Reputation and Adverse Selection: Theory and Evidence from eBay*

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Abstract

Adverse selection among sellers on eBay is prevalent, as shown by many authors, and ever since Akerlof [1970], it is known that adverse selection can hinder trade. In this paper, I study how actors in a marketplace can introduce mechanisms to overcome adverse selection, and I focus on one mechanism employed by eBay: sellers' *reputation*. Using a unique data set that follows sellers on eBay over time, I show that reputation, according to various measures, is a major determinant of variations in the prices of homogeneous goods sold on eBay, in particular, for iPods. Inspired by this observation, I develop a model of firm dynamics where firms have heterogeneous qualities that are unobservable by consumers. Reputation is used as a signal of private information to buyers in order to improve allocations. I structurally estimate this model to uncover deep parameters of buyers' utility and sellers' costs as well as sellers' unobservable qualities. The estimated model suggests that reputation has a positive effect on the expected profits of high quality sellers and their market shares. I perform a counterfactuals to establish the value of reputation. Removing reputation mechanisms put in place by eBay significantly increases the market share of low quality sellers and decreases the market share of high quality sellers. This will lowers the price in the market which as a result lowers the quantity of items sold in the market. Finally, the counterfactual shows that buyers' welfare is significantly improved as a result of the reputation mechanism.

JEL Classification: D8, L2

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1 Introduction

In recent years, there has been a surge in the use of online marketplaces, such as eBay and Amazon, where trading occurs in a very decentralized fashion. While these marketplaces have proved to be popular, they have given rise to asymmetric information problems: sellers can misrepresent the objects they sell, they can mishandle the shipping of the items sold, etc. Various reputational mechanisms have been introduced in order to remedy these problems. While the role of reputation in overcoming adverse selection problems is known (for example: Mailath and Samuelson [2001], Board and Meyer-ter Vehn [2010], and Board and Meyer-ter Vehn [2011], among others), the empirical validation of this claim remains unknown. This paper sheds light on the value of reputation in overcoming adverse selection by studying reputation among sellers on the eBay marketplace.

The eBay marketplace, as pointed out by many authors (Resnick et al. [2006], Brown and Morgan [2006], and Yamagishi and Matsuda [2002], among others), is plagued by information asymmetries. Moreover, as Bar-Isaac and Tadelis [2008] mention, eBay provides a very good environment for economists to study the effects of reputation on sellers' actions and profits. First, economists can observe all the sellers' characteristics observable by buyers. Second, sellers and buyers have little to no interactions with each other outside the eBay website; therefore, buyers do not have additional information about the sellers which is unobservable to economics. Third, economists can track sellers over time which gives them an extra information about the sellers which is unobservable to buyers; this information can potentially be used to estimate underlying model parameters.

In this paper, I base my study on sellers on eBay and use a unique dataset that follows sellers over time. To show the value of reputation, I first analyze the determinants of price variation in a set of homogeneous goods (iPods). Second, I develop and estimate a model of sellers' behavior over time where they have heterogeneous unobserved qualities and build up their reputation over time by selling objects and acquiring eBay store status and eBay powerseller status. Finally, using the estimated model, I perform a counterfactual to analyze the effect of reputation on profits and market outcome.

To empirically analyze the role of reputation, I examine the data on sellers of iPods between 2008 and 2009 which contains around 168,000 items sold. The dataset follows sellers on eBay and collects the number of items sold, the information provided by the sellers on their website, the final price of items sold, and the sellers' characteristics. Consistent with other studies about eBay, there is plenty of variation in the prices of iPods sold. In this context, there are two main variables of interest that are related to reputation: *powerseller status* and *eBay registered store status*. A seller becomes a powerseller if he/she sells 100 items per month over 3 consecutive months or more than $1000 worth of goods per month for 3 consecutive months. Moreover, the percentage of their positive feedback has to be higher than 98%. A seller can acquire an eBay registered store status by paying a monthly fee of \$16-\$300 dollars.

Using these two variables as proxies for reputation, I show that reputation has a significant role in explaining price variations. In particular, prices of new iPods are positively correlated with reputation. Among sellers of new iPods, being a powerseller, keeping all the other characteristics of sellers and item as fixed, increases prices by approximately \$5 dollars, while being an eBay store, keeping all the other characteristics of sellers and item as fixed, increases prices by approximately \$6. This is suggestive evidence that reputation can account for a portion of variation in prices. Although search costs and other factors can also contribute to price dispersion among identical objects, I argue that the variation in prices cannot only be accounted for by search costs. Moreover, using Regression Discontinuity methods, I show that seller's revenues increase as a result of becoming a powerseller.

The above empirical analysis, although suggestive, cannot really inform us about the value of reputation. Reputation or uninformed outsider's belief about a seller is a dynamic variable that sellers build over time. Hence, we need a dynamic model of sellers' reputation in order to estimate the value of reputation and perform a counterfactual. Using a dynamic model of reputation formation, one can think about the value of reputation in the current mechanisms put in place by eBay as well as optimal reputation systems. To do so, I equip standard models of firm dynamics with adverse selection and reputation. To the best of my knowledge, this is the first study to estimate the value of reputation using a structural model of firm dynamics.

The structural model in this paper consists of two sets of agents: buyers and sellers. Buyers are short-lived and derive utility from the purchased goods, while sellers are long lived and can sell different quantities over time. Sellers are heterogeneous in the *quality* of the goods they are selling. Quality is defined to be the way buyers derive utility from consumption of the good; the higher the quality of the object, the higher the buyers' utility from purchasing one unit of the goods.[1] Quality is assumed to be fluctuating over time; at the beginning of the game, sellers draw their quality type and future qualities fluctuate around this value in an i.i.d. manner. To capture adverse selection, I assume that the qualities are privately known to sellers; buyers do not observe the quality of the object. Moreover, since buyers are short lived, they do not observe the quality of the object bought by previous buyers from the same seller, i.e., learning through previous observations of quality cannot happen. It is in line with eBay's policy: buyers cannot observe the quantities of the objects sold by sellers.[2]

In the environment described above, I introduce eBay's reputation system: eBay store and pow-

[1] Although quality can be thought to affect cost, as it will become clear later, this way of modeling quality helps in identification of private information.

[2] Buyers have access to feedback left by previous buyers but this is not a complete history of items sold by a seller. The same results will go through by assuming the existence of buyers that do not use this information in their advantage; either because it is costly for them or because they do not take it into account.

erseller status. Sellers with a high quality can choose to pay a monthly fee in order to become eBay stores. Moreover, sellers should fulfill two requirements to become powersellers: they should sell more than the threshold, set by eBay, and their quality should be higher than another threshold. Since buyers value high quality sellers more than others, they realize that they are able to sell more objects and therefore become powersellers and/or eBay stores. Hence, when facing a powerseller or an eBay store, buyers change their expectations of the quality of the seller. Knowing the buyers' behavior, higher quality sellers behave in such a way to become powersellers or eBay stores. Therefore, this is an equilibrium model of reputation formation and adverse selection.

