# Essays on Reputation

A DISSERTATION
SUBMITTED TO THE FACULTY OF THE GRADUATE SCHOOL
OF THE UNIVERSITY OF MINNESOTA
BY

Maryam Saeedi

IN PARTIAL FULFILLMENT OF THE REQUIREMENTS
FOR THE DEGREE OF
Doctor of Philosophy

Patrick Bajari
Thomas Holmes

August, 2012

# Acknowledgements

I am deeply indebted to Patrick Bajari and Thomas Holmes, my advisors, for their constant support, guidance and advice throughout my graduate studies. Pat and Tom are excellent mentors and have left an indelible mark on my professional life and approach to research.

I also owe special thanks to the rest of my committee members: Amil Petrin and Joel Waldfogel. They have generously given their time in helping me write the dissertation and to guide me through my professional life.

Many of my friends and professors have contributed to this work through various discussions and helpful comments. In particular, I would like to thank V.V. Chari, Konstantin Golyaev, Larry Jones, Patrick Kehoe, Kiyoo-il Kim, Tina Marsh, Ellen McGrattan, Minjung Park, Jack Shen, Neel Sundaresan, and Robert Town. Jack Shen and Neel Sundaresan are my coauthors in the second chapter and I would like to specially thank them for their collaboration.

Last but not least, I would like to thank my family. My parents have constantly supported me throughout my life. They give me the encouragement to dream big and to believe that I can reach what I desire. I also would like to thank my best friend in life, Ali Shourideh, for his support and encouragement. This work would have not been possible without numerous discussions with him. This dissertation is dedicated to my family for all of their love and support.

## Abstract

In the dissertation, we study the value of reputation in a market prone to adverse selection and also the incentives of the individuals in that market to participate in the reputation mechanism. Ever since [Akerlof, 1970], it is known that adverse selection can hinder trade. Reputation can be used as a possible mechanism in mitigating adverse selection problems, resolving the inefficiencies caused by asymmetric information and help the marketplace to thrive. There are a number of examples of such online markets which have been conceived, have survived and have thrived during the internet age. These markets have been kept alive by their built-in reputation systems. In this dissertation, I focus on the effects of reputation on eBay online market.

In chapter 1, 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 counterfactual 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 the market share of low quality sellers and decreases the market share of high quality sellers. Finally, buyers' welfare is significantly improved as a result of the reputation mechanism.

In chapter 2, we focus on incentives of buyers and sellers in leaving feedback and their effect on emergence of reputation systems in online markets. To do so, we analyze how such systems work and we turn our focus on eBay. We start by analyzing the feedback behavior of buyers and sellers over time. We use a key policy change, that sellers cannot leave negative feedback for buyers, as an identifier. Our data analysis points to the existence of retaliation between buyers and sellers before the policy change. Furthermore, we develop a model of feedback behavior as a dynamic game between buyers and sellers and structurally estimate the model. The structural estimation further establishes the existence of retaliation incentives between buyers and sellers. Finally, we perform various welfare and counterfactual analysis.

# Contents

**Acknowledgements** **i**

**Abstract** **ii**

**List of Tables** **vii**

**List of Figures** **viii**

**1 Reputation and Adverse Selection:**
**Theory and Evidence from eBay** **1**

1.1 Introduction . . . . . . 1

1.2 Data . . . . . . 8

1.2.1 eBay . . . . . . 9

1.2.2 Data Summary . . . . . . 13

1.2.3 Reputation and Price . . . . . . 14

1.3 Model . . . . . . 16

1.3.1 Buyers . . . . . . 16

1.3.2 eBay . . . . . . 17

1.3.3 Sellers . . . . . . 18

1.3.4 Equilibrium . . . . . . 19

1.3.5 Demand Formula . . . . . . 20

1.4 Identification . . . . . . 22

1.4.1 Analysis of Quantity Choice . . . . . . 22

1.4.2 Identification Procedure . . . . . . 24

1.5 Estimation . . . 25
1.5.1 Estimating Structural Demand . . . 26
1.5.2 Estimating Policy Functions and Sellers' Quality . . . 27
1.5.3 Simulation . . . 32
1.5.4 Perturbations . . . 32
1.5.5 Estimation . . . 33
1.6 Analysis . . . 34
1.6.1 Estimating the Value of Powerseller Status . . . 34
1.6.2 Estimating the Value of Store . . . 35
1.6.3 The Probability of High Volume of Sale . . . 35
1.7 Counterfactual: Value of Reputation . . . 37
1.7.1 No Reputation Mechanism . . . 37
1.8 Conclusion . . . 42

**2 From Lemon Markets to Managed Markets: An Analysis of Reputation System Evolution** **45**
2.1 Introduction . . . 45
2.2 Background . . . 49
2.3 Data . . . 51
2.3.1 Existence of Retaliation . . . 51
2.3.2 Feedback Adoption . . . 54
2.3.3 Timing of Feedback . . . 55
2.3.4 Reduction of Adverse Selection . . . 55
2.3.5 Sellers' Performance . . . 61
2.4 Model . . . 62
2.4.1 Timing . . . 63
2.4.2 Buyers' Problem . . . 63
2.4.3 Sellers' Problem . . . 64
2.4.4 After Policy Change . . . 65
2.4.5 Characterization of Equilibrium . . . 65
2.5 Identification Strategy . . . 67
2.6 Results . . . 69

2.7 Conclusion . . . . . . . . . . . . . . . . . . . . . . . . . . . . . . . . . . . 72

**Bibliography** **74**

**Appendix A. Appendix to Chapter 1** **79**

A.1 Proof of Proposition 1 . . . . . . . . . . . . . . . . . . . . . . . . . . . . . . 79

A.2 Regression Discontinuity Design for Powerseller Status . . . . . . . . . . . . 82

A.3 Demand Function Estimation Robustness . . . . . . . . . . . . . . . . . . . . 88

**Appendix B. Appendix to Chapter 2** **93**

B.1 Data: Collectibles and Stamps . . . . . . . . . . . . . . . . . . . . . . . . . 93

# List of Tables


1.1 Data Summary . . . . . 14
1.2 Reputation and Price . . . . . 15
1.3 First Stage Estimation, Demand . . . . . 26
1.4 First Stage Estimation, Policy Functions . . . . . 28
1.5 Parametric Estimation Unobserved Quality . . . . . 31
1.6 Goodness of Fit . . . . . 32
1.7 Cost Estimations . . . . . 33
1.8 Effect of Becoming a Powerseller . . . . . 34
1.9 Effect of Becoming a Registered Store . . . . . 35
1.10 Change in Consumer Surplus, sellers and eBay Profit . . . . . 40
2.1 Sellers' Action, Electronics . . . . . 52
2.2 Timing of Feedback . . . . . 55
2.3 Sellers' Performance, Electronics . . . . . 61
2.4 Sellers' Actions in the First Period, Electronics . . . . . 69
2.5 Buyers' Actions in the Second Period . . . . . 70
2.6 Sellers' Actions in the Third Period . . . . . 70
2.7 Buyers' Utility Values . . . . . 71
2.8 Sellers' Utility Values . . . . . 72
A.1 Reasons for Removal from Powerseller Program . . . . . 83
A.2 Regression Result for iPod . . . . . 91
A.3 Regression Result for iPod, New vs. Used Items . . . . . 92
B.1 Sellers' Actions, Collectibles and Stamps . . . . . 93
B.2 Timing of Feedback . . . . . 93

# List of Figures


1.1 Different models of iPods and their prices over time. . . . . . . . . . . . . . 9
1.2 Snapshot of an iPod Auction . . . . . . . . . . . . . . . . . . . . . . . . . 11
1.3 Snapshot of Bid History page . . . . . . . . . . . . . . . . . . . . . . . . . 12
1.4 Timing of Sellers' Choices and Shocks . . . . . . . . . . . . . . . . . . . . . 17
1.5 Probability Distribution of Number of Sales, Actual vs. Poisson and Negative-Binomial . . . . . . . . . . . . . . . . . . . . . . . . . . . . . . . . . . 29
1.6 Probability of Sale > 2 for Sellers with Different Quality . . . . . . . . . . . 36
1.7 Total Quantity Sold by non-Powersellers . . . . . . . . . . . . . . . . . . . . 41
1.8 Total Quantity Sold, Powersellers and non-Powersellers . . . . . . . . . . . . 41
1.9 Change in Expected Profit . . . . . . . . . . . . . . . . . . . . . . . . . . . 42
2.1 Share of Positive Feedback for Buyers, Electronics . . . . . . . . . . . . . . 53
2.2 Share of Positive Feedback for Buyers Conditional on Buyers' Feedback, Electronics . . . . . . . . . . . . . . . . . . . . . . . . . . . . . . . . . . 54
2.3 Adoption Rate for Feedbacks, Electronics . . . . . . . . . . . . . . . . . . . 56
2.4 Timing of the Feedback, Comparing to The End of Transaction, Electronics 57
2.5 Share of Positive Feedback for Sellers, Electronics . . . . . . . . . . . . . . . 58
2.6 Share of Positive Feedback for Powersellers . . . . . . . . . . . . . . . . . . . 60
A.1 Average Final Price, Sellers Who Became Powersellers in Period 0 . . . . . 85
A.2 Number of Sales, Sellers Who Became Powersellers in Period 0 . . . . . . . 85
A.3 Average Revenue, Sellers Who Became Powersellers in Period 0 . . . . . . . 86
A.4 Average Prices, Sellers Who Lost Their Powerseller Status in Period 0 . . . 86
A.5 Number of Sales, Sellers Who Lost Their Powerseller Status in Period 0 . . 87
A.6 Average Revenue, Sellers Who Lost Their Powerseller Status in Period 0 . . 87

B.1 Share of Positive Feedback for Buyers, Collectibles and Stamps . . . . . . . 94
B.2 Adoption Rate for Feedbacks, Collectibles and Stamps . . . . . . . . . . . 95
B.3 Timing of the Feedback, Comparing to The End of Transaction, , Collectibles and Stamps . . . . . . . . . . . . . . . . . . . . . . . . . . . . . . . . . . . 96
B.4 Share of Positive Feedback for Sellers, Collectibles and Stamps . . . . . . . 97
B.5 Share of Positive Feedback for Sellers. . . . . . . . . . . . . . . . . . . . . . . 98
B.6 Share of non-Positive Feedback for Sellers vs. Timing of Feedback. . . . . . 99
B.7 Number of Positive Feedback for Sellers, Before and After Policy Change . 101
B.8 Number of Negative Feedback for Sellers, Before and After Policy Change . 102
B.9 Number of Neutral Feedback for Sellers, Before and After Policy Change . . 103

# Chapter 1

# Reputation and Adverse Selection: Theory and Evidence from eBay

## 1.1 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: [Holmström, 1999], [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, Lucking-Reiley et al., 2007, Kollock, 1999], 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. We can think of powerseller status as a *screening* mechanism; by requiring high quantities sold for a certain amount of time, the market can separate good sellers from bad ones. Similarly, eBay store status can be thought of as a signaling mechanism; by paying the store fee, high quality sellers are able to signal their type and therefore enjoy higher profits.

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

[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.

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 powerseller 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

[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.

models using a two-step procedure; for example work by [Bajari et al., 2007], [Aguirregabiria and Mira, 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.

**Related Literature.** This paper contributes to two lines of literature: theoretical papers on reputation and empirical work on eBay reputation system. [Bar-Isaac and Tadelis, 2008] have an excellent summary on both lines of the literature. Although many papers have worked on each of these two lines of literature, to best of my knowledge, this paper is the first paper to empirically estimate the role of reputation based on a dynamic model of firm behavior.

Related to this paper is a large literature that studies firm dynamics in a theoretical context: examples are [Jovanovic, 1982] , [Hopenhayn, 1992], and [Ericson and Pakes, 1995] among others. Firm dynamics arise in [Jovanovic, 1982] because different agents do not know their productivity levels and they learn them over time. [Hopenhayn, 1992] has a dynamic model of firms' entry and exit. [Ericson and Pakes, 1995] study the firm dynamics where sellers accumulate capital over time. While the model developed in this paper shares few similarities to the mentioned papers, in these papers buyers perfectly observe the quality of goods offered and there is no source of adverse selection in these models. What distinguishes this paper is that I allow sellers' quality to be unobservable to buyers and introduce a role for reputation to partially resolve the possible adverse selection problems.

In this paper, reputation can help mitigate adverse selection problems, similar to an extensive literature on modeling reputation as beliefs about behavioral types (papers such as [Milgrom and Roberts, 1982], [Kreps and Wilson, 1982], [Holmström, 1999], and [Mailath and Samuelson, 2001] to name a few).[3] The closest paper is perhaps [Holmström, 1999] where managers have private productivity types and an outsider can learn about the type over time. The main difference between this line of research and my paper is that I abstract form learning. Reputation in the model developed here is the mechanisms introduced by the marketplace (in this case eBay) that can help signal sellers' private types.

