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INTERNET AND ANONYMITY: DISCRIMINATION BY GENDER AND FOREIGNNESS IS A MATTER OF SORTING

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Abstract

This study shows that sorting--self-selecting based on personal characteristics—is an underlying mechanism of discrimination. In an experiment using anonymity, a common feature in the steadily increasing number of internet interactions, we exclude the possibility to sort into online auctions by username. Half of the sellers disclose their names in their usernames and the other half conceal their names. When the auction ends the seller's name is always automatically disclosed to the buyer. There is no or very modest buyer price discrimination on gender and foreignness when the possibility of sorting is present. However, more important, discrimination in feedback only occurs if sellers are anonymous—prevented form sorting by name. Male sellers with foreign-sounding names receive fewer numbers of feedbacks than non-foreign female sellers. This highlights that sorting can be one reason behind competitive markets displaying no price discrimination. Interestingly, this discrimination is only present among female buyers.

Keywords: *anonymity, discrimination, gender, foreignness, online auctions*

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1. Introduction

This study shows that sorting—self-selection based on personal characteristics—can be an underlying mechanism of discrimination. Sorting can occur in all economic and social interactions. Individuals can choose from whom they buy or not buy, or who they game with, based on their current information. Sorting can for example be based on personal characteristics such as gender or foreignness. In a Becker (1957) model these characteristics can affect the utility of the individual (in our case the buyer). Competitive markets (markets with many sellers and buyers) provide a possibility to execute one's taste based preferences by sorting, e.g. choosing with whom to buy from or not based on group characteristics. In competitive markets are often found to display little or no price discrimination (see for example Doleac and Stein, 2013; Prezipiorka 2012). Competitive markets thus seem to diminish or eradicate price discrimination. Although various groups on average receive the same price for a commodity, there may still be an underlying discrimination in sorting into the various interactions (perhaps depending on the composition of the characteristics of buyers and sellers).

What happens to discrimination in outcome variables after an auction if buyers have no means of sorting when entering the auction, i.e. when the seller is anonymous? Hence, this study contributes to two sides of the same coin: anonymity and sorting. E-markets are growing in both usage and economic importance and anonymity, in various forms and degrees, is a common feature of these online economic interactions (Findahl, 2011; SCB, 2013). It is thus of importance to understand the consequences of online market features. In this study we ask if anonymity, by preventing sorting on personal characteristics, can create discrimination in a competitive market.

In this study we create an online field experiment using a competitive market on eBay to, where half of the sellers disclose their names in their usernames and the other half use anonymous usernames. However all names, buyer and seller, are revealed when an auction ends. The transient anonymity case excludes the possibility for buyers to sort into (or away from) auctions by seller characteristics. Buyer price discrimination (on seller characteristics) is therefore not possible. However, after an auction is closed and names are revealed feedback is provided to sellers. Discrimination in feedback is hence possible. Firstly, when there is no anonymity (sorting was possible) we find no or little evidence of customer price discrimination.. Secondly, and most important, we find that anonymous usernames spur buyer discrimination in feedback (sorting was not possible). If foreign male sellers use anonymous usernames they receive a smaller share of feedback than non-foreign female sellers. This discrimination is not present if seller reveals their name in the username (non-anonymous)—allowing for sorting by name. The discrimination in feedback seems to be present only among female buyers. This highlights that one reason behind competitive markets displaying no discrimination in price is because of sorting.

In contrast to *offline* interactions, the foundation of *online* interactions, such as buying goods, can be described as anonymous. Buyers expect to face a computer screen instead of a physical seller. Internet opens up possibilities of concealing and altering personal information available for buyer and sellers and this can potentially change human behaviour in social interaction. A seller can easily disclose their identity by, for example, using an email address or username which does not reveal any personal information. The username can contain true, false, or no signals of e.g. group belongings of the seller. Anonymous usernames are common practice; approximately half of all usernames employed on "customer to customer" sites such as eBay do not contain any information such as signals of gender or foreignness. (A data set collected from the same market a year before the experiment showed that 50% of the accounts concealed their real name in the username, see Table A1 in appendix). Thus, online trading lacks the usual means of building trust; a buyer cannot inspect the product before bidding, or shake hands with the seller. However, online, the feedback systems fill this deficiency. Buyers and sellers providing feedback to each other is a crucial part of sustaining online commerce (e.g. Bolton et al 2004). It also bears economic relevance within the market. More feedback implies higher price for the product sold, which increases sales. In a general sense feedback also have implications for example brand building, product development, and quality assurance (see Cook et al, 2009 for a review). In this study we are interested in discrimination in online feedback.

Unequal treatment is found in most societies, with minority groups and women often faring the worst (for reviews see Anderson, Fryer and Holt, 2006; Riach and Rich 2002; Pager and Shepherd, 2008). A large number of these studies indicate that individuals from specific groups are discriminated against on the basis of their names.[1] Throughout history, anonymity and pseudonymity have been used to protect privacy and avoid unfair treatment. A recent example are the public and private calls to combat discrimination in the labor market by means of anonymous application procedures which allow minority groups and women to receive an unbiased evaluation and a fair chance of being invited to an interview.[2] However, anonymity can also prevent sorting, i.e. self-selection into interactions based on for example gender and foreignness. If identity is later revealed it can lead to discriminatory behavior at a later stage in the interaction. Anonymity online can therefore potentially have both positive and negative consequences.

Only a handful of studies in economics have addressed anonymity in relation to situations of discrimination. Goldin and Rouse (2000) revealed discrimination of female musicians in hiring, by using anonymous auditions, applicants performed behind a curtain. Edin and Lagerström (2006) studied a situation in which Swedish online job applicants could choose whether or not to disclose their names. Women who did not reveal their gender increase their probability of being contacted by an employer by 15%. Åslund and Nordström-Skans (2008) corroborated this, anonymous application procedure in Sweden increase the probability of being interviewed for women and individuals with foreign names. They also found that

[1] Arai and Thoursie (2009) have shown that there are also clear benefits in earnings for immigrants who change their names in order to sound less foreign (from a Swedish perspective). On the other hand, Fryer and Levitt (2004) found that name had no impact on a set of life outcomes in the USA, controlling for circumstances around the time of birth.

[2] See for example the discussion in the press about the British government's call for anonymous application procedures: http://www.telegraph.co.uk/finance/jobs/hr-news/9009722/Government-proposes-anonymous-CVs-to-end-discrimination.html, accessed 2013-01-31.

anonymous applications increased women’s, but not foreign names’, chance of receiving a job offer after the interviews. Bog and Kranandonk (2011) confirmed these findings using data from Holland. These last two studies are the only studies we are aware of that study outcomes after the veil of anonymity is revealed. In this case anonymity seems to prevent the employer from selecting application on gender and foreignness of name and provide an objective evaluation measure of a performance, thus *creating positive effects*.

Discrimination is however complex, in other situations, where the agents themselves have to sort in interaction, such as in a buyer and seller situation, anonymity may affect discrimination differently. Internet dating is similar, individuals can conceal information such as race or height and weight that will be revealed in a future face-to-face interaction, preventing a first sorting on these characteristics. Could this affect future behavior? Or, when customers hail a cab in the street or use home delivery they cannot choose a driver or delivery persons based on visible characteristics. In a study on hailing cabs, Ayres et al (2011) found that minority drivers receive less tip by all customer types (by race), controlling for performance, i.e. *a negative effec*t. However, the authors (Ayres et al 2011) do not have the counter factual case where customers can select a taxi based on race, and are therefore not able to disentangle whether this discrimination arise only when sorting is prevented. In our study we add the counterfactual. To our knowledge this is the first study to investigate anonymity, sorting, and customer discrimination.