In order to model the interaction between the sellers, I use the equilibrium concept introduced by Weintraub et al. [2008]: *Oblivious* equilibrium. This equilibrium concept assumes that when making their choice, the sellers do not take into account the choices by other sellers and only take into account a long run stationary aggregate choice by others. This way of modeling the industry equilibrium makes the model more tractable as opposed to the Markov Perfect Equilibrium concept used by Ericson and Pakes [1995]. This equilibrium concept approximates the Markov Perfect Equilibrium when the number of sellers becomes large (see Weintraub et al. [2006]).

Recently, there has been an important development in the estimation of dynamic structural models using a two-step procedure; for example work by Bajari et al. [2007], Pakes et al. [2004], and Pesendorfer and Schmidt-Dengler [2003]. In these methods, in two main steps the deep parameters of the model get estimated without actually solving for the dynamic model, e.g. Rust [1987]. In these methods, the first step estimates the reduced form policy functions and the law of motion for state variables. The second step estimates preference and cost parameters that rationalize the observed actions of players in the market.

I follow this literature in using a two-step estimator, and specifically I use the approach of Bajari et al. [2007]. The estimation process assumes that the observed data is the outcome of the sellers' maximization problem and therefore sellers' behaviors are their optimal behavior. This implies that perturbing sellers' behaviors in various directions can only decrease the sellers' profits. Thus, using these perturbations, one can estimate deep parameters of the model, for example cost associated with different actions that sellers are taking. As a first step, I need to estimate the stochastic process for qualities. To do so, I use the fact that some of the policy functions are increasing in quality; this relationship allows me to non-parametrically estimate qualities from quantity choices of sellers. Since each data point in my dataset is an observation of one sale, I use a non-parametric bi-nomial estimation. As for the estimation of the cost parameters, I minimize the loss function with respect to cost parameters. The loss function is defined as the sum of the occasions that a sellers' perturbed value function gets higher than the original value function.

Using the above estimated model, I perform a counterfactual to estimate the value of reputation. In the counterfactual, I remove eBay's reputation mechanisms. This implies that the problem solved by the sellers becomes a static problem; there is no dynamic incentive for sellers to change their behavior. I show that under this change in policy, low quality sellers' profits increase and high quality sellers' profits decrease. Moreover, I show that as a result of removing reputation mechanism, market share of low quality sellers increases and the market share of high quality sellers decreases. In particular, the change in the policy decreased buyers' surplus by 60%, total sellers' profit by 73% and total eBay's profit by 84%. This suggests that reputation by increasing market share of high quality sellers, decreases the adverse selection in the marketplace.

The paper is organized as follows: in section 2, I describe the dataset analyzed in this paper and I give an overview of market structure on eBay. In section 3, I develop the dynamic model of seller's behavior and their interactions with buyers through eBay. In section 4, I describe the identification procedure for the deep parameters of the model. In sections 5, I describe the estimation of the model. In section 6, I perform a counterfactual exercise to estimate the value of reputation. Finally, section 7 concludes.

2 Data

The dataset consists of all transactions of iPods on the eBay website over eight months in 2008-2009. Summary statistics of the data come in Table 1. This market is a narrow market, which enables me to understand it and factors that affect customers' preferences and the final price of items. I collected data from the eBay website using a spider program.[3] The program searched for all completed iPods listings and saved the information contained on the eBay website into a file. The program ran frequently to collect new data points. Using the program I further analyzed the data and collected variables of interest, e.g. items' characteristics, sellers' characteristics, and auction format.

Sellers can sell their items either through an auction or by setting a fixed price for their item, an option called "Buy it Now." The auction mechanism is similar to a second price or Vikery auction. A seller sets the starting bid of an auction and bidders can bid for the item. Each bidder observes all previous bids except for the current highest bid. A bidder should bid an amount higher than the current second highest bid plus some minimum increment.[4] If this value is higher than the current highest bid, the bidder becomes the new highest bidder. Otherwise, he becomes the second highest bidder. The winner has to pay the second highest bid plus the increment or his own bid, whichever is smaller. Auctions last for three to ten days and they have a pre-determined and fixed ending time which cannot be changed once the auction is active.

[3] The program is written in python, a scripting language.

[4] The increment is a function of second highest bid and is fixed for all auctions and is set by eBay.

Sellers could register as an "eBay store." An "eBay store" pays lower listing fees but has to pay a fixed monthly fee to eBay. In addition, they should follow eBay policies and have a high seller standard rating.[5] Sellers can become "powersellers" if they have a high enough feedback score and have sold more than a fixed value in the past three months and have a high seller standard rating.[6] This information is observed by the buyers on the listing page as well.

2.1 Data Summary

Table 1 shows the data summary of variables used in this paper. eBay store and powerseller status are indicator variables. As it is shown, 36% of listings in my dataset are sold by eBay stores and 48% of them are sold by powersellers.

Two other variables associated with the reputation of sellers that has been studied in depth are the "Seller Feedback Number" and the "Seller Feedback Percentage". Feedback Number is the total number of positive feedback received minus the total negative feedback received. Feedback percentage is the percentage of positive feedback that sellers have received. The standard deviation of Feedback percentage is very low and most sellers have a feedback percentage higher than 99%. One of the requirements for becoming a powerseller is to have a feedback percentage higher than 98%, and another requirement is to have high volume of sale on the eBay website. I will show later that these two variables have a low effect on prices after controlling for powerseller status. Their effects are embedded in powersellers status, both the part that feedback number signals the size of seller and also the part that high feedback percentage signals the quality of sellers.

2.2 Reputation and Price

The eBay registered store status and the powerseller status signal sellers' reputation. They show that the sellers are following eBay rules closely and have a good track record on eBay. Table 2 shows that the final prices of items sold on eBay are higher when the sellers are powersellers or when they are eBay registered stores. The first column of the table includes the average price of all the iPods in my dataset. Having store status or powerseller status increase the average of final price of items for sellers. This increase in price may be result of a selection problem: if sellers with powerseller status or store status tend to sell items with higher value, they will get a higher price but not because of they have higher level of reputation. The selection problem can be account by controlling for the item

[5] Seller standard rating includes many different variables, such as low open disputes, few number of low DSR, and no outstanding balance.

[6] The requirements for becoming a powerseller are: Three Month Requirement: a minimum of $1,000 in sales or 100 items per month, for three consecutive months.
Annual Requirement: a minimum of $12,000 or 1,200 items for the prior twelve months. Achieve an overall Feedback rating of 100, of which 98% or more is positive. Account in good financial standing.
Following eBay rules.

