zu meinen bevorzugten Verkäufern hinzufügen
- **Andere Artikel des Verkäufers**

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Angebots- und Zahlungsdetails: Ausblenden

Angebotsbeginn:	20.11.06 18:30:00 MEZ	Zahlungsmethoden:	Überweisung Plus
Startpreis:	EUR 1,99		Weitere Details

Beschreibung — Der Verkäufer ist verantwortlich für das Angebot.

Artikelmerkmale - Speicherkarten

Zustand:	**Neu**		
Format:	**SD Memory Card Standard**	Kapazität:	**1 GB**
		Hersteller:	**Sandisk**

Größeres Bild

ns: $\chi^2_{(1)} = 2.23$, $p = 0.135$

Online appendix for:

Does herding undermine the trust enhancing effect of reputation? An empirical investigation with online-auction data

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The functioning of eBay's auction mechanism

eBay employs a so called second-price sealed bid auction mechanism with proxy bidding. In a second-price sealed bid auction, the highest bidder wins the auction and pays the reservation price of the second highest bidder. The mechanism is easiest to imagine if one thinks of a group of potential buyers of a particular item, who submit a sealed envelope with their reservation price to the auctioneer. The auctioneer opens all envelops and sells the item to the highest bidder at the second highest bid. Proxy bidding does exactly this, except for the auctioneer is a computer and "envelopes" can be submitted and reservation prices can be increased (but not decreased) for the duration of the auction.

Figure 1 in the main paper shows a screen shot of a completed eBay auction of a 1GB SD memory card. The seller "detlef6307" posted this item at a starting price of €1.99 on November 20, 2006, at 6:30 pm. The auction lasted for three days, received six bids in total and was sold for €6.05 (excluding shipping costs) to the highest bidder, "peacemaker9999". Figure A1 shows the corresponding bids list. Note that every time a bid was submitted for that item, the information on the bids list changed. In what follows, we are going to reconstruct how the bids list looked at each time point a new bidder joined this auction.

Figure A1: Bids list of completed auction shown in Figure 1

The bids list shows that on November 11, 2006, at 23:07 and 12 seconds, "malle1406" submitted the first bid. After the bid was submitted, the bids list contained one entry indicating that "malle1406" had submitted a bid equal to or higher than the initial price. From that moment, and until the second bid was submitted, the current price of the item was the initial price of €1.99. The second bid was submitted by "bab-schreck" on the next day at 16:14 and 18 seconds. From that moment, and until the third bid was submitted, the current price shown was €2.49, the minimum bid increment of €0.50 higher than the reservation price of the previous bidder.[1] Not until the third bid was submitted by "ringelschnatz1", around one and a half hours later, did the second row of the bids list show the reservation price of the second bidder (€3.03) and the third row the current price of €3.53 (i.e. the reservation price of the second bidder plus the bid increment of €0.50). Then, "ringelschnatz1" figured that a reservation price of exactly €5 may be too focal and easily outbid, and submitted a new bid of €5.10, 20 seconds later. The current price shown in the bids list remained unchanged at €3.53 (it is not possible to outbid oneself on eBay). Half an hour later, "kill_kenny2501" submitted a bid of €5.55. The current price immediately shown on the bids list was €5.55 because the bid increase was lower than the minimum bid increment of €0.50. At this point, the bids list also revealed the two records of "ringelschnatz1". Finally, about five minutes later, "peacemaker9999" submitted a bid of €6.05 or higher. We cannot know for sure what the reservation price of "peacemaker9999" for that item was because the last bid increased the current price only by the bid increment. The auction ended 17 seconds later and "peacemaker9999" won the auction.

eBay's auction mechanism follows precise rules. This makes it possible to reverse-engineer what each new bidder saw at the time point he or she joined the auction. Based on the final bids lists, which we collected for most auctions (the bids lists of 1955 auctions are missing), we could extract the number of existing bidders, these bidders' reputation scores, the current item price and the time until the end of the auction when a new bidder joined it. With these variables, we could model and estimate the herding effect more precisely.

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[1] The minimum bid increment is €0.50 if the current price is between €1 and €50; it is €1 if the current price is between €50 and €500; and it is €5 if the current price is between €500 and €1000. No item in our sample reached a higher price than €1000.

Item, offer and seller characteristics

Table A1: Descriptive statistics of main outcome, explanatory and control variables

