Wirtschaftswissenschaftliches Zentrum (WWZ) der Universität Basel

May 2014

Shill Bidder's Behavior in a Second-Price Online Auction

WWZ Discussion Paper 2014/03

Dominic Herzog

Corresponding Author:

Dominic Herzog, Assistant

Finanzmarkttheorie
Wirtschaftswissenschaftliches Zentrum der
Universität Basel (WWZ)
Peter Merian-Weg 6
CH - 4002 Basel

+41(0) 267 24 52

dominic.herzog@unibas.ch

A publication of the Center of Business and Economics (WWZ), University of Basel.

Shill Bidder's Behavior in a Second-Price Online Auction

DOMINIC HERZOG

University of Basel

12th May 2014

Shill bidding is a fraudulent in-auction strategy where a seller participates as a bidder in his own auctions. This is the first paper on shill bidding that is based on a data set which includes personal details. Along with bidding histories, I can prove that on the investigated platform 0.3% of all auctions were influence by obvious shill bidders. The majority of the proven shill bidders' behavior in this paper does not fulfill any of the shill bidder types' criteria discussed in the literature. I adopt two algorithms which aim to identify shill bidders based on public information. On average, these approaches assign a higher probability of being a shill bidder to the accounts of bidders who certainly shilled on auctions in my data set. However, a reliable identification of proven shill bidders and honest bidders is only possible to a limited extent.

Key words: auction, shill bidding, bidding behavior

JEL classification: D12, D44

INTRODUCTION

Shill bidding describes the auction behavior of a seller who also participates as a bidder in his own auctions and allows the seller to drive up the sales price or to reach a desired minimum price that is exempt of the insertion fee. The anonymity of the web facilitates this type of fraudulent selling activity because even an attentive observer can hardly ever assign a user account to a specific person. "The most crucial issue is that online identities are easily created and cannot be tracked back to the physical identities without inside information." (Ockenfels *et al.*, 2006, p. 25) The auctioneer, however, has access to the participants' personal details, and is therefore optimally positioned to prohibit shill bidding. Unfortunately, the auctioneer's incentive to fight this fraudulent behavior is limited. His main source of revenue from sold articles is the final value fee and, therefore, his profit rises along with the sales price. If the auctioneer publishes a bonafide warning that shill bidding is prohibited, this might encourage more aggressive bidding behavior and, therefore, his profit. However, he still has an incentive to disregard such misconduct in order to profit from price-pushing shill bids.

Several studies (e.g., Trevathan and Read, 2007; Engelberg and Williams, 2009; Kauffman and Wood, 2005; Ford *et al.*, 2013; Dong *et al.*, 2010) have recognized this incentive problem and have developed approaches to tackle misconduct of this kind. They use public information such as bidding histories in order to identify suspicious behavior. In particular, pairs of sellers and bidders are seen as suspect if their accounts are observed to participate regularly in the same auctions, where the bidder hardly ever wins. These studies successfully identify shill bid accounts by use of their algorithm in their training data set. However, owing to the lack of field data documenting proven shill bidders, the precision of their suggested approaches are difficult to verify.

This paper focuses on the online auction platform ricardo.ch. Ricardo.ch AG is a Swiss subsidiary of the multinational media company Naspers. With over 3 million user accounts and 20,000 sold articles per week, ricardo.ch operates the most frequently used auction platform in Switzerland (ricardo.ch AG, 2014a). They offer second-price auctions with a proxy bidding system, similar to the auction design used by eBay.

While searching for transmitted information on auction details, I noticed that ricardo transmits valuable information that is not displayed in the browser. Along with user's nicknames, ricardo submits unsolicited personal details (e.g., full postal address, phone number) of users to everyone browsing their website. Moreover, all maximum bids that have been entered in the proxy bidding system are involuntarily submitted as well. By aggregating this information and collating it with publicly observable data, I created a large data set which provides unique insights into (shill-) bidding behavior.

Confidential information such as an individual's personal details and the maximum bid are not publically available for good reasons. However, ricardo.ch's negligence in ensuring data protection has provided a unique opportunity to obtain the personal details of all their user accounts for scientific purposes. According to Naspers (2014), three additional European auction houses belong to the ricardo Group, namely: ricardo.gr (operating in Greece); qxl.dk (operating in Denmark); and qxl.no (operating in Norway). All four auction houses transfer the maximum bid, entered for proxy bidding, of all bidders along with the bidding history. In addition, personal details were also available for ricardo.gr.

These auction data allow me to assign all accounts on ricardo.ch and ricardo.gr to individuals and identify shill bidders based upon information that is normally only accessible to the auctioneer. In addition, I am able to monitor and judge ricardo's attempts to prohibit shill bidding and to test shill-bidder identification algorithms.

Most studies on auctions use data about behavior on eBay. In order to evaluate to what extend the findings about shill bidding on ricardo can be applied to eBay, I compare the bidding behavior on ricardo to comparable figures on eBay (USA) auctions presented by Hayne *et al.* (2003).

The remainder of the paper is structured as follows. Section I discusses the related literature and highlights the contribution of this paper. In Section II, I describe in more detail the data collection and summarize my acquired data set. Section III analyzes the behavior of proven shill bidders. Moreover, I apply two shill-bidder identification algorithms to my data in order to check whether they identify the proven shill bidders. Section IV compares the bidders' behavior across the four country-specific auction houses provided by the ricardo Group and eBay (USA). Finally, Section V concludes.

I LITERATURE

The rising popularity of online auctions has recently entailed an abundance of studies in this field (Ockenfels *et al.*, 2006, Aleem and Antwi-Boasiako, 2011). One branch of this literature investigates in-auction fraud; i.e., fraudulent behavior of any participant during a running auction. Such fraudulent behavior can emanate either from the auction house (e.g., Bag *et al.*, 2000), from buyers (e.g., Sher, 2012; Chen and Tauman, 2006), or from the seller (e.g., Chakraborty and Kosmopoulou, 2004; Izmalkov, 2004; Hlasny, 2006). The latter contains shill bidding (the short form being 'shills').

(a) Motivating Shills

Shill bidding describes the fraudulent in-auction behavior of a single individual, who influences the auction by using multiple accounts in order to submit bids (Yokoo *et al.*, 2004). Even though auctions exists where potential buyers use shill bids (Sher, 2012, Yokoo *et al.*, 2004), I focus on sellers who bid on articles they are selling and use the term 'shill bid' in this narrower sense. Shills can differ with regard to the sellers' motivation (e.g., Kaur and Verma, 2013; Engelberg and Williams, 2009; Watanabe and Yamato, 2008): (1) Reserve-Price Shilling occurs early in the auction and ensures a minimum price, without paying the fees associated with an official reserve price; (2) Buy-Back Shilling occurs late in the auction and is aimed at prohibiting the sale of the article; (3) By Competitive Shilling, the seller continuously outbids the highest bidder (up to a certain amount); and (4) Discover-and-Stop Shilling is a strategy in auctions with proxy bidding, where the seller tries to discover the maximum bid and places a shill bid just below this value.

The Discover-and-Stop strategy is based on eBay's proxy bidding rules (Engelberg and Williams, 2009). If the current (hidden) maximum bid exceeds an incoming bid by at least one increment, then the system places a proxy bid which exceeds the incoming bid by exactly one increment. If, however, the current (hidden) maximum bid exceeds an incoming bid by less than one increment, then a proxy bid is placed at the maximum entered value. The Discover-and-Stop strategy carries the risk of accidentally becoming the highest bidder. However, this risk can be reduced when bidders bid in predictable units. Engelberg and Williams (2009) became the highest bidder in 16 out of 46 Discover-and-Stop attempts and won 7 out of 30 auctions. Such failed shill bid attempts are falsely classified as Competitive Shills. Ricardo's proxy bidding rules differ from those on eBay and do not allow the highest bidder's entered maximum bid to be revealed. Suppose the current highest bidder H entered b_H as his maximum bid. Later on, another bidder A enters the amount b_A as his maximum bid. If $b_H \geq b_A$, then ricardo's proxy bidding system places a bet at b_A for H. H remains the highest bidder because earlier bids are given priority.

(b) Model that Deals with Shill Bidding

Chakraborty and Kosmopoulou (2004) analyze a common value auction without considering the auctioneer's reputation, being aware that reputation potentially affects the auctioneer's long-run profitability. They show that bidders cannot be fooled in equilibrium, because bidders correctly anticipate the potential participation of the seller. Since the seller sometimes wins an auction, the possibility of shill bidding lowers the expected payoff for buyers and sellers. However, an auction house which only cares about the sales price and not about who wins the auction gains from shill bidding. Kosmopoulou and Silva (2007) provide experimental evidence for this model. They find that bidders bid less aggressively if they believe that shilling is possible and is tolerated by the auction house.