Table 1: Data Summary

Characteristics of Listings and iPods sold

Variable	Obs	Mean	Std. Dev	Min	Max
eBay Store	174280	0.36	0.48	0	1
Powerseller	174280	0.48	0.50	0	1
Feedback Number	174154	14120.3	48971.8	-3	1026575
Feedback Percentage	22366	99.22	1.88	33.3	100
Sold with Buy it Now	174273	0.08	0.27	0	1
Buy it Now option	174280	0.29	0.45	0	1
Secret Reserve	174280	0.04	0.27	0	2
Number of Bidders	146597	7.29	4.82	0	30
Items Sold	167199	1.00	1.84	0	180
New Item	174280	0.25	0.43	0	1
Refurbished Item	174280	0.19	0.40	0	1
Internal Memory	159234	19.68	27.51	1	240

Table 2: Reputation and Price

	Average Prices		Fitted Values	
	All iPods	New iPod Nano	Average Item	New, Nano, 8GB
All Sellers	\$131.81	\$132.95	\$136.51	\$135.34
Non-Powersellers & Non-Store	\$130.70	\$130.15	\$122.18	\$131.19
Stores	\$135.96	\$134.09	\$128.80	\$139.96
Powersellers	\$134.95	\$137.44	\$137.79	\$140.90
Powersellers & Stores	\$139.90	\$135.29	\$145.35	\$142.09

characteristics, I control for the brand of the iPod: iPod Nano, and the condition of the iPod: New, to get the second column averages. We still observe the positive effect for powersellers and stores. Last, I use the regression formulation that I later use to estimate the buyers' demand to show the fitted values for New iPod Nano with internal memory of 8GB. The average prices are in the third column.

Additionally, reputation can have an effect on the sellers' decision about the number of items they will list over time. It has a dynamic effect on sellers, especially for the powerseller status: sellers should sell more than the threshold set by eBay for three consecutive months to be eligible for the powerseller program.

3 Model

To capture the dynamic effects of reputation, I developed a dynamic model of reputation which is similar to Holmstrom [1999] and Mailath and Samuelson [2001]. There are three major players in this market: buyers, sellers, and the eBay reputation system. Sellers have heterogeneous qualities which are unobservable to the buyers. eBay can observe the quality of sellers and has set up the signaling mechanism for sellers to signal their quality to buyers.[7] This reputation system helps buyers distinguish high quality sellers and low quality sellers, and to give the sellers with higher quality a higher profit.

3.1 eBay

eBay is the market designer in this setup. They have set up different mechanisms for sellers to signal their quality. I assume they observe the quality of sellers. eBay can observe these values based on the history of sellers in the market. It also has access to more detailed information about sellers which is not disclosed to the buyers, like the number of disputes a seller has from buyers.

The mechanisms that I model in this paper are powerseller status and store status. Sellers who sell more than Q^p, a threshold which is set by eBay, for three consecutive periods and have a quality, r_{jt}, higher than μ^p are signaled as powersellers. A seller should not pay any fixed or monthly fee to be included in this program. Sellers who have a quality, r_{jt} higher than μ^s, set by eBay, can register their account as an eBay store. They have to pay a monthly fee to eBay to participate in this program, c^s.

3.2 Buyers

Buyers are short lived and cannot track sellers over time. Each period, every buyer decides to either buy one of the items offered by one of the sellers or to buy the outside good.[8] Buyers observe the item characteristics but they do not observe the quality of sellers; they only observe the two signals which are correlated with sellers' quality: powerseller status and store status.

The buyer i, gets random utility u_{ijt} from purchasing the good x from the seller j at the time period t:

$$u_{ijt} = -\alpha p_{jt} + \beta_r r_{jt} + \beta_x x_{jt} + \xi_t + \xi_{jt} + \epsilon_{ijt}$$

where p_{jt} is the price of the item with characteristics x_{jt} sold by the seller j at the time period t. x_{jt} are the observable characteristics of the item: the type of iPod, its condition, and its internal memory capacity. r_{jt} is the quality of the seller j at the time period t which is unobservable to buyers.[9] There are two signals for this variable: powerseller status and store status. ϵ_{ijt} is the unobservable utility random variable with a logit distribution.

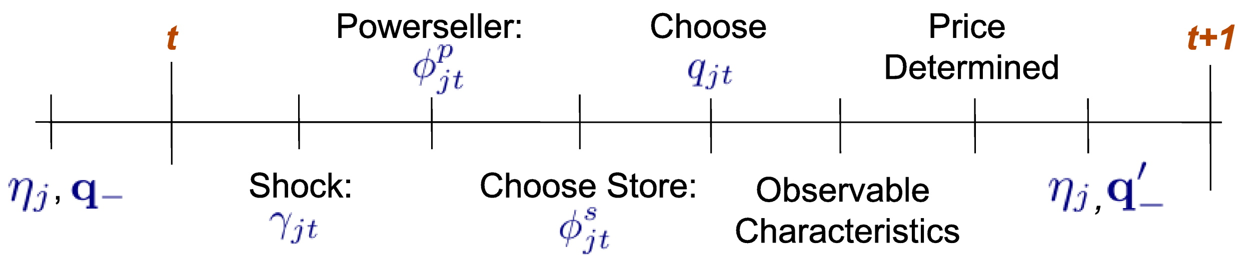


Figure 1: Timing of Sellers' Choices and Shocks

3.3 Sellers

Sellers are born with different persistent level of quality, η_j. In each period, which I assumed to be one month, sellers decide on the number of items to list on the eBay's website, q_j, and their store status, ϕ^j_t. The type of iPods and their characteristics, x_{jt}, are randomly selected and sellers do not choose them, I assume that the characteristics of iPods come from a distribution F. They are subject to two different reputational variables: powerseller status, ϕ^p, and store status, ϕ^s. Timing of the sellers decision is as described in Figure 1. At the beginning of each period, sellers learn about the shock to their quality, γ_{jt}, which is i.i.d. distributed with a distribution G.[10] Their quality at period t is:

$$r_{jt} = \eta_j + \gamma_{jt}$$

Having determined their level of quality at this period, sellers' powerseller status, ϕ^p_t, is determined by the following formulation:

$$\phi^p_{jt} = 1 \Leftrightarrow \begin{cases} q_{jt-1} + q_{jt-2} + q_{jt-3} > 3Q^p \\ r_{jt} > \mu^p \end{cases} \tag{1}$$

After knowing their powerseller status and quality level, sellers make a decision about their store status. They can only decide to be a store if $r_{jt} > \mu^s$. Next, they choose the number of items they want to sell. At the end, the characteristics of the item is revealed, x_{jt}, drawn from distribution F.

[7] In this paper, eBay is not optimizing the reputation mechanism to get the highest payoff. I am taking the strategy of the eBay as given.

[8] The outside good is buying another model of MP3 player.

[9] The sellers' quality can pick up information about the sellers that are important for buyers, like the honesty of the sellers about the item characteristics or their customer service.

[10] In this paper I have assumed that the quality of the sellers are determined exogenously and they will not affect their quality directly by putting an effort or investing in quality, as some theory papers have formulated before (for example: Holmstrom [1999], Mailath and Samuelson [2001], Board and Meyer-ter Vehn [2010], and Board and Meyer-ter Vehn [2011]). The main reason for this simplifying assumption in the model is the lack of data. I do not observe quality of the sellers and also their efforts of investment or any other variable about the way they run their online store, therefore I cannot estimate the two variables separately.