From an empirical perspective, a line of research in industrial organization has paid much

[3] Many papers have introduced the techniques introduced in this literature to more applied problems including [Chari et al., 2010], [Board and Meyer-ter Vehn, 2010], and [Board and Meyer-ter Vehn, 2011]

attention to reputation on the eBay marketplace. [Bajari and Hortaçsu, 2004] and [Dellarocas, 2005] have excellent summaries of this line of literature. Examples of major empirical work in this area are [Resnick and Zeckhauser, 2002], [Melnik and Alm, 2002], [Houser et al., 2006], [Resnick et al., 2006], [Reiley et al., 2007], and [Masclet and Pénard, 2008]. These papers study the role of feedback system on eBay. They find a positive correlation between the price of an item and the feedback that a seller has received. [Cabral and Hortacsu, 2009] empirically study the feedback system in a dynamic setup, and they find that the first negative feedback has a negative effect on sellers but the consecutive negative feedback ratings do not have large effects on sellers' performance. I build on these papers by providing evidence on the role of powerseller status and eBay store status in affecting sellers' revenues and profits and structurally estimate the value of reputation using a dynamic model of reputation.

In my analysis, empirical and theoretical, reputation and adverse selection play key roles. A few studies have pointed out the significance of the adverse selection problem on eBay. Using a new approach, [Yin, 2003] shows that the final price of the object is negatively correlated with the dispersion in the perceived value of the object. This observation implies that the higher the dispersion in perceived value, the higher the discount at which the buyers are willing to buy. This points to the existence of information asymmetries and their negative effects on the final price of an item. [Lewis, 2011], however, shows that by selectively revealing information, sellers decrease the dispersion of the perceived value and thereby increase their final price. In his paper he considers the number of photos and the amount of text a seller provides for an object to be the main source of revealing information. He finds that the final price increases with the number of photos put on the auction page and also the amount of text on the website.

The paper is organized as follows: in section 1.2, I describe the dataset analyzed in this paper and I give an overview of market structure on eBay. In section 2.4, I develop the dynamic model of seller's behavior and their interactions with buyers through eBay. In section 2.5, I describe the identification procedure for the deep parameters of the model. In sections 1.5 and 1.6, I describe the estimation of the model and its analysis. In section

1.7, I perform a counterfactual exercise to estimate the value of reputation. Finally, section 2.7 concludes.

## 1.2 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 1.1. 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.[4] 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.

iPods come in different models and each model has several generations. Each generation of a model can have varying levels for internal memory. In the new generations of a model usually the available options for the internal memory increase. The newest model introduced is "iPod Touch" and the first model introduced is "iPod Classic". Some models of iPod are out of production such as "iPod Mini". Figure 1.1 shows the time-table of different models of iPods produced by Apple and their initial date of release and their price at the launching time. One important advantage of studying iPod market is the homogeneity of these products. Additionally, there are few or no promotions outside the eBay website for these products and usually their price stay the same before the introduction of a new generation of the iPods.

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


Figure 1.1: Different models of iPods and their prices over time.

### 1.2.1 eBay

Data was collected from eBay, an online auction and shopping website where individuals can sell or buy a wide variety of items. It is the largest online auction website on the Internet. In early 2008, eBay counted hundreds of millions of registered users, more than 15,000 employees and revenues of almost $7.7 billion.

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.[5] 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.

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

After each transaction on the eBay website, sellers and buyers can leave each other feedback. Feedback can be negative, neutral, or positive. A summary of feedback history for sellers is available on the auction page. After 2007 the buyers can also rate the sellers in four different criteria: Item as Described, Communication, Shipping Time, and Shipping and Handling Charges, called detailed seller ratings. This extra information is not shown on the auction page but it is accessible through the seller's web page.

Figures 2.1 and 2.3 show a snapshot of a finished auction page and also bid history for the same item. At the top of the page there is information about the object and bid history. On the top right side of the page, information about the seller can be found. The rest of the page contains more detailed information about the object sold in the auction. Bidders also have access to the bid history page, which shows previous bidders' short form IDs,[6] their bids, and the time they submitted their bid.

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.[7] 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.[8] This information is observed by the buyers on the listing page as well.

[6] eBay stopped showing the complete ID of the bidders in 2007. eBay mentioned the following reasons: to keep the eBay community safe, enhance bidder privacy, and protect eBay's members from fraudulent emails.

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

[8] 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.

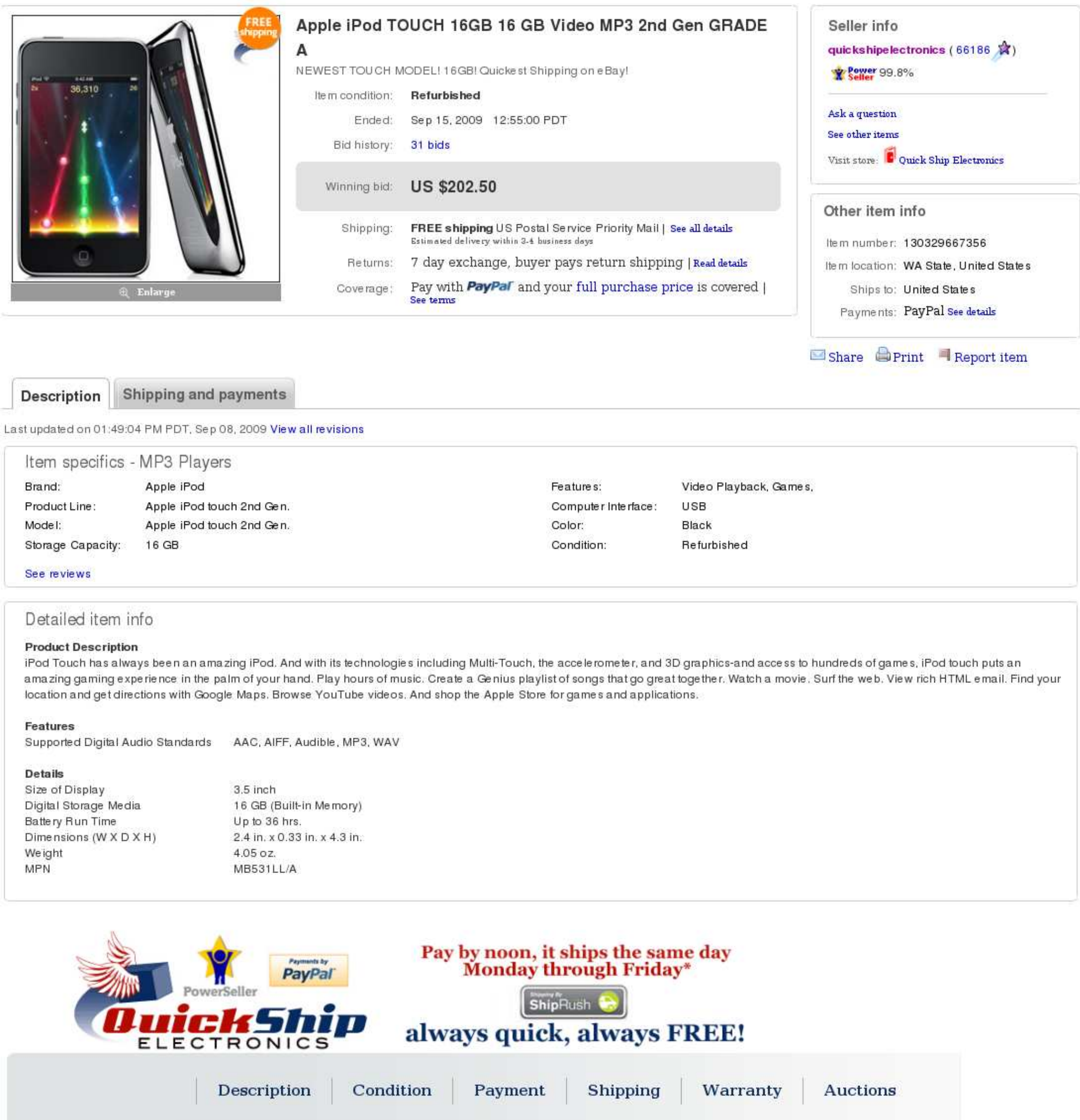
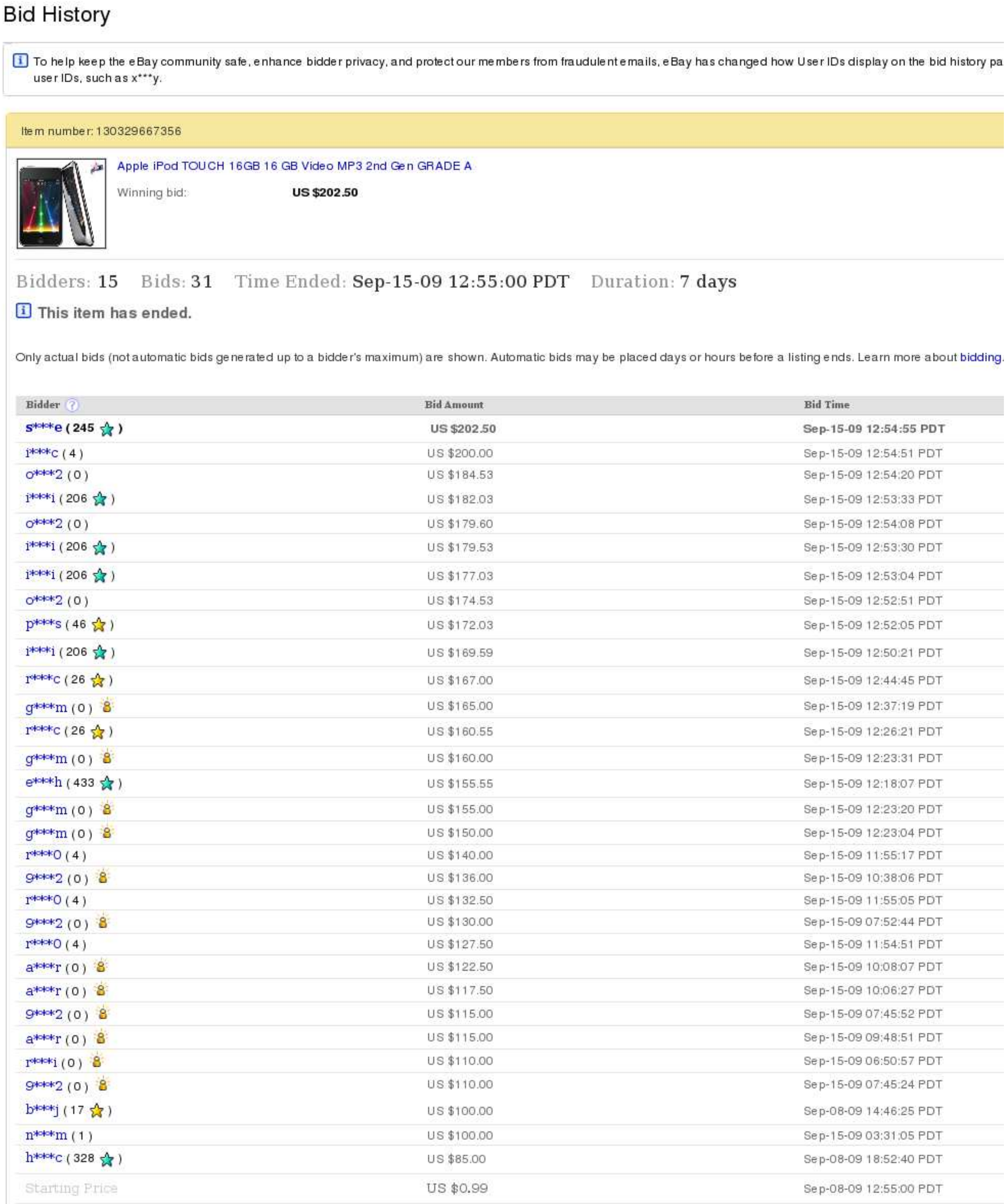



Figure 1.2: Snapshot of an iPod Auction



Bid History

To help keep the eBay community safe, enhance bidder privacy, and protect our members from fraudulent emails, eBay has changed how User IDs display on the bid history pa
user IDs, such as x***y.