variables		descriptive statistics						
label	description	N	N/A	mean	P$_{50}$	S.D.	P$_5$	P$_{95}$
sold	item is sold (0/1)	91724	0	0.71	1	0.46	0	1
iprice	initial price in €)	91724	0	6.08	1.99	8.80	0.01	23.54
bifb	time to first bid in h	62759	1955	36.45	22	42.00	1	145
bidders	number of bidders	91724	0	3.08	3	2.86	0	8
eprice	final price in €	64714	0	14.90	13.31	11.10	1.79	31.55
sepos	# positive ratings	91705	19	38957.91	9623	75329.03	33	275862
seneg	# negative ratings	91705	19	341.55	45	746.78	0	1892
durset	auction dur. in d	91723	1	2.30	1	2.23	1	7
scavg	∅ shipping costs in €	90448	1276	9.36	8.99	4.29	3.50	17.12
paypal	PayPal (0/1)	91724	0	0.71	1	0.45	0	1
pcard	credit card (0/1)	91724	0	0.07	0	0.25	0	1
ptrans	bank transfer (0/1)	91724	0	0.63	1	0.48	0	1
pcheck	check (0/1)	91724	0	0.19	0	0.39	0	1
pcod	cash on delivery (0/1)	91724	0	0.01	0	0.08	0	0
pcash	cash on pick-up (0/1)	91724	0	0.03	0	0.17	0	0
scinsur	shipping insurance (0/1)	91724	0	0.73	1	0.44	0	1
iret	return guarantee (0/1)	91724	0	0.47	0	0.50	0	1
list	# self-advertisement	91724	0	0.87	1	0.42	0	1
seisid	has verified ID (0/1)	91724	0	0.17	0	0.38	0	1
sehasme	has Me-page (0/1)	91724	0	0.37	0	0.48	0	1
seindus	is industrial (0/1)	91724	0	0.74	1	0.44	0	1
semsm	membership dur. in mo.	91705	19	36.56	33	25.42	3	92
seactiv	seller activity	91724	0	2733.97	1548	2988.26	5	6717
secomp	competition	91724	0	10094.53	10571	2265.29	5429	12574
ides	length item descript.	91724	0	19863.44	14574	19382.36	1889	43143
timeec	time in d (centered)	91724	0	0.82	2	17.36	-28	27
weekend	auction ends weekend (0/1)	91724	0	0.44	0	0.50	0	1
tusbr	with USB reader (0/1)	91724	0	0.01	0	0.09	0	0
tcase	with case (0/1)	91724	0	0.01	0	0.07	0	0
tadap	with adapter (0/1)	91724	0	0.02	0	0.14	0	0

Descriptive statistics are the number of observations, the number of missing observations, the arithmetic mean, the median, the standard deviation and the 5%- as well as the 95%-quantiles. Except for the first five variables, all variables listed in this table are included in all model estimations. Most interval scaled variables are log transformed before they are used in model estimations. Regression tables only report the joint test of the last three variables accounting for accessories offered with the item.

Table A2: Absolute and relative frequencies of SD card memory capacities

memory capacity (in MB)	freq.	%
16	166	0.18
32	163	0.18
64	1021	1.11
128	2811	3.06
256	2122	2.31
512	12644	13.78
1024	40154	43.78
2048	29755	32.44
4096	2838	3.09
(missing)	50	0.05

Only the joint tests of the factor 'memory capacity' are reported in the regression tables.

Table A3: Absolute and relative frequencies of SD card formats

format	freq.	%
standard	55197	60.18
mini	21309	23.23
micro	9242	10.08
(unknown)	3845	4.19
ultra	1467	1.60
(multiple)	664	0.72

Only the joint tests of the factor 'format' (incl. categories 'unknown' and 'multiple') are reported in the regression tables.

Table A4: Absolute and relative frequencies of seller countries of origin

seller origin	freq.	%
Germany	18842	20.54
USA	15958	17.40
UK	15932	17.37
Hong Kong	15880	17.31
China	13362	14.57
Malaysia	4311	4.70
Singapore	2191	2.39
Canada	1552	1.69
Australia	1382	1.51
France	779	0.85
Italy	731	0.80
Belgium	272	0.30
Austria	179	0.20
Netherlands	131	0.14
Switzerland	113	0.12
(other)	90	0.10
(missing)	19	0.02

Only the joint tests of the factor 'seller origin' (incl. category 'other') are reported in the regression tables.

Table A5: Absolute and relative frequencies of SD card conditions

condition	freq.	%
new	69768	76.06
packed	15784	17.21
(unknown)	4138	4.51
used	2034	2.22

Only the joint tests of the factor 'condition' (incl. category 'unknown') are reported in the regression tables.

Table A6: Absolute and relative frequencies of SD card brands

brand	freq.	%
Sandisk	38700	42.19
(unknown)	18359	20.02
Toshiba	9112	9.93
Kingston	5347	5.83
Transcend	3422	3.73
(other)	2378	2.59
Emtec	2276	2.48
(multiple)	2081	2.27
A-Data	1395	1.52
Extrememory	1066	1.16
OEM	955	1.04
Topram	780	0.85
Technaxx	702	0.77
Benchip	676	0.74
PQI	650	0.71
Kodak	503	0.55
Magu	503	0.55
Dane-Elec	502	0.55
Panasonic	451	0.49
Lexar	396	0.43
PNY	322	0.35
Fuji	316	0.34
Hama	222	0.24
Corsair	182	0.20
Reekin	155	0.17
Canon	151	0.16
Supertalent	122	0.13

Only the joint tests of the factor 'brand' (incl. category 'unknown' and 'multiple') are reported in the regression tables.

Table A7: Absolute and relative frequencies of auction ending times (h of day)

h of day	freq.	%
0	3588	3.91
1	2546	2.78
2	2537	2.77
3	2308	2.52
4	2223	2.42
5	2065	2.25
6	1705	1.86
7	1404	1.53
8	1090	1.19
9	1941	2.12
10	2714	2.96
11	3916	4.27
12	4327	4.72
13	3748	4.09
14	3842	4.19
15	3773	4.11
16	4981	5.43
17	4409	4.81
18	4641	5.06
19	5969	6.51
20	6783	7.40
21	7560	8.24
22	8304	9.05
23	5350	5.83

Only the joint tests of the factor 'hour of day' are reported in the regression tables.