Sellers profit function at time t is:

$$\pi(q_{jt}, \phi^p_{jt}, \phi^s_{jt}, x_{jt}) = p(q_{jt}, \phi^p_{jt}, \phi^s_{jt}, x_{jt})q_{jt} - cq_{jt} - c^s\phi^s_t$$

where c is the marginal cost of acquiring an item for sellers,[11] and c^s is the monthly fee of being a store. This fee is set and charged by eBay. $p(q_{jt}, \phi^p_{jt}, \phi^s_{jt}, x_{jt})$ is the price of the iPods in the market. The price is the outcome of the buyers problem and in section 3.5 I will go into details of the formulation of the demand function.

Sellers interact with each other in an oblivious equilibrium, the concept introduced by Weintraub et al. [2008]. In this equilibrium concept, sellers do not take into account the state variables of every other seller in the market and only take into account a long run stationary aggregate choice by other sellers. This helps me later in the estimation process.

Given $\mathbf{q}_- = \{q_{jt-1}, q_{jt-2}, q_{jt-3}\}$, I can formulate the sellers' decision problem as follows:

$$V(\eta_j, \gamma, \mathbf{q}_-) = \max_{q_j, \phi^s_j} \int \left(\pi(q_j, \phi^p_j, \phi^s_j, x_j) + \beta \int V(\eta_j, \gamma', \mathbf{q}'_-)g(\gamma)d\gamma\right) f(x)dx \tag{2}$$

subject to:

$$\begin{aligned} \mathbf{q}'_- &= (q_j, q_{j,-1}, q_{j,-2}) \\ \phi^s &= 0 \quad \text{if} \quad \eta_j + \gamma < \mu^s \\ \phi^p_j &= 1 \quad \text{if} \quad \begin{cases} q_{j,-1} + q_{j,-2} + q_{j,-3} > 3Q^p \\ \eta_j + \gamma > \mu^p \end{cases} \end{aligned} \tag{3}$$

Let $q^*(\eta, \gamma, \mathbf{q}'_-)$ be the non-negative integer solving the above problem and $\phi^{s*}(\eta, \gamma, \mathbf{q}'_-)$ be the zero-one function solving the above problem. β is sellers' discount factor; F is the distribution of different values of x_j, characteristics of the items, and $q_{j,-t}$ is the number of items produced by seller j, t periods ago. There is no entry into this economy after period 0. There is no permanent exit from the market either. Sellers can decide to sell no items one period which can be interpreted as exiting the market, however, they can return to the market without paying a fee in the following periods.

3.4 Equilibrium

I use the oblivious equilibrium concept as introduced by Weintraub et al. [2008]. Equilibrium is a set of quantities, characteristics of sellers, buyers' beliefs, average total quantity, and prices such that:

[11] The marginal cost of an iPod is assumed to be fixed, this can be interpreted as the average cost of acquiring an iPod or we can restrict our attention to a particular type and condition of iPod in which sellers have the same marginal cost of obtaining that particular type and condition of iPod.

Given quantities, characteristics of sellers', and buyers' beliefs prices are the outcome of buyers' demand function,

sellers are maximizing their value function given demand function, buyers' beliefs, and average total quantity,

powerseller status and store status are determined based on eBay rules,

buyers' beliefs are consistent with sellers' behavior,

average total quantity is consistent with sellers' individual quantity choices,

market clears.

3.5 Demand Formula

Buyers do not observe the quality of sellers however the quality of the sellers affect their utility. Their expected utility from buying an item is:

$$E(u_{ijt}) = -\alpha p_{jt} + \beta_r E(\eta_j) + \beta_x x_{jt} + \xi_t + \xi_{jt} + \epsilon_{ijt}$$

Assume that a seller only sells one type of good each period. Then the market share of seller j at time t, given that the distribution of error terms is coming from a logit distribution, will be:

$$s_{jt} = \frac{exp(-\alpha p_{jt} + \beta_r E(r_{jt}|\phi^p_{jt}, \phi^s_{jt}) + \beta_x x_{jt} + \xi_t + \xi_{jt})}{1 + \sum exp(-\alpha p_{j't} + \beta_r E(r_{j't}|\phi^p_{j't}, \phi^s_{j't}) + \beta_x x_{j't} + \xi_t + \xi_{j't})}$$

Following Berry [1994], I assume the utility of outside good to be normalized to zero. Then I can decompose the formulation for the market share using the formulation of outside good share, s_{0t}:

$$log(s_{jt}) - log(s_{0t}) = -\alpha p_{jt} + \beta_r E(\eta_j) + \beta_x x_{jt} + \xi_t + \xi_{jt}$$

therefore:

$$p_{jt} = (-log(s_{jt}) + log(s_{0t}) + \beta_r E(\eta_j) + \beta_x x_{jt} + \xi_t + \xi_{jt})/\alpha$$

The demand function can be generalized in the case that buyers observe signals of quality: powerseller, ϕ^p_{jt} and store status, ϕ^s_{jt}. In this case, buyers' expected utility function is:

$$E(u_{ijt}|\phi^p_{jt}, \phi^s_{jt}) = -\alpha p_{jt} + \beta_r E(\eta_j|\phi^p_{jt}, \phi^s_{jt}) + \beta_x x_{jt} + \xi_t + \xi_{jt} + \epsilon_{ijt}$$

The same set of analysis as above will lead to the following pricing function:

$$p_{jt} = (-log(s_{jt}) + log(s_{0t}) + \beta_r E(\eta_j|\phi^p_{jt}, \phi^s_{jt}) + \beta_x x_{jt} + \xi_t + \xi_{jt})/\alpha$$

where $E(\eta_j|\phi^p_{jt}, \phi^s_{jt})$ is the expectation of a seller's quality based on its two reputational signals. This expectation is endogenously determined by equilibrium decisions of sellers in the market and is subject to change based on the market setup. Note that ϕ^p_{jt} and ϕ^s_{jt} are discrete variables and can only be zero or one and let $\bar{r}_{mn} = E(r_{jt}|\phi^p_{jt} = m, \phi^s_{jt} = n)$. Then, $E(\eta_j|\phi^p_{jt}, \phi^s_{jt})$ can be written as:

$$E(\eta_j|\phi^p_{jt}, \phi^s_{jt}) = \bar{r}_{00} + (\bar{r}_{10} - \bar{r}_{00})\phi^p_{jt} + (\bar{r}_{01} - \bar{r}_{00})\phi^s_{jt} + (\bar{r}_{00} - \bar{r}_{10} - \bar{r}_{01} + \bar{r}_{11})\phi^p_{jt}\phi^s_{jt}$$

Substituting the above expression into the demand function formula I get the following:

$$\begin{aligned} p_{jt} &= [-log(s_{jt}) + log(s_{0t}) + \beta_x x_{jt} + \xi_t + \xi_{jt}]/\alpha \\ &\quad +\beta_r/\alpha[\bar{r}_{00} + (\bar{r}_{10} - \bar{r}_{00})\phi^p_{jt} + (\bar{r}_{01} - \bar{r}_{00})\phi^s_{jt} + (\bar{r}_{00} - \bar{r}_{10} - \bar{r}_{01} + \bar{r}_{11})\phi^p_{jt}\phi^s_{jt}] \\ &= [-log(s_{jt}) + log(s_{0t}) + \beta_x x_{jt}]/\alpha + \bar{r}_{00}\beta_r/\alpha + \beta_p\phi^p_{jt} + \beta_s\phi^s_{jt} + \beta_{ps}\phi^p_{jt}\phi^s_{jt} + [\xi_t + \xi_{jt}]/\alpha \quad (4) \end{aligned}$$