(c) Evidence of Shill Bidding

Although shill bidding is strictly prohibited (ricardo.ch AG, 2014c; eBay Inc, 2013), previous research as well as court rulings (Schwartz and Dobrzynski, 2001) prove that this behavior distorts the course of numerous auctions. The anonymity provided by internet auctions facilitates shilling, because bidders can hardly identify whether or not another bidder is shilling on behalf of the seller. Shilling is even advantaged when the auction house permits multiple nicknames per person (ricardo.ch AG, 2014c; eBay Inc, 2013). Auction houses therefore have an important role to play in prohibiting shill bids. Along with bidding histories, they have exclusive access to the personal data of all the nicknames and are therefore able to link nicknames and detect individuals who obviously shill on their own articles.

(d) Identifying Shill Bidders

Auction houses prefer to preserve their good reputation by prohibiting shills, which encourage a more aggressive bidding behavior. Unfortunately, as the auctioneer's revenue is a share of the sales price, they are not opposed to inconspicuous shill bidders who artificially buoy up the final price.

The fact that auction houses have insufficient incentives to fight shill bidding has prompted several studies which attempt to identify shill bidders based on public information. These studies suggest 'shilling variables' which capture suspicious bidding characteristics and describe how to calculate and condense them into a 'shill score' or into a shill probability, respectively. They test their approach either on simulated data or on auctions where they identify shill bidders according to a specific strategy.

Trevathan and Read (2005) developed an algorithm which calculates a shill score based on six shilling variables. This shill score indicates whether a seller and a specific buyer are engaged in collusive shill-biding behavior. In Trevathan and Read (2007), they extend their approach in order to identify sellers who use multiple accounts to place shill bids. Their suggested collusion score combines the shill score with dependencies among nicknames using a graph theory approach.

Engelberg and Williams (2009) show that eBay's proxy bidding design allows for a *Discover-and-Stop* strategy. By incremental bidding, the seller can discover the maximum bid of the highest bidder and stop bidding just below this value. Based on betting behavior characteristics, they estimate that 1.39 percent of all bids on eBay are placed according to their identified Discover-and-Stop strategy and are therefore shills. Engelberg and Williams (2009) use a probit model to validate their suggested shilling variables. Moreover, they experimentally demonstrate the profitability of the Discover-and-Stop strategy and highlight the associated risk of overbidding.

Kauffman and Wood (2005) use premium bids as a proxy for shills. A premium bid is a bid which is placed at an auction while another auction exists on the same article at a lower current price. They find that premium bidding occurs in 23% of all auctions in their data set.

Ford *et al.* (2013) developed an algorithm based on a feed-forward, back-propagation neural network in order to detect suspicious bidders. Suspicious bidders can then be analyzed in more detail by an external shill verifier. Such a shill verifier is, for example, suggested by Dong *et al.* (2010) who use an approach based on the Dempster-Shafer theory of evidence.

II Data

Auctions on ricardo follow the rules of a second-price auction and offer the possibility of proxy bidding. Proxy bidding means that a bidder can enter his maximum bid and the system autonomously raises this bidder's bid up to the desired amount. Ricardo uses a 'soft close' ending rule. The automatic run-time expansion is three minutes. Regarding this criterion, ricardo differs slightly from eBay's (who uses a 'hard close') auction format. Ockenfels and Roth (2006) analyze how different ending rules influence bidder's behavior.

Owning multiple accounts is not prohibited in the terms and conditions of ricardo. However, ricardo explicitly prohibits shill bids placed by the seller, by persons living in the seller's household or by any person acting on behalf of the seller. Breach of this paragraph is sanctioned by issuing a caution or suspension (ricardo.ch AG, 2014c; ricardo.ch AG, 2014b).

(a) Origin of the Data

In order to display dynamically changing contents in a user's browser, the ricardo Group's websites use 'Asynchronous JavaScript and XML' (AJAX) requests. In practice, this means that whenever a user addresses ricardo.ch, then: (1) the browser receives a source code which contains placeholders; (2) the browser requests the current values for those placeholders from the server; (3) the server replies with those values; and (4) the browser combines all information in order to display the requested website.

In December 2013, I noticed very valuable information that was submitted by ricardo.ch's server in response to the implemented AJAX requests. Along with the public variables' values (e.g., nickname), the server submitted personal details such as the user's postal address or his (mobile) phone number. Whenever an individual was browsing ricardo.ch's auctions, the browser received the personal details of all participating users. Even though this confidential information is not displayed in the browser, its submission clearly breaches data protection rules. Privacy protection concerning the account data is not only in the consumers' interest. Ricardo itself is anxious to prevent any communication between auction participants, as the participants may collude and arrange price agreements in order to avoid auction fees.

Shill bidders who attempt to raise the sales price, but also wish to avoid ending up as the highest bidder, typically have to make decisions under uncertainty about the maximum bid that another (proxy) bidder has entered. However, the AJAX standard request about the bidding history of (running) auctions on ricardo returns the value of the entered maximum bid along with the bidding history. Therefore, the combination of ricardo's proxy bidding system and their information leakage which submits the highest bidder's maximum bid is virtually an invitation to shill.

On April 22, 2014, ricardo.ch blocked my IP address and, therefore, I stopped the recording. I advised ricardo.ch of their platforms' information leakage which was then closed by ricardo.ch within a few hours.

(b) Data Collection

The data recording occurred in the period between December 21, 2013 and April 22, 2014. To collect all the data necessary for a comprehensive analysis, I programmed three algorithms in JAVA, with the purpose of collecting: (1) user details; (2) auction details and their bidding histories; and (3) rating details.

Ricardo.ch does not prohibit the use computer systems for gathering information about the activities undertaken on their platform, as long as these do not interfere with its normal performance. Collecting and using these (personal) data for scientific research conforms to the Swiss data protection law, DSG, Article $13^2(e)$.

The requests to ricardo.ch's server in order to gain the desired items of information are described below. Similar requests were possible for the three other European auction houses which belong to the ricardo Group: ricardo.gr; qxl.dk; and qxl.no. Only the domain and the value of the variable PartnerNr had to be changed according to Table 5.

User Details Ricardo assigns a unique user number *userNr* to each user account. This identification number remains the same, irrespective of whether the personal details or the *nickName* change. The algorithm requested and recorded the personal details of all currently available user accounts. The requests took the following structure:

> http://www.ricardo.ch/DataService/Proxy.aspx?DataService.svc/json/
> GetAuctionSellerInfos?UserNr=*userNr*&PartnerNr=2&IsHttps=false

The server's response to the request on my account contained, amongst other things, the following excerpt:

[...] 'PhoneNumber':'0041615546909' [...] 'City':'Basel' [...] 'Street':'Winkelried-platz','StreetNr':'9','ZipCode':'4053' [...] 'UserFirstName':'Dominic', 'UserLast-Name':'Herzog' [...]

Table 1 lists the variables which were recorded for each account and indicates for which platform the corresponding value was submitted. The information about the ratings' value as well as whether or not an account has been suspended were recorded along with the rating details.

[Table 1 here]

Auction Details and Their Bidding Histories Ricardo assigns a unique *articleID* to each auction. This number remains the same even if an article has not been sold and the item is re-auctioned. Details on closed auctions as well as their bidding history remain available for about three months. Therefore, available data on past auctions were recorded. In addition, the algorithm stored articleIDs from current auctions and requested the auction's information once the auction was closed. The requests took the following structure:

http://auto.ricardo.ch/DataService/Proxy.aspx?DataService.svc/json/
GetBidsHistory?AuctionNr=*articleID*&PartnerNr=2&NbBidsToShow=20000
&IsArchived=false&IsHttps=false

The auction's details and the bidding history were recorded for each auction. Table 2 and Table 3 list the recorded variables.

[Table 2 here]

[Table 3 here]

Rating Details I extracted the rating details of all accounts directly from the website's source code. The requests for this purpose were submitted via one of the two following links:

http://www.ricardo.ch/online-shop/*nickName*/?SeeComments=True
&SellerNickName=*nickName*

http://auto.ricardo.ch/accdb/ViewUser.asp?IDU=*userNr*

Whenever possible, the rating details were extended with information about the rating history during the last 12 months. These additional data show who's rated who, and therefore allow for more in-depth network analysis among accounts. The ratings received and given are recorded and contain the variables described in Table 4. These requests were made according to one of the two following links:

> http://www.ricardo.ch/online-shop/*nickName*/?SellerNickName=*nickName* &SeeComments=True&RatingPeriod=12&PageSize=120&CurrentPage=*pageNumber*
>
> http://www.*domain*/accdb/ViewUser.asp?IDU=*userNr* &RatingType=7&RatingDate=12 &PageNr=*pageNumber*

[Table 4 here]

(c) Data Summary

Table 5 summarizes the recorded data set based upon these requests. On qxl.dk and qxl.no, I only recorded the account's details from users who took part in at least one recorded auction. Comparing the number of accounts as well as the number of ratings across ricardo and qxl platforms is, therefore, not possible. The average values shown in Table 5 refer to auctions where the article was sold. The number of bids is the number of times a bidder entered a new (maximum) bid.