Regression tables

Table A8 (full Table 1 plus robustness checks): Regression models of probability of sale and selling price testing hypotheses H1 and H2

	M1 (logit)	M2 (OLS)	M-a (probit)	M-b.1 (Heckman) (OLS)	M-b.2 (Heckman) (Probit)
Const.	10.405***	3.322***	5.534***	3.381***	5.490***
	(1.434)	(0.364)	(0.785)	(0.368)	(0.773)
Main explanatory variables					
log(# positive ratings + 1)	0.333***	0.093***	0.192***	0.094***	0.189***
	(0.075)	(0.020)	(0.040)	(0.020)	(0.039)
log(# negative ratings + 1)	-0.213*	-0.084***	-0.120*	-0.083***	-0.118*
	(0.092)	(0.019)	(0.050)	(0.019)	(0.049)
log(initial price in €)	-1.005***	0.058***	-0.539***	0.049**	-0.556***
	(0.125)	(0.015)	(0.056)	(0.015)	(0.062)
auction duration 1d (0/1)	ref.	ref.	ref.	ref.	ref.
auction duration 3d (0/1)	0.487**	0.117	0.270**	0.122	0.263**
	(0.172)	(0.079)	(0.099)	(0.077)	(0.098)
auction duration 5d (0/1)	0.393*	0.228**	0.186	0.229**	0.190
	(0.198)	(0.078)	(0.110)	(0.078)	(0.109)
auction duration 7d (0/1)	0.368	0.253***	0.193	0.256***	0.187
	(0.237)	(0.077)	(0.123)	(0.076)	(0.122)
auction duration 10d (0/1)	0.564*	0.200*	0.301*	0.204*	0.290*
	(0.265)	(0.102)	(0.147)	(0.100)	(0.147)
Payment and shipping options offered					
log(∅ shipping costs in €)	-2.158***	-0.731***	-1.175***	-0.757***	-1.161***
	(0.262)	(0.071)	(0.140)	(0.073)	(0.142)
PayPal or credit card (0/1)	0.917	0.312	0.527	0.336	0.518
	(0.565)	(0.177)	(0.308)	(0.175)	(0.303)
bank transfer (0/1)	0.433	0.344*	0.295	0.367*	0.282
	(0.579)	(0.174)	(0.315)	(0.174)	(0.311)
shipping insurance (0/1)	-1.300***	-0.261	-0.772***	-0.286*	-0.788***
	(0.293)	(0.154)	(0.174)	(0.143)	(0.173)
return guarantee (0/1)	-0.583*	-0.077	-0.320	-0.081	-0.313
	(0.285)	(0.051)	(0.165)	(0.052)	(0.161)
Number of measures of self-advertisement on listing page					
none	ref.	ref.	ref.	ref.	ref.
one (0/1)	1.115***	0.260***	0.635***	0.281***	0.636***
	(0.235)	(0.073)	(0.119)	(0.075)	(0.120)
two (0/1)	1.159*	0.329***	0.574*	0.348***	0.557*
	(0.485)	(0.095)	(0.261)	(0.099)	(0.260)
three (0/1)	2.636***	0.483**	1.211**	0.517**	1.209**
	(0.798)	(0.176)	(0.453)	(0.184)	(0.445)
four (0/1)	3.077***	0.639***	1.702***	0.688***	1.689***
	(0.444)	(0.161)	(0.247)	(0.166)	(0.247)
Seller and item characteristics					
has verified ID (0/1)	0.281	-0.047	0.139	-0.044	0.131
	(0.267)	(0.053)	(0.150)	(0.053)	(0.150)
has Me-page (0/1)	-0.133	0.109	-0.096	0.097	-0.068
	(0.287)	(0.063)	(0.161)	(0.061)	(0.165)
is industrial (0/1)	-0.389	-0.062	-0.190	-0.064	-0.189

	(0.260)	(0.056)	(0.146)	(0.056)	(0.145)
membership duration in mo.	-0.349***	-0.014	-0.193**	-0.018	-0.194***
	(0.105)	(0.028)	(0.059)	(0.028)	(0.058)
log(seller activity)	0.036	-0.002	0.020	-0.002	0.027
	(0.062)	(0.015)	(0.034)	(0.015)	(0.034)
log(competition)	-0.144*	-0.017	-0.071	-0.019	-0.071
	(0.069)	(0.018)	(0.041)	(0.018)	(0.040)
log(length item descript.)	-0.007	-0.001	-0.004	-0.001	-0.004
	(0.005)	(0.001)	(0.002)	(0.001)	(0.002)
time in d (centered)	0.000	-0.005***	0.001	-0.005***	0.001
	(0.004)	(0.001)	(0.002)	(0.001)	(0.002)
auction ends on weekend (0/1)	-0.163***	-0.012	-0.091***	-0.013	-0.090***
	(0.034)	(0.008)	(0.020)	(0.008)	(0.020)