4 Equilibrium Characterization and Identification Procedure

In this section, I, first, characterize the equilibrium quantity choice of the sellers in more details. Then using this result, I describe the method to identify the main parameters of the model using the data. These parameters include the sellers' unobservable quality, sellers' cost parameters, and buyers' utility function. These are the deep parameters of the model that will affect buyers and sellers decisions and are used in counterfactual analysis. In particular, I assume, they are invariant if we remove powerseller and store status and sellers cannot signal their quality. I start from the key implication of the model, that policy functions are increasing as a function of quality, and show how that help in identification of unobserved qualities.

4.1 Analysis of Quantity Choice

One of the decisions sellers make each period is the number of items to sell. Given eBay's market structure, i.e., sellers sell their items in auctions, I have assumed that sellers do not set the prices but the number of items to sell. In my setting, this is a dynamic decision that sellers are making, since the number of items they sell will affect their powerseller status in the future. In other words, there is a *dynamic complementarity* between quality and quantity choice of sellers. The following proposition states that the sellers' quantity choice is increasing in their persistent level of quality, η. This is one of the main implications of the model that helps in identifying qualities.

Proposition 1 *Suppose that the solution to the functional equation (2) is unique. Then, the policy function $q^*(\eta, \gamma, \mathbf{q}_-)$ is increasing in persistent level of quality, η.*

Proof. Here, I sketch the proof. Appendix A contains a complete and more detailed version of the proof. Recall the functional equation (2) in section 3.3. To prove the proposition, I use a method similar to Hopenhayn and Prescott [1992], adopted from Topkis [1998], and I show that the objective function has increasing differences. To do so, first note that the optimal choice of ϕ^s does not affect future values. Hence, I can define the following period profit function:

$$\hat{\pi}(\eta, \gamma, q, \underbrace{q_{-1}, q_{-2}, q_{-3}}_{\mathbf{q}_-}) = \max_{\phi^s \in \{0,1\}} \int \pi\left(q, \phi^s, \phi^p, x\right) f\left(x\right) dx \tag{5}$$

subject to:

$$\begin{aligned} \phi^s &= 0 \quad \text{if} \quad \eta + \gamma < \mu^s, \\ \phi^p &= 1 \quad \text{if} \quad \begin{cases} q_{-1} + q_{-2} + q_{-3} > 3Q^p \\ \eta + \gamma > \mu^p \end{cases} \end{aligned}$$

I prove the proposition in three steps:

Step 1. $\hat{\pi}\left(\eta, \gamma, q, q_{-1}, q_{-2}, q_{-3}\right)$ is supermodular in (η, q) and in (η, q_{-i}) for $i = 1, 2, 3$.

Step 2. I show that the solution to the functional equation (2) is supermodular in (η, q_{-i}) for $i = 1, 2, 3$.

Step 3. The policy function is increasing in quality η. ■

The intuition for this result is the dynamic complementarity between quality and quantity choice of sellers. A seller with a higher value of persistent quality will have a higher probability to meet the quality eligibility of powerseller status in the future. Moreover, given the results of demand estimation, being a powerseller increases the final price of the items sellers can sell. Thus this seller, with high level of persistent quality, has more incentive to sell more items to meet the quantity eligibility of powerseller status. Proposition 1 also makes it clear that the only determinant of firm size dynamics is reputation. That is sellers are willing to increase their size in anticipation of future powerseller and store status. Absent these mechanisms, firms have no incentive to change their size.

Another implication of the model on the quantity choice of sellers is that sellers optimal quantity choice can be represented as a function of sellers' persistent level of quality, their powerseller and store status, and their quantity in the last two periods. In other words after controlling for powerseller and store status we can drop sellers' transitory shock to quality, γ_{jt}, as well as their quantity three periods ago, q_{-3}.

Lemma 1 *The policy function $q^*\left(\eta, \gamma, \mathbf{q}_-\right)$ can also be represented as $q^*\left(\eta, \phi^s, \phi^p, q_{-1}, q_{-2}\right)$.*

Proof. Sellers choose quantity of items to sell after the powerseller status is determined and they have chosen the store status. Profit function of sellers: $\pi(q_j, \phi_j^p, \phi_j^s, x_j)$ and their expectation of continuation value function $\int V(\eta_j, \gamma', \mathbf{q}'_-)g(\gamma)d\gamma f(x)dx$ are not directly a function of γ or q_{-3}. Therefore, sellers' choice of quantity should not depend on them after we control for ϕ_j^p and ϕ_j^s. ■

The above lemma will help me in modeling the sellers choice of quantity in section 5. Note than the Proposition 1 can be also extended to the policy function with the new representation, and policy function is weakly increasing in persistent level of quality given the new formulation as well.

4.2 Identification Procedure

I need to identify three main sets of parameters: buyers' utility function, sellers' unobservable quality, and sellers' cost parameters. I estimate the first two sets of parameters using a 3-step procedure. The third set is identified using a 2-step method similar to Hotz and Miller [1993] and Bajari et al. [2007]. [12]

The 3-step procedure used to estimate the unobservable sellers' quality and buyers' utility is as follows:

1 Estimating the structural demand function.

This will give us the estimate of β_x, α, β_p, β_s, and β_{ps}.

2 Estimating the realized policy functions.

Given the Proposition 1 and Lemma 1, the quantity choice of sellers can be used to identify the quality of sellers. When modeling sellers dynamic choice of quantity, by controlling for powerseller and store status of sellers, and their quantity choice in the last two periods, sellers fixed effect will be an index of sellers' persistent level of quality.

3 Using the Simulated Method of Moments to estimate the deep parameters of the model.

Having an index of sellers' permanent level of quality from step 2, I can parametrically estimate sellers' quality using two moments from demand function, (Equation 4).

$$\begin{aligned}&(\bar{r}_{10} - \bar{r}_{00})/\beta_p - (\bar{r}_{01} - \bar{r}_{00})/\beta_s = 0 \\ &(\bar{r}_{10} - \bar{r}_{00})/\beta_p - (\bar{r}_{00} - \bar{r}_{10} - \bar{r}_{01} + \bar{r}_{11})/\beta_{ps} = 0 \qquad (6)\end{aligned}$$

I also use average number of powersellers and average number of stores in addition to above moments condition to simultaneously estimate sellers' quality, quality thresholds for powerseller and store status, and β_r, the coefficient of quality in the utility function of buyers. More details of estimation procedure comes in Section 5.2.3.