The rest of this article proceeds as follows. Section 2 discusses previous literature relating to discrimination and online auctions. In section 3 we describe the features of eBay and outline our experimental design. Section 4 presents our hypotheses, section 5 reveals the collected data set, and section 6 presents our results and further analysis. Finally, section 7 comprises a discussion of the results.

2. Previous literature

There are two prevailing theories of discrimination in economics. Becker (1957) describes discrimination as taste based, where individuals have a dislike for interacting with members of certain groups; here discrimination will decrease with competition. Statistical discrimination on the other hand (Phelps 1972; Arrow 1973) arises due to informational friction. The decision maker bases decisions upon observable characteristics as a proxy for unobservable outcome relevant characteristics.

Becker (1957) mentions customer discrimination as an example where taste based discrimination can occur. However, most theory and empirical work study discrimination from employers, landlords, or salespersons. Customer discrimination has been investigated *offline* as well as *online*. In several markets there is evidence of customer price discrimination based on group belonging of the seller, for example when selling baseball cards (e.g. Andersen and LaCroix, 1991; List, 2004 Livingstone and List, 2010), or in restaurant tipping (e.g. Lynn et al, 2008). Customer discrimination also prevails online; Ayres et al (2011) found clear price discrimination against dark-skinned sellers when studying the market for baseball cards on eBay. This finding was corroborated in non-auction online markets in the USA, in a study by Doleac and Stein (2013) on the sale of iPods. However, this result was only present in less competitive markets. Przepiorka (2012) conducted a price discrimination study on eBay, and found that Turkish seller names elicited lower prices in comparison with German seller names when selling DVDs and USB sticks. The study also found that discrimination is only present when competitive pressure is low (ibid.). The study by Przepiorka (2012) includes a replication of Shohat and Much (2003) that did not find price discrimination.

An online auction, such as eBay, can be described as a trust game. A potential buyer places a bid, indicating the trust as willingness to pay for the item—trust that the seller will send an item with appropriate quality. Upon receiving the money the seller sends the item to the buyer. The buyer (and seller) can then reciprocate by providing feedback (Dellarochas et al 2003; Bolton et al 2004). In the field of behavioral economics and psychology, there are a number of studies on differential treatment using a trust game (see the review by Ostrom and Walker [eds], 2005). Some studies found evidence of discrimination in trust and reciprocity as a result of belonging to a minority group (e.g.

Fershtman and Gneezy, 2001; Buchan et al, 2002; Johansson-Stenman et al, 2008), while other studies did not (e.g. Bouckaert and Dhaene, 2004; Glaeser et al 2000). Fershtman and Gneezy (2001) investigated both dimensions, and found that discrimination in trust was only dependent on ethnicity among males. However, they found no ethnic discrimination in reciprocity. Slonim and Guillen (2010) conducted a trust game where the gender of the counterpart was known; with and without the possibility of selecting counterpart by gender. When participants could select partner by gender they trusted the opposite gender more compared to when participants could not select.

3. Design of the study

Buying and selling on eBay

On eBay, the world's largest online marketplace, 89% of all interactions are one-shot (unique interactions and to some extent anonymous). Swedish eBay is mainly a consumer to consumer business, and is not dominated by small businesses; and eBay account holders are usually both sellers and buyers. In comparison to offline transactions, these transactions typically rely less on long-term economic relationships, and lacks means of building trust between sellers and buyers (e.g. Resnick and Zeckhauser, 2002). To sustain trust internet marketplaces have implemented publically displayed reputation systems; so called feedback systems (e.g. Bolton et al 2004; Bolton et al, 2008). These systems provide the interacting parties with the means of building up reputation by proving feedback ratings on each other's "performance". This feedback system actually seems to increase and sustain trust (e.g. Bolton et al 2012). Feedback is of economic importance to the seller; more feedback implies an increased chance of selling and a greater willingness to pay among buyers (e.g. Lucking-Reiley et al 1999; Resnick et al 2006; Jian et al 2010). Since providing feedback is voluntary, it is shown to be partly a reciprocal act (e.g. Dellarochas et al 2003).

Buying and selling on eBay involves a sealed-bid second-price auction, where the winner pays the second-highest bid, plus a minimum bidding increment. When the auction is closed, eBay sends an email disclosing the names and email addresses of the seller and buyer to each other, so they can establish contact. Next, the buyer transfers the money for the item and the pre-specified delivery costs. When the seller receives the money, they ship the good to the buyer. Finally, both buyers (and sellers) can optionally provide feedback of the experience as positive or negative, write a short comment, and rate the experience on a scale from 1 to 5. The buyer and seller have 60 days after an auction has ended to use the feedback system. All ratings are immediately displayed publically on the seller's and buyer's eBay profile page. Average grades on eBay are generally high, with very little variation, and rarely fall below an average of 4.5. Before the seller or buyer receives 10 unique ratings, the account will be publically displayed as "new" to the market. However, previous literature has found that 5 ratings are enough to learn the rules of the eBay market and feedback system, and for other sellers and buyers to treat you as experienced (see for example Jian et al 2010).

Swedish eBay requires each account to be connected to a Swedish social security number, and so all buyers and sellers are registered by the Swedish tax authorities as living in Sweden. We collaborate with a group of sixteen individuals who were asked to create new eBay accounts in their names, for us to manage. We also created Hotmail accounts using these names, in order to provide payment information to buyers. The names of the sellers we collaborate with were categorized by gender and by whether or not the name sounded foreign. Our non-foreign sellers all have common Swedish first names and patronyms as surnames (ending with -son). To construct the group of sellers with foreign names, we asked a convenience sample of twenty students at Stockholm University to match full names (first names and surnames) of *potential* sellers to a gender and a region (coded into six regions according to Statistics Sweden: Latin America and South America, the Middle East and North Africa, EU15+, the rest of Europe, the rest of Asia, and the rest of Africa). We then collaborate with sellers whose names were correctly matched by all twenty students to the relevant gender and to the region of the Middle East and North Africa. A similar process of categorizing names has previously been used by Arai et al (2011). In another study Arai and Thoursie (2009) found a high positive correlation between a judgment-based regional coding of names and the actual regions of birth, indicating that identifying the region of birth by observing an individual's name is relatively straightforward.

Experimental setup

Half of our sellers create usernames consisting of their real first names (*non-anonymous usernames*), and the other half to create usernames consisting of their initials (*anonymous usernames*). In the first group buyers can sort into (or away from) auctions by username. The usernames include only the first name and not the surname, since this is a common feature of usernames. With the three dimensions of anonymity of username, gender, and foreignness, the study consists of eight groups in total, with two seller names in each category. As we are interested in the buyers' behavior the implicit assumption will be random assignment of buyers sorting into the seller categories when sellers have anonymous usernames. We therefore view the anonymous case as the baseline experiment comparing it with the non-anonymous categories; thus investigating what happens if sorting is prevented. The non-anonymous categories can be compared to the design of previous studies of online buyer discrimination (see for example Doleac and Stein 2013); where sorting is a possibility. The full list of seller categories is given in Table 1.

Table 1. The eight seller name categories.*****

Non-anonymous seller names (Sorting possible)	**Anonymous seller names (Sorting not possible)**
Male foreign-sounding names	Male foreign-sounding names
Male non-foreign-sounding names	Male non-foreign-sounding names
Female foreign-sounding names	Female foreign-sounding names
Female non-foreign-sounding names	Female non-foreign-sounding names

*The list of seller names used in the study can be found in Table A2 in the appendix. There two are names in each category.