Item number: 130329667356

Apple iPod TOUCH 16GB 16 GB Video MP3 2nd Gen GRADE A

Winning bid: **US $202.50**

Bidders: **15** Bids: **31** Time Ended: **Sep-15-09 12:55:00 PDT** Duration: **7 days**

**This item has ended.**

Only actual bids (not automatic bids generated up to a bidder's maximum) are shown. Automatic bids may be placed days or hours before a listing ends. Learn more about bidding.

| Bidder | Bid Amount | Bid Time |
|---|---|---|
| **s***e ( 245 )** | **US $202.50** | **Sep-15-09 12:54:55 PDT** |
| i***c ( 4 ) | US $200.00 | Sep-15-09 12:54:51 PDT |
| o***2 ( 0 ) | US $184.53 | Sep-15-09 12:54:20 PDT |
| i***i ( 206 ) | US $182.03 | Sep-15-09 12:53:33 PDT |
| o***2 ( 0 ) | US $179.60 | Sep-15-09 12:54:08 PDT |
| i***i ( 206 ) | US $179.53 | Sep-15-09 12:53:30 PDT |
| i***i ( 206 ) | US $177.03 | Sep-15-09 12:53:04 PDT |
| o***2 ( 0 ) | US $174.53 | Sep-15-09 12:52:51 PDT |
| p***s ( 46 ) | US $172.03 | Sep-15-09 12:52:05 PDT |
| i***i ( 206 ) | US $169.59 | Sep-15-09 12:50:21 PDT |
| r***c ( 26 ) | US $167.00 | Sep-15-09 12:44:45 PDT |
| g***m ( 0 ) | US $165.00 | Sep-15-09 12:37:19 PDT |
| r***c ( 26 ) | US $160.55 | Sep-15-09 12:26:21 PDT |
| g***m ( 0 ) | US $160.00 | Sep-15-09 12:23:31 PDT |
| e***h ( 433 ) | US $155.55 | Sep-15-09 12:18:07 PDT |
| g***m ( 0 ) | US $155.00 | Sep-15-09 12:23:20 PDT |
| g***m ( 0 ) | US $150.00 | Sep-15-09 12:23:04 PDT |
| r***0 ( 4 ) | US $140.00 | Sep-15-09 11:55:17 PDT |
| 9***2 ( 0 ) | US $136.00 | Sep-15-09 10:38:06 PDT |
| r***0 ( 4 ) | US $132.50 | Sep-15-09 11:55:05 PDT |
| 9***2 ( 0 ) | US $130.00 | Sep-15-09 07:52:44 PDT |
| r***0 ( 4 ) | US $127.50 | Sep-15-09 11:54:51 PDT |
| a***r ( 0 ) | US $122.50 | Sep-15-09 10:08:07 PDT |
| a***r ( 0 ) | US $117.50 | Sep-15-09 10:06:27 PDT |
| 9***2 ( 0 ) | US $115.00 | Sep-15-09 07:45:52 PDT |
| a***r ( 0 ) | US $115.00 | Sep-15-09 09:48:51 PDT |
| r***i ( 0 ) | US $110.00 | Sep-15-09 06:50:57 PDT |
| 9***2 ( 0 ) | US $110.00 | Sep-15-09 07:45:24 PDT |
| b***j ( 17 ) | US $100.00 | Sep-08-09 14:46:25 PDT |
| n***m ( 1 ) | US $100.00 | Sep-15-09 03:31:05 PDT |
| h***c ( 328 ) | US $85.00 | Sep-08-09 18:52:40 PDT |
| Starting Price | US $0.99 | Sep-08-09 12:55:00 PDT |

Figure 1.3: Snapshot of Bid History page

### 1.2.2 Data Summary

Table 1.1 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.

Moreover, most of the items sold on the eBay website in my dataset were sold using an auction method and only 8% of them were sold using a fixed price method. Therefore, in my model section I assume that sellers are setting the quantity and the price is determined in the market.

In an auction setting, sellers can set a secret reserve value; if the final bid is lower than this value the trade will not occur. Only 4% of listings have this option; thus I do not model it further in the model section.

I also have a set of characteristics for items listed, such as the condition of the item, new, refurbished, or used, the level of internal memory of iPod, and the brand of iPod. Most iPods sold on eBay are used items; 25% of listings are new items and 19% are refurbished items. One would expect to see a higher effect for reputation when I focus on used items, since there are more sources of adverse selections for those items: they battery may

Table 1.1: 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 |

not be working, the screen may be scratched or for the touch pad screens it may not work properly, and so on. In the Appendix C, I show that the effect of powerseller status and store status increase when I focus on the used items.

### 1.2.3 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 1.2 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 characteristics, I control for the brand of the iPod: iPod Nano, and the condition of the iPod: New,

Table 1.2: 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 |

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.

In addition, I study the effect of becoming a powerseller for the first time or the effect of losing powerseller status on sellers' final prices, quantity choices, and revenues, using regression discontinuity methods. I show that becoming a powerseller increases the revenue of sellers while losing the status decreases their revenue. These studies are in the Appendix B of this paper.

To estimate the dynamic effects of reputation on sellers' actions and their profit I develop a dynamic model of reputation. The model also enables me to simulate the actions of the sellers in absence of these reputational variables for a complete comparison between the two regimes and the effect of reputation on the market.

## 1.3 Model

To capture the dynamic effects of reputation, I developed a dynamic model of reputation which is similar to [Holmström, 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. This reputation system helps buyers distinguish high quality sellers and low quality sellers, and to give the sellers with higher quality a higher profit.

### 1.3.1 Buyers

There is a measure of $M$ buyers and $N$ sellers in the economy. Buyers are short lived and cannot track sellers over time. Each period, each buyer decides to either buy a single item from one of the sellers or to buy the outside good 0. Buyers do not observe the quality of sellers and 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. There are two signals for this variable: powerseller status and store status. $\epsilon_{ijt}$ is the unobservable utility random variable with a logit distribution.

I will show that buyers infer information about the sellers' quality based on these two signals, powerseller status and store status, and the sellers' equilibrium strategy. This will lead to a structural demand function based on the equilibrium parameters and the two

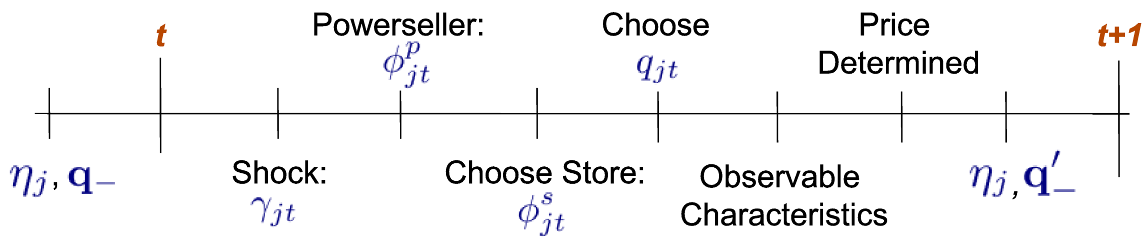



Figure 1.4: Timing of Sellers' Choices and Shocks

reputational signals. I will further discuss the demand structure in the Section 1.3.5.

### 1.3.2 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. Powerseller status can be interpreted as a screening mechanism. 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 $\mu^p$ are signaled as powersellers. A seller should not pay any fixed or monthly fee to be considered in this program.

Store status can be interpreted as a signaling mechanism. Sellers who have a quality, $r_{jt}$ higher than $\mu^s$, 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.

### 1.3.3 Sellers

Sellers are born with different levels of quality, $\eta_j$. 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, $\phi_t^j$. 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, $\phi^p$, and store status, $\phi^s$.

At the beginning of each period, sellers learn about the shock to their quality, $\gamma_{jt}$, which is i.i.d. distributed with a distribution $G$. Their quality at period $t$ is:

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

After learning their quality, they learn their powerseller status, $\phi_t^p$, which is determined by the following formulation:

$$\phi_{jt}^p = 1 \Leftrightarrow \begin{cases} q_{jt-1} + q_{jt-2} + q_{jt-3} > 3Q^p \\ r_{jt} > \mu^p \end{cases} \tag{1.1}$$

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 $F$. Sellers profit function at time $t$ is:

$$\pi(q_{jt}, \phi_{jt}^p, \phi_{jt}^s, x_{jt}) = p(q_{jt}, \phi_{jt}^p, \phi_{jt}^s, x_{jt})q_{jt} - cq_{jt} - c^s\phi_t^s$$

where $c$ is the marginal cost of acquiring an item for sellers,[9] and $c^s$ is the monthly fee of being a store. This fee is set and charged by eBay. 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.

[9] The marginal cost of an iPod is assumed to be fixed, this can be interpreted as the average cost of acquiring an iPod.

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

$$V(\eta_j, \gamma, \mathbf{q}_-) = \max_{q_j, \phi_j^s} \int \left( \pi(q_j, \phi_j^p, \phi_j^s, x_j) + \beta \int V(\eta_j, \gamma', \mathbf{q}'_-) g(\gamma) d\gamma \right) f(x) dx \tag{1.2}$$

subject to:

$$\begin{aligned} \mathbf{q}'_- &= (q_j, q_{j,-1}, q_{j,-2}) \\ \phi^s &= 0 \quad \text{if} \quad \eta_j + \gamma < \mu^s \\ \phi_j^p &= 1 \quad \text{if} \quad \begin{cases} q_{j,-1} + q_{j,-2} + q_{j,-3} > 3Q^p \\ \eta_j + \gamma > \mu^p \end{cases} \end{aligned} \tag{1.3}$$

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. $\beta$ 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 by they can return back to the market without paying a fee in the following periods.

### 1.3.4 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:

- 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.

Note that when sellers maximize their value function, they do not take into account other sellers" individual actions and their state space in the market, rather they care about the average of these values. This is called an oblivious equilibrium as discussed in [Weintraub et al., 2008], and it approximates the Markov Perfect equilibrium as in [Ericson and Pakes, 1995] when the number of sellers is large. This method is based on the idea that when the number of sellers is large, the individual sellers' shocks will average out because of law of large numbers and the average state stays roughly the same. In the next chapter when estimating the model, the number of sellers is more than seven hundreds. [Weintraub et al., 2006] show that when the number of sellers is in the order of magnitude of a hundred then the error caused by using oblivious equilibrium instead of Markov Perfect equilibrium is very low.

### 1.3.5 Demand Formula

Buyers do not observe the quality of sellers but the quality of the sellers affect their utility. Suppose first that they do not observe any signal from sellers. Then their expected utility from buying an item will be:

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

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, $\phi^p_{jt}$ and store status, $\phi^s_{jt}$. 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 $\phi^p_{jt}$ and $\phi^s_{jt}$ 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:

$$\begin{aligned} p_{jt} &= (-log(s_{jt}) + log(s_{0t}))/\alpha + \beta_x x_{jt}/\alpha \\ &\quad + \beta_r/\alpha[\bar{r}_{00} + (\bar{r}_{10} - \bar{r}_{00})\phi^p_{jt} + (\bar{r}_{01} - \bar{r}_{00})\phi^s_{jt} + (\bar{r}_{00} - \bar{r}_{10} - \bar{r}_{01} + \bar{r}_{11})\phi^p_{jt}\phi^s_{jt}] \\ &= (-log(s_{jt}) + log(s_{0t}))/\alpha + \bar{r}_{00} + \beta_p\phi^p_{jt} + \beta_s\phi^s_{jt} + \beta_{ps}\phi^p_{jt}\phi^s_{jt} + \beta_x x_{jt}/\alpha \qquad (1.4) \end{aligned}$$

This formulation can be used to estimate the parameters of demand function which gives us an estimate to deep parameters of buyers' utility function. The estimation of the above formula comes in the Section 1.5.

## 1.4 Identification

In this section, I describe how the main parameters of the model are identified from the data. These include the sellers' distribution of 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 unchanged in counterfactuals. In particular, they are invariant when 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.

### 1.4.1 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, $\eta$. This is one of the main implications of the model that helps in identifying qualities.

**Proposition 1.1** *Suppose that the solution to the functional equation (1.2) is unique. Then, the policy function* $q^* (\eta, \gamma, \mathbf{q}_-)$ *is increasing in quality* $\eta$*.*

**Proof.** Here, I sketch the proof. Appendix A contains a complete and more detailed version of the proof. Recall the functional equation (1.2) in section 1.3.3. 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 $\phi^s$ does not affect future values. Hence, I can define the following period profit function:

$$\hat{\pi}(\eta, \gamma, q, \underbrace{q_{-1}, q_{-2}, q_{-3}}_{\mathbf{q}_{-}}) = \max_{\phi^s \in \{0,1\}} \int \pi\left(q, \phi^s, \phi^p, x\right) f\left(x\right) dx \tag{1.5}$$

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 $(\eta, q)$ and in $(\eta, q_{-i})$ for $i = 1, 2, 3$.

**Step 2.** I show that the solution to the functional equation (1.2) is supermodular in $(\eta, q_{-i})$ for $i = 1, 2, 3$.

**Step 3.** The policy function is increasing in quality $\eta$.

■

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 1.1 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, $\gamma_{jt}$, as well as their quantity three periods ago, $q_{-3}$.

**Lemma 1.2** *The policy function* $q^*(\eta, \gamma, \mathbf{q}_-)$ *can also be represented as* $q^*(\eta, \phi^s, \phi^p, q_{-1}, q_{-2})$.

**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 $\gamma$ or $q_{-3}$. Therefore, sellers' choice of quantity should not depend on them after we control for $\phi_j^p$ and $\phi_j^s$. ■

The above lemma will help me in modeling the sellers choice of quantity in section 1.5. Note than the Proposition 1.1 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.

### 1.4.2 Identification Procedure

Given the Proposition 1.1 and Lemma 1.2, 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. Furthermore, I can parametrically estimate sellers' quality using two moments from demand function, (Equation 1.4).

$$\begin{aligned}
&(\bar{r}_{10} - \bar{r}_{00})/\beta_p - (\bar{r}_{01} - \bar{r}_{00})/\beta_s = 0 \\
&(\bar{r}_{10} - \bar{r}_{00})/\beta_p - (\bar{r}_{00} - \bar{r}_{10} - \bar{r}_{01} + \bar{r}_{11})/\beta_{ps} = 0 \qquad (1.6)
\end{aligned}$$

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 using a simulated method of moments. More details of estimation procedure comes in Section 1.5.2.

## 1.5 Estimation

To estimate the model, I use a two-step estimator method introduced by [Hotz and Miller, 1993] and later advanced by [Bajari et al., 2007]. The method uses the basics of revealed profit to estimate the deep parameters of 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.