Next to estimate the cost parameters of sellers, I use a two-step estimator method introduced by Bajari et al. [2007]. The method uses the basics of revealed profit to estimate the deep parameters of

[12] Some of the steps in identification of unobservable quality and cost parameters do overlap.

the model and in this case to estimate cost parameters: average monthly cost sellers should pay to become a registered store on eBay and the average cost of obtaining an iPod for sellers to put it for sale on the eBay website.

In the first step of this method, I estimate the structural demand function of buyers and policy functions of sellers. Then assuming the estimated policy functions are the optimal choices of sellers, any perturbation of these functions should yield to a value function lower than the realized value function with the realized policy function. The cost parameters are those that satisfy the above condition. The two step estimation procedure is as follows:

1A Estimating the structural demand function,

1B Estimating the realized policy functions,

2A Perturbing the policy functions,

2B Simulating the model using the realized policy functions and the perturbed policy functions,

2C Defining the loss function as a function of model parameters

$$\sum_{sellers,perturbations} (V_{perturbed}(\theta^c) - V_{realized}(\theta^c))\mathbf{1}[(V_{perturbed}(\theta^c) - V_{realized}(\theta^c)) > 0]$$

where C is the vector of cost parameters, $V_{perturbed}(\theta^c)$ is the value function using perturbed policy functions, and $V_{realized}(\theta^c)$ is the value function using the realized policy functions. $\mathbf{1}[V_{perturbed}(\theta^c) - V_{realized}(\theta^c) > 0]$ is an indicator function that is equal to one if $V_{perturbed}(\theta^c) - V_{realized}(\theta^c) > 0$, and it is otherwise equal to zero. If this expression is positive it means that the seller's value function is higher for perturbed policy functions which cannot be the case if C is the true cost parameter. The summation is over all sellers and different perturbations.

2D Estimating the cost parameters by minimizing the loss function as defined above.

Under the true cost parameters of the model, the estimated policy functions should be optimal. Therefore, the cost parameters that survive the above perturbation method will be the true ones.

5 Estimation

In this section, I estimate the deep parameters of the model using the identification procedure explained in Section 4.2.

Table 3: First Stage Estimation, Demand

	Price	
	Coef	Std. Dev
$log(s_0) - log(s_j)$	4.05	0.06
Powerseller	15.60	0.42
Store	6.62	0.65
Powerseller*Store	0.93	0.73
New	37.48	0.38
Refurbished	13.11	0.33
Internal Memory	1.42	0.01
R^2	0.94	

5.1 Estimating Structural Demand

To estimate the structural demand function, I use the demand equation (4) derived in the section 3.5. This formula translate into a simple OLS regression of price over the logarithm of share of the seller minus share of outside good, powerseller status, store status, and characteristics of the item. Note that this formula does not have any structural error term; there is no firms' unobservable quality which is observable to buyers but not to the econometricians.

Table 3 shows the results of the regression and it is worth discussing. The effect of changes in $log(s_0) - log(s_j)$ is captured by $1/\alpha$ and it is positive. This means that when sellers sell more items, they sell at a lower price per unit. Therefore, the demand function is elastic . Moreover, the coefficient of powerseller status is positive which shows that the expectation of quality is higher for the sellers with powerseller status. Finally, the coefficient of store status is positive which shows that the expectation of quality is higher for the sellers who are registered stores than the sellers who are not registered store. Both of these observations are consistent with the Section 3: sellers with high level of quality become powersellers and stores.

5.2 Estimating Policy Functions and Sellers' Quality

In this section, I estimate the sellers' policy functions and their persistent level of quality using the actual sellers' actions. Sellers have two policy functions in this model: number of items to sell and store status. Persistent level of quality, η_j, can be identified using the dynamic quantity choice of sellers based on Section 4.

Powerseller status each month is a function of performance of the seller in the last three months and the unobservable quality of sellers; these two numbers should be higher than two cut-off values, set by eBay, Q^p and μ^p. I estimate μ^p later by matching the average percentage of powersellers in the market in the dataset and simulated model.

Table 4: First Stage Estimation, Policy Functions

		Coef	Std. Dev.
Quantity Choice	Store	0.65	0.34
	Powerseller	0.33	0.15
	q_{-1}	0.003	0.0007
	q_{-2}	-0.001	0.0004
	Dispersion	0.90	0.03
Store Status	Powerseller	1.54	0.10
	q_{-1}	0.013	0.002
	q_{-2}	0.008	0.001
	Fixed Effect	-0.37	0.04
	Constant	-2.33	0.10

In the following sections I go into detail of estimation of each policy function as well as quality estimation. I assume that sellers decide on their store status each period, and this variable can affect their decisions on the number of items to sell.

5.2.1 Number of Sales

One of the decisions that sellers make each period is the number of items they list on the eBay website. Note that most transacted items on eBay in my dataset are sold using the auction method; therefore, I assume that sellers do not set prices and they decide on the number of items to sell and the price is determined in the market using the demand function estimated is Section 5.1.

Sellers' optimal quantity choice depends on their persistent level of quality, powerseller status, store status, and their choice of quantity in the last two periods as discussed in Section 4.1. I can control for all the parameters except for persistent level of quality, η_j. I have also shown in Proposition 1 in Section 4.1 that sellers quantity choice is an increasing function of their persistent level of quality. Therefore after controlling for all other variables sellers fixed effect can be interpreted as an index of quality.

The sellers' decision can be modeled using a discrete choice model in which sellers can choose any non-negative number. I have considered the Negative Binomial distribution models. When estimating the Negative Binomial distribution with sellers' and time fixed effects, I use the following formula:

$$q_{tj} \sim nb(\phi_t^s, \phi_t^p, q_{t-1}, q_{t-2}, \nu_j, \delta_t, \xi)$$

The estimated coefficients of $q_{jt-1}, \phi_t^s, \phi_t^p$ and ξ the dispersion parameter of Negative Binomial distribution are in Table 4.

While eBay decides on the thresholds for powerseller status and store status based on η_j, since

Table 5: Parametric Estimation Unobserved Quality

Effect of Quality on Price	
	Parameter
λ	0.24
β_r/α	3.34

ν_j is a non-decreasing function of η_j, the eBay decisions can be interpreted as a cut-off based on ν_j. They are used later on to estimate the level of threshold set by eBay, μ^p and μ^s. I also parametrically estimate level of η_j as a function of ν_j is Section 5.2.3.

5.2.2 Store Status

Sellers who meet the quality requirement for becoming a store status, can register as eBay stores, for which they pay a monthly fee and will be shown as an eBay store on the listing page. I assume that sellers decide on their store status each period after knowing the shock to their quality and their powerseller status.

Sellers who meet the quality requirement can choose to become a store and based on the model this decision is based on their state variables. However, based on a similar argument to that of the quantity choices of sellers, the sellers' choice can be classified as a choice based on their powerseller status, persistent level of quality, and the quantity in the past two periods: $\phi^{s*}(\eta, \phi^p, q_{-1}, q_{-2})$. I use the index for quality estimated in the previous section to control for η. This decision is a binary choice for the sellers; and I model it using a logit model. Table 4 shows the results of the regression.