All sellers sell two cinema vouchers. A cinema voucher is a customary and homogeneous good where the price and quality are common knowledge, implying a good internal validity. These vouchers are commonly given as presents between individuals and from employers to employees; they are commonly bought and sold offline as well as online. Buyers do not risk receiving a damaged good, but they may perceive a risk of fraud, e.g. the voucher having already been used. By acting as perfect sellers in all treatments we try to minimize this risk potentially perceived by buyers. The average price of the vouchers is rather low, which also decreases a potential perceived risk of fraud. Trust in this experiment therefore related more to risk of fraud and seller misconduct than to receiving a good of lower quality than expected.

All auctions were carried out using the same seller conduct across name categories, all acting as ‘perfect sellers’. The buyers are not aware of being part of an experiment. Four sellers, two from the anonymous seller group and two from the non-anonymous group, place vouchers sequentially on the market every day. Two auctions starts before lunch and two in the afternoon.[3] Each auction places two vouchers on sale. We also use a standard presentation of the vouchers, and randomly employ one out of three commonly used pictures of cinema vouchers, as well as one of three standard voucher descriptions. The lowest bid is set to 1 SEK. When the bidding starts, the only information available to potential bidders is the seller’s username and previous feedback. All of our sellers started as new, with no previous feedback ratings.[4] When each auction closed, the real names of the buyers and sellers were revealed in an email sent by eBay, but only to each other. In addition to real names, addresses are also disclosed when the auction ends. We exogenously impose addresses from the same local area to keep everything constant across name groups, apart from the names themselves. We then send an email to the winning buyer with payment instructions, using a standardized text. No email correspondence was initiated before an auction closed. As with most transactions on Swedish eBay, we use bank-to-bank transfers as the method of payment. The same day as the payment was registered; we sent the vouchers to the buyer by regular post.

After an auction closes, the buyer and seller can rate each other’s behavior. According to Jian

[3] The starting times, before and after lunch, are also randomly chosen (before lunch: between 07:00 and 12:00, and after lunch: between 13:00 and 20:00). We used five days as the length of the auction, as this seems to be the average length of an auction in this market.

[4] The number of feedback ratings became endogenous during the experiment. In the analysis, we control for whether the seller is new or experienced before the auction ended.

et al (2010), the buyers are first to provide feedback in 85% of the cases, and the majority of buyer feedback is provided rather quickly or not at all. Cabral and Li (2012) confirm that, on average, a well-behaved seller receives feedback after ten days. In order to capture buyers who only provide feedback after the seller does so, we gave feedback to any remaining buyers after ten days, provided that payment has been made.[5] We rated the buyer as soon as the buyer had rated us as a seller. When our sellers rated the buyers, we provided a common positive feedback rating, a grade point of 5, and a brief standardized positive comment. Negative ratings are very rare in general, and not used in the experiment as we acted as 'perfect sellers'. Figure 1 in the appendix displays a screenshot from one of our sellers' publically available accounts, taken approximately in the middle of the experiment.

Sellers were informed about every step of the procedure in the experiment as well as the purpose of the study. The study was approved by an IRB vetting the ethics of research involving humans (EPN Stockholm, 19 October 2011).

The measures we collect from the experiment are primarily *price* (the willingness to pay), and *provision of feedback*. In addition, we assess the number of days between the auction ends and buyer payment and feedback respectively. We also collect information on the buyers' characteristics, namely the gender and foreignness of the buyer's name. The buyers' names are categorized by employing a similar procedure as used for the sellers' names. We asked three of our sellers to match the list of buyer names to gender and region. We also asked whether they perceived the name as sounding foreign or not.

4. Hypotheses and summary of results

Arai et al (2011) investigate discrimination in the intersection of gender and foreignness. They

[5] On ten occasions, the buyer provided *payment* after ten days. These buyers did not receive feedback until they had paid. Inclusion and exclusion of these buyers in the analysis do not lead to qualitative differences in the results.

find that foreign men in Sweden is the group which fares the worst. Hence, there seem to be no double discrimination. Moreover, Fershtman and Gneezy (2001) found that ethnic discrimination in trust was present only among men. We therefore investigate discrimination in the four categories: male foreign seller, male non-foreign seller, female foreign seller and female non-foreign seller. *We use male sellers with foreign-sounding names as the reference category in the hypotheses and analyses.* Discrimination is analyzed separately among the anonymous and non-anonymous usernames. Table 2 provides a summary of our hypotheses and results.

Table. 2. Summary of hypotheses and results.

Variable	**Group studied**	**Hypothesis***	**Results**	**Hypothesis supported?**
Price	Sorting	MFS≤MNS	MFS≤MNS	Yes
		MFS≤FNS	MFS=FNS	Yes
		MFS≤FFS	MFS=FFS	Yes
Share of feedback	Sorting	MFS≤MNS	MFS=MNS	Yes
		MFS≤FNS	MFS=FNS	Yes
		MFS≤FFS	MFS=FFS	Yes
	No sorting	MFS<MNS	MFS≤MNS	Yes
		MFS<FNS	MFS<FNS	Yes
		MFS<FFS	MFS=FFS	No

MFS=male foreign-sounding name, MNS=male non-foreign-sounding name, FFS=female foreign-sounding name, FNS=female non-foreign-sounding name. In the results column, = indicates that the hypothesis of a difference could not be rejected in a regression with and without additional control variables, and ≤ indicates that the hypothesis was rejected with borderline significance in a regression without additional control variables.

*Regarding other comparisons between pairs of name categories results are provided in the appendix.

Sorting, anonymity and discrimination

Our experimental set up leaves more room for taste-based discrimination and minimizes statistical discrimination. Previous studies investigating similar products have revealed price discrimination, but not when competition increase (e.g. Ayres et al, 2011; Nunely et al, 2011; Doelac and Stein, 2013; List and Livingstone, 2010; Przepiorka, 2010). *If something, we* *expect to find some price discrimination with foreign male sellers receiving the lowest pay (in the non-anonymous group). We do not expect to find discrimination among the anonymous group.*

Fershtman and Gneezy (2001) found no ethnic discrimination in reciprocity, and Buchan et al (2002) found that individuals were not preferentially trustworthy towards either gender. If the buyer has information about the seller when entering an auction, the buyer can base their entry decisions on this. This possibility of sorting can make the buyers less inclined to employ differential treatment in the provision of feedback when the auction has ended, compared to when there is no room for self-selection. *For the seller categories with non-anonymous usernames, we expect little or no differential treatment in the provision of feedback.* However, if buyers (dis)like or have a prejudice against a specific group, and are only exposed to information after having interacted with a seller from this specific group, it may trigger differential treatment in the provision of feedback. In the work of Areys et al (2011) with customers who could not choose their taxicab driver, evidence emerged of discrimination against Afro-American taxicab drivers in terms of tipping. *For the seller categories with anonymous usernames, we expect differential treatment in the provision of feedback, with male foreign sellers receiving the lowest share.*

In addition, we measure the number of days between the end of the auction and payment/feedback, conditional on having paid or having provided feedback (reciprocated). We analyze these in an exploratory manner, since we have no expectations regarding the impact of transient anonymity on these two variables.