Table 1.3: 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 | |

**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.

### 1.5.1 Estimating Structural Demand

To estimate the structural demand function, I use the demand equation (1.4) derived in the section 1.3.5. 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 1.3 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 2.4: sellers with high level of quality become powersellers and stores.

Moreover, the above regression also determines how characteristics of the iPods sold affect their price. The "New" iPods got sold on average \$37.48 more than the used iPods, and refurbished iPods got sold on average \$13.11 more. Each extra gigabyte of internal memory on an iPod results in an extra \$1.42 in price. I have also included fixed effect for the type of iPods: Nano, Touch, Classic, Mini, Video, and Shuffle; their coefficients were as expected, highest for Touch and lowest for Shuffle. Additional robustness checks on demand formulation by adding more characteristics of sellers and by focusing on a subset of data are in the Appendix C.

### 1.5.2 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, $\eta_j$, can be identified using the dynamic quantity choice of sellers based on Section 2.5.

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 $\mu^p$. I estimate $\mu^p$ later by matching the average percentage of powersellers in the market in the dataset and simulated model.

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.

Table 1.4: 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 |

**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 1.5.1.

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 1.4.1. I can control for all the parameters except for persistent level of quality, $\eta_j$. I have also shown in Proposition 1.1 in Section 1.4.1 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. In the Section 1.5.2, I parametrically estimate the value of quality based on the sellers' fixed effect estimated in this section.

The sellers' decision can be modeled using a discrete choice model in which sellers can

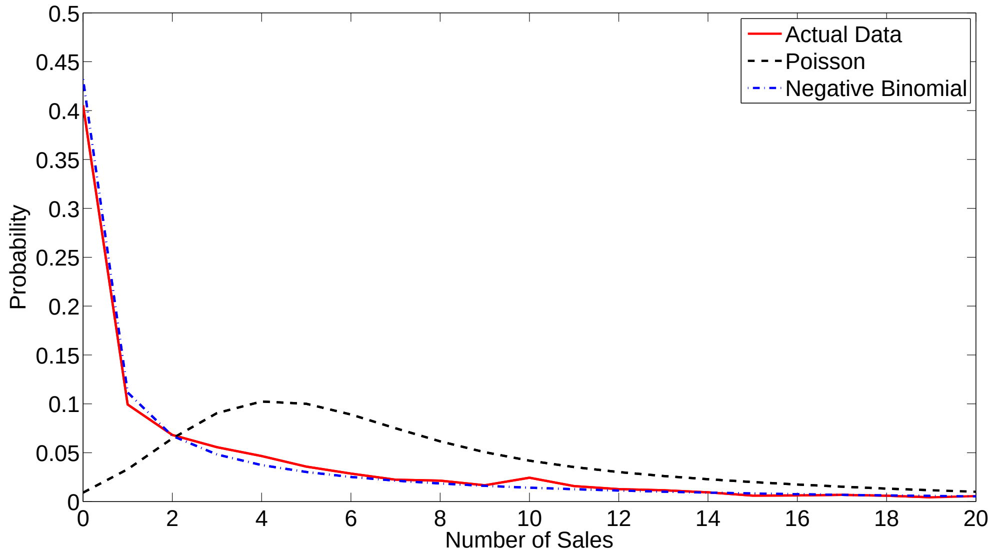



Figure 1.5: Probability Distribution of Number of Sales, Actual vs. Poisson and Negative-Binomial

choose any non-negative number. I have considered Poisson and Negative Binomial distribution models and the latter matches the data the best as shown in 1.5. In this figure, the actual data represents the ratio of time that sellers in the market has sold $n$ number of items. The dashed line shows that the probability prediction of estimated Poisson distribution over different number of sales, taking the average over all the sellers in the market; the doted-dashed line shows the same thing but using the estimated Negative Binomial distribution.

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 $\xi$ the dispersion parameter of Negative Binomial distribution are in Table 1.4. To estimate the probability of each event for each seller

I use the following formula:

$$\begin{aligned}
\rho_{jt} &= exp([\phi_t^s, \phi_t^p, q_{jt-1}, q_{jt-2},] * \beta + \nu_j + \delta_t) \\
r &= 1/\xi \\
p(0) &= (r/(r + \rho_{jt}))^r \\
p(k) &= p(k-1) * (r + k - 2)/(k-1) * \rho_{jt}/(\rho_{jt} + r);
\end{aligned}$$

where $p(k)$ is the probability that the seller $j$ at time period $t$ sells $k$ items. Store status, powerseller status, and sellers' fixed effects affect $\rho$ in the above formula and $\xi$, the dispersion parameter, is fixed among all sellers. This will result in positive correlation between number of sales and store status, lag number of sales, and powerseller status.

While eBay decides on the thresholds for powerseller status and store status based on $\eta_j$, since $\nu_j$ is a non-decreasing function of $\eta_j$, the eBay decisions can be interpreted as a cut-off based on $\nu_j$. They are used later on to estimate the level of threshold set by eBay, $\mu^p$ and $\mu^s$. I also parametrically estimate level of $\eta_j$ as a function of $\nu_j$ is Section 1.5.2.

**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 $\eta$. This decision is a binary choice for the sellers; and I model it using a logit model. Table 1.4 shows the results of the regression.

Table 1.5: Parametric Estimation Unobserved Quality
Effect of Quality on Price

| | Parameter |
|---|---|
| $\lambda$ | 0.24 |
| $\beta_r/\alpha$ | 3.34 |

**Estimating Unobservable Quality**

In this section, I estimate the sellers' unobservable persistent level of quality. As mentioned in the Proposition 1.1, number of items sellers sell is increasing in their unobservable persistent level of quality, $\eta_j$. Based on this proposition , I estimate $\nu_j$, the sellers' fixed effect in the quantity choice function. $\nu_j$ is an index of $\eta_j$ and based on the Proposition 1.1, it is a non-decreasing function of this value. As explained in Section 2.5, 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 1.6.

I also assume the following parametric formulation for the $\eta_j$, which is increasing in $\nu$:

$$\eta_j = \nu_j + \lambda \nu_j^3$$

Then by minimizing the joint differences between moment conditions mentioned above in the model and data, I estimate the value of $\lambda$, $\mu^p$, $\mu^s$, and variance of random shocks to utility, $\gamma_{jt}$. Then using the estimate of $\lambda$, I can estimate the value for $\beta_r/\alpha$ the coefficient of $r_{jt}$ in the demand function. Table 1.5 shows the estimated values for $\lambda$ and $\beta_r/\alpha$. Note that $\beta_r/\alpha$ is positive, therefore buyers enjoy buying an item from a seller with higher level of quality.

Table 1.6: 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 |

Average simulated results after simulating the model for 9 periods.

### 1.5.3 Simulation

Using the first stage estimation results and given an initial value for $\mu^s$ and $\mu^p$, I can simulate the model over time. To estimate the correct value of these two parameters, $\mu^s$ and $\mu^p$, 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 1.6 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.

### 1.5.4 Perturbations

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.

Moreover, perturbations should give us movements in both directions and both small and big changes in the variables, i.e., to have changes in actions of sellers in both directions

Table 1.7: Cost Estimations

| | Specifications | |
|---|---|---|
| | I | II |
| c | 129.39 | 128.62 |
| Store | | 39.57 |

and have enough inequalities to determine the value of cost parameters. To get estimates for the cost parameters, I perturb the policy function associated with number of sales and store status.

### 1.5.5 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 1.7 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

Table 1.8: Effect of Becoming a Powerseller

| | Original | Powerseller=1 | Powerseller=0 | Difference |
|---|---|---|---|---|
| Average Value Function | \$437 | \$626 | -\$420 | \$ 1,0461 |

estimate is \$39.57 per month which is in the range of these values.

## 1.6 Analysis

In this section, I estimate the dynamic values associated in becoming a powerseller and becoming a store. In order to estimate these values in each case I simulate data using three different initial conditions for the sellers: first, the actual initial condition observed in the data, second, by fixing the initial powerseller status or store status of sellers to be one, and third, by fixing the initial value of these parameters to be zero. The difference between simulated value functions of theses different cases shows the average value these actions add to the sellers' expected profit over the simulated time period.

### 1.6.1 Estimating the Value of Powerseller Status

Given the cost estimates and the sellers' initial conditions, I can estimate the expected profit of sellers. To estimate the value of becoming a powerseller, I start from the initial conditions of sellers in the market. Once I assign all the sellers to start from not being a powerseller and calculate their value functions, then I assign their starting powerseller status to be one and calculate their value function for these condition.The difference between their value functions in these two situations will give us an estimate of the value of being a powerseller.

I simulate the sellers' actions for eight periods, eight months, keeping all the other initial values of sellers fixed in all three setups and only changing the powerseller status. The

Table 1.9: Effect of Becoming a Registered Store

| | Original | Store=1 | Store=0 | Difference |
|---|---|---|---|---|
| Average Value Function | \$437 | \$689 | \$62 | \$627 |

average difference in value function, shown in Table 1.8, is \$1,0461 for the set of the largest 326 sellers with the highest number of sales in iPods.

### 1.6.2 Estimating the Value of Store

Given the cost estimates and the sellers' initial conditions, I can estimate the expected profit of the sellers. To estimate the value of becoming a registered store on eBay, I start from the initial conditions of the sellers in the market. First I assign all the sellers to start from not being a store and calculate their value functions, then I assign their starting store status to be one and estimate their expected value function.The average difference between their value functions in these two situations will give us an estimate of the value of becoming a registered store on eBay.

I simulate the sellers' actions for eight periods, eight months, keeping all the other initial values of the sellers fixed in all three setups and only changing the store status. The average difference in the value function, shown in Table 1.9, is \$637 for the set of the largest 326 sellers with the highest number of sales in iPods.

### 1.6.3 The Probability of High Volume of Sale

Many sellers on eBay leave the website after being active on the website for few months. To have a market with a high percentage of high quality sellers, we must have a situation such that high quality sellers stay in the market with a higher probability than that of low quality sellers. This will result in a positive feedback loop for sellers. High quality sellers

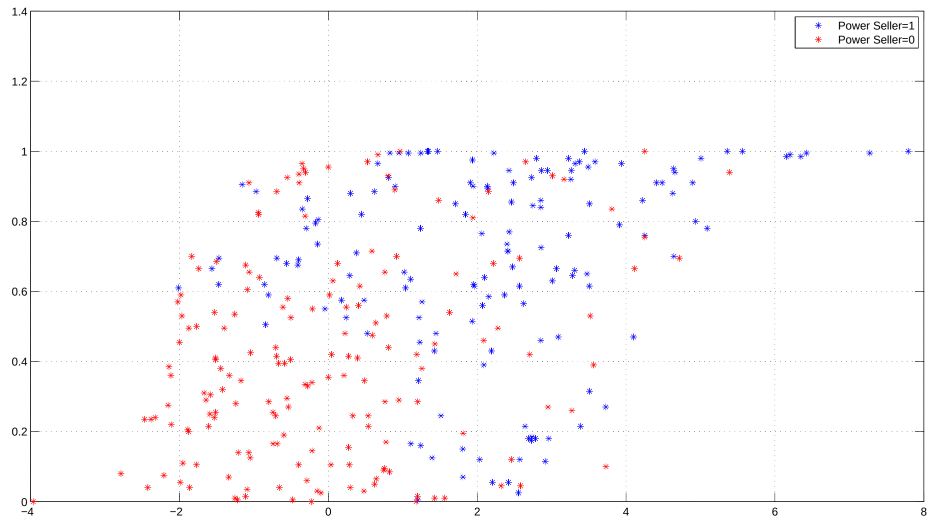



Figure 1.6: Probability of Sale > 2 for Sellers with Different Quality

will have high reputation, and higher reputation will lead to higher prices, quantities, and survival probabilities for sellers. Additionally this will result in a market with a higher percentage of high quality sellers and a market less prone to adverse selection, and therefore a market with a high efficiency.

Although I do not have endogenous exit decisions in this model, but sellers decide on the number of items they want to sell each period and their market share can vary by their quality level. I define a seller to be active in the market if the seller is selling more than two items that period. Figure 1.6 shows the probability that a seller is active after simulating the model for eight months. Each point on the graph represents a seller. The horizontal axis represents the level of $\nu_j$, a non-decreasing function of reputation, $\eta_j$ which is the unobservable quality of seller $j$. Blue stars represent sellers who are powersellers and red circles represent the sellers who are not powersellers.

Figure 1.6 shows that sellers with a high unobservable quality have a higher probability of staying active in the market. Moreover, powersellers are more likely to stay active in the market. This will complete the positive feedback loop and it shows that the reputation mechanism helps sellers with a high level of quality to be active in the market with a higher probability.

## 1.7 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. Even though changing eBay policy will affect buyers' demand function, it will not affect buyers' utility function. Therefore, using the estimated structural demand I can estimate the demand function of buyers after the change in the policy.

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.

### 1.7.1 No Reputation Mechanism

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.