5.2.3 Estimating Unobservable Quality

Proposition 1 states that the number of items a seller would sell is increasing in their unobservable persistent level of quality, η_j. Based on this proposition , the estimated ν_j, the sellers' fixed effect in the quantity choice function, should be an increasing function of η_j, unobservable seller's quality. As explained in Section 4, I use simulated method of moment by matching five different moments from data and model: percentage of powersellers, percentage of stores, percentage of powersellers and stores, two moments from demand as shown in 6.

I assume the following parametric formulation for the η_j, which is increasing in ν: $\eta_j = \nu_j + \lambda\nu_j^3$. Then by minimizing the joint differences between moment conditions mentioned above in the model and data, I estimate the value of λ, μ^p, μ^s, and variance of random shocks to utility, γ_{jt}. Then using the estimate of λ, I can estimate the value for β_r/α the coefficient of r_{jt} in the demand function. Table 5 shows the estimated values for λ and β_r/α. Note that β_r/α is positive, therefore buyers enjoy buying an item from a seller with higher level of quality.

Table 6: Goodness of Fit

	Model	Actual Data
Powerseller	0.75	0.83
Store	0.59	0.58
Sales	91.6	87.5
Revenue	14,033	12,636

Table 7: Cost Estimations

	Specifications	
	I	II
c	129.39	128.62
Store		39.57

5.3 Simulation and Pertabation

Using the first stage estimation results and given an initial value for μ^s and μ^p, I can simulate the model over time. To estimate the correct value of these two parameters, μ^s and μ^p, I match the actual and simulated results in different periods. I have data for eight months and each period in my model is one month, given the initial conditions I simulate the model. Table 6 shows the simulated results after simulating the model for nine periods, the number of periods I collected data for. The results show that my simulations follow the actual data very closely. This means that the model estimates the actions of sellers closely and I can use this base model to estimate the cost parameters.

In the second step, I perturb the policy functions and simulate actions of sellers over time and estimate the value functions of sellers for each perturbation. This will help us determine some out of equilibrium revenue values for sellers. To get the perturbations one should only perturb one seller at the time, otherwise I may get into another equilibrium of the model which may give higher expected profit to some of the sellers.

5.4 Estimation

Having the perturbed actions of the sellers and also the actual simulated actions of sellers over time, I can estimate the expected value function for sellers given a set of initial conditions for cost parameters. Actual cost parameters result in higher expected value functions driven from non-perturbed policy functions compared to those driven from perturbed policy functions.

To estimate the cost parameters I construct a loss function, summing up difference in value functions when the perturbed value function is higher for the perturbed seller. Cost parameters are the parameters that minimize this function:

$$\sum_{sellers,perturbations} (V_{perturbed}(\theta^c) - V_{realized}(\theta^c))\mathbf{1}[(V_{perturbed}(\theta^c) - V_{realized}(\theta^c)) > 0]$$

Table 7 shows the estimated cost parameters for two different specifications. In the first specification, I forced the monthly cost of becoming an store to be zero and I estimate the marginal cost of acquiring an iPod for sellers that rationalize sellers' choices. In the second specification, I jointly estimate the marginal cost of acquiring an iPod for sellers as well as a the monthly fee for becoming a store. The actual monthly fee charged by eBay for store is between \$15-\$300, for different types of stores, which I abstract from modeling, my estimate is \$39.57 per month which is in the range of these values.

6 Counterfactual: Value of Reputation

In this section, I estimate the effects of a change in eBay policy and environment on buyers' perception of sellers' equality, and sellers' final prices and quantity choice. I am interested in finding the effect of removing the reputation mechanism. I assume that even though changing eBay policy will affect buyers' demand function, it will not affect buyers' utility function. Therefore, using the estimated structural utility function, I can estimate the demand function of buyers given the new environment settings.

Sellers' actions will also change after changing the eBay policy since they are facing a new demand function which will affect the sellers' problem. However, I assume that sellers' cost parameters remain the same as the original setup and are equal to estimated results in previous sections.

6.1 No Reputation Mechanism - Optimal Quantity

As mentioned before, the powerseller status and store status are tools used by eBay to signal sellers' quality. This will help a high quality seller to sell more products on eBay. Furthermore, it helps buyers find a high quality seller and have a better experience in the marketplace. A counterfactual to consider is the effect of removing powerseller status and store status altogether. Without these quality signals, sellers are all pooled together. Therefore, the high quality sellers would not benefit from price and quantity premiums by using the reputational signals.

In absence of the reputational signals, buyers' demand function will change as well as the problems that sellers are facing. Buyers will no longer observe the reputational signals for quality. Therefore, the buyers cannot infer sellers' quality based on these signals and their demand function will thus no longer depend on these signals. On the other hand, sellers cannot signal their quality levels to the buyers; therefore, sellers with different quality levels will face the same problem.

6.1.1 Sellers' Problem

Given the demand formulation, I need to solve the new problem that sellers are facing. In the new setup, sellers cannot signal their quality using the reputational signals and their qualities do not affect the final price of items they want to sell. Therefore, their different levels of quality do not affect sellers' decisions. In the new environment, sellers maximize their expected profit, assuming that their marginal costs stay the same. Sellers' period t profit function is:

$$\pi(q_{jt}, x_{jt}) = p(q_{jt}, x_{jt})q_{jt} - cq_{jt}$$

Sellers, first, make a decision on the the number of items to sell then they will learn the characteristics of items they sell. Their decisions each period do not affect their decisions in the consecutive periods and all their decisions are static. They maximize their expected profit function over different values of x_{jt} each period.

$$\max_{q_{jt}} \int \pi(q_{jt}, x_{jt}) f(x_{jt}) dx_{jt} = \int \left(p(q_{jt}, x_{jt})q_{jt} - cq_{jt}\right) f(x_{jt}) dx_{jt}$$

This is a static problem for sellers; the signaling mechanism was the source of dynamics in the sellers' problem in the original settings. This is a simple maximization problem for sellers that can be solved to determine their choice of quantity given the demand function.