[Table 5 here]

Ricardo.ch is by far the most frequently used platform. In comparison with the other ricardo Group platforms, over twenty times as many articles were sold via the Swiss auction house. In addition, auctions on ricardo.ch attract on average the most bids and the most bidders. Articles sold on ricardo.ch have the highest values about median and average number of page views. A high number can either result from more potential bidders or from repeated page requests. This value is, therefore, a proxy for the buyers' interest and activity on the platform.

Assuming independently and identically distributed private values among bidders, the seller's expected revenue equals the expected valuation of the second-highest bidder. This expected value of the second-order statistic rises as the number of bidders increases. Therefore, the higher average participation rate on ricardo.ch might give reasons for the higher number of offered, respectively sold, articles. However, the insertion fee as well as the final value fee differ between ricardo's platforms, which might influence a seller's decision to list an article.

The optimal reserve price does not depend on the number of bidders involved in a standard auction model (see, for example, Krishna, 2009). However, if only one bidder participates in the auction, then the reserve price is most important in order to prevent the article from being sold at the starting price. The auction house encourages sellers to abstain from a reserve price, which is the same as the starting price on ricardo, by priority listing of auctions with a start price of 1.00 CHF/EUR/DKK/NOK and by insertion fees which typically increase with higher reservation prices. While priority listing occurs on all four platforms, the insertion fees differ across platforms and article categories. However, the insertion fees are relatively low compared with the final value fees. The Danish and Norwegian platforms charge an insertion fee even for the lowest possible starting price, which might be responsible for the low share of auctions without a reserve price. However, ricardo.gr did not charge any insertion fee during the observation period and even the fact that most auctions attracted only one bidder did not induce the sellers to set a reserve price.

III Analyzing Shill Bidders

The seller's and the bidder's accounts are both identified as shill bidder accounts if, in a specific auction, the individuals behind the seller and a bidder live in the same household.

(a) Identify Shill Bidders: Personal Data

Accounts which are registered with an identical full name, address, postal code and zip are assigned to one single person (*fullAddress*). The same mobile phone number also indicates the same person, and the same phone number indicates, at least, that the persons live in the same household (*phoneNumber*). In addition, I treat accounts with identical last name, address, postal code and zip as individuals inhabiting the same household (*shortAddress*), being aware of the fact that this criterion might contain incorrect relationships. As some accounts might be identified through more than one of these criteria, *potentialShillBidAccounts* and *shillBidAccounts* count the number of accounts that fulfill at least one criterion.

This approach does not have the capacity to identify relationships between individuals who have different last names or who do not live at the same address. In particular, I cannot assign two accounts to one specific individual if the person moved and opened up a new account afterwards.

Table 6 implies that on ricardo.ch 54% of all accounts belong to individuals who own one single account. Most individuals with multiple accounts are identified according to their phone number, whereas half of all users specified their mobile phone number as the phone number by which they can be contacted. Owning multiple accounts can be interpreted as indicating fraudulent dealings. However, there are other innocent reasons for having multiple accounts, as when individuals simply forget their log in data or even forget that they already possess an account.

[Table 6 here]

A shill bidder cannot be identified simply by the number of accounts he owns, but instead by whether or not he uses more than one account in a specific auction. The data set contains very few individuals who used more than one shill bidder account in order to bid for a specific article. This result validates the focus on shill bids where an individual participates in his own auction with one shill bidder account. Table 7 shows the number of identified shill bid accounts as well as the number of individuals owning them.

[Table 7 here]

The 3,795 *shillBidAccounts* on ricardo.ch placed shill bids in 5,799 auctions (0.34% of the total). On ricardo.gr, the share of auctions in which a shill bid occurred is 0.24% on the total. However, this share results from only two identified shill bids and the low number of sold articles. For this reason, the following shill bid analysis addresses solely the shill bidding behavior on ricardo.ch.

(b) Categorizing Identified Shill Bids

The literature generally describes four different types of shill bidding, namely: Reserve-Price Shilling; Competitive Shilling; Buy-Back Shilling; and Discover-and-Stop Shilling. The aim of this subsection is to determine which shilling strategy most commonly occurs on ricardo.ch. Shill bids are, as in the previous subsection, identified either through the *phoneNumber*, the *fullAddress* or the *shortAddress*. Rather than categorizing the account, I regard and categorize each shill bid or each shill bid sequence, respectively. This approach allows for individuals who use different shill bidding strategies.

The Discover-and-Stop Shilling strategy described by Engelberg and Williams (2009) cannot be applied on ricardo due to differences in ricardo's and eBay's proxy bidding system. However, I assign bids as if Discover-and-Stop Shilling would be possible on ricardo in order to examine whether the behavior of some shill bidders nonetheless meets the Discover-and-Stop Shilling criterion.

The Competitive Shilling strategy as well as the Discover-and-Stop Shilling strategy typically need more than one bid. I name these bids 'Auxiliary Shill Bids'. As the value of *maxBid* can be publicly observed on ricardo, a shill bidder can simply bid the same maximum price in order to raise the current sales price. I call this strategy 'Insider Shilling'. In order to increase the number of bids that can be assigned to a type, I define two additional types which allow for a more tolerant interpretation of the Discover-and-Stop and Competitive Shilling strategy. The Conservative Discover-and-Stop Shilling strategy considers that the expected lost profits from overbidding the highest bidder increase along with higher prices. This risk causes the shill bidder to stop discovering the highest price even though the hidden maximum price is still more than one increment over the currently highest bid. Another interpretation would be, that the shill bidder is not aware of the Discover-and-Stop Shilling strategy and simply tries to raise the price while trying to avoid becoming the highest bidder. *Conservative Discover-and-Stop* differs from *Discover-and-Stop* by allowing the bidder to underbid the maximum bid by up to 10 increments. The Aggressive Competitive Shilling strategy allows a shill bidder to overbid the current maximum bid by up to 10 increments. This strategy reduces the shill bidder's number of bids which he has to enter on a specific article. These time savings might offset the higher risk of buying the article in the end, especially if the competing bidder does not use the proxy bidding system. If a shill bid does not satisfy any of these eight criteria, then this bid is assigned to the type 'Others'.

I assign shill bids according to the flowchart shown in Figure 1, whose decisions are based on the following criteria:

is an *Auxiliary Shill Bid*: An Auxiliary Shill Bids is identified: (1) if the shill bid is followed by another shill bid within 10 minutes; and (2) if one proxy bid occurred between these two shill bids.

follows an *Auxiliary Shill Bid*: This shill follows an *Auxiliary Shill Bid*, but is not labeled as an *Auxiliary Shill Bid* itself.

is auction's first bid: This bid is the first bid of the auction.

relative bid time: Bid time relative to the auction's duration.

is winning bid: This bid is the winning bid.

inc_min: The bid's increment compared to the minimal bid required.

inc_max: The bid's increment compared to the current *maxBid*.

[Figure 1 here]

Table 8 shows that the used criteria assign 6,563 of 8,789 shill bids to a specific strategy. Around two fifths (39%) of the shill bids are identified as (Aggressive) Competitive Shill bids and about one fifth (22%) of the shill bids follow the (Conservative) Discover-and-Stop Shilling strategy. Insider Shilling was observed 16 time and even these occurrences might meet the criteria by chance. Therefore, the information leakage about the current maximum bid seems to be unknown to the identified shill bidders. Around one quarter (25.3%) of the identified shill bids do not match one strategy's criterion and are categorized as *Others*. This value would have been considerably higher without the more tolerant strategies *Conservative Discover-and-Stop* and *Aggressive Competitive*.

[Table 8 here]

Even though Discover-and-Stop Shilling is not possible on ricardo, about one fifth of the shill bids are classified as (Conservative) Discover-and-Stop Shills. Table 8 shows that (Aggressive) Competitive Shilling occurs most often. However, the facts that other shill bidding strategies are also important and a large share of shill bids cannot be categorized hinders reliable identification of the shill bidders based on their behavior.

(c) Ricardo's Attempt to Prohibit Shill Bidding

Shill bidding violates ricardo's terms and conditions. Shill bidders, as well as individuals who place bids for reasons other than winning the auction, get cautioned for their first offense. For a second offense, they are barred from the platform. The numerous attempts to identify shill bidders based on public information indicates that the auction house's effort to fight shill bidders is challenged by these authors. Previous studies estimate that the share of auctions influenced by shill bidder ranges between 1% and 10 % (Ockenfels and Roth, 2006). Through identity details, I prove that shill bids are placed in at least 0.3% of all auctions on ricardo.ch. I am not able to certainly identify shill bidders who use third-party accounts and, therefore, I do not try to estimate their influence.