### 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.

### 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:

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

Since there is no entry and exit, $\int \eta_j l(r_{jt}) dr_{jt}$ stay the same over time. In addition, assuming $\gamma_{jt}$ 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 $\epsilon_{ijt}$ follows an extreme value distribution, the demand function as explained in Section 1.3.5 will be as follows:

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

where $\alpha$ and $\beta_x$ have the same parametric values as estimated parameters in Table 1.3 in previous section and they are invariant to the change of the policies by eBay. I use the results in the section 1.5.2 to estimate $\beta_r/\alpha \int r_{jt} l(r_{jt}) dr_{jt}$, which gives me an estimate of $\beta_r/\alpha$ and also an estimate of $\eta_j$, assuming $\gamma$ is distributed i.i.d. with mean zero I can also estimate the second part of the expression.

Table 1.10: 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% |

**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 1.10. 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 1.7, 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 1.8 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 stay powerseller.

Figure 1.9 shows the relationship between the change of the expected profit of sellers and their unobservable quality as a result of removing powerseller status. Each point in the graph represents a seller in the dataset. A negative number means that after the change the seller is worse off and a positive number means that the seller has gained from the change. Blue dots represent the sellers that in the original settings were powersellers and

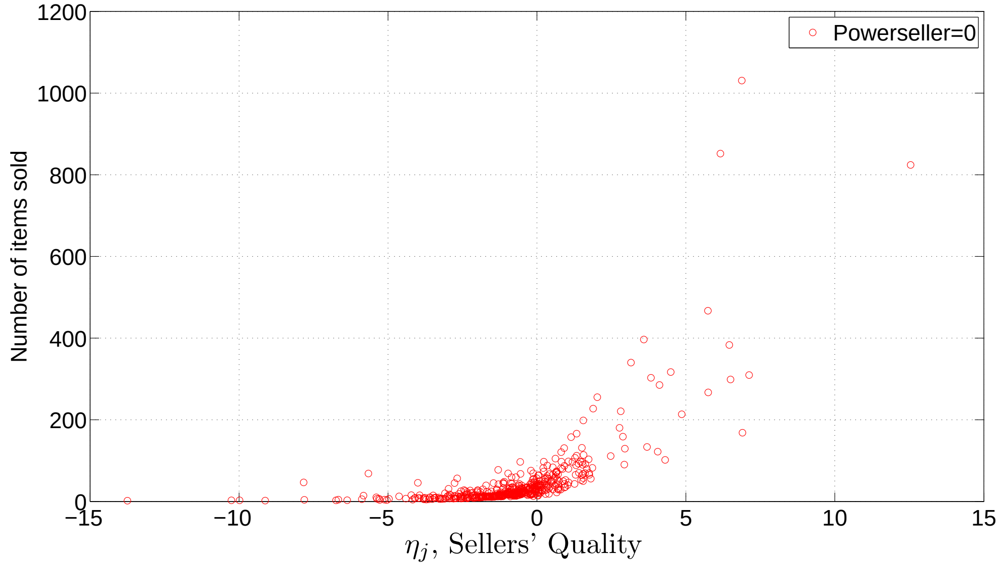



Figure 1.7: Total Quantity Sold by non-Powersellers

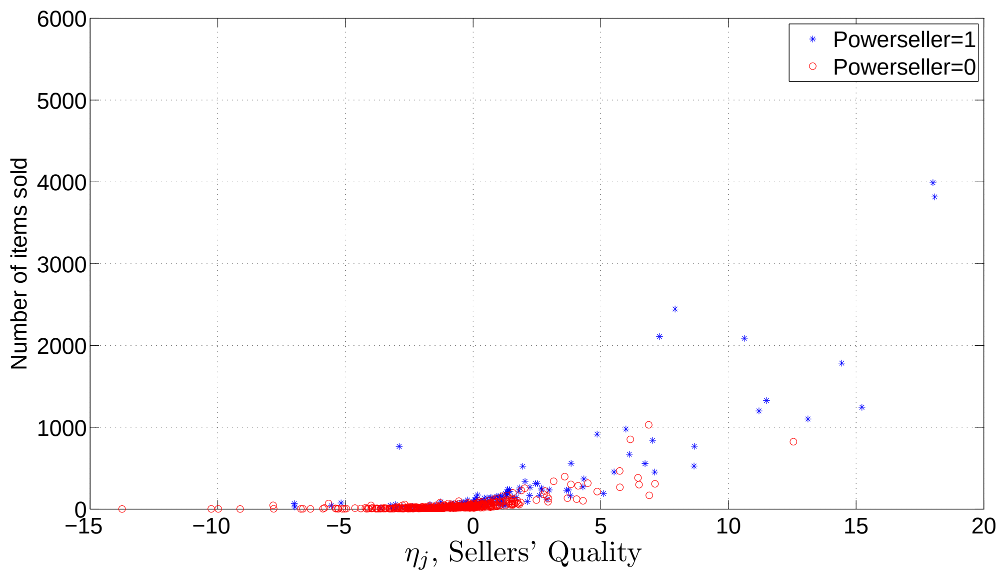



Figure 1.8: Total Quantity Sold, Powersellers and non-Powersellers

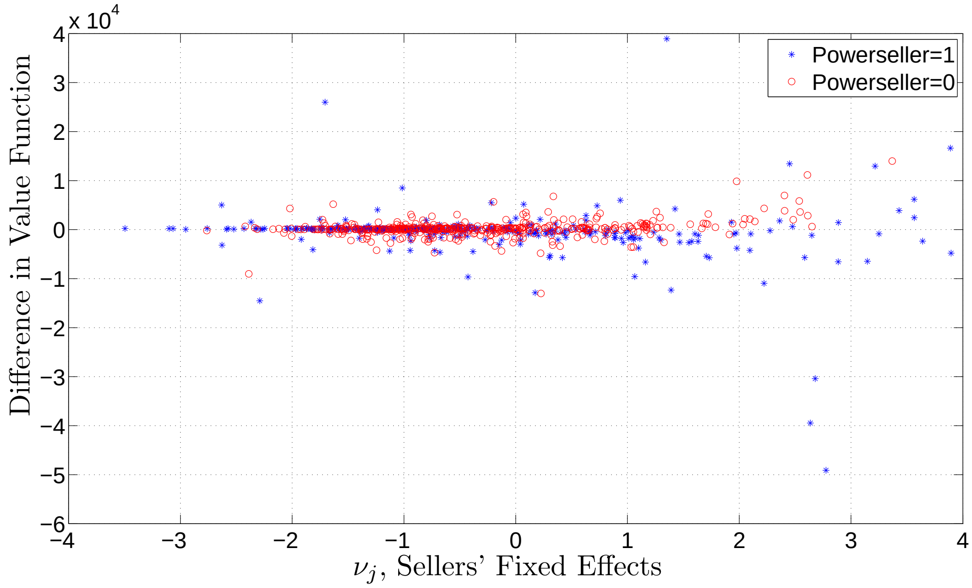



Figure 1.9: Change in Expected Profit

red dots represent sellers which were not powersellers. The horizontal axis shows the level of sellers' unobservable quality. As shown in the graph most of the sellers with high quality and powerseller status are worse off while the other sellers gained from the change. This means that the market share of sellers with low quality has improved, and the market is more prone to adverse selection.

## 1.8 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.

# Chapter 2

# The Value of Feedback: An Analysis of Reputation System

## 2.1 Introduction

As the internet has grown leaps and bounds, user generated content has taken the front stage. Consumer rating sites (e.g. yelp[1] , tripadvisor), content sites (e.g. youtube, blogspot, digg), television (e.g. youtube, trouble, sumo tv), art (e.g. deviantart, fanart), and commerce (e.g. eBay, craigslist, Amazon[2] ) are popular. One property consumer or user generated sites have in common is that there is no well-specified standards for the quality of the content. Without appropriate checks and balances such a platform can deteriorate over time with poor quality content/product overwhelm the marketplace. This can be compared to the notion of lemon markets introduced by [Akerlof, 1970] who proves that existence of adverse selection in lemon markets can lead to potential breakdown of trading or high inefficiencies in a marketplace. In this paper, we study how such checks and balances work in reputation systems by analyzing buyers and sellers' rating incentives as well as their interactions.

[1] [Anderson and Magruder, 2011] and [Luca, 2011] look at the effect of a higher rating on yelp on restaurant sale.

[2] [Chevalier and Mayzlin, 2006] argue that Amazon ratings leads to higher purchase from this website.

We focus on one such marketplace, eBay. As many authors have noted,[3] eBay is a market prone to adverse selection. When adverse selection hinders trade, reputation can be used as a possible mechanism in mitigating lemon problems.[4] At the center of the eBay reputation systems is the feedback system by buyers and sellers. Feedback by buyers affect sellers' future status as Powerseller as well as eBay Store and as shown in [Saeedi, 2011], these "tags" can significantly increase sellers' profits over time. Thus, an analysis of feedback behavior and its effect on market size is of utmost importance.

The goal of this paper is to study the users' incentives in using feedback and the use of feedback as a proxy for reputation using the eBay Marketplace platform as a running example as well as to understand the effects of the policy changes on the participation and the participants. We believe that the research and the learnings are transferable to other similar platforms as well. Over the last fifteen years, eBay as a commerce platform has matured and evolved from being a completely reputation driven, user generated platform to a more managed marketplace. We take a close look at the feedback mechanism on eBay and the game the buyer and the seller get into after the end of the transaction for leaving feedback for each other. We also study moving from a two-sided feedback system to a system where sellers cannot leave negative or neutral feedback for buyers. This change is aimed at removing the possible retaliatory behavior of the sellers and to increasing efficiency in the market.

We start by analyzing the data on buyer and seller feedback over time. Examining the data shows sellers and buyers on eBay leave feedback for each other in more than 60% of the transactions. We also observe that users with a higher transaction volume on eBay leave and receive feedback more often. These evidences suggest that buyers and sellers put a strong emphasis on the reputation system implemented by eBay. Further, we consider the trend in feedback left by sellers and buyers when a new policy is put in place and study its effect on sellers and buyers of various characteristics. The evolution of the market, e.g.

[3] Examples of such studies are [Kollock, 1999], and [Yamagishi and Matsuda, 2002]

[4] As noted by many authors, reputation mechanisms has helped eBay in its growth over time. See for example, [Resnick et al., 2006], [Brown and Morgan, 2006], [Lucking-Reiley et al., 2007], and [Saeedi, 2011], among others

change in market share, price dispersion, and concentration, as a result of these policy changes will direct us to a better understanding of the role of reputation over time, across various characteristic groups. In addition the study of the changes of eBay policies, can help us to test different theories regarding reputation system and how different players in the market conceive the role of the reputation in this market.

Furthermore, we show evidence on the existence of retaliation before the policy change[5] . We observe that in more than a third of transactions that they have received a negative feedback they retaliate with a negative feedback. This can also be a consequence of a mutual bad experience. In addition, we observe that the sellers will rarely leave any negative feedback for the buyers when they move first but this percentage increases by almost tenfold after the buyer has moved and left them a feedback.

Following this policy change, sellers of different segments and in particular more experienced sellers, leave feedback for buyers more often. On the other hand, buyers leave feedback for sellers less often. In addition, we also observe that sellers leave their feedback more promptly, on average after six days of end of the transaction versus fifteen days. Buyers only response one day sooner than before the policy change, fourteen days versus fifteen days. These changes can be explained as follows: sellers can no longer leave negative feedback for buyers as a retaliation mechanism, therefore they do not have any incentives to wait for the buyer to leave her feedback first. On the opposite side, buyers after receiving a positive feedback from sellers have less incentive to leave a feedback for sellers.

One striking result is that after the policy change, the percentage of positive feedbacks left by buyers for the sellers has increased. This result is surprising since one would think that with the lack of retaliation the buyers should respond honestly and leaving a negative feedback for the seller should not have a cost for them. One justification can be that the

[5] [Bolton et al., 2009, Dellarocas and Wood, 2008, Masclet and Pénard, 2008, Dellarocas, 2002], and [Resnick and Zeckhauser, 2002] have noted the possibility that buyers are not completely truthful in their feedback left for sellers in fear of retaliation from sellers with a negative feedback. In January 2008, eBay announced eBay sellers can only leave positive feedback for buyers from May 2008 to remove retaliation and to have a more truthful reputation system.

buyers will have an overall better experience because the sellers leave more positive feedbacks and they leave their feedbacks sooner but the interesting result is that the buyers leave more positive feedbacks even if they are the party that moves first. Another justification is that in the absence of retaliation, sellers, especially the sellers with lower quality, loose a tool to control the market outcome by intimidating the buyers. As a result sellers should exercise more effort for the transactions and as a result we are dealing with a market less prone to adverse selection. This last statement is supported by looking at other indications of market quality, like percentage of transactions with a dispute from a buyer. Disputes are made to eBay from the buyers when buyers and sellers could not resolve an issue among themselves. The number of disputes have decreased by 25% during this time period.

In order to further analyze the interaction of feedback incentives by buyers and sellers , we construct a new model to capture the feedback interaction between buyers and sellers. We model seller and buyer behavior via a a dynamic game of leaving feedback once the transaction has occurred. The seller and the buyer can move in different periods and each can leave positive, negative, or no feedback for their opponents, depending on the quality of the transaction. We show that qualitative features of the model are consistent with basic stylized facts of the data.