Further seller and item characteristics [only joint sig. test statistic $\chi^2_{(df)}$ or $F_{(df1, df2)}$]

accessories	10.56*	4.98**	12.71**	14.05**	12.75**
	(3)	(3, 3050)	(3)	(3)	(3)
memory capacity	144.28***	150.04***	167.15***	959.02***	163.49***
	(8)	(8, 3050)	(8)	(8)	(8)
format	64.11***	34.56***	66.36***	149.84***	66.43***
	(5)	(5, 3050)	(5)	(5)	(5)
brand	160.06***	5.40***	179.88***	133.93***	163.26***
	(26)	(26, 3050)	(26)	(26)	(26)
condition	56.41***	10.89***	58.85***	33.27***	58.20***
	(3)	(3, 3050)	(3)	(3)	(3)
seller origin	99.78***	6.87***	99.94***	102.53***	102.15***
	(15)	(15, 3050)	(15)	(15)	(15)
hour of day	35.73*	1.86**	32.08	42.55**	32.52
	(23)	(23, 3050)	(23)	(23)	(23)

athrho				0.136	
				(0.097)	
lnsigma				-0.445**	
				(0.156)	
N_1	88452	61744	88452	88452	
N_2	3248	3051	3248	3248	
pseudo R^2	0.44		0.44		
adj. R^2		0.68			
BIC (*df*)	61881 (109)	121275 (108)	62094 (109)	183287 (218)	

Notes: The table lists coefficient estimates (*** $p < 0.001$, ** $p < 0.01$, * $p < 0.05$, for two-sided tests) of logit, OLS, probit, and Heckman selection models. Cluster-robust standard errors are in parentheses. The binary outcome variable of models M1 and M3 is one if the auction received at least one bid and is zero otherwise. M1 is a logit regression while M3 is a probit regression of the same outcome variable. The outcome variable of model M2 is the log transformed selling price (in EUR) of auctions that received at least one bid. M4a is the part of the Heckman selection model which predicts the log transformed selling price (in EUR) of auctions that received at least one bid. M4b is the part of the Heckman selection model which predicts whether the auction received at least one bid. N_1 denotes the number of cases (auctions) and N_2 denotes the number of clusters (sellers).

Table A9 (full Table 2): Logit models of probability of additional bidder testing hypotheses H3 through H5

	M3	M4	M5	M6
Constant	2.777**	1.988*	2.207**	2.191*
	(1.003)	(0.857)	(0.855)	(1.038)
Main explanatory variables				
log(# positive ratings + 1)	0.131**	0.144***	0.147***	0.293*
	(0.043)	(0.038)	(0.037)	(0.115)
log(# negative ratings + 1)	-0.102*	-0.116**	-0.115**	-0.311*
	(0.050)	(0.043)	(0.043)	(0.148)
log(current price in €)	-1.154***	-1.009***	-1.023***	-1.161***
	(0.246)	(0.202)	(0.202)	(0.236)
log(# existing bidders + 1)	1.447***	3.742***		1.872***
	(0.085)	(0.201)		(0.330)
× log(# existing bidders + 1)		-1.198***		
		(0.094)		
× log(# positive ratings + 1)				-0.121
				(0.073)
× log(# negative ratings + 1)				0.162
				(0.099)
0 existing bidders (0/1)			ref.	
1 existing bidder (0/1)			1.580***	
			(0.120)	
2 existing bidders (0/1)			2.756***	
			(0.179)	
3 existing bidders (0/1)			3.043***	
			(0.134)	
4 existing bidders (0/1)			2.893***	
			(0.129)	
5 existing bidders (0/1)			2.756***	
			(0.140)	
6 existing bidders (0/1)			2.571***	
			(0.156)	
7 existing bidders (0/1)			2.416***	
			(0.155)	
8 existing bidders (0/1)			2.316***	
			(0.164)	
9 existing bidders (0/1)			2.188***	
			(0.176)	
10 existing bidders (0/1)			1.986***	
			(0.170)	
11 existing bidders (0/1)			2.128***	
			(0.193)	
12 existing bidders (0/1)			1.942***	
			(0.280)	
13 existing bidders (0/1)			2.230***	
			(0.332)	

14 existing bidders (0/1)			2.119***	
			(0.461)	
15 existing bidders (0/1)			2.087**	
			(0.742)	
16 existing bidders (0/1)			3.148***	
			(0.933)	
17 existing bidders (0/1)			1.487	
			(0.930)	
log(min to auction end)	0.463***	0.468***	0.457***	0.463***
	(0.018)	(0.015)	(0.015)	(0.017)
Payment and shipping options offered				
log(∅ shipping costs in €)	-1.334***	-1.348***	-1.355***	-1.310***
	(0.193)	(0.166)	(0.164)	(0.184)
PayPal or credit card (0/1)	0.768**	0.768**	0.745**	0.682*
	(0.289)	(0.277)	(0.272)	(0.310)
bank transfer (0/1)	0.609*	0.616*	0.604*	0.579*
	(0.256)	(0.250)	(0.247)	(0.259)
shipping insurance (0/1)	-0.867***	-0.926***	-0.923***	-0.810***
	(0.197)	(0.185)	(0.177)	(0.206)
return guarantee (0/1)	-0.255	-0.271*	-0.263*	-0.274
	(0.148)	(0.135)	(0.132)	(0.144)
Number of measures of self-advertisement on listing page				
none	ref.	ref.	ref.	ref.
one (0/1)	0.792***	0.748***	0.736***	0.784***
	(0.168)	(0.149)	(0.148)	(0.172)
two (0/1)	0.787**	0.805***	0.803***	0.796***
	(0.242)	(0.217)	(0.216)	(0.234)
three (0/1)	1.214**	1.103**	1.082**	1.338***
	(0.431)	(0.385)	(0.379)	(0.399)
four (0/1)	1.686***	1.391***	1.436***	1.667***
	(0.397)	(0.369)	(0.357)	(0.398)
Seller and item characteristics				
has verified ID (0/1)	0.006	0.013	0.010	0.029
	(0.134)	(0.121)	(0.117)	(0.135)
has Me-page (0/1)	0.005	0.047	0.044	0.033
	(0.124)	(0.116)	(0.114)	(0.127)
is industrial (0/1)	-0.195	-0.177	-0.182	-0.205
	(0.134)	(0.121)	(0.118)	(0.137)
membership duration in mo.	-0.000	-0.000	-0.001	-0.001
	(0.002)	(0.002)	(0.002)	(0.002)
log(seller activity)	0.057	0.053	0.051	0.051
	(0.033)	(0.029)	(0.029)	(0.033)
log(competition)	-0.070	-0.076	-0.082	-0.067
	(0.056)	(0.045)	(0.043)	(0.056)
log(length item descript.)	-0.106	-0.083	-0.082	-0.102
	(0.056)	(0.051)	(0.050)	(0.058)
time in d (centered)	-0.000	-0.001	-0.001	-0.001
	(0.003)	(0.003)	(0.003)	(0.003)