Table 9 shows that in my observation period, shill bids were placed by 1,382 different bidders. In total, 55% of these accounts shilled in one single auction. Either they were cautioned and abstained from further shill bids or the observation period did not capture further shills. However, more important than this percentage, are the remaining 45%. According to ricardo's terms and conditions, these bidders as well as the corresponding sellers should have been barred from further auction participation. Only 10% of the buyers' accounts who placed shill bids were either suspended or closed at the end of April 2014. Whether these accounts were barred as a result of their shill bidding behavior or owing other offenses is unknown to me. Accounts from other buyers who themselves influence over 80 auctions were not barred.

[Table 9 here]

Identifying shill bids through personal details was the easiest case, as this could be automatized and, therefore, would not entail much effort from the auction house. If the auction house does not even make an serious effort to fight the shill bidders who are clearly identifiable, then I doubt that the auction house tries to prevent shill bidding placed by third-party accounts.

(d) Shill-Bidder Identification Algorithms

In this subsection, I adopt two algorithms, one suggested by Trevathan and Read (2005) and the other by Engelberg and Williams (2009), and I check whether their suggested methods can reliably identify the proven shill bidder accounts in my data set.

(d).1 Algorithm suggested by Trevathan and Read (2005)

Trevathan and Read (2005) identify shill bidders based on the weighted average of six shilling variables, namely:

α: The participation rate of the bidder in auctions provided by a particular seller.

β: The bidder's average bid as a proportion of all the auctions he participated in.

γ: The share of auctions the bidder won (normalized value).

δ: The bidder's average inter-bid time (normalized value).

ε: The bidder's average inter-bid increment (normalized value).

ζ: The bidder's average commencing time (normalized value).

The bidders' behavior is summarized in a shill score: $SS = \frac{w_1\alpha+w_2\beta+w_3\gamma+w_4\delta+w_5\varepsilon+w_6\zeta}{w_1+w_2+w_3+w_4+w_5+w_6} \times 10$. All shilling variables' values range between 0 and 1. A higher value implies a higher probability that this bidder is shilling. Decisive for the calculation of β, δ and ε are the entered maximum bids and not the bids placed by the proxy bidding system. If a bidder won the auction, his α, β, δ, ε and ζ values for this auction are set to zero. Further details on the shilling values' calculation and their associated weights are provided in Trevathan and Read (2005).

Trevathan and Read (2007) further increase the algorithm's accuracy by adding a graph theory approach in order to detect shills when a seller uses multiple shill bidders in a particular auction. However, such a behavior has rarely been observed on ricardo.ch.

I check their method on a subset for which the algorithm should perform best. This subset includes only auctions from shill bidding sellers. I further exclude 16 sellers who used more than one shill bidder accounts in a specific auction and another 78 sellers who used more than one shill bidder over all auctions. Therefore, if a bidder is not marked as shill bidder, then this bidder is almost certainly not a shill bidder. Finally, the analyzed subset contains 1,285 sellers who sold 35,892 articles. 58,164 pairs of sellers and buyers are rated.

For each pair of sellers and buyers, I calculate: the shill score; the absolute shill score ranking of a bidder compared to the other bidders who bid on articles of this seller; and, the relative shill score ranking of a bidder compared to the other bidders who bid on articles of this seller. Figure 2 shows, on the left-hand side, the score's or ranking's distribution for shill bidders as well as honest bidders. The Student's t-test as well as the Kolmogorov-Smirnov-test are significant to the 1 percent level and therefore imply that the types' score distributions differ. The right-hand side of the Figure 2 shows the algorithm's false-positive rate and false-negative rate for different threshold values.

[Figure 2 here]

Even though the shill score and the ranking provide an indication of whether the bidder's behavior is suspicious, the type II error prevents a reliable identification of the proven shill bidders in this subset. For example: If bidders whose absolute shill score ranking equals 1 are incriminated as shill bidders, then 215 (15.1%) of the actual shill bidders will be correctly incriminated, while 1,040 (1.8%) of the honest bidders will be falsely incriminated. The type II error would become even higher if the auctions of honest sellers were included.

(d).2 Algorithm suggested by Engelberg and Williams (2009)

Engelberg and Williams (2009) identify shill bidders by using their newly identified Discover-and-Stop strategy as a proxy for shill bidding. They estimate a probit regression model that is based on six publically observable variables in order to identify bidders who follow the Discover-and-Stop strategy. These shilling variables are:

BidderCount: The number of bidders in an auction.

ClosingPrice: The sales price at which the auction ended.

BRating: The user rating as a proxy for experience.

NumAuctions: The number of auctions provided by a particular seller in which the bidder participated.

FracBid: The participation rate of the bidder in auctions provided by a particular seller.

FracLose: The share of auctions the bidder lost.

In order to separate the calculation of *NumAuctions*, *FracBid* and *FracLose* from the Discover-and-Stop identification, Engelberg and Williams (2009) split their sample into two distinct time periods. Engelberg and Williams (2009) considered only Event Ticket auctions, because they expected heterogeneous private values and considerable bid amount dispersion in this category.

I am able to use my whole observation period to calculate the variable values, because shill bidders are identified according to their personal details and not according to their behavior. Table 10 shows the probit regressions' output based on several subsets of my ricardo.ch data set.

[Table 10 here]

Column (4) refers most closely to the subsets used by Engelberg and Williams (2009) which are shown in Column (5) and Column (6). For this subset, the algorithm is able to reliably identify shill bidders. However, the coefficients of the regression output differ with regard to their value and significance. The coefficient values for BidderCount and FracBid are not significant for the ricardo sample, but ClosingPrice and FracLose are. The positive coefficient value for ClosingPrice might imply that shill bidding is not anticipated by the other bidders and has a price-pushing effect or that shill bids occur more often on valuable Event Tickets.

The coefficient values in Column (3) refer to a subset which includes all identified shill bids and not only Discover-and-Stop Shills. The regression value of the ClosingPrice is significantly negative. However, the OLS regression which I ran as a robustness check found no significance for the ClosingPrice. A higher number of involved bidders in an auction reduces the possibility that a pair of sellers and buyers is shilling. Therefore, the negative influence of BidderCount can be reasoned by the fact that a higher number of bidders increases competition and leads to a more aggressive bidding behavior. In such an environment, shill bids are not as profitable as they are in auctions with only a few bidders.

The subsets used for the regression results in Column (1) and Column (2) contain auctions from all categories. In contrast to Column (1), Column (2) is based on auctions which were solely offered by shilling sellers.

The regressions' coefficient values differ with regard to their significance as well as whether they increase or decrease the bidder's probability of being a shill bidder. In addition, the type II error incriminates more honest bidders of shilling than actual shill bidders are caught. Figure 3 shows the distribution of the estimated probability that a bidder shills as well as the type I and type II error of the bidder's identification. Only the carefully selected subset used for the regression in Column (4) provides reliable evidence of shill bidders.

[Figure 3 here]

The differences in these regression outputs might be explained by the fact that the Discover-and-Stop Shilling strategy cannot be used on ricardo and, therefore, these shill bidders do solely behave as if this strategy were available.

IV Analyzing Bidders' Behavior

This section compares selected characteristics of the bidders' behavior across eBay and the four platforms provided by the ricardo Group. The comparative figures for 11,495 USA-based auctions on eBay originate from Hayne *et al.* (2003). This transnational comparison in Table 11 aims to assess whether or not the previous results on ricardo.ch can be applied to other platforms. In this section, I use only data from auctions with at least two bidders. On the one hand, these auctions are more interesting as they allow observations, such as multiple bids per bidder in an auction. On the other hand, since Hayne *et al.* (2003) calculated his values for auctions with more than one bidders I therefore adopt this restriction.

Only one tenth of all auctions on ricardo.gr received bids from more than one bidder. In contrast to this, on ricardo.ch, qxl.dk and qxl.no one half of all auctions had more than one bidder. The highest share of auctions with multiple bidders, around two thirds, has eBay. Table 11 shows that each individual (unique bidders) recorded in ricardo's data placed around 10 bids on average, whereas only a few individuals in the data provided by Hayne *et al.* (2003) placed bids in more than one auction. The total number of bidders sums up the number of unique bidders in an auction over all auctions. The average bidders' experience is very different across the platforms. The lowest value is reported for ricardo.gr. The ratings on ricardo.gr most likely resulted from fixed price offers or auctions with only one bidder. Therefore, these bidders' experience in competitive auctions tends to be considerably smaller. The mean number of bids and of unique bidders is almost identical for all platforms. My data set contains the information about the winning bidder's maximum bid that he entered in the proxy bidding system. Therefore, all bids, or respectively bidders, can be classified for ricardo. In addition, Table 11 shows that the winner's mean entered proxy bid is between 20% and 50% higher than the mean sales price.