Next, we identify the model using the outcome of the transactions and the feedbacks received by sellers and buyers. We use both before the policy change and after the policy change data for the identification and we get the deep utility parameters of the users. The identifying assumption is that the main structure of the game doesn't change before and after the policy change. This finding can be used to predict the effect of different counterfactuals, e.g. the effect of reducing the cost of leaving a feedback by adding incentives to buyers and sellers, the effect of automatic positive feedback if no feedback was left, the effect of unanimous feedbacks from buyer and sellers, many other examples.

The rest of the paper is organized as follows: in section 2.2, we give an overview of the market structure on eBay and the feedback system. We also explain the change in the eBay policy that happens during our data collection time period. In section 2.3, we explain the new policy in depth and we describe the data before and after the policy change. In section 2.4, we develop a model explaining sellers' and buyers' incentives for leaving feedback. Section 2.5 explains the identification strategy for the deep parameters of the model. Finally, section 2.7 concludes.

## 2.2 Background

eBay is an online auction and shopping website that individuals can use it to sell or buy a wide variety of items. eBay was first started as a medium of trade with little or no guarantee for the buyers and sellers. Over the years eBay has introduced different methods to improve the interactions between sellers and buyers without loss of their privacy. It has introduced different means for sellers and buyers to signal their quality and to gain reputation in the marketplace.

Feedback system was the first tool introduced on the eBay website as a signaling mechanism for participants in this market. After each transaction on eBay website, sellers and buyers can leave each other a feedback. Feedback can be negative, neutral, or positive. Seller's feedback summary is available on the auction page. This addition has been counted as one of the main reasons eBay has overcome the asymmetry information problem that exists among sellers and buyers.

The feedback system helps keep the very worst participants out of the market; sellers with very low feedback ratings are forced out of market because they usually cannot sell in the market. However, some of low quality sellers would find ways to prevent getting negative feedback ratings. In a two-way feedback system a retaliatory approach may be used where poor quality sellers wait for buyers to leave their feedback before leaving a feedback, and if they receive a negative feedback then retaliate with a negative feedback [Dellarocas and Wood, 2008, Masclet and Pénard, 2008, Dellarocas, 2002, Resnick and Zeckhauser, 2002]. The retaliation lowers the effectiveness and value of reputation system. To help remove this problem, eBay introduced detailed sellers rating and also has prevented sellers from leaving negative feedback for buyers.

The simplicity of the feedback system–a positive, negative or a neutral rating–made it widely popular and helped sustain the market, and it also had a pollyannic effect. Most feedback scores were positive and did not carry more information than that of the textual content related to the feedback. Mining the textual content of the feedback reveals more information than a positive feedback score; e.g. why the buyer felt positive about the transaction [Ganesan et al., 2008, Lu et al., 2009]. Many of these are related to communication, shipping time, shipping fees, and product condition. Since 2007 the buyers can leave detailed sellers' rating over four different criteria: Item as described, Communication, Shipping Time, and Shipping and Handling Charges. The detailed seller rating provides more detailed information about the transaction. More importantly, sellers cannot observe what rating exactly a particular buyer has left for them. Therefore, sellers cannot punish buyers based on the rating, and it is expected that buyers are more honest when leaving a detailed sellers' rating. This policy change has been studies in depth by [Bolton and Ockenfels, 2008].

To completely overcome the retaliation problem and improve the reputation system, on May 2008 eBay implemented a policy to remove the ability of sellers to leave negative or neutral feedback for buyers. Therefore, changing the feedback system to a one-sided system that only the sellers get rated in transactions; buyers can only get positive feedback or no feedback. In this paper we study the effect of this policy change in depth on sellers' and buyers' actions and on the overall marketplace.

eBay has tens of minor markets like collectibles, stamps, electronics, toys, and so on. Each of these markets have different properties of user participation, use of trust mechanism, and adoption of sale formats like fixed price or auctions [Shen and Sundaresan, 2011]. In this paper we consider three different categories on eBay: Electronics, Stamps, and Collectibles. Due to the diversity in the nature of these categories we make a hypothesis that these users react differently to policy changes in each category. Considering multiple categories helps us determine whether the effect of a policy change is only restricted to a specific category or it is common across different categories. Stamps and collectibles are two categories which existed on eBay for a long time. On the other hand, electronics is a category with a high growth in sales volume on eBay in recent years and has gone through many changes. Throughout the main body of the paper we discuss the data from the Electronics category and in the Appendix, we show the same graphs and data for Stamps and Collectible categories. The results turn out to be mainly similar and we observe the same patterns among these three categories, but the levels of change are different across different categories.

## 2.3 Data

In this section we show different facts from data. First, we show some evidence of existence of retaliation from the sellers before the implementation of the no-negative-feedback-from-sellers' policy. Next, we show response of the sellers and buyers to this change of the policy. We show the change in the adoption rate for feedbacks, the timing of the leaving feedback, and also on the percentage of positive feedbacks left.

We will use the guidance from this section for developing a model that fits the actions of sellers and buyers. We will also use this data to identify the model and to find the deep parameters of the model in Section 2.5.

### 2.3.1 Existence of Retaliation

We first investigate the feedback interactions between buyers and sellers before the policy was implemented. We show that before the change in policy, buyers and sellers were engaged in retaliation strategies: after leaving a negative feedback for sellers, buyers were very likely to receive a negative feedback from sellers. This effect can be seen in Table 2.1. After a negative feedback is received from a buyer, a seller will respond with a negative feedback in more than 30% of the transactions, comparing to less than 1% negative feedback rates when they leave a feedback first or if a buyer leaves a positive feedback for a seller.

Another evidence of sellers strategic behavior as of result of a negative feedback is illustrated in Figure 2.1. This figure represents the percentage of positive feedback for buyers as a function of number of days buyers leave feedback after the sellers; positive numbers on x axis corresponds to transactions were the seller has moved first, and negative numbers are those with the buyer moving first.[6] When the sellers are moving first there are hardly any negative feedback left for the buyer, but when they move after the buyer the percentage of negative feedbacks increased about tenfold. Note that we do not make the judgment as to whether or not the seller or buyer was in the wrong; all we observe is that the transaction has gone sour. After the change in the policy sellers no longer can leave a negative feedback for buyers and this problem has been resolved.

Table 2.1: Sellers' Action, Electronics

| Sellers' Actions After Receiving a Feedback from Buyers | | | |
|---|---|---|---|
| Buyers' Feedback | Positive | Negative or Neutral | No Feedback |
| Negative or Neutral | 5% | 37% | 58% |
| Positive | 88.47% | 0.04% | 10.49% |

Another figure that shows some evidence of existence of retaliation is Figure 2.2. In this figure, the share of positive feedbacks for buyers from sellers is shown for different buyers feedbacks: positive, negative, and neutral. This numbers are all for before the change in the policy. When the seller is leaving feedback first most of the feedbacks left are positive, but when the buyer has left feedback first, the sellers' feedback seems to be retaliatory to some extend. We will explore this more in Section 2.4.

[6] For cases in which seller and buyer left feedback on the same day, we separate these group by the exact time that they leave a feedback. 0.5 on the x-axis corresponds to the transactions in which the seller left feedback first and the buyer left feedback after the seller but in the same day, and -0.5 corresponds to the transactions in which the buyer left her feedback first.

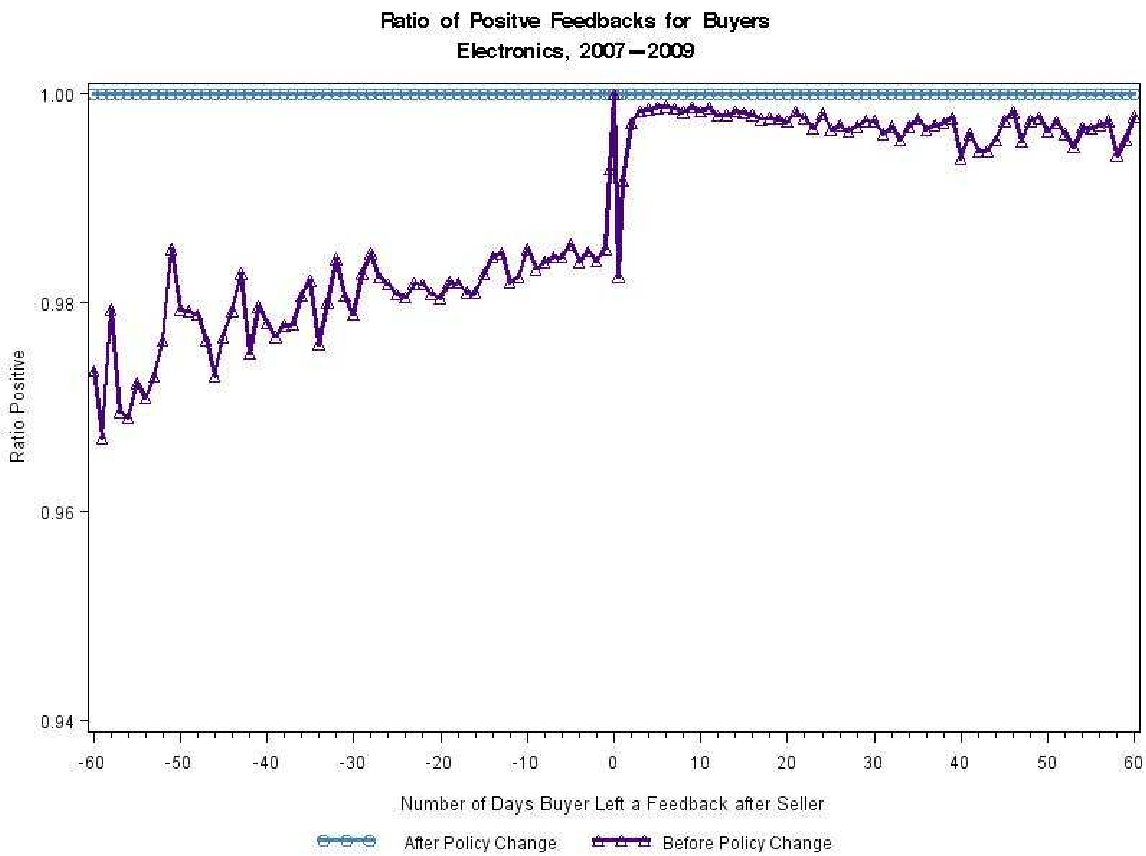



Figure 2.1: Share of Positive Feedback for Buyers, Electronics

X axis: The number of days the seller has left a feedback before the buyer.
Y axis: Percentage of positive feedbacks over the total feedback left at the same day.

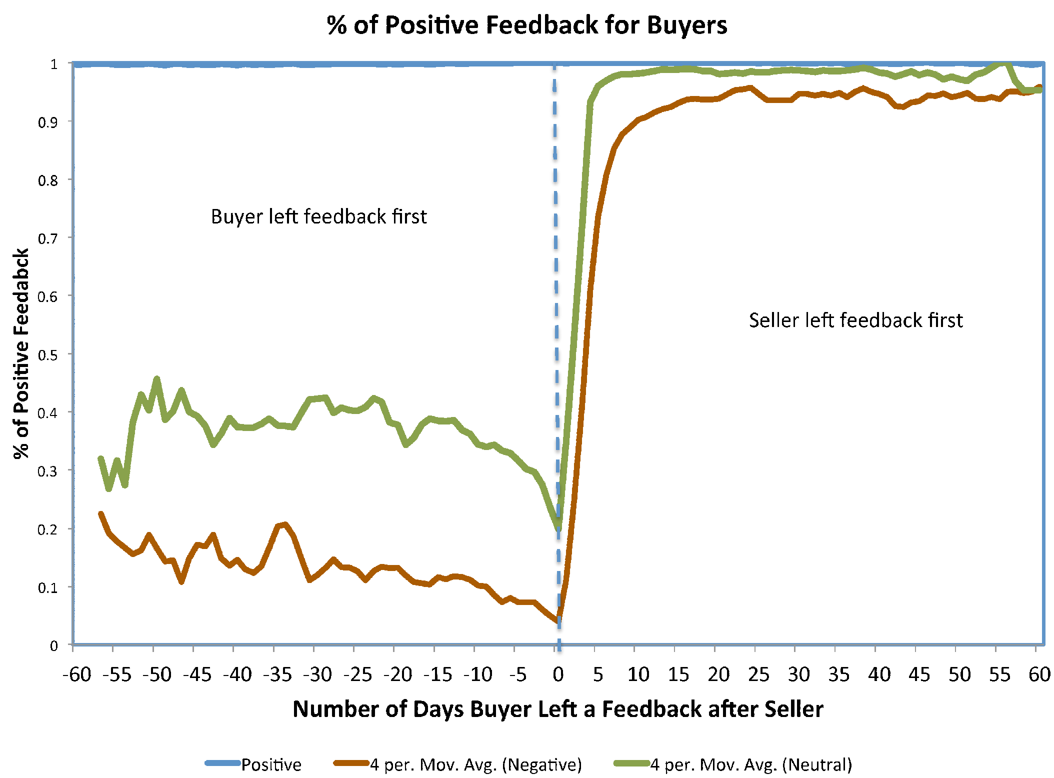



Figure 2.2: Share of Positive Feedback for Buyers Conditional on Buyers' Feedback, Electronics

X axis: The number of days the seller has left a feedback before the buyer.
Y axis: Percentage of positive feedbacks over the total feedback left at the same day.