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auction ends on weekend (0/1)	-0.039	-0.048**	-0.052**	-0.039
	(0.020)	(0.018)	(0.019)	(0.020)

Further seller and item characteristics [only joint sig. test statistic $\chi^2_{(df)}$]

accessories	6.49	7.27	6.88	5.84
	(3)	(3)	(3)	(3)
memory capacity	132.74***	188.85***	196.06***	143.05***
	(8)	(8)	(8)	(8)
format	62.15***	62.42***	62.24***	61.02***
	(5)	(5)	(5)	(5)
brand	108.78***	122.54***	121.41***	99.97***
	(26)	(26)	(26)	(26)
condition	24.87***	24.38***	25.12***	26.65***
	(3)	(3)	(3)	(3)
seller origin	88.02***	100.01***	98.65***	96.56***
	(15)	(15)	(15)	(15)
hour of day	69.99***	86.85***	83.73***	73.90***
	(23)	(23)	(23)	(23)
N_1	356374	356374	356373	356374
N_2	3201	3201	3201	3201
pseudo R^2	0.37	0.39	0.40	0.37
BIC (df)	253386 (107)	242600 (108)	241866 (123)	252838 (109)

Notes: The table lists coefficient estimates (*** $p < 0.001$, ** $p < 0.01$, * $p < 0.05$, for two-sided tests) of logit regression models and cluster-robust standard errors in parentheses. The binary outcome variable of all models is one if the auction is joined by a / another bidder and is zero otherwise. N_1 denotes the number of cases (bidder-joins-auction events) and N_2 denotes the number of clusters (sellers).

Robustness Checks

In this section we provide a number of robustness checks for the models reported in Table 1 and Table 2 in the main part of the paper.

The Heckman selection model predicts simultaneously the probability that an item will be sold and the final price of the item, provided that the item is sold. Hence, the model uses information from unsold items to improve the estimates of the OLS model. While non-random selection of sold items is a potentially serious problem, in our case it does not seem to be an important issue. Models M-b.1 and M-b.2 in Table A8 above list the estimates of the Heckman selection model. M-b.1 is the OLS part of the model that predicts the final price. M-b.2 is the part of the model that predicts whether an item will be sold or not. Both parts are fitted simultaneously. The estimates of M-b.1 are very similar to the OLS estimates of M2, which predicts the final price of sold items. Similarly, the estimates of M-b.2 are very similar to the estimates of M-a, which predicts the probability that an item will be sold with a probit specification. We thus conclude that a potential non-random selection of sold items is not a problem in our case.

Table A10 below includes estimates for five additional models that predict the probability of a new bidder joining the auction. M1 is a linear probability model that includes seller fixed effects. A logistic regression with seller fixed effects did not converge (perhaps because of the well-known "incidental parameter problem"). M1 shows that including seller fixed effects does not change the inverse-u shaped association between the number of existing bidders and the probability of next bidder joining the auction. The local maximum of the quadratic function in M1 corresponds to three existing bidders. Note that due to seller fixed effects seller characteristic that do not change within a seller cannot be estimated in M1. M2 is another linear probability model that does not include seller fixed effects. A comparison of M1 with M2 shows that including seller fixed effects hardly changes the estimates of the main parameters of interest.

M3 includes interaction terms that involve seller reputation and the number of existing bidders with a quadratic specification for the number of existing bidders. In line with the results presented in the main manuscript, there is no evidence in the data in support of the hypothesis that the effect of seller reputation changes with the number of existing bidders in the auction. Moreover, we applied Simonsohn's (2018) two-lines approach using the "Robin Hood" algorithm to test the inverse u-shaped relation implied in hypothesis H4. At the

moment this method applies to linear regression specifications and does not generalize to logistic regression. Therefore, we fit a variant of M4 in Table 2 with a linear probability specification (hence the predicted y-axis in the results can be outside the [0,1] range). We include the non-logged version of the number of existing bidders as an independent variable. All other variables, including control variables reported for M4 in Table 2 are included in the model (the model is not shown). The result is shown in Figure A2. The average slope is positive up to 4 existing bidders and then it becomes negative. Both slopes are statistically significant. We conclude that the two-lines test of Simonsohn (2018) confirms the results we reported in the main text: the chance of attracting new bidders and the number of existing bidders have an inverse-u type of relationship.