[Table 11 here]

Table 11 shows that the five platforms are almost identical regarding the frequency classification whether a bid is a single or multi-bid and whether bidders tend to place single or multiple bids. However, on qxl.dk and qxl.no, single and multiple bidders are equally experienced, whereas on the other platform single bidders exhibit a 50% higher experience rating than multiple bidders.

Ricardo as well as eBay recommend proxy bidding to the bidders (entering their article's valuation), as this behavior is the weakly dominant strategy in a second-price auction. Incremental bidding is often associated with inexperienced bidders who behave as if the articles are auctioned in a first-price auction. This argument could explain the large difference in the bidders' behavior on ricardo.gr compared to the other platforms. The share of bids classified as proxy is similar, ranging from 60% to 75%, on ricardo.ch, qxl.dk, qxl.no and eBay. The share of bidders who placed both proxy and incremental bids is higher on ricardo, at the expense of bidders who only placed proxy bids. The auction designs of ricardo and eBay differ in their ending rules (see Section II) which might explain this behavioral difference. If bidders place proxy bids which are lower than their valuation (or if they adjust their valuation over time), then the time expansion rule on ricardo might tempt proxy bidders to react to other bidders' late bids. In contrast to this, eBay's hard close ending rule favors sniping which does not allow for further (incremental) bids and results in the higher success rate of proxy bids on eBay. Finally, the data set does not support the supposition that incremental bidders are inexperienced because these bidders have the highest average experience rating compared with proxy bidders and bidders who place both, proxy and incremental bids.

V CONCLUSION

In contrast to the existing literature, I was able to exploit an information leakage in order to record a data set that contains personal details along with bidding histories. These personal details allowed me to correctly assign multiple user accounts to individuals. Moreover, the data set contains the highest bidders' maximum bids which were entered into the proxy bidding system. This information is necessary in order to fully analyze the behavior of the two highest bidders.

I have provided evidence that 0.3% of all auctions on ricardo.ch were influenced by obvious shill bids. In these auctions, either the phone number or the address (including the user's last name) were identical for the seller and at least one bidder. I detected neither shill bidders who use different phone numbers and addresses for their accounts, nor persons who use third-party accounts to place bids. Therefore, more cautious shill bidders remained unidentified. However, this is the first study that does not need to infer shill bidders from a specific kind of behavior.

I assigned the proven shill bids to shill-bidding types which have been characterized in previous studies. Competitive Shilling, where the seller continuously outbids the highest bidder up to a certain amount, occurred most often. However, around one quarter of the identified shill bids did not match any type's criterion. This share would have been considerably higher without the more tolerant strategies *Conservative Discover-and-Stop* and *Aggressive Competitive*.

I adopted two methods which aim to identify shill bidders based on public information in order to check whether the proven shill bidders can be reliably identified according to the suggested algorithms. Both algorithms, one suggested by Trevathan and Read (2005) and the other by Engelberg and Williams (2009), assign actual shill bidders a higher probability of being a shill bidder on average. Using a subsample from my data that corresponds to the criteria of the data set used by Engelberg and Williams (2009), I am able to show that their algorithm reliably identifies shill bidders based on public information. Notwithstanding this case, both algorithms incriminate a greater number of truthful bidders than actual shill bidders are identified. Although these approaches may indicate suspicious accounts, their type II errors are too high. If shill bidding is perceived as a severe enough in-auction fraud, then this data set might be used as a training data set for the purpose of extending these detection algorithms. However, the auction house is still in an optimal position to prohibit obvious shill bids, and, thereby, enforce its terms and conditions.

The transnational comparison of bidder's behavior shows that bidding behavior is almost the same over all platforms provided by the ricardo Group and eBay (USA). Therefore, the results of this paper should be generally applicable to other auction platforms.

Acknowledgements

I warmly thank Yvan Lengwiler for valuable comments and discussions. I also thank Hermione Miller-Moser for polishing up my English.

REFERENCES

ALEEM, A. and ANTWI-BOASIAKO, A. (2011). Internet auction fraud: The evolving nature of online auctions criminality and the mitigating framework to address the threat. *International Journal of Law, Crime and Justice*, **39** (3), 140 – 160.

BAG, P. K., DINLERSOZ, E. M. and WANG, R. (2000). More on phantom bidding. *Economic Theory*, **15** (3), 701–707.

CHAKRABORTY, I. and KOSMOPOULOU, G. (2004). Auctions with shill bidding. *Economic Theory*, **24** (2), 271–287.

CHEN, C.-L. and TAUMAN, Y. (2006). Collusion in one-shot second-price auctions. *Economic Theory*, **28** (1), 145–172.

DONG, F., SHATZ, S. M. and XU, H. (2010). Reasoning under uncertainty for shill detection in online auctions using Dempster-Shafer theory. *International Journal of Software Engineering and Knowledge Engineering*, **20** (07), 943–973.

EBAY INC (2013). eBay User Agreement. October 2013. URL: pages.ebay.com/help/policies/user-agreement.html.

ENGELBERG, J. and WILLIAMS, J. (2009). eBay's proxy bidding: A license to shill. *Journal of Economic Behavior & Organization*, **72** (1), 509–526.

FORD, B. J., XU, H. and VALOVA, I. (2013). A real-time self-adaptive classifier for identifying suspicious bidders in online auctions. *The Computer Journal*, **56** (5), 646–663.

HAYNE, S. C., SMITH, C. and VIJAYASARATHY, L. R. (2003). Who wins on ebay: An analysis of bidders and their bid behaviours. *Electronic Markets*, **13** (4), 282–293.

HLASNY, V. (2006). Testing for the occurrence of shill-bidding (in Internet auctions). *Graduate Journal of Social Science*, **3** (1), 61–81.

IZMALKOV, S. (2004). Shill bidding and optimal auctions.

KAUFFMAN, R. J. and WOOD, C. A. (2005). The effects of shilling on final bid prices in online auctions. *Electronic Commerce Research and Applications*, **4**, 2005.

KAUR, A. and VERMA, G. (2013). Shill detection techniques and research challenges in online auction. *International Journal of Advanced Research in Computer Science and Software Engeneering*, **3** (10), 1303–1308.

KOSMOPOULOU, G. and SILVA, D. G. D. (2007). The effect of shill bidding upon prices: Experimental evidence. *International Journal of Industrial Organization*, **25** (2), 291 – 313.

KRISHNA, V. (2009). *Auction Theory*. Academic Press.

NASPERS (2014). Operations. May 2014. URL: http://www.naspers.com/internet.php.

OCKENFELS, A., REILEY, D. and SADRIEH, A. (2006). *Online Auctions*. NBER Working Papers 12785, National Bureau of Economic Research, Inc.

— and ROTH, A. E. (2006). Late and multiple bidding in second price Internet auctions: Theory and evidence concerning different rules for ending an auction. *Games and Economic Behavior*, **55** (2), 297 – 320, mini Special Issue: Electronic Market Design.

RICARDO.CH AG (2014a). Corporate Key Figures. March 2014. URL: http://www.ricardo.ch/ueber-uns/de-ch/unternehmen.aspx.

— (2014b). Guidance. March 2014. URL: http://www.ricardo.ch/ueber-uns/portals/ch-ueber-uns/docs/downloads-pdf-de/wegleitung_de.pdf.

— (2014c). Terms and Conditions. March 2014. URL: http://www.ricardo.ch/ueber-uns/portals/ch-ueber-uns/docs/downloads-pdf-de/agb_de.pdf.

SCHWARTZ, J. and DOBRZYNSKI, J. H. (2001). 3 men are charged with fraud in 1,100 art auctions on ebay. *The New York Times*, March 9, 2001.

SHER, I. (2012). Optimal shill bidding in the VCG mechanism. *Economic Theory*, **50** (2), 341–387.

TREVATHAN, J. and READ, W. (2005). *Detecting Shill Bidding in Online English Auctions*. Tech. rep.

— and — (2007). Investigating shill bidding behaviour involving colluding bidders. *Journal of Computers*, **2** (10).

WATANABE, T. and YAMATO, T. (2008). A choice of auction format in seller cheating: A signaling game analysis. *Economic Theory*, **36** (1), 57–80.

YOKOO, M., SAKURAI, Y. and MATSUBARA, S. (2004). The effect of false-name bids in combinatorial auctions: New fraud in Internet auctions. *Games and Economic Behavior*, **46** (1), 174 – 188.