### 2.3.2 Feedback Adoption

In addition to addressing the retaliation problem, the policy change has other interesting and noteworthy effects. One observation is that sellers are leaving feedback for buyers more often, as shown in Figure 2.3. Specifically, data on electronics shows that following May 2008, the likelihood of sellers leaving feedback has increased relative to the number of feedback left by buyers. In addition, Figure 2.3 shows that buyers are leaving feedback less often. To explain this observation, we should first note that sellers often ask buyers to leave feedback prior to the sellers. After the policy change, many sellers leave feedback earlier than buyers (since retaliation incentives do not exist anymore). This implies that the buyers do not feel compelled to leave feedback and hence the number of feedback left by buyers is lower.

### 2.3.3 Timing of Feedback

As for the timing of feedback, it is observed that sellers leave feedback earlier than buyers. This observation is shown in Table 2.2. As Table 2.2 shows, sellers significantly move first in terms of leaving feedback after the end of the transactions. Additionally, as shown in Figure 2.4, both buyers and sellers leave feedback faster as a result of the policy change.

Table 2.2: Timing of Feedback
Sellers Left Feedback before Buyers

| | Before Policy Change | After Policy Change |
|---|---|---|
| Electronics | 29% | 51% |

### 2.3.4 Reduction of Adverse Selection

One of the main observations that we want to emphasize is the behavior of buyers as a result of the change in policy. One would expect that buyers should be more honest in their feedbacks and therefore leave negative feedback for sellers more often since they are

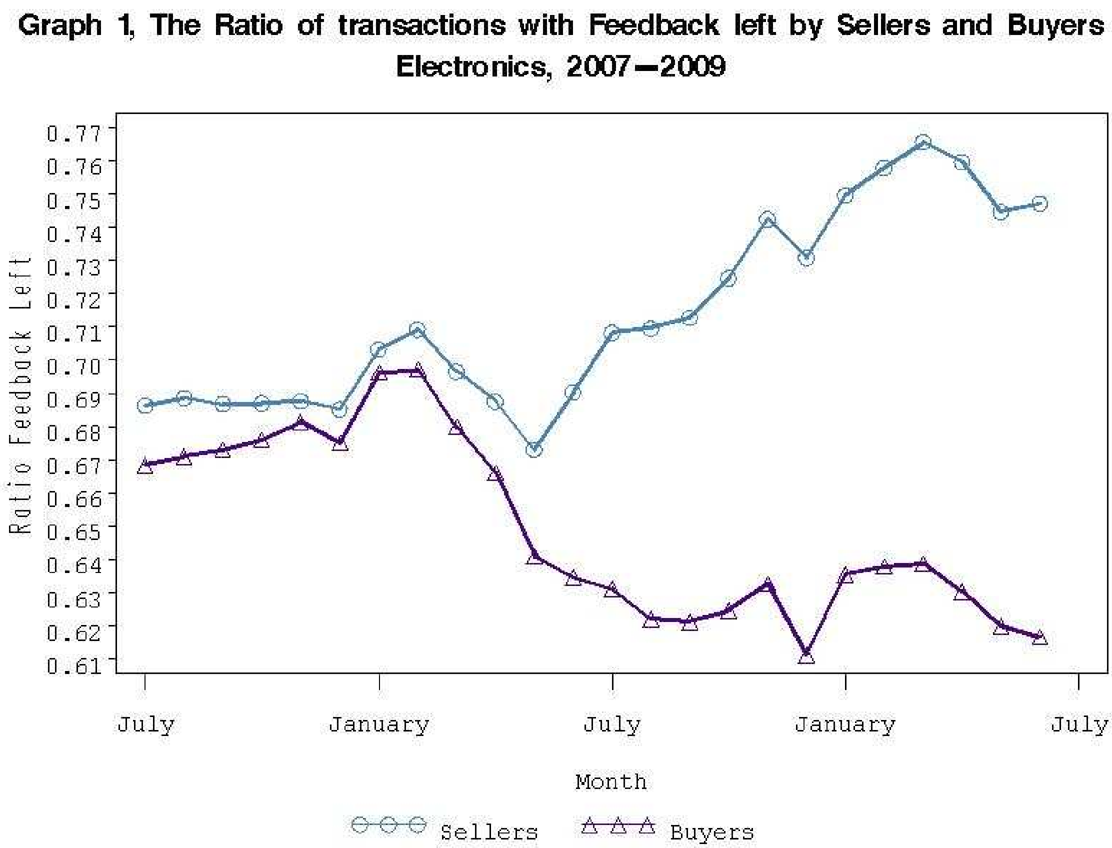



Figure 2.3: Adoption Rate for Feedbacks, Electronics

X axis: Time period. The policy Change happens in May 2008.
Y axis: Share of transactions with a feedbacks from the sellers and buyers.

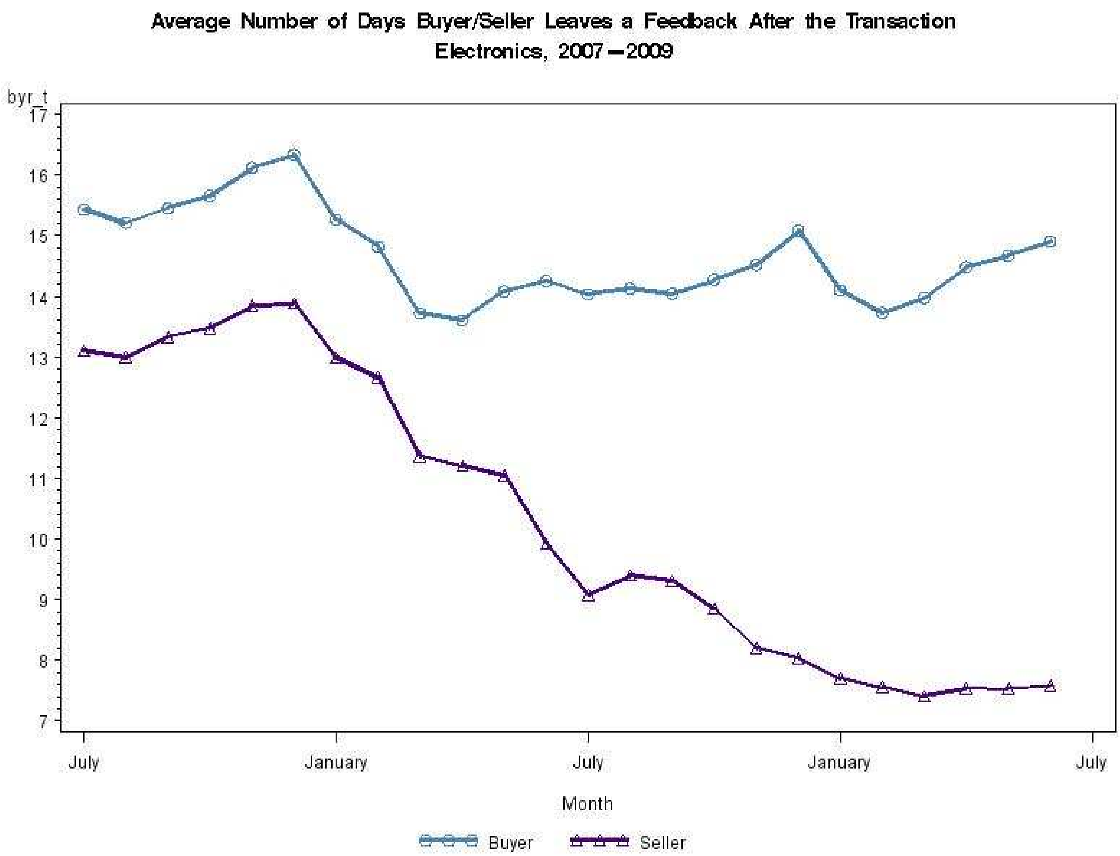



Figure 2.4: Timing of the Feedback, Comparing to The End of Transaction, Electronics

X axis: The time period. The policy Change happens in May 2008.
Y axis: The number of days participants in the market wait before leaving a feedback.

not threatened by retaliation any more. However, we observe that the buyers leave positive feedback for sellers more often.

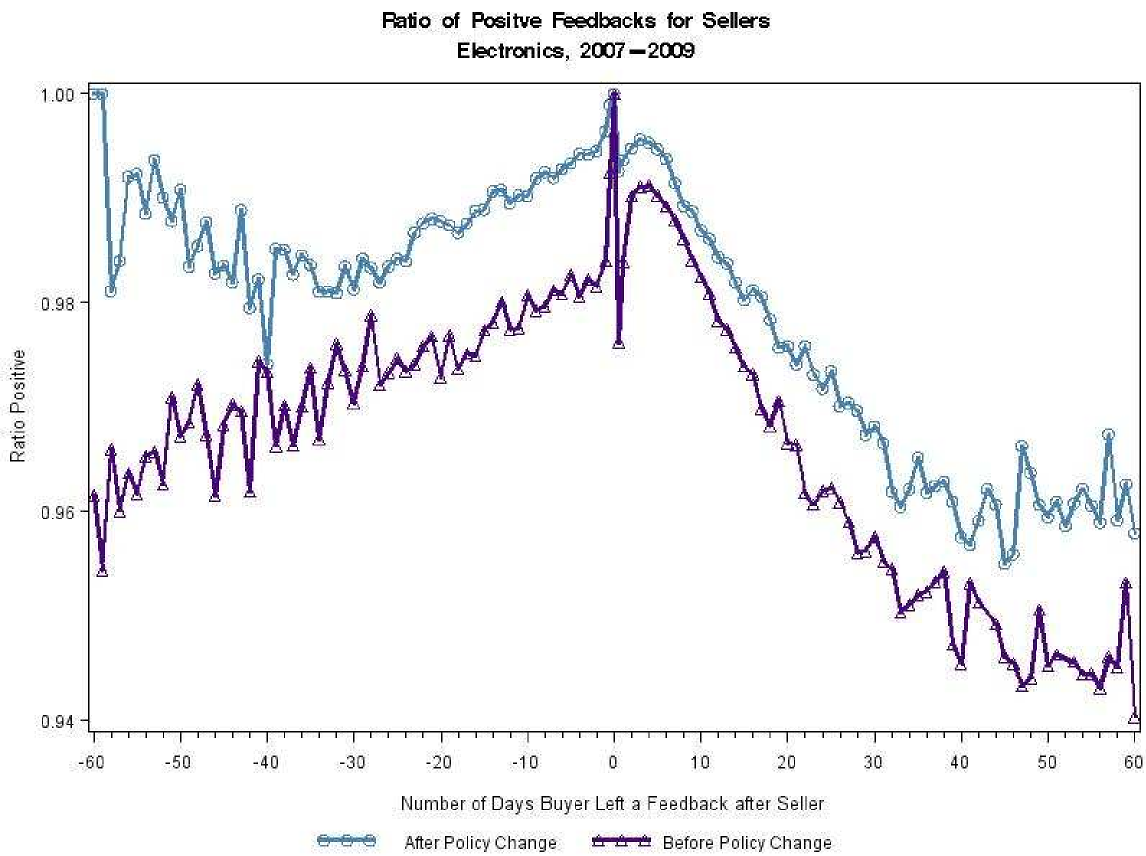



Figure 2.5: Share of Positive Feedback for Sellers, Electronics

X axis: The number of days the buyer has left a feedback after the seller.
Y axis: Percentage of positive feedbacks over the total feedback left at the same day by buyers for sellers.

Figure 2.5 plots the share of positive feedback for sellers as a function of the time difference between the time that sellers and buyers left feedback. It can be seen that independent of the time difference, buyers are consistently leaving more positive feedback after the policy change comparing to their actions before the policy change. A puzzling observation is that when buyers leave feedback earlier than sellers, i.e., negative values on the x-axis, they leave positive feedback more often. This is puzzling because retaliation incentives are removed by the new policy change and it is expected for buyers to be more honest and emphasize their true experience on the marketplace.

Finally, the above data analysis shows that the effect of the policy change is more pronounced in the electronics category. This suggests that reputation has a bigger effect in resolving adverse selection problems and hence this market is more prone to adverse selection.

There can be few different justifications for this observation. First, forcing sellers not to leave a negative feedback eliminates retaliation from buyers side as well. Buyers will no longer leave a negative feedback in response to a negative feedback from sellers which can increase the share of positive feedback. This justification implies that before the policy change buyers and sellers were involved in tit-for-tat type strategies and the policy change takes this option away from them. But this explanation is not consistent with the fact that buyers leave positive feedback more often for sellers even when they are the party who leaves the feedback first.

A second justification can be that buyers get a positive benefit by receiving a positive feedback, the only choice for sellers after the policy change, but this effect does not explain the actions of the buyers when they are leaving feedback first.