M4 and M5 include interactions between memory size of an item and the number of existing bidders with a quadratic specification for the number of existing bidders. M4 shows that those interactions are statistically significant. Because the number of existing bidders is included in the model with a quadratic specification, it is somewhat difficult to interpret the interaction effects of M4. Figure A3 helps with the interpretation. Figure A3 shows that the inverse-u shape association between the number of existing bidders and the probability of a next bidder joining the auction applies particularly to the items with a large memory size. For items with small memory sizes, the association seems monotonically increasing. In other words, for relatively large items herding is stunted after three existing bidders but for small items herding is apparent even after the number of existing bidders exceeds three. Note that there are relatively fewer small items in the dataset, so the inverse-u shape observed for larger items is the most common pattern. This is why an inverse-u shaped pattern emerges when the interactions are not included in the model. Figure A4 also helps with the interpretation of the difference between small and large items. Figure A4 shows the marginal effects of log(# existing bidders + 1) on the probability of another bidder joining the auction for different numbers of existing bidders broken down by memory size. The figure shows that the marginal effect turns negative after a certain number of bidders have joined, but only for large items. For small items the marginal effect remains positive throughout. Figure A4 is based on M5 which is fitted after collapsing the number of memory categories to two for ease of interpretation.

Table A10: Linear probability and logit models of probability of additional (robustness checks)

	M1	M2	M3	M4	M5
Const.	0.070	0.054	-2.911**	-1.172	-2.370
	(0.118)	(0.126)	(0.948)	(0.921)	(1.231)
$\log$(# positive ratings + 1)	0.001	0.006	0.194*	0.139***	0.067+
	(0.011)	(0.006)	(0.082)	(0.037)	(0.039)
$\log$(# negative ratings + 1)	-0.001	-0.000	-0.194	-0.113**	-0.063
	(0.018)	(0.007)	(0.108)	(0.043)	(0.053)
$\log$(# existing bidders + 1)	0.353***	0.478***	3.683***	-2.198	2.394***
	(0.017)	(0.022)	(0.644)	(1.128)	(0.552)
$\log$(# existing bidders + 1) ^{2}	-0.127***	-0.150***	-1.121***	1.889*	0.042
	(0.008)	(0.009)	(0.269)	(0.939)	(0.309)
$\log$(# positive ratings + 1) $\times \log$(# existing bidders + 1)			-0.015		
			(0.119)		
$\log$(# positive ratings + 1) $\times \log$(# existing bidders + 1) ^{2}			-0.013		
			(0.048)		
$\log$(# negative ratings + 1) $\times \log$(# existing bidders + 1)			0.041		
			(0.139)		
$\log$(# negative ratings + 1) $\times \log$(# existing bidders + 1) ^{2}			0.013		
			(0.055)		
Memory size					
16MB	ref.	ref.	ref.	ref.	
32MB	-0.030	0.058	0.719*	0.222	
	(0.062)	(0.041)	(0.292)	(0.549)	
64MB	-0.047	-0.125	-1.558**	-4.218***	
	(0.075)	(0.070)	(0.548)	(0.754)	
128MB	0.138	0.040	0.314	-1.096	
	(0.075)	(0.049)	(0.571)	(0.991)	
256MB	0.355***	0.201***	2.330***	1.094	
	(0.074)	(0.043)	(0.374)	(0.591)	
512MB	0.367***	0.229***	3.064***	1.551**	
	(0.079)	(0.044)	(0.391)	(0.553)	
1024MB	0.505***	0.366***	4.800***	3.310***	
	(0.079)	(0.043)	(0.436)	(0.596)	
2048MB	0.568***	0.454***	6.095***	4.638***	
	(0.083)	(0.049)	(0.538)	(0.703)	
4096MB	0.543***	0.462***	6.853***	5.935***	
	(0.086)	(0.057)	(0.667)	(0.853)	
< 128MB					ref.
≥ 128MB					3.061***
					(0.602)
Memory size # existing bidder interactions					
16MB × $\log$(# existing bidders + 1)				ref.	
32MB × $\log$(# existing bidders + 1)				2.125	
				(1.621)	
64MB × $\log$(# existing bidders + 1)				6.268***	
				(1.642)	
128MB × $\log$(# existing bidders + 1)				3.882**	
				(1.350)	
256MB × $\log$(# existing bidders + 1)				5.081***	
				(1.217)	
512MB × $\log$(# existing bidders + 1)				5.182***	
				(1.205)	

1024MB × log(# existing bidders + 1)				5.802***	
				(1.132)	
2048MB × log(# existing bidders + 1)				6.320***	
				(1.133)	
4096MB × log(# existing bidders + 1)				4.429***	
				(1.341)	
16MB × log(# existing bidders + 1)^2				ref.	
32MB × log(# existing bidders + 1)^2				-1.230	
				(1.282)	
64MB × log(# existing bidders + 1)^2				-1.105	
				(1.358)	
128MB × log(# existing bidders + 1)^2				-1.494	
				(1.081)	
256MB × log(# existing bidders + 1)^2				-2.648**	
				(0.966)	
512MB × log(# existing bidders + 1)^2				-2.559**	
				(0.946)	
1024MB × log(# existing bidders + 1)^2				-2.996**	
				(0.930)	
2048MB × log(# existing bidders + 1)^2				-3.290***	
				(0.934)	
4096MB × log(# existing bidders + 1)^2				-2.468*	
				(0.977)	
<128MB × log(# existing bidders + 1)					ref.
≥ 128MB × log(# existing bidders + 1)					1.435*
					(0.568)
<128MB × log(# existing bidders + 1)^2					ref.
≥ 128MB × log(# existing bidders + 1)^2					-1.128***
					(0.312)