TABLES

TABLE 1
SUBMITTED VARIABLES UPON A SERVER REQUEST ON USER DETAILS

Variable Name	Description	ricardo. ch	ricardo. gr	qxl. dk	qxl. no
userNr	unique user ID	x	x	x	x
nickName	user nickname	x	x	x	x
* *firstName*	user first name	x	x		
* *lastName*	user last name	x	x		
* *street*	user address: street	x	x		
* *streetNr*	user address: street number	x	x		
* *compStreet*	user address: street complementary	x	x		
* *zip*	user address: ZIP code	x	x		
* *city*	user address: city	x	x		
* *country*	user address: country	x	x		
* *phoneNr*	user (mobile) phone number	x	x		
* *company*	company's name	x	x		
memberSince	registration date	x	x	x	x
rating	positive ratings minus negative ratings received	x	x	x	x
sharePosRating	share of positive ratings received	x	x	x	x
boughtItems	total number of items bought	x	x	x	x
soldItems	total number of items sold	x	x	x	x
pos_2	positive ratings received during the last 2 months	x	x	x	x
pos_6	positive ratings received during the last 6 months	x	x	x	x
pos_12	positive ratings received during the last 12 months	x	x	x	x
pos_all	overall positive ratings received	x	x	x	x
pos_diffUser	*pos_all* received from heterogeneous users	x	x	x	x
neu_2	neutral ratings received during the last 2 months	x	x	x	x
neu_6	neutral ratings received during the last 6 months	x	x	x	x
neu_12	neutral ratings received during the last 12 months	x	x	x	x
neu_all	overall neutral ratings received	x	x	x	x
neu_diffUser	*neu_all* received from heterogeneous users	x	x	x	x
neg_2	negative ratings received during the last 2 months	x	x	x	x
neg_6	negative ratings received during the last 6 months	x	x	x	x
neg_12	negative ratings received during the last 12 months	x	x	x	x
neg_all	overall negative ratings received	x	x	x	x
neg_diffUser	*neg_all* received from heterogeneous users	x	x	x	x
* *buyerStatus*	values: 0-4 (interpretation unknown)	x	x	x	x
* *hasGlasses*	values: TRUE and FALSE (interpretation unknown)	x	x	x	x
* *isCertified*	values: TRUE and FALSE (interpretation unknown)	x	x	x	x
* *memberClass*	values: 0-4 (interpretation unknown)	x	x	x	x
* *sellerStatus*	values: 0-4 (interpretation unknown)	x	x	x	x
* *sellerType*	values: 0-4 (interpretation unknown)	x	x	x	x
* *stats*	values: 0-640 (interpretation unknown)	x	x	x	x
* *userRating*	rating the user gave	x	x	x	x
suspended	account has been blocked or suspended	x	x		
suspendedDate	date when the account has been blocked or suspended	x	x		

Notes
This table lists and describes the variables which were recorded for each account. At this time, unfortunately, the interpretation of seven variables could not be revealed. The variables' values were submitted and recorded for the platforms marked with an 'x'.
* indicates non-public information.

TABLE 2
SUBMITTED VARIABLES UPON A
SERVER REQUEST ON AUCTION DETAILS

Variable Name	Description
articleID	referred article ID
requestDate	request date
startPrice	auction's starting price
fixPrice	auction's fixed-price
sellPrice	final sales price
* *maxBidPrice*	the winner's maximum bid entered
bidIncrement	minimal bid increment
it_highestBidder	winner's nickname
highest_bidder_id	winner's user ID
endDateLong	auction's end date
* *startDateLong*	auction's start date
timeLeftLong	time left until the auction ends
seller_id	seller's user ID
it_sellerNick	seller's nickname
it_condition	article's condition
it_availability	number of items available
it_pageViews	number of page requests
it_delivery_link	delivery expenses
it_ArticleDescription	article's description

Notes
This table lists and describes the variables which were recorded for each auction. The variables' values were submitted and recorded for ricardo.ch, ricardo.gr, qxl.dk and qxl.no.
* indicates non-public information.

TABLE 3
SUBMITTED VARIABLES UPON A
SERVER REQUEST ON THE AUCTION HISTORY

Variable Name	Description
articleID	referred article ID
userNr	unique user ID
nickName	user nickname
BidPrice	bid
* *MaxBidPrice*	maximum bid
BidDate	bid's date
BidStatus	values: 0,1,4,8
BiddedQuantity	number of items desired

Notes
This table lists and describes the variables which were recorded for each auction. The variables' values were submitted and recorded for ricardo.ch, ricardo.gr, qxl.dk and qxl.no. The *userNr* has not been recorded for qxl.dk and qxl.no.
The values for the variable *BidStatus* mean: (0) this bidder placed a higher bid later on; (1) winning bid; (4) retrieved bid; and, (8) this bidder's highest bid.
* indicates non-public information.

TABLE 4
SUBMITTED VARIABLES UPON A
SERVER REQUEST ON USER RATINGS

Variable Name	Description
nickNameReceiver	rating receiver's nickname
nickNameSender	rating sender's nickname
rating	rating value (positive, neutral or negative)
ratedAs	was the sender a buyer or seller
ratingDate	date when the rating was given
message	reason for the rating
articleID	referred article ID

Notes
This table lists and describes the variables which were recorded for each rating. The variables' values were submitted and recorded for ricardo.ch, ricardo.gr, qxl.dk and qxl.no.

TABLE 5
DATA SET SUMMARY

Domain (PartnerNr)	ricardo.ch (2)	ricardo.gr (14)	qxl.dk (12)	qxl.no (20)
Number of auctions	1,754,895	11,334	97,896	92,529
Number of bids	6,559,027	17,692	296,497	245,564
Number of accounts	3,054,104	516,206	17,796[1]	12,533[1]
Number of ratings	19,068,780	60,148	492,917[1]	521,545[1]
Average bids per auction	3.74	1.56	3.03	2.65
Average bidders per auction	2.39	1.30	2.08	1.89
Average page views per auction	131	44	30	27
Median page views per auction	65	20	21	16
Auctions without reserve price (%)	37.7%	59.9%	14,7%	11.3%

TABLE 6
IDENTIFICATION OF MULTIPLE ACCOUNTS

	ricardo.ch		ricardo.gr	
	Accounts	Individuals	Accounts	Individuals
phoneNumber	814,312	348,361	299,979	134,653
fullAddress	378,862	171,198	33,715	15,514
shortAddress	726,753	305,366	42,254	19,169
potentialShillBidAccounts	1,414,609	487,986	330,043	140,318

Notes
This table shows: the number of individuals who own multiple accounts, the number of accounts these individuals own; and through which personal details variable the assignment occurs. As some accounts might be identified through more than one of these criteria, *potentialShillBidAccounts* counts the number of accounts that fulfill at least one criterion.

TABLE 7
IDENTIFIED SHILL BID ACCOUNTS

	ricardo.ch		ricardo.gr	
	Accounts	Individuals	Accounts	Individuals
identicalUser	none		none	
phoneNumber	2,452	1,178	2	1
fullAddress	281	139	none	
shortAddress	1,900	940	2	1
shillBidAccounts	3,795	1,382	4	2

Notes
This table shows: the number of individuals who are proven shill bidders, the number of accounts these individuals used for their shills (seller and buyer accounts); and through which personal details variable the they are identified. As some accounts might be identified through more than one of these criteria, *shillBidAccounts* counts the number of accounts that fulfill at least one criterion.

TABLE 8
IDENTIFIED STRATEGY BEHIND SHILL BIDS

	ricardo.ch
Reserve-Price	507
Buy-Back	619
Insider	16
Competitive	1,978
Aggressive Competitive	1,429
Discover-and-Stop	870
Conservative Discover-and-Stop	1,054
Auxiliary Bids	90
Others	2,226
Total	8,789

Notes
This table shows the categorization of the identified shill bids. Discover-and-Stop reports bids which meet this strategy's criteria even though Discover-and-Stop Shilling is not possible on ricardo.

TABLE 9
INFLUENCE OF SINGLE SHILL BIDDERS

influenced auctions	number of bidders	thereof blocked	thereof suspended
1	760	48	35
2	251	14	4
3-20	347	32	8
21-40	15	3	0
41-60	4	0	0
61-80	2	0	0
over 80	3	1	0
Total	1,382	98	47

Notes
This table shows how many auctions a single bidder has influenced through a shill bid account. On April 22, 2014, about 10% of these shill bid accounts were blocked or suspended.