5. Data

The study was carried out between 30 April and 30 August 2012 in the market for cinema vouchers on Swedish eBay. We conducted a total of 461 auctions. Interacting more than once may influence trust and induce dependence between observations, so we exclude all but the first interaction between each buyer and seller. This occurred only 20 times, and so more than 95% of our interactions were one-shot. This is in line with previous literature (Resnick and

Zeckhauser, 2002). We also exclude 15 observations which involved communication problems with the buyer. In total, our data set comprises 426 observations. Another 21 of the subjects did not pay the auction. The main analysis is therefore based on 405 observations.

Table 3 shows a summary of our four main variables together with the buyers' characteristics. The average price of two vouchers is 140 SEK, or approximately 70% of the original price. In all, 70% of our paid auctions received feedback, and all feedback received was positive. The buyers in our data set are heterogeneous with respect to gender, foreign-sounding names, residential area, and previous feedback.

Table 3. Summary statistics.

Variables	**Mean**	**Sd**	**n**
Price	140.05	10.64	405
Number of pieces of feedback	0.70	0.46	405
Days to payment	2.31	2.59	405
Days to feedback	8.37	9.74	285
Female buyer	0.49	0.50	405
Buyer has foreign-sounding name	0.34	0.47	405
Big-city buyer	0.50	0.50	405
New buyer*	0.20	0.40	405
Buyer has negative feedback**	0.30	0.46	405

* 1 if the buyer has 5 or fewer pieces of feedback at end of auction, 0 otherwise.

** 1 if the buyer has at least 1 piece of negative feedback at end of auction, 0 otherwise.

There are no general differences in outcomes between having an anonymous or non-anonymous username; we tested whether price, feedback and time to payment and time to feedback differed between the two groups (see Table A3 in appendix). We also compared each seller category which revealed their name with a baseline constructed from the average price from all groups which conceal their names. We did not find any significant price differences (see Table A4 in the appendix).

6. Results

Throughout the analysis, we use ordinary least squares regressions.[6] Analyses are conducted in the statistical software STATA. All regressions are presented using dummies for each seller group, with and without additional control variables. The baseline category in all regressions is male sellers with foreign-sounding names. The additional control variables are; gender of the buyer and whether or not the buyer has a non-foreign-sounding name, as well as a set of variables previously shown to be important in the outcomes of auctions on eBay. These variables include, whether the buyer and seller are new to eBay, the buyer's previous amount of feedback, whether the buyer has received at least one piece of negative feedback, whether the buyer lives in a big city or not, and day fixed effects. The control variables are described in Table A5 in the appendix.

We conducted multiple tests and this can increase the probability of Type I errors. When designing the experiment we did unfortunately not take multiple corrections into account. To avoid an increase of Type II error we did not include corrections for multiple testing in the analysis.

Discrimination in price

The regressions in Table 4 have price as an outcome variable; both when sorting is possible and not possible. Regression 1 and 2 are comparable to other studies investigating discrimination experimentally; here the sellers reveal their names. In line with findings of discrimination on

[6] We also altered the specifications of the regressions; for price and time to feedback, we also ran Tobit regressions (lower limit set to 115 and upper limit set to 175; and lower limit set to 0 and upper limit set to 60 respectively), and for share of feedback we also ran a logit regression. This does not qualitatively change our results.

competitive markets we find no or little evidence of price discrimination by name category, measured as the price paid by the buyer, among the non-anonymous seller groups. On average, all seller categories seem to receive SEK 140 for two vouchers. Point estimates indicate less favorable pay for male sellers with foreign-sounding names compared to all other groups, but this is not significant. When including additional controls, a borderline effect occurs. Male sellers with foreign-sounding names seem to receive SEK 3.3 less for the same product compared to male sellers with non-foreign-sounding names (p=0.08). However, comparing the group of male foreign-sounding sellers with all other seller categories respectively we find no discrimination. Calculating the effect size for this borderline discrimination, the proportion of the variance attributed to this effect taking the error size into account is 0.018.[7] Regression 3 and 4 presents the price for the anonymous sellers, per category. Here there is, as expected, no differences in price.

Table 4. Price.*****

VARIABLES	(1) **Sorting possible** (non-anonymous seller)	(2) **Sorting possible** (non-anonymous seller)	(3) **No sorting possible** (anonymous seller)	(4) **No sorting possible** (anonymous seller)
Male non-foreign seller name	2.143	**3.534***	2.077	1.528
	(2.100)	(1.906)	(1.966)	(1.871)
Female non-foreign seller name	1.049	1.148	1.560	0.251
	(2.060)	(1.863)	(2.092)	(1.918)

[7] We also conduct an ex post sample size analysis comparing price between male sellers with foreign and non-foreign sounding names. We would need 979 additional auctions to reach a significant difference on a 5% level, assuming 80% power.

Female foreign seller name	2.200	2.415	-0.760	-1.711
	(1.969)	(1.761)	(1.983)	(1.919)
Additional control variables	No	Yes	No	Yes
Observations	206	206	199	199
R-squared	0.007	0.261	0.012	0.230

Robust t-statistics in parentheses.*** p<0.01, ** p<0.05, * p<0.1. Standard errors are clustered on buyer username.

*The regression is performed on sellers with non-anonymous usernames, when selection into auction by name is possible.

The control variable “new seller” (having less than 5 pieces of feedback) has a clear negative effect on price. This corroborates previous literature, and indicates that receiving *feedback* has a clear economic impact for the seller on eBay. A new seller receives on average SEK 11 less than an experienced seller (p<0.01). All results for additional variables and comparisons between other seller categories are given in Table A6 in the appendix.

Differences in the seller’s level of experience can also be important in terms of price discrimination. There is, however, no reason to believe that experience has different implications for sellers with anonymous and non-anonymous usernames. During the experiment, the feedback the sellers received from the buyers became endogenous. We have too few observations to compare the price between all seller categories at each feedback level. In the regressions, we control for being an experienced seller or not, using a variable that take the value 1 if the seller has 5 or fewer pieces of feedback and 0 otherwise. Increasing the number of pieces of feedback from 5 to 10 marginally strengthens the discrimination against male foreign-sounding sellers in regression 2.

Discrimination in share of feedback

To explore the possible effect of preventing sorting, we compare discrimination in the provision of feedback between non-anonymous and anonymous seller categories. Feedback is measured as 1 if the buyer provided feedback, 0 otherwise. Regressions 1 and 2 in Table 5 show no sign of discrimination. Here the names are present in the sellers' usernames and the buyers could use the name to sort. In contrast regressions 3 and 4, display differential treatment by seller categories. Here we find a marginal significant results; female sellers with non-foreign-sounding names receive approximately 12.6% more feedback compare to male sellers with foreign-sounding names (regression 3: p=0.07). When control variables are included, we find that male sellers with foreign-sounding names receive less feedback compared to both male and female sellers with non-foreign-sounding names (regression 4; male non-foreign sellers: p=0.04; female non-foreign sellers: p=0.02). Calculating the effect sizes; the proportions of the variance attributed to these two effects, taking the error size into account, are 0.024 and 0.029 for foreign male sellers compared to male and female sellers with non-foreign-sounding names respectively. Coefficients on control variables and the comparison between other seller categories are displayed in Table A7a in the appendix.

Table 5. Share of feedback.

	(1)	**(2)**	**(3)**	**(4)**
VARIABLES	**Sorting possible** (non-anonymous seller)	**Sorting possible** (non-anonymous seller)	**No sorting possible** (anonymous seller)	**No sorting possible** (anonymous seller)
Male non-foreign seller name	-0.084	-0.061	0.115	**0.126****
	(0.090)	(0.049)	(0.090)	(0.061)

Female non-foreign seller name	-0.047	0.043	**0.160***	**0.132****
	(0.091)	(0.058)	(0.088)	(0.059)
Female foreign seller name	-0.028	0.023	0.060	0.036
	(0.085)	(0.053)	(0.092)	(0.061)
Additional control variables	No	Yes	No	Yes
Observations	206	206	199	199
R-squared	0.004	0.660	0.017	0.579

Robust t-statistics in parentheses.*** p<0.01, ** p<0.05, * p<0.1. Standard errors are clustered on buyer username.