Controls					
log(current price in €)	-0.027***	-0.050***	-1.016***	-1.063***	-0.605***
	(0.007)	(0.009)	(0.194)	(0.201)	(0.073)
log(∅ shipping costs in €)	-0.100*	-0.089***	-1.345***	-1.343***	-0.649***
	(0.040)	(0.020)	(0.162)	(0.157)	(0.137)
log(min to auction end)	0.070***	0.069***	0.467***	0.466***	0.519***
	(0.002)	(0.002)	(0.015)	(0.014)	(0.013)
PayPal or credit card (0/1)	0.042	0.102	0.727*	0.753**	0.404
	(0.052)	(0.055)	(0.295)	(0.277)	(0.269)
bank transfer (0/1)	0.007	0.093*	0.602*	0.617*	0.270
	(0.051)	(0.046)	(0.253)	(0.252)	(0.230)
shipping insurance (0/1)	-0.245	-0.119*	-0.901***	-0.935***	-0.829**
	(0.126)	(0.060)	(0.193)	(0.180)	(0.256)
return guarantee (0/1)	0.025	-0.019	-0.281*	-0.261*	-0.230
	(0.062)	(0.023)	(0.130)	(0.131)	(0.148)

Number of measures of self-advertisement on listing page					
none	ref.	ref.	ref.	ref.	ref.
one (0/1)	0.192***	0.092***	0.740***	0.750***	1.088***
	(0.037)	(0.022)	(0.149)	(0.144)	(0.176)
two (0/1)	0.171***	0.085**	0.809***	0.840***	1.292***
	(0.041)	(0.028)	(0.210)	(0.207)	(0.268)
three (0/1)	0.140***	0.121**	1.169***	1.131**	1.502***
	(0.040)	(0.039)	(0.343)	(0.365)	(0.263)
four (0/1)	0.555***	0.068	1.381***	1.278***	2.080***
	(0.106)	(0.067)	(0.367)	(0.359)	(0.401)

seller has verified ID (0/1)	0.006	0.005	0.018	0.004	0.028
	(0.008)	(0.024)	(0.120)	(0.119)	(0.192)

seller has Me-page (0/1)	0.021	-0.026	0.059	0.052	-0.208
	(0.012)	(0.019)	(0.117)	(0.117)	(0.145)
seller is industrial (0/1)	-0.012	-0.014	-0.178	-0.169	-0.152
	(0.016)	(0.020)	(0.122)	(0.122)	(0.168)
log(length item descript.)	-0.009	-0.014	-0.080	-0.087	-0.217***
	(0.017)	(0.009)	(0.052)	(0.050)	(0.062)
log(seller activity)	0.000	0.011*	0.050	0.056	0.113***
	(.)	(0.005)	(0.029)	(0.029)	(0.033)
log(market competition)	-0.010	-0.005	-0.075	-0.077	-0.042
	(0.008)	(0.008)	(0.045)	(0.044)	(0.071)
membership duration in mo.	0.002	0.000	-0.000	-0.000	-0.000
	(0.007)	(0.000)	(0.002)	(0.002)	(0.002)
time in d (centered)	0.000	0.001*	-0.001	-0.001	0.005*
	(0.000)	(0.000)	(0.003)	(0.003)	(0.002)
auction ends on weekend (0/1)	-0.010***	-0.005	-0.048**	-0.052**	-0.037*
	(0.002)	(0.003)	(0.018)	(0.018)	(0.019)
Further controls	$F_{(k, 3200)}$	$F_{(k, 3200)}$	χ^2	χ^2	χ^2
accessories	51.02***	5.25**	6.85	8.75*	11.01*
	(3)	(3)	(3)	(3)	(3)
format	1.43	6.92***	62.37***	65.39***	11.69*
	(5)	(5)	(5)	(5)	(5)
brand	8.92***	3.19***	119.10***	117.87***	183.85***
	(25)	(26)	(26)	(26)	(26)
condition	1.22	4.29***	26.76***	23.04***	25.66***
	(3)	(3)	(3)	(3)	(3)
seller origin	302.41***	8.34***	116.90***	104.27***	105.10***
	(2)	(15)	(15)	(15)	(15)
hour of day	10.25***	4.73***	90.37***	86.39***	79.43***
	(23)	(23)	(23)	(23)	(23)
N_1	356374	356374	356374	356374	356374
N_2	3201	3201	3201	3201	3201
(pseudo) R^2	0.25	0.35	0.40	0.40	0.34
BIC (df)	224250.5	261768.7	242534.3	241328.8	262855.9
	(90)	(108)	(112)	(124)	(103)

Notes: The table lists coefficient estimates and standard errors (*** $p < 0.001$, ** $p < 0.01$, * $p < 0.05$, for two-sided tests). The binary dependent variable is one if the auction is joined by another bidder and it is zero otherwise. M1 and M2 are Linear Probability Models. M1 includes seller fixed effects. M3 to M5 are logistic regression models. M3 includes interactions between seller reputation and the number of existing bidders with a quadratic specification. M4 includes interactions between memory size of the item and the number of existing bidders with a quadratic specification. M5 is a simplified version of M4 in which the number of categories of memory size is reduced to two. N_1 denotes the number of cases (items) and N_2 denotes the number of clusters (sellers). In all models standard errors are calculated taking clustering within a seller into account.