TABLE 10
PERFORMANCE OF THE ENGELBERG AND WILLIAMS (2009) IDENTIFICATION ALGORITHM

	ricardo.ch				eBay[1]	
	(1)	(2)	(3)	(4)	(5)	(6)
Intercept	-2.134***	-0.557***	-2.436***	-0.787*	-2.093***	-2.158***
	(0.002)	(0.020)	(0.207)	(0.460)	(0.021)	(1.078)
BidderCount	0.0018**	-0.0013***	-0.0080**	0.0026	0.021***	0.0022**
	(0.0004)	(0.0006)	(0.004)	(0.010)	(0.003)	(0.009)
ClosingPrice	34.5***	80.6***	-2,078***	20,133***	-4.40	-10.50
	(2.58)	(6.63)	(500)	(2770)	(21.3)	(16.6)
BRating	-0.515***	-0.670***	-20.142***	-84.426***	-0.3691***	-0.2145
	(0.015)	(0.018)	(0.148)	(22.36)	(0.061)	(0.163)
NumAuctions	-0.935***	-3.54	39.90***	58.97***	6.52**	7.71***
	(0.10)	(0.19)	(2.53)	(7.26)	(2.03)	(2.09)
FracBid	-1.047***	-1.132***	-1.119***	-0.231	0.221***	0.350***
	(0.015)	(0.022)	(0.093)	(0.338)	(0.051)	(0.071)
FracLose	-0.193***	-0.372***	0.937***	-1.113**		-0.033
	(0.016)	(0.027)	(0.212)	(0.499)		(0.090)
# of observations	4,575,636	126,432	65,801	65,801	104,545	10,087
# of shill bids observations	6,822	6,822	271	145	2,711	295
Only auctions from shilling seller	No	Yes	No	No	No	No
Only DiscNStop shills	No	No	No	Yes	Yes	Yes
Only losing (B,S) pairs	No	No	No	Yes	Yes	Yes
Only Event Tickets	No	No	Yes	Yes	Yes	Yes

Standard errors are in parentheses. *, ** and *** indicate significance at the 1 percent, 5 percent and 10 percent level, respectively. Closing Price is multiplied by 1,000,000, BRating is multiplied by 1,000, and NumAuctions is multiplied by 1,000 to reduce the number of decimal places.
[1] Comparable figures on eBay auctions originate from Engelberg and Williams (2009).

TABLE 11

TRANSNATIONAL COMPARISON OF BIDDERS' BEHAVIOR IN AUCTIONS

	ricardo.ch	ricardo.gr	qxl.dk	qxl.no	eBay[1] (USA)
Data Summary					
number of auctions,	828,847	1,189	43,870	37,842	11,495
total number of bids	5,632,829	7,552	242,471	190,877	77,926
total number of uniques bidders	377,131	360	12,484	10,092	40,754
total number of bidders	3,258,257	4,539	149,565	119,998	45,797
average experience rating	754	71	2,491	2,283	112
mean number of bids	6.80	6.35	5.53	5.04	6.78
mean number of unique bidders	3.93	3.81	3.41	3.17	3.98
mean starting price	40.89	29.81	40.95	96.51	19.36
mean winning bid amount	106.66	53.94	125.25	252.09	63.10
winner's mean entered proxy bid	158.77	63.16	153.00	323.00	NA
Bids Classified by Frequency					
single bid (%)	37.21	39.66	39.69	40.87	38.63
multi-bid (%)	62.79	60.34	60.31	59.13	61.37
Auction Success of Bidders Classified by Frequency					
single bid bidders (%)	64.33	65.98	64.34	65.00	65.72
auctions won (%)	56.67	67.75	54.62	57.67	57.93
success rate (%)	61.16	70.71	60.04	63.17	NA
average experience rating	947	80	2,593	2,815	155
multi-bid bidders (%)	35.67	34.02	35.66	35.00	34.28
auctions won (%)	43.33	32.25	45.38	42.33	42.07
success rate (%)	66.57	41.44	67.86	65.56	NA
average experience rating	640	64	2,568	2,048	100
Bids Classified by Bid Strategy					
proxy bids (%)	73.55	30.77	61.72	62.27	75.01
incremental bids (%)	26.45	69.23	38.28	37.73	20.06
unclassifiable bids (%)	0	0	0	0	4.93
Auction Success of Bidders Classified by Bid Strategy					
only proxy bidders (%)	53.82	12.40	39.42	40.12	73.14
auctions won (%)	59.35	14.45	54.81	60.49	72.10
success rate (%)	78.92	30.79	73.66	76.30	81.23
average experience rating	658	44	2,116	2,202	145
only incremental bidders (%)	16.40	32.49	22.31	21.82	13.58
auctions won (%)	15.04	52.41	15.08	11.85	5.57
success rate (%)	20.82	55.60	20.06	16.52	12.61
average experience rating	1,112	107	3,004	3,315	133
proxy and incremental bidders (%)	29.20	54.82	38.26	38.06	10.05
auctions won (%)	21.99	2.61	30.11	27.65	9.46
success rate (%)	47.76	42.24	54.86	52.42	29.35
average experience rating	744	58	2,894	2,118	78
unclassifiable bidders (%)	0	0	0	0	3.23

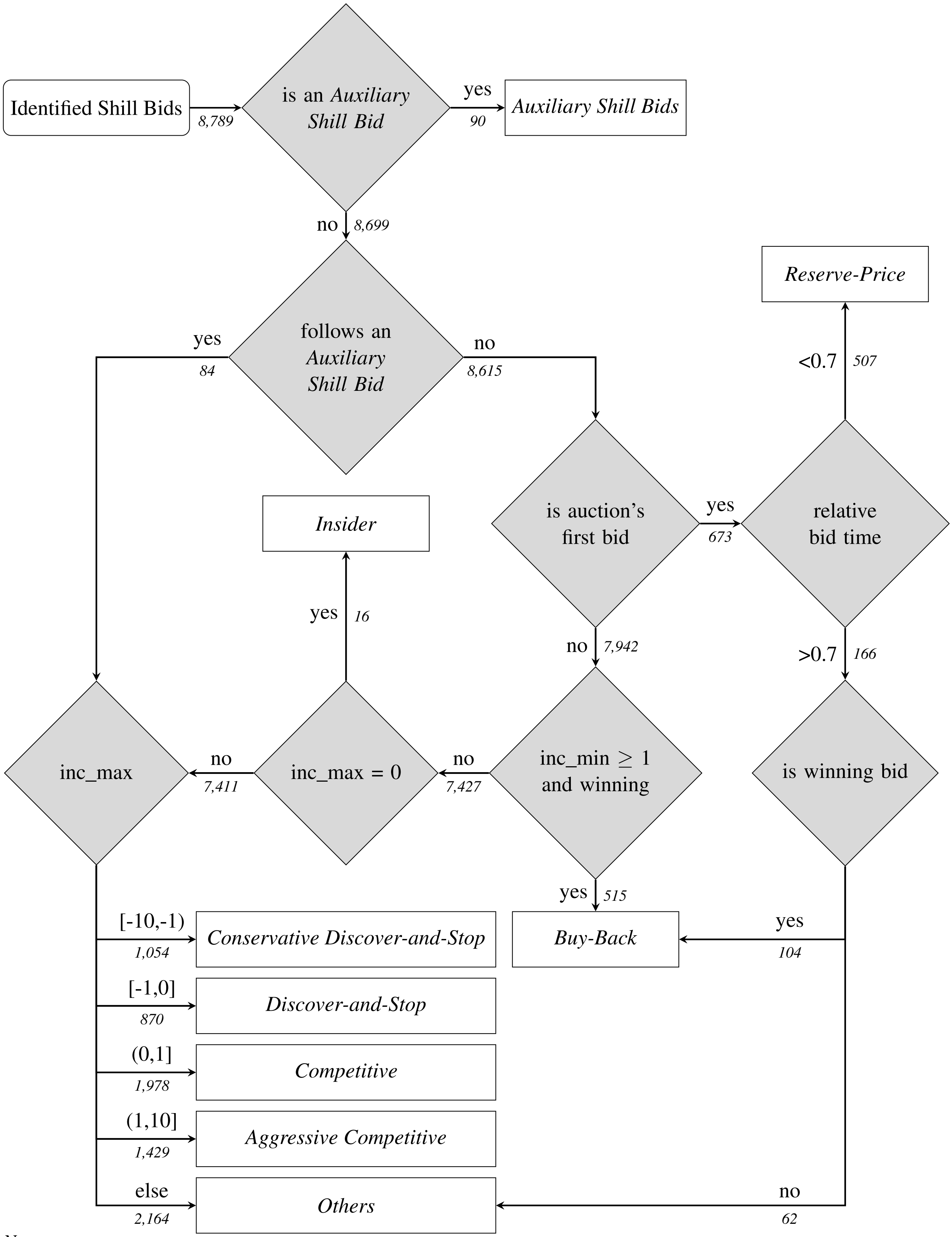
Notes

This table shows a transnational comparison of bidder's behavior in auctions with more than one bidder.

[1] The comparative figures for 11,495 USA-based auctions on eBay originate from Hayne *et al.* (2003).