Buyers can provide feedback before or after the seller provides feedback (i.e. by construction of this study before or after ten days). In the first case, buyers run the risk of receiving negative feedback from sellers, and in the second buyers run no such risk. Providing before could be interpreted as a trusting behavior and after as a reciprocal behavior. To probe into this we conduct the regressions from Table 5 on the subgroup of buyers that provided feedback after and before the seller, respectively. We find a similar discriminatory pattern within both subgroups. In the group that provides the feedback after the seller did the standard errors are larger, but the discrimination pattern is qualitatively similar compared to the full sample. See Tables A7b-c in the appendix.

The experience of the seller could also potentially affect discrimination. However, we control for the number of pieces of feedback the seller has and this variable is further *not* significant. Hence, in our sample the level of experience of a seller do not seem to affect the share of feedback provided by buyers (regression 4: p=0.895).

Who is discriminating?

The question that may come into mind reading the results is who is driving this type of discrimination? We conduct separate regressions 1, 2, 3 and 4 for all four name categories by buyer; male foreign buyer, male non-foreign buyer, female foreign buyer, and female foreign buyer. As for the full sample, there is no discrimination within any of the four categories when sellers have revealed their name in the usernames. Again in similar vein as full sample, discrimination occurs when sorting is prevented by using anonymous username. However, it does not occur among all buyer name categories. In contrast to many other studies, we find that this type of discrimination is mainly present among women. Female buyers with non-foreign names display the most robust discriminatory behavior (when sorting is not possible); results are presented in Table 6. It seems like they focus on the foreignness dimension. This buyer group give male non-foreign sellers substantially more feedback than male foreign sellers, without and with control variables (regression 3: p<0.001; regression 4: p=0.015). Further, they provide female non-foreign sellers with marginally more feedback (p=0.094).

Table 6. Share of feedback. Subpopulation of female non-foreign buyers

	(1)	(2)	(3)	(4)
VARIABLES	**Sorting possible** (non-anonymous seller)	**Sorting possible** (non-anonymous seller)	**No sorting possible** (anonymous seller)	**No sorting possible** (anonymous seller)
Male non-foreign seller name	0.089	-0.051	**0.429*** **	**0.292** **
	(0.149)	(0.076)	(0.111)	(0.116)
Female non-foreign seller	-0.056	0.053	0.229	**0.200***

name	(0.165)	(0.090)	(0.142)	(0.117)
Female foreign seller name	-0.061	0.025	0.179	0.156
	(0.155)	(0.080)	(0.146)	(0.127)
Additional control variables	No	Yes	No	Yes
Observations	76	76	69	69
R-squared	0.016	0.789	0.119	0.546

Robust t-statistics in parentheses.*** p<0.01, ** p<0.05, * p<0.1. Standard errors are clustered on buyer username.

We have too few female foreign buyers to properly estimate the same four regressions. However, running the regressions without control variables there are indications of discriminatory behavior against male foreign sellers. In the case of male non-foreign buyers a significant behavioral difference appears only when we control for additional variables, favoring female non-foreign sellers compared to male foreign sellers (p=0.047), but not in relation to other categories. Male foreign buyers do not display any discriminatory behavior (see Tables A6d-f in appendix).[8]

To summarize, we find that anonymity seem to create buyer discrimination once the identity

[8] In the main analysis, we have categorized the results according to the question of whether the name sounds foreign or not. Investigating discrimination categorizing the buyer names matched with the region of the Middle East and North Africa as foreign, all our results stay qualitatively the same.

of the seller s revealed. When sellers use anonymous usernames, buyers cannot sort into or abstain from a specific auction based on gender and foreignness. We find no or only little evidence of the price the customers pay being dependent on the gender and foreignness of the seller's username. This is expected in a competitive market with many buyers and sellers. Surprisingly however, we find discrimination in feedback (after the auction) *only* when buyers could not sort into or abstain from entering a specific auction. Male sellers with foreign-sounding names receive less feedback than non-foreign female sellers. This is furthermore found merely among female buyers.

Potential mechanisms

The discrimination clearly only occurs when the usernames are anonymous. However, we have no means of clearly disentangling the mechanisms behind this type of discrimination. An individual can execute his or her distaste by not entering into auctions where the username signals a specific group belonging or sort into auction where the username signals a groups belonging of one's liking. Further, if an individual dislike members of a specific group s/he may also chose not to enter an auction with an anonymous username; to avoid a potential surprise. We cannot detect motives, but we can compare the composition of buyer characteristics in the anonymous seller groups (no sorting) with the composition of buyer characteristics when the buyers have the possibility to sort. Participating in the market is to some extent endogenous; table 7 indicates that the proportion of male foreign buyers is smaller when sorting is possible compared to when it is not. Despite this, discrimination is not present among this group. This can imply sorting of some type. There are, on the other hand, more female foreign buyers when sorting is possible compared to not, and in this group there is some indicative evidence of discriminatory behavior. The proportions of male non-foreign buyers do not differ between these two situations, and this group displays a slight differential behavior, favoring female non-foreign sellers. The share of female non-foreign buyer does not differ between the two situations, and they display the most robust discriminator behavior.

Speculating, the discrimination can be caused by a "surprise" effect, when the names are revealed it is not what the individual expected. Women that are sophisticated, i.e. aware of being averse to not being in control would probably choose to enter an auction with a username containing a clear signal. If there, however, is a proportion of women that are naïve about their aversion to not to being in control, and on average expect the anonymous seller to be a non-foreign man or women, this may spur the discriminatory behavior in feedback.

Table 7. Proportion of buyer characteristics by seller anonymity

VARIABLES		Female non-foreign buyer name	Male non-foreign buyer name	Female foreign buyer name	Male foreign buyer name
Sorting not possible (anonymity)	Share	0.35	0.29	0.10	0.26
	n	209	209	209	209
Sorting possible (no anonymity)	Share	0.36	0.30	0.18	0.16
	n	217	217	217	217
ttest	p-value	0.751	0.863	0.019	0.010

We find no indications or anecdotal evidence of outspoken dislike. Approximately 70% of all buyers provide a text message connected to the feedback and this does not differ by seller category, irrespective of whether anonymous usernames are used. Further we received a total of 15 email from buyers that clearly signaled distrust. All seller categories, except anonymous foreign males, received at least one such and email.

Further analyses

We also measure *days to payment* from the day the auction ended, and whether this differs between seller categories. A total of 21 buyers did not pay and did not receive the vouchers, and these are equally distributed across seller categories. We find no differences in time to payment by seller category among the buyers facing non-anonymous sellers—when they can sort. On average, all groups receive payment after just over 2 days. Again, we find differences among the buyers who face the anonymous name categories; male sellers with foreign-sounding names receive payment *faster* than female sellers with both non-foreign and foreign names, although the latter is marginally significant (see Table A8a in the appendix). A quick response can be interpreted as being either negative or positive; it may, for example, imply that the buyer wants to end the interaction as quickly as possible. We additionally ran regressions separately for buyers who provided *feedback* and those who did not (among the anonymous seller group). The discriminatory behavior in Table A8a is only present among buyers who did not provide feedback, indicating potentially that the buyers wish to end the interaction as fast as possible (see Table A8b in the appendix).