Figure A2. Simonsohn's (2018) two-lines test of the inverse-U relationship. Y-axis: chance of attracting new bidder, x-axis: number of existing bidders.
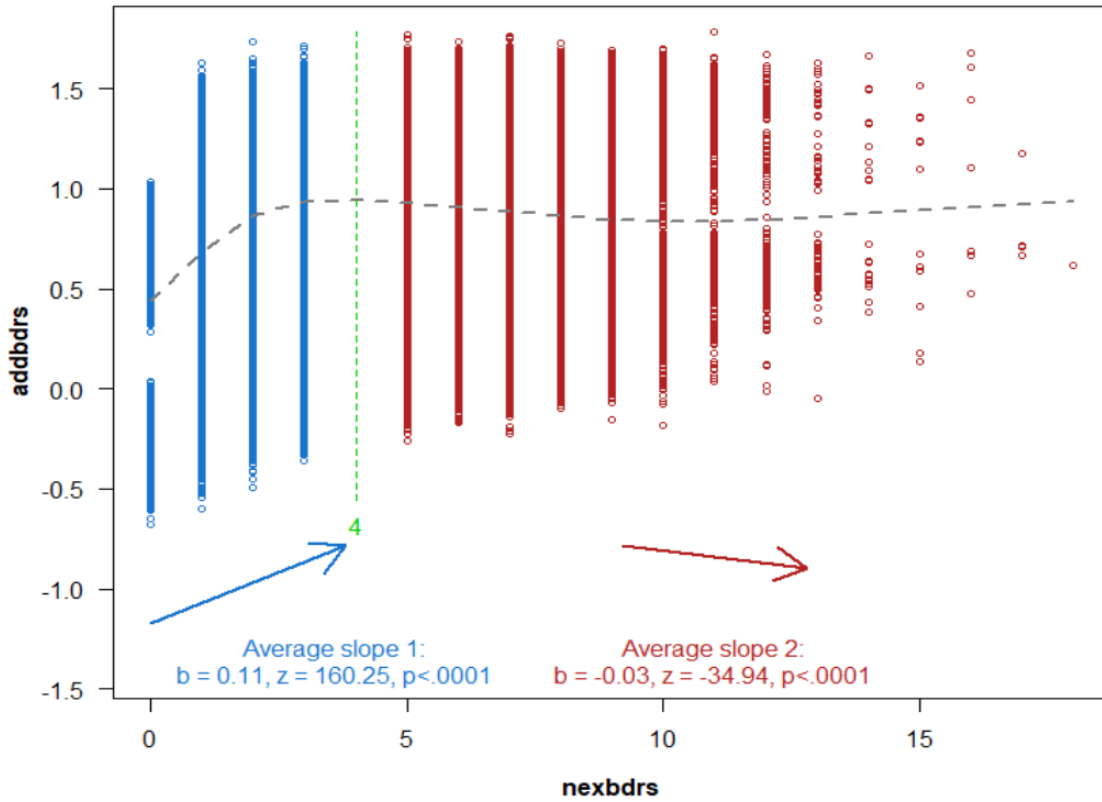

Figure A3. Association between the number of existing bidders and the probability of a next bidder joining the auction broken down by memory size of the product. The figure is based on M4 in Table A10.
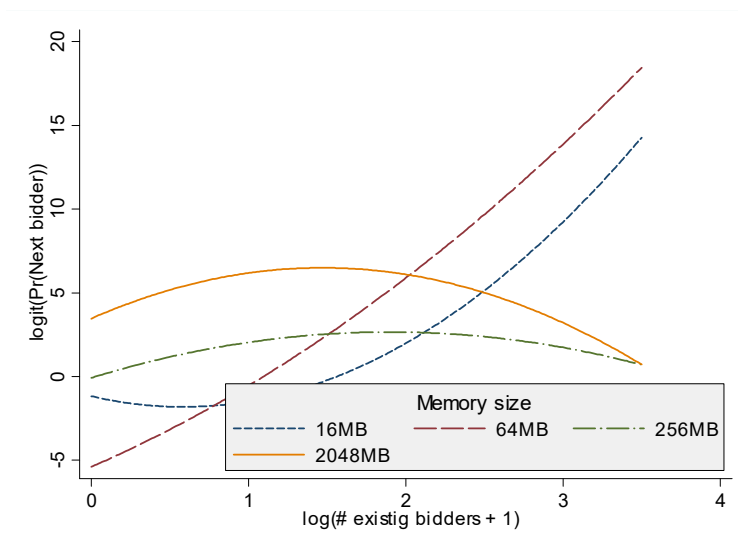
Figure A4: Average marginal effects of log(number of existing bidders + 1) on the probability of a next bidder joining the auction broken down by memory size of the product obtained from M5 in Table A10.