FIGURES

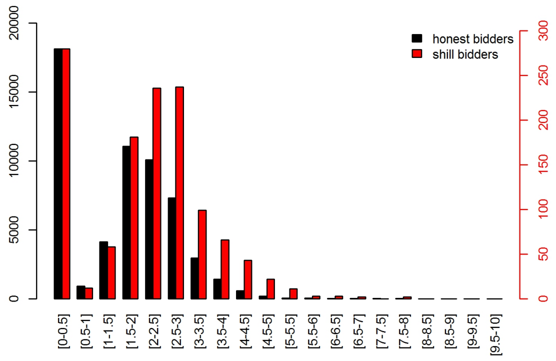
FIGURE 1
CATEGORIZING IDENTIFIED SHILL BIDS



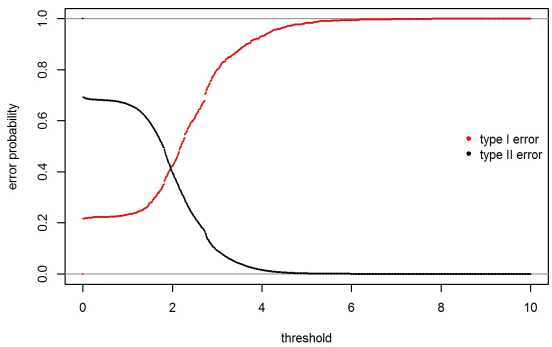
Notes
This figure shows how I categorize identified shill bidders into different shill bidding types. The bid's increment compared to the lowest possible bid is labeled as inc_min. The bid's increment compared to the current *maxBid* is labeled as inc_max. The italic numbers express how many bids feature a specific characteristic.

FIGURE 2

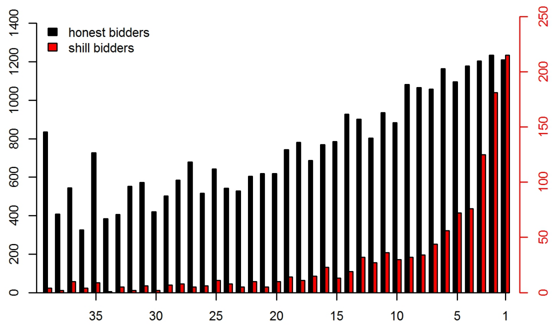
PERFORMANCE OF THE TREVATHAN AND READ (2005) IDENTIFICATION ALGORITHM



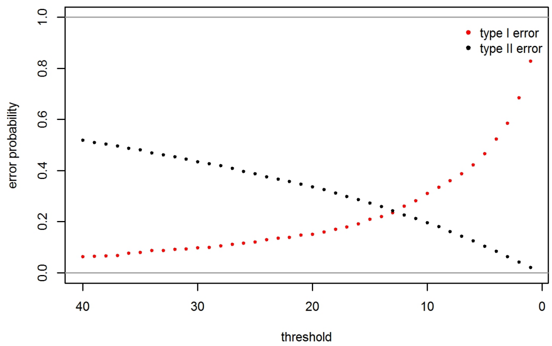
(A)
Shill Score: Distribution



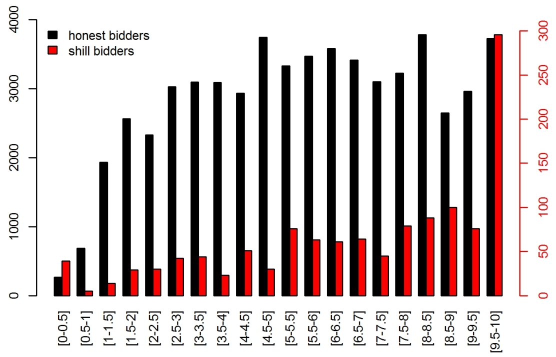
(B)
Shill Score: Identification Errors



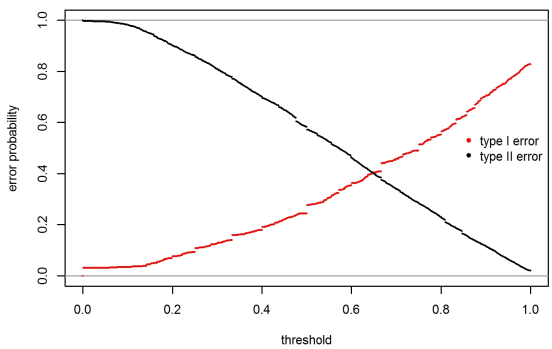
(C)
Absolute Shill Ranking: Distribution



(D)
Absolute Shill Ranking: Identification Errors



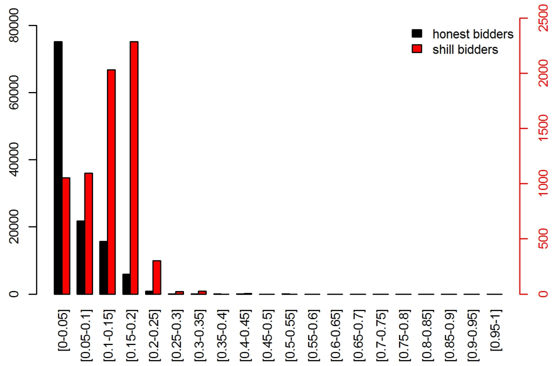
(E)
Relative Shill Ranking: Distribution



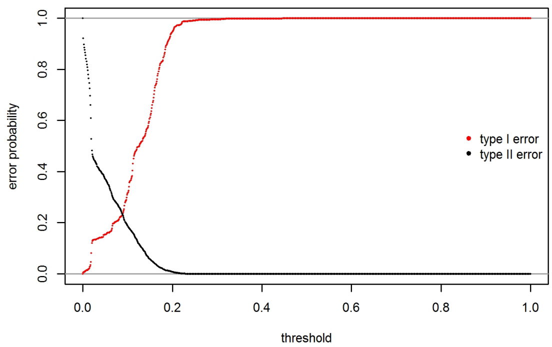
(F)
Relative Shill Ranking: Identification Errors

Notes
The histograms on the left-hand side show the score's or, respectively, the ranking's distribution for shill bidders and honest bidders. The figures on the right-hand side show the type I and type II error of the bidder's identification for different threshold values.

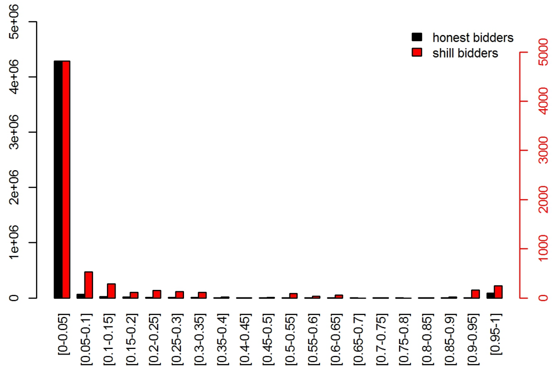
FIGURE 3
PERFORMANCE OF THE ENGELBERG AND WILLIAMS (2009) IDENTIFICATION ALGORITHM



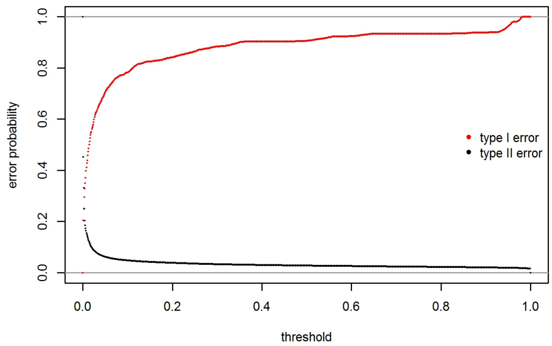
(A)
Distribution: Table 10, Column (2)



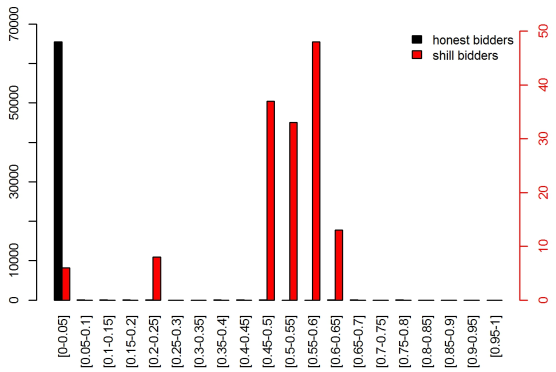
(B)
Identification Errors: Table 10, Column (2)



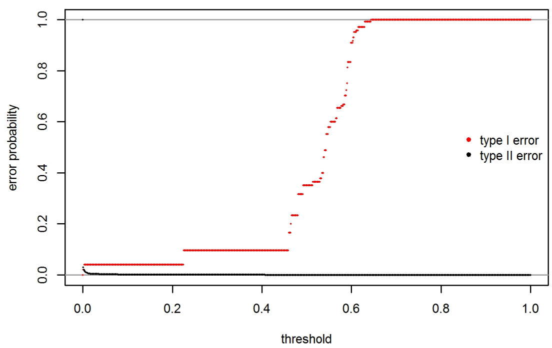
(C)
Distribution: Table 10, Column (3)



(D)
Identification Errors: Table 10, Column (3)



(E)
Distribution: Table 10, Column (4)



(F)
Identification Errors: Table 10, Column (4)

Notes
The histograms on the left-hand side show the distribution of the estimated probability that a bidder shills, for both; shill bidders and honest bidders. The figures on the right-hand side show the type I and type II error of the bidder's identification for different threshold values.