Among the buyers providing feedback, we also measure discrimination in *days to giving feedback*. The number of days until feedback is measured from the day on which the auction ends.[9] Here as well we find that discrimination between seller categories is only present when sellers employ anonymous usernames (no sorting). As for time to payment, male sellers with foreign names seem to receive feedback *faster* than female sellers with foreign-sounding names, but only when control variables are included (p=0.05; see Table A9 in appendix). One reason for providing feedback late or at the last minute could be because a buyer (or seller) wants to leave negative feedback while minimizing the risk of retaliation. However, we only received positive feedback. Even if this discrimination can be hard to interpret, the results clearly show that using anonymous names may spur differential treatment.

[9] We also measured the number of days to feedback starting from the day of payment, and as hours to feedback. These measures provide qualitatively the same results.

Robustness

Only the price, not feedback, seems to be dependent on the experience of the seller, i.e. the number of pieces of feedback the seller has received. To further investigate the relationship between experience and price discrimination, we ran all the regressions including interactions of being a new seller with all the respective seller categories. All seller categories receive better pay when they are more experienced. Looking at mere numbers, it also seems like it took each seller category roughly the same number of auctions to receive five pieces of feedback and ten pieces of feedback, respectively (within the anonymous and non-anonymous seller groups respectively).

Several studies show that higher competition in online markets decreases price discrimination (e.g. Ayres et al, 2011; Nunely et al, 2011; Doelac and Stein, 2013; List and Livingstone, 2010; Przepiorka, 2010). Compared to the baseball card market in the U.S., (for example Livingstone and List, 2010), the market for cinema vouchers in Sweden is small. In August a year before the experiment, there were on average 70 ongoing auctions each day; the same number of ongoing auctions as during our experiment. Unfortunately we did not collect the number of bidders for each auction. As mentioned, 95% of our auctions are one-shot. Anecdotally, during the experiment it seems like this market had more buyers than sellers, which can create competition among buyers. A large market share could potentially affect the price. We did not continuously estimate the size of the market share we had each day, but we do not seem to have affected the market price. The average price for two cinema vouchers before we ran the experiment, in August 2011, was 151 SEK, and the average price our sellers received during August 2012 was 149 SEK. We also collected prices from auctions ending a month after the experiment closed; the average price for two vouchers in September 2012 was 149 SEK (see Table A9 in the appendix).

A voucher is a homogeneous good where the price and quality are common knowledge, thus providing good internal validity. This may imply that the results do not extend to other goods and markets. The proportion of female buyers in our sample of buyers is the same as in the general population. On the other hand, we seem to have a large share of buyers with foreign-sounding names. We have no means of looking into the socio-demographics of our buyers. It is also possible that customers buying cinema vouchers on eBay might care more about small sums of money and have more time compared to the general population. However, buying all kinds of goods online is gaining popularity. During April 2008 and March 2009, 62% of the Swedish population aged 17-64 bought goods online (see Statistics Sweden, 2010). Due to its potentially lower external validity we should be careful not to draw direct inferences from this study to other settings and groups. Nevertheless, this study provides an interesting and important example of how anonymity and the possibility of sorting can affect customer discrimination. In addition, our design can be employed with ease in future online research.

7. Discussion

This study digs into the contemporary question of how anonymity can affect buyer discriminatory behavior in online markets—with no face to face communication—a topic of growing importance since more and more economic and social interactions are conducted online. We conducted an experiment on Swedish eBay where we asked individuals with varying names (by gender and foreignness) to sell a homogenous product. Half the sellers used anonymous usernames and half the sellers employed their real names as usernames. After an auction end eBay reveals the names to the buyer and seller in each auction. All seller groups acted identically and as ‘perfect sellers’.

We argue that sorting possibilities is important in understanding discriminatory behavior. In an online auction setting anonymity prevents buyers from sorting into or shying away from specific auctions (or specific sellers) by username.

To shed light on this question we first look at *price* discrimination when soring is possible and then we compare buyer discrimination *in feedback* when buyers can sort and when they cannot. In contrast to most other previous experimental discrimination studies we find little evidence of price discrimination and feedback seems to be the most important determinant of the price. However, this is in line with results looking at thick markets, where competition is found to reduce price discrimination (e.g. Doleac and Stein, 2013; Prezipiorka 2012). Despite this, a thick market containing sufficient numbers of buyers and sellers can allow for sorting without affecting the price. We find clear evidence of buyer discrimination when sorting is not possible compared when sorting is a possibility. Discrimination in feedback occurs only when the sellers have employed anonymous usernames (measured after the auctions have ended and names have been automatically revealed by eBay). We find that male sellers with foreign-sounding names receive less feedback than sellers with non-foreign-sounding names. The amount of feedback can increase both sales and profit of the seller. Thus, there may be long term price differences between sellers of different gender and foreignness among the group employing anonymous usernames. We are however not able to explore this due to the limits of our data. In contrast to most previous discrimination literature this type of discrimination seems to be driven mainly by female buyers with non-foreign sounding names. Speculating, discrimination in this setting can be caused by a surprise effect for example when the name revealed is not in line with the expectations of the individual. Thus, anonymity prevents buyers from being in control of who they trade with using typical face-to-face characteristics such as gender and foreignness. Women are sometimes found to react more to social cues compared to men (Corson and Gneezy 2009). If there is a proportion of women that are naïve about their aversion to not to being in control, and on average expect the anonymous seller to be a non-foreign man or women, this may spur the discriminatory behavior in feedback.

Our results corroborate previous findings on customer discrimination in tipping of taxicab drivers found by Ayres et al, 2011. In this study we have a counter factual case. Novel is that in a buyer seller situation anonymity implies prevention of choosing who to buy (or sell) from by usernames. Our result therefore places some evidence that the reason behind thick markets displaying no discrimination is because of sorting; buyers and seller choose who to interact with. This also implies that future discrimination research should take sorting mechanisms into account.

Reputation online spreads rapidly and at a low cost through methods such as feedback systems. Anonymity can have both positive and negative effects; transient anonymity in eBay auctions seems to have a clear negative effect. Besides bearing economic relevance within the market, these transient anonymous situations may affect discrimination in feedback with implications for example brand building, product development, and quality assurance (see Cook et al, 2009 for a review). Online economic and social interactions are growing in number of users and area of usage. It is crucial to further the understanding of how online features such as different types of anonymity affect human behavior.

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Appendix

Table A1. Summary of the market in August 2011, August 2012, and September 2012.

	August 2011	August 2012	September 2012
Average price	151.27	148.52	148.58
Buyer negative*	0.54	0.32	0.23
New buyer**	0.13	0.20	0.23
Anonymous***	0.45	0.50	0.59

* 1 if buyer has at least 1 piece of negative feedback at end of auction, 0 otherwise.

**1 if buyer has 5 or fewer pieces of feedback at end of auction, 0 otherwise.

***1 if username is anonymous (does not contain any information about gender or foreignness), 0 otherwise.

Table A2. Full names and usernames of the sellers.