6.1.2 Updated Demand Function

In the new setup buyers do not observe the quality of the sellers nor they observe any signals related to the quality. Therefore, the expected value of the quality affects the buyers' expected utility function. The expectation is taken over all the listings and sellers in the market. Note that since the sellers cannot make any signals about their quality, there is no observable heterogeneity among sellers. The sellers are facing the same final price and the same sellers' problem. Therefore, all the sellers will set the same levels for quantity, $q_{jt} = q_t$. Given that sellers' quality distribution comes from distribution function L, buyers expected utility function is:

$$\begin{aligned}
E(u_{ijt}) &= \int u_{ijt} q_{jt} l(r_{jt}) dr_{jt} / \int q_{jt} l(r_{jt}) dr_{jt} \\
&= -\alpha p_{jt} + \beta_r \int r_{jt} l(r_{jt}) dr_{jt} / \int l(r_{jt}) dr_{jt} + \beta_x x_{jt} + \xi_t + \xi_{jt} + \epsilon_{ijt} \\
&= -\alpha p_{jt} + \beta_r \int (\eta_j + \gamma_{jt}) l(r_{jt}) dr_{jt} + \beta_x x_{jt} + \xi_t + \xi_{jt} + \epsilon_{ijt} \\
&= -\alpha p_{jt} + \beta_r \int \eta_j l(r_{jt}) dr_{jt} + \beta_r \int \gamma_{jt} l(r_{jt}) dr_{jt} + \beta_x x_{jt} + \xi_t + \xi_{jt} + \epsilon_{ijt}
\end{aligned}$$

Table 8: Change in Consumer Surplus, sellers and eBay Profit

	Before the Change	After the Change	Percentage Loss
Total Consumers' Surplus	7.1e+05	2.8e+05	60%
Total Sellers' Profit	9.7e+04	2.6e+04	73%
eBay's Profit	5.7e+05	8.5e+04	84%

Since there is no entry and exit, $\int \eta_j l(r_{jt}) dr_{jt}$ stay the same over time. In addition, assuming γ_{jt} is iid over time and different sellers, by law of large number $\int \gamma_{jt} l(r_{jt}) dr_{jt}$ will not change across time and it is invariant to market rules because it does not get affected by sellers' action and it is only a function of distribution of sellers in the market which is invariant when we are in a steady state.

Given the above utility function and assuming that ϵ_{ijt} follows an extreme value distribution, the demand function as explained in Section 3.5 will be as follows:

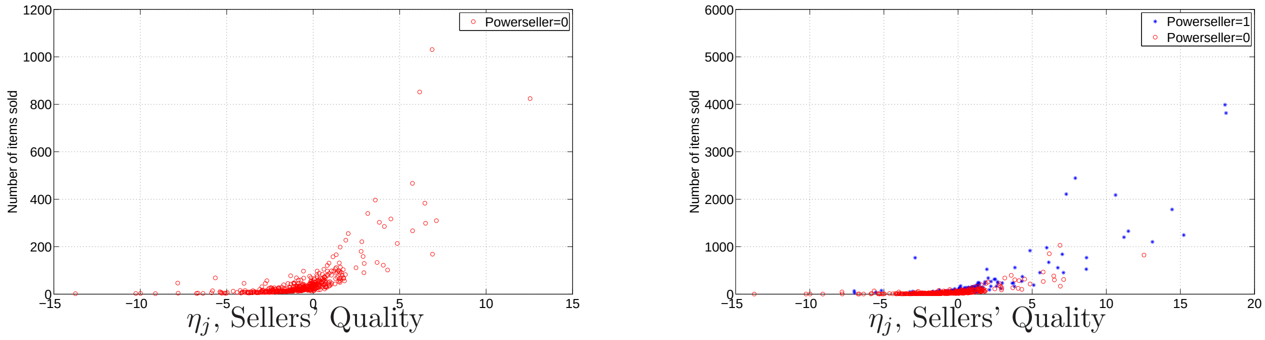
$$p_{jt} = (-log(s_{jt}) + log(s_{0t}))/\alpha + \beta_r/\alpha \int r_{jt} l(r_{jt}) dr_{jt} + \beta_x x_{jt}/\alpha + \xi_t/\alpha + \xi_{jt}/\alpha \qquad (7)$$

where α and β_x have the same parametric values as estimated parameters in Table 3 in previous section and they are invariant to the change of the policies by eBay. I use the results in the section 5.2.3 to estimate $\beta_r/\alpha \int r_{jt} l(r_{jt}) dr_{jt}$, which gives me an estimate of β_r/α and also an estimate of η_j, assuming γ is distributed i.i.d. with mean zero I can also estimate the second part of the expression.

6.1.3 Result

After solving for sellers' new policy functions, I simulate the model to get sellers' expected value function, eBay's Profit, and buyers consumers' surplus. The results are shown in Table 8. The consumer surplus has decreased by 60% by the change in the policy. The change in the policy has also decreased eBay Profit by 84% and the total sellers' expected profit by 73%. I also compare the individual sellers' new expected value to the sellers' expected value in the previous setup with powerseller status and store status. As a result of this change, sellers with high quality suffer, and sellers with lower quality prosper.

One reason I get large effects as a result of removing the reputation mechanism, as shown in Figure 2a, is that even among the sellers who are not powerseller, the sellers with higher quality amounts will sell more. Because they have higher probabilities to become powersellers in the future and they have incentive to sell more than their static optimal values. This will give us a high value for the average quality of items sold even by non-powersellers, when we have the reputation mechanism in place. Figure 2b shows the number of items sold with powersellers and non-powersellers in the equilibrium. Sellers with higher quality values sell more, and powersellers have an extra incentives to sell more to



(a) Quantity Sold by non-Powersellers

(b) Quantity Sold, Powersellers and non-Powersellers

stay powerseller.

7 Conclusion

In this paper, I have studied the value of reputation in eBay. To do so, I have developed a model of firm dynamics where sellers have heterogeneous qualities that are unobservable by consumers. Reputation is used as a signal of private information to buyers in order to improve allocations. By structurally estimating this model, I uncover deep parameters of buyers' utility and sellers' costs as well as their unobservable qualities. The estimated model suggests that reputation has a positive effect on the expected profits of high quality sellers as well as their market share. A counterfactual has been performed to establish the value of reputation. Removing reputation mechanisms put in place by eBay will increase the profits of low quality sellers and will decrease the profits of high quality sellers. Moreover, removing reputation mechanisms significantly increases market share of low quality sellers and decreases the market share of high quality sellers. Moreover, buyers' welfare as well as eBay's profit are significantly improved as a result of the reputation mechanism.

Some extensions of the model are worth discussing. One extension is to consider additional sellers' characteristics (e.g. age in the market , amount of text entered, number of photos entered). I have extensively studied this extension for the limited number of sellers in the study. The cost estimates for these variables were mainly small and did not affect the overall story I am interested in.

An important extension to the model is endogenizing the level of quality as a choice parameter for sellers. There are both empirical and theoretical challenges in implementing this extension. First, I need to have feedback from buyers to sellers, such as the eBay disputes system, which is considered much more informative than the regular feedback system. This will enable me to estimate the percentage of time that a seller will provide a low quality service as a function of their reputation. Using this, one would be able to figure out whether sellers abuse their reputation or the long run value of reputation is high enough to sustain high quality service for a long period of time.

Another extension worth mentioning is endogenizing entry and exit of the sellers into the market. In this case, sellers would get a signal of their reputation upon entry to the market and they can decide either to stay in the market or exit; and based on their past history at each period they decide to either stay in the market and sell or exit the market. This will give me a better understanding of the effect of reputation on the market and on the distribution of active sellers in the market.

In the current version of this paper, the counterfactual is considered in a very extreme setup where sellers do not have any heterogeneity among them. As a result of this extreme assumption, sellers' choice of quality is the same among sellers which is not what we observe in the usual models of firms' interactions. In the extensions to this paper, I should add another source of heterogeneity other than the signals that I study. Sellers can be different in their marginal costs or they may have another weaker source to signal their qualities.

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