Name	Surname	Username	Name category*
Daniel	Johansson	daniel012	MNS, 1
Tomas	Larsson	tomas012	MNS, 1
Savas	Calsikan	Savasc	MFS, 2
Alireza	Behtuoi	alirezaB	MFS, 2
Pernilla	Andersson	pernilla04	FNS, 3
Tone	Johansson	tone012	FNS, 3
Khadra	Seerar	khadra01	FFS, 4
Afamia	Maraha	Afamia	FFS, 4
Karl-Göran	Karlsson	Kgka	MNS, 5
Fredrik	Mattsson	Frmat	MNS, 5

Hossein	Ali	hoal01	MFS, 6
Tiglat	Maraha	tima01	MFS, 6
Louise	Johanesson	lojo01	FNS, 7
Eva	Karlsson	evka0	FNS, 7
Fatima	Nekshbandi	fane01	FFS, 8
Doaa	Mohamed	domo01	FFS, 8

*Name categories: MNS=males with non-foreign names, FNS=females with non-foreign names, MFS=males with foreign names, FFS=females with foreign names. Categories 1-4 reveal their names in their usernames, and categories 5-8 conceal their names.

Table A3. Summary of main variables, divided by anonymity or not (sorting possibility or not).

	Sorting possible			**No sorting possible**			**t-test**
Variables	**Mean**	**Sd**	**N**	**Mean**	**Sd**	**N**	**p-value**
Price	139.99	11.06	217	140.38	10.33	209	0.706
Feedback	0.68	0.49	217	0.67	0.47	209	0.868
Time to payment*	2.34	2.44	206	2.28	2.74	199	0.791
Time to feedback**	7.93	9.04	147	9.13	11.04	140	0.375

*Days counted from the day the auction ended.

** Days counted from the day the auction ended.

Table A4. Price for different groups in the non-anonymous treatment compared to a baseline*

	Mean for group	**Baseline**	**p-value**
MNS	140.64	140.38	0.874

FNS	139.81	140.38	0.703
MFS	138.63	140.38	0.245
FFS	140.80	140.38	0.784

MNS=males with non-foreign names, FNS=females with non-foreign names, MFS=males with foreign names, FFS=females with foreign names.

* Baseline is calculated as the mean in the group with anonymous usernames.

Table A5. Description of control variables

Feedback first	1 if the buyer provided feedback before the seller, 0 otherwise
New seller	1 if the seller has less than 5 pieces of feedback, 0 otherwise
Female buyer	1 if the buyers name is female, 0 otherwise
Non-foreign buyer	1 if the buyers name is rates as sounding foreign, 0 otherwise
Number of feedback of buyer	# feedback of the buyer
Buyer has negative feedback	1 if the buyer has previous negative feedback, 0 otherwise
New buyer	1 if the buyer has less than 5 pieces of feedback, 0 otherwise
Big-city buyer*	1 if the buyer lives in a big city (according to Statistics Sweden), 0 otherwise
Day fixed effect	The date when the auction ended.
Number of bids	# bids from all individuals taking part in the auction

*** A big city is defined as a having 200 000 inhabitants or more.**

Table A6. Price, additional control variables. Results from regression 2 and 4 Table 4.

	(2)	(2)	(4)	(4)
	Sorting possible		**No sorting possible**	

VARIABLES	Reg. coefficient	p-value	Reg. coefficient	p-value
New seller	-11.003***	0.000	-9.518***	0.000
Female buyer	-1.763	0.251	-0.056	0.970
Non-foreign buyer	1.021	0.581	1.130	0.469
Number of feedback of buyer	-0.003*	0.069	-0.004***	0.003
Buyer has negative feedback	1.448	0.410	2.850**	0.044
New buyer	1.244	0.469	1.759	0.303
Big-city buyer	2.329	0.150	0.210	0.880
Day fixed effect	0.009	0.663	0.019	0.303
Number of bids	0.017	0.733	0.067	0.221

Price, comparing the other name categories (regression coefficients)

MNS vs. FNS	-1.871	0.322
MNS vs. FFS	-0.971	0.632
FNS vs. FFS	0.900	0.625

MNS=males with non-foreign names, FNS=females with non-foreign names, FFS=females with foreign names.

Table A7a: Share of feedback, additional control variables.

	(2)	(2)	(4)	(4)
	Sorting possible		No sorting	

VARIABLES	Reg. coefficient	p-value	possible Reg. coefficient	p-value
Feedback first	0.679	0.000	0.652	0.000
New seller	-0.042	0.453	0.008	0.895
Female buyer	-0.142	0.001	-0.005	0.921
Non-foreign buyer	-0.074	0.142	0.048	0.407
Number of feedback of buyer	0.000	0.021	0.000	0.399
Buyer has negative feedback	-0.082	0.119	0.014	0.822
New buyer	-0.138	0.003	-0.059	0.344
Big-city buyer	-0.051	0.250	-0.093	0.055
Day fixed effect	0.000	0.595	-0.000	0.715
Number of bids	0.002	0.257	-0.002	0.087
Price	0.002	0.384	-0.005	0.064
Share of feedback, comparing the other name categories				
MNS vs. FNS	0.104	0.064	0.007	0.910
MNS vs. FFS	0.083	0.100	-0.090	0.166
FNS vs. FFS	-0.020	0.723	-0.096	0.144

MNS=males with non-foreign names, FNS=females with non-foreign names, FFS=females with foreign names.

Table A7b: Share of feedback among buyers who provided feedback before the sellers provided feedback.

VARIABLES	(1) **Sorting possible** (non-anonymous seller)	(2) **Sorting possible** (non-anonymous seller)	(3) **No sorting possible** (anonymous seller)	(4) **No sorting possible** (anonymous seller)
Male non-foreign seller name	-0.084	-0.113	0.115	**0.159***
	(0.090)	(0.092)	(0.090)	(0.085)
Female non-foreign seller name	-0.047	-0.030	**0.160***	**0.199****
	(0.091)	(0.087)	(0.088)	(0.085)
Female foreign seller name	-0.028	-0.055	0.060	0.029
	(0.085)	(0.083)	(0.092)	(0.092)
Additional control variables	No	Yes	No	Yes
Observations	206	206	199	199
R-square	0.004	0.158	0.017	0.142

Robust t-statistics in parentheses.*** p<0.01, ** p<0.05, * p<0.1. Standard errors are clustered on buyer username.

Table A7c: Share of feedback among buyers who provided feedback after the sellers provided feedback.

VARIABLES	(1) Sorting possible (non-anonymous seller)	(2) Sorting possible (non-anonymous seller)	(3) No sorting possible (anonymous seller)	(4) No sorting possible (anonymous seller)
Male non-foreign seller name	-0.107	-0.130	0.201	**0.253***
	(0.135)	(0.143)	(0.136)	(0.131)
Female non-foreign seller name	0.110	0.107	0.213	**0.252***
	(0.150)	(0.132)	(0.142)	(0.140)
Female foreign seller name	0.098	0.077	0.096	0.017
	(0.149)	(0.134)	(0.129)	(0.132)
Additional control variables	No	Yes	No	Yes
Observations	85	85	88	88
R-square	0.039	0.416	0.034	0.197

Robust t-statistics in parentheses.*** p<0.01, ** p<0.05, * p<0.1. Standard errors are clustered on buyer username.

Table A7d. Share of feedback. Subpopulation of female foreign buyers

	(1)	(2)	(3)	(4)

VARIABLES	**Sorting possible** (non-anonymous seller)	**Sorting possible** (non-anonymous seller)	**No sorting possible** (anonymous seller)	**No sorting possible** (anonymous seller)
Male non-foreign seller name	-0.022		0.400	
	(0.194)		(0.246)	
Female non-foreign seller name	-0.400		**0.667****	
	(0.269)		(0.305)	
Female foreign seller name	-0.255		**0.700*****	
	(0.204)		(0.145)	
Additional control variables	No		No	
Observations	35		20	
R-squared	0.102		0.199	

Robust t-statistics in parentheses.*** p<0.01, ** p<0.05, * p<0.1. Standard errors are clustered on buyer username.

Table A7e. Share of feedback. Subpopulation of male non-foreign buyers

	(1)	**(2)**	**(3)**	**(4)**

VARIABLES	Sorting possible (non-anonymous seller)	Sorting possible (non-anonymous seller)	No sorting possible (anonymous seller)	No sorting possible (anonymous seller)
Male non-foreign seller name	-0.258	-0.220	0.015	0.040
	(0.160)	(0.138)	(0.162)	(0.075)
Female non-foreign seller name	-0.028	0.008	0.191	**0.177****
	(0.143)	(0.117)	(0.142)	(0.087)
Female foreign seller name	0.063	0.088	-0.058	0.040
	(0.137)	(0.128)	(0.192)	(0.084)
Additional control variables	No	Yes	No	Yes
Observations	63	63	59	59
R-squared	0.082	0.616	0.056	0.637

Robust t-statistics in parentheses.*** p<0.01, ** p<0.05, * p<0.1. Standard errors are clustered on buyer username.

Table A7f. Share of feedback. Subpopulation of male foreign buyers

	(1)	**(2)**	**(3)**	**(4)**
	Sorting possible (non-anonymous	**Sorting possible** (non-anonymous	**No sorting possible**	**No sorting possible**

	seller)	seller)	(anonymous seller)	(anonymous seller)
VARIABLES				
Male non-foreign seller name	-0.262	-0.044	-0.128	0.130
	(0.273)	(0.250)	(0.182)	(0.148)
Female non-foreign seller name	0.042	-0.084	-0.067	0.003
	(0.206)	(0.180)	(0.183)	(0.129)
Female foreign seller name	0.167	0.014	-0.238	-0.158
	(0.169)	(0.147)	(0.201)	(0.118)
Additional control variables	No	Yes	No	Yes
Observations	32	32	50	50
R-squared	0.189	0.625	0.025	0.597

Robust t-statistics in parentheses.*** p<0.01, ** p<0.05, * p<0.1. Standard errors are clustered on buyer username.

Table 8a. Number of days to payment.

VARIABLES	(1) **Sorting possible** (non-anonymous seller)	(2) **Sorting possible** (non-anonymous seller)	(3) **No sorting possible** (anonymous seller)	(4) **No sorting possible** (anonymous seller)
Male non-foreign seller name	-0.672	-0.542	0.714	0.637
	(0.467)	(0.477)	(0.487)	(0.435)
Female non-foreign seller name	-0.615	-0.560	**0.580***	0.422
	(0.549)	(0.566)	(0.340)	(0.363)
Female foreign seller name	-0.351	-0.281	**1.280****	**1.382****
	(0.534)	(0.521)	(0.567)	(0.609)
Additional control variables	No	Yes	No	Yes
Observations	206	206	198	198
R-squared	0.011	0.066	0.028	0.080

Robust t-statistics in parentheses.*** p<0.01, ** p<0.05, * p<0.1. Standard errors are clustered on buyer username.

Table A8b: Number of days to payment in the sorting treatment. Subpopulation of buyers who provided feedback vs. buyers who did not.

	No feedback.		**Feedback**	
VARIABLES				
Male non-foreign seller name	2.211	**2.719***	0.194	0.103
	(1.524)	(1.617)	(0.321)	(0.348)
Female non-foreign seller name	1.211	1.182	0.452	0.295
	(0.744)	(1.086)	(0.382)	(0.417)
Female foreign seller name	**2.961***	**3.573****	0.510	0.430
	(1.553)	(1.750)	(0.340)	(0.365)
Additional control variables	No	Yes	No	Yes
Observations	59	59	139	139
R-square	0.079	0.183	0.017	0.077

Robust t-statistics in parentheses.*** p<0.01, ** p<0.05, * p<0.1. Standard errors are clustered on buyer username.

Table A9. Number of days to feedback.

	(1)	**(2)**	**(3)**	**(4)**
	Sorting possible (non-anonymous seller)	**Sorting possible** (non-anonymous seller)	**No sorting possible** (anonymous seller)	**No sorting possible** (anonymous seller)
VARIABLES				

Male non-foreign seller name	0.670	1.629	**4.178***	1.547
	(0.382)	(1.181)	(1.948)	(1.059)
Female non-foreign seller name	**4.031***	1.503	**4.089***	2.118
	(1.743)	(1.072)	(1.706)	(1.371)
Female foreign seller name	0.599	-0.887	3.189	**2.589****
	(0.478)	(-0.794)	(1.563)	(2.012)
Additional controls	No	Yes	No	Yes
Observations	285	285	285	285
R-squared	0.013	0.628	0.651	0.007

Robust t-statistics in parentheses.*** p<0.01, ** p<0.05, * p<0.1. Standard errors are clustered on buyer username.

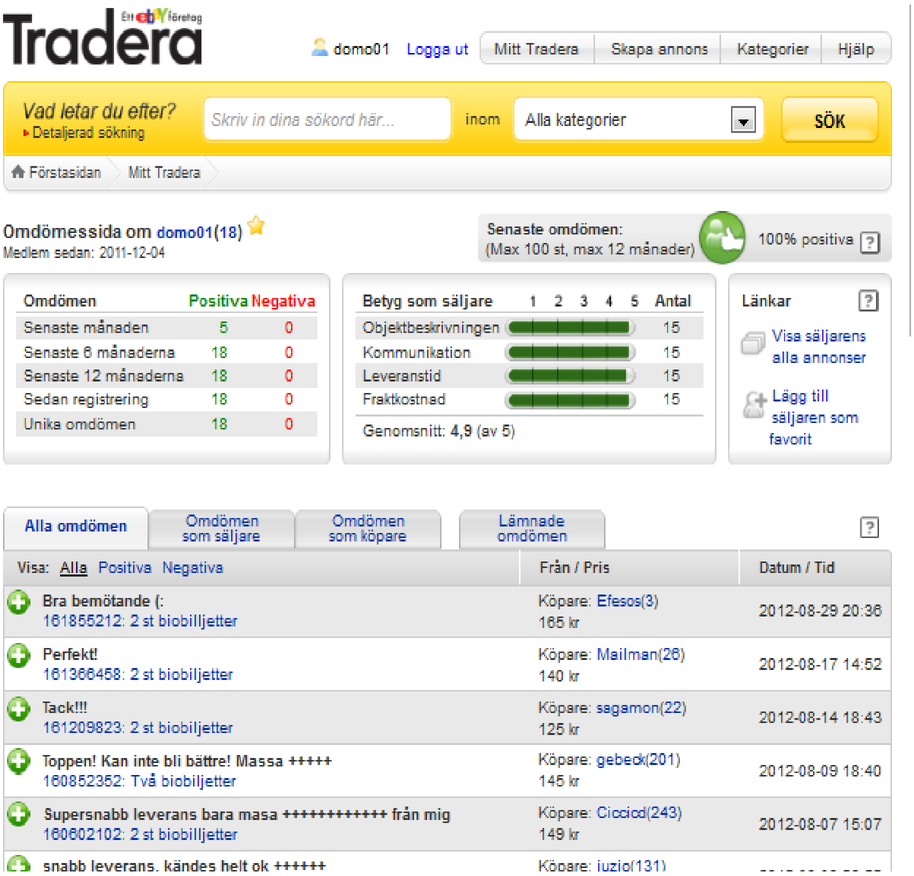

Figure 1. Screenshot from a seller with an anonymous username.

*When this screenshot was taken, domo01 had 18 unique pieces of feedback from previous auctions.