A third explanation can be the change in the market share of business sellers, or powerseller in the market over time. The bigger sellers tend to perform better on eBay and they tend to get higher percentage of positive feedbacks. Figure 2.6 shows the percentage of the positive feedbacks for powersellers in the market as a function of number of days buyers left a feedback after they have received feedback from the seller. Another justification is that, when sellers are unable to leave negative feedback, the sellers loose a tool that helped them in staying in the market and staying successful, for example low quality sellers can no-longer sustain in the market. This will force sellers to spend more

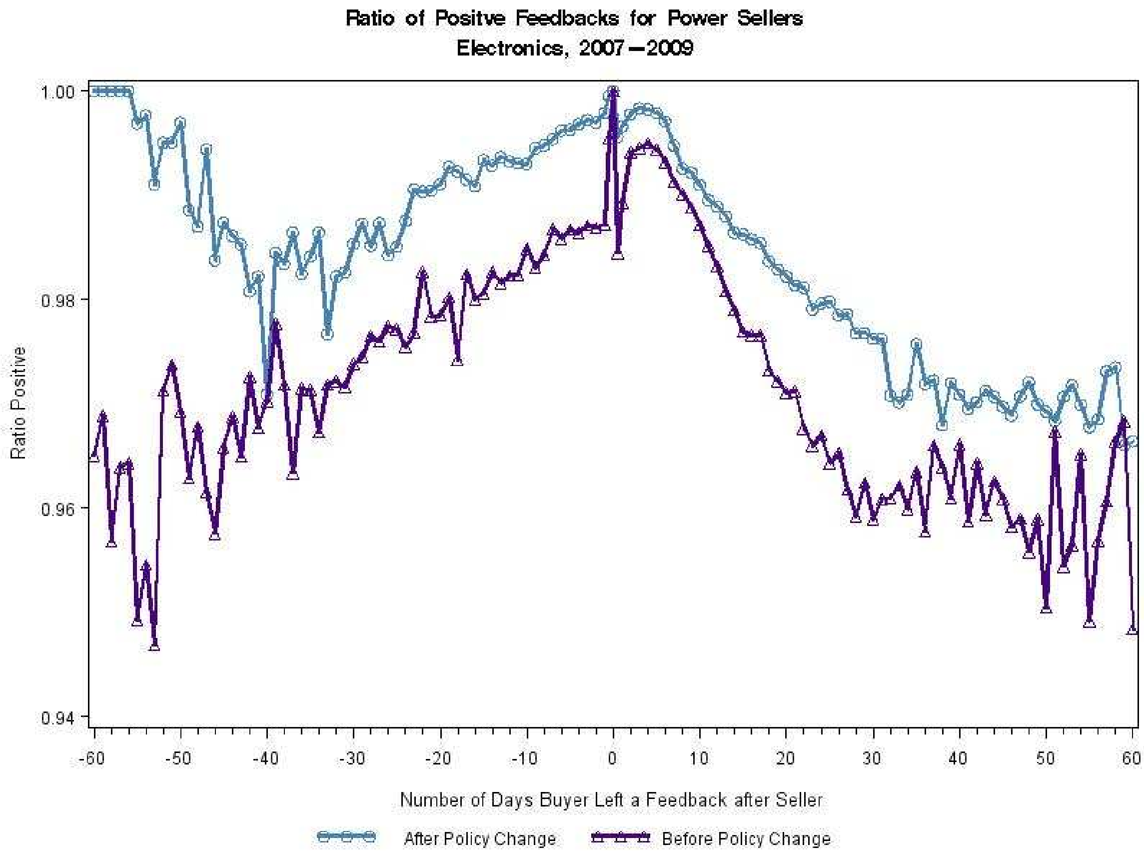



Figure 2.6: Share of Positive Feedback for Powersellers .

X axis: The number of days the buyer has left a feedback after the seller.
Y axis: Percentage of positive feedbacks over the total feedback left at the same day by buyers for sellers.
Powersellers are more reputable sellers on eBay which get a badge on the website, the tend to be bigger sellers in the market.

effort when dealing with the buyers, which further implies that the market shifts toward higher quality sellers and as a result the number of positive feedback would increase. The following section introduces a model consistent with the observation in this section.

### 2.3.5 Sellers' Performance

If our claim in the past section is true and the change in the feedback policy leads sellers to be higher quality sellers, we should see the effects in other determinants of the market performance. There are few other variables that show sellers' performance in the market: disputes, detailed sellers' ratings, and charge backs. Buyers can dispute a transaction directly to eBay. Detailed sellers' rating works the same way as feedback but it is anonymous and sellers cannot see what the buyers have left them. Buyers can rate sellers in five different sections and in each of them they should give sellers a rating from 1 to 5. Buyers can get a charged back from their credit card company, bank, and/or PayPal if they argue the item was not as described or was not shipped to them. Table 2.3 shows the frequency of each of these actions.

As it is shown in the Table 2.3 the sellers performance has improved in all of these categories and the market has moved to a less prone to adverse selection market.

Table 2.3: Sellers' Performance, Electronics

| | Before Policy Change | After Policy Change |
|---|---|---|
| Disputes | 4.2% | 3.5% |
| Low DSR | 2.1% | 1.7% |
| Charge Back | 0.04% | 0.02% |

## 2.4 Model

In this section, we develop a model to explain the sellers and buyers actions before and after the policy change. This a dynamic model where sellers and buyers can move in different time periods.

For simplicity, we assume that the outcome of the transaction is exogenous and is the same for the seller and the buyer: $x \in \{0, 1\}$, where 0 represents a bad outcome for the transaction and 1 represents a good outcome. Buyers can have three different actions in response to the outcome of the transaction: $y \in \{-1, 0, 1\}$, where 0 represents leaving no feedback, 1 leaving a positive feedback, and $-1$ leaving a negative feedback for the seller. Sellers, similarly, have three actions: $z \in \{-1, 0, 1\}$, where 0 represents leaving no feedback, 1 leaving a positive feedback, and $-1$ leaving a negative feedback for the buyer.

The buyer's utility from leaving and receiving feedback is characterized by: $\alpha_{xyz}$ which is a function of the outcome of transaction, buyer's action, and seller's action. Similarly, the seller's utility from the feedback stage is characterized by: $\beta_{xyz}$, where $x$, $y$, and $z$ are as explained. $\alpha_{x0z}$ is the disutility the buyers get from leaving a feedback and $\beta_{xy0}$ is the disutiliy sellers get from leaving a feedback.

Sellers and buyers have a chance to leave feedback for the other party over time. The utility buyers get from each action can be described as follows:

$$u_b = \begin{cases} \alpha_{x,-1,z} - \alpha_{x0z}, & \text{Buyer plays } -1 \\ 0, & \text{Buyer plays } 0 \\ \alpha_{x1z} - \alpha_{x0z}, & \text{Buyer plays } 1 \end{cases}$$

and for sellers we similarly have:

$$u_s = \begin{cases} \beta_{x,y,-1} - \beta_{xy0}, & \text{Seller plays } -1 \\ 0, & \text{Seller plays } 0 \\ \beta_{xy1} - \beta_{xy0}, & \text{Seller plays } 1 \end{cases}$$

where:

$$\begin{aligned} \alpha_{xyz} &= \bar{\alpha}_{xyz} + \eta_y \qquad y = -1, 0, 1 \\ \beta_{xyz} &= \bar{\beta}_{xyz} + \gamma_z \qquad z = -1, 0, 1 \end{aligned}$$

For each outcome there is a permanent component: $\bar{\alpha}$ and $\bar{\beta}$ which is known to both players in the market. There is a random component of players' payoff, which is only known to them but not to their opponents: $\eta_y$ and $\gamma_z$.

### 2.4.1 Timing

At $t = 0$ the outcome of the transactions is realized to both buyer and seller: $x \in \{0, 1\}$. At $t = 1$, seller has a chance to move first and leave a feedback for the buyer. At $t = 2$, buyer can observe the action of the seller and leave a feedback at this stage. At $t = 3$, the seller has a final chance to leave a feedback for the buyer if he has not moved in the first period to leave a feedback.

### 2.4.2 Buyers' Problem

At the beginning of the period 2, the buyer observes if the seller has left her a feedback and if the feedback is positive or negative. At this stage they have a chance to leave a feedback for the other player. For simplicity, we assume that the buyers are myopic. When they decide to act at period 2 they take the action of the seller at period 1 as his final action and does not consider the possibility of the seller to move in the period 3.

Assuming the buyer is myopic, the optimal strategy of the buyer is simple, she, given $x$ and $z$, will choose the action that maximizes her payoff, and she compares the three values:

$$\max\{\alpha_{x,-1,z}, \alpha_{x0z}, \alpha_{x1z}\}$$

### 2.4.3 Sellers' Problem

After the transaction: $x \in \{0, 1\}$, the seller has the option of leaving a feedback for the buyer either in the first period or in the third period. If the seller leaves a feedback in period 1 he cannot change his feedback. But if he decides to wait he can leave a feedback at the third period.

If the seller has not left a feedback in period 1, his optimal strategy in the third period is simple. The buyer has moved in period 2 and the seller should choose the action that maximizes his utility given $x$ and $y$, the buyer's action:

$$\max\{\beta_{x,y,-1}, \beta_{xy0}, \beta_{xy1}\}$$

The sellers optimal strategy in the first period depends on their expectation about the buyer's shock. Given the optimal strategy of the buyer and himself in the next two periods, the seller's expected utility given each strategy in the period 1 is explained in the following theorem:

**Theorem 2.1** *Sellers expected utility from playing actions* 0*,* 1*, and* $-1$ *in the first period is:*

$$u_s = \begin{cases} \frac{\sum_y \exp(\bar{\alpha}_{xyz}) \max\{\beta_{x,y,-1}, \beta_{xy0}, \beta_{xy1}\}}{\sum_y \exp(\bar{\alpha}_{xyz})} - \beta_{xy0}, & \textit{Seller plays } z = 0 \\ \frac{\sum_y \exp(\bar{\alpha}_{xyz}) \beta_{xyz}}{\sum_y \exp(\bar{\alpha}_{xyz})} - \beta_{xy0}, & \textit{Seller plays } y \in \{-1, 1\} \end{cases}$$

**Proof.** After the seller plays $y$ in the first period, the buyer choose an action that maximizes her utility:

$$\max\{\alpha_{x,-1,z}, \alpha_{x0z}, \alpha_{x1z}\}$$

where $\alpha_{xyz} = \bar{\alpha}_{xyz} + \eta_y$ where $\eta_y$ is an iid random variable with extreme value distribution. The share of time that the action $i$ is maximized is:

$$\frac{\exp(\bar{\alpha}_{xyz})}{\sum_k \exp(\bar{\alpha}_{xkz})}$$

And if the buyer plays $i$ the sellers return will depends on his strategy in the first period. If the seller has already moved and $y \in \{-1, 1\}$ then the return in $\beta_{xyz}$, otherwise the seller has another chance to maximize. Therefore his return will be: $\max\{\beta_{x,y,-1}, \beta_{xy0}, \beta_{xy1}\}$. ■

### 2.4.4 After Policy Change

After the policy change the sellers no longer have the option of leaving a negative feedback. The sellers will have only two choices at period 1 and period 3. But it does not change their strategy only they choose the choice that maximizes their utility.

I assume that the percentage of the positive transactions, the ones with $x = 1$ could change as a result of the policy change. The probability of different outcomes using both before the policy change and after policy change can help us identify this game.

### 2.4.5 Characterization of Equilibrium

In this section we characterize the equilibrium further by making a few assumptions on the relationships between the parameters of sellers' and buyers' return from feedback. These assumptions will enable us to analytically show sellers and buyers reaction to the change in the policy.

**Assumption 2.2** *Buyers' average return from the feedback is supermodular.*

$$\bar{\alpha}_{xij} + \bar{\alpha}_{xi'j'} \leq \bar{\alpha}_{x,\max\{i,i'\},\max\{j,j'\}} + \bar{\alpha}_{x,\min\{i,i'\},\min\{j,j'\}}$$

**Assumption 2.3** *Buyers' and sellers' return are increasing with their rivals' action.*

Assumption 2.2 implies the increasing differences on the returns for buyers. This assumption is similar to concavity. Assumption 2.3 implies that players benefit from a positive feedback while they do not like a negative feedback from their opponent.[7]

**Theorem 2.4** *Given Assumption 2.2, the probability that the buyer plays* 1 *is increasing in the seller's action in period 1.*

**Proof.** Assume that $j > j'$ is the seller's actions in the two case, we show that the probability that the buyer plays one is higher for $z = j$.

$$\frac{\exp(\bar{\alpha}_{x1j})}{\exp(\bar{\alpha}_{x,-1,j}) + \exp(\bar{\alpha}_{x0j}) + \exp(\bar{\alpha}_{x1j})} \geq \frac{\exp(\bar{\alpha}_{x1j'})}{\exp(\bar{\alpha}_{x,-1,j'}) + \exp(\bar{\alpha}_{x0j'}) + \exp(\bar{\alpha}_{x1j'})}$$
$$\Rightarrow \exp(\bar{\alpha}_{x1j} + \bar{\alpha}_{x,-1,j'}) + \exp(\bar{\alpha}_{x1j} + \bar{\alpha}_{x0j'}) \geq \exp(\bar{\alpha}_{x1j'} + \bar{\alpha}_{x,-1,j}) + \exp(\bar{\alpha}_{x1j'} + \bar{\alpha}_{x0j})$$

[7] We consider these assumptions to be reasonable assumptions. When it comes to estimation in the next chapter we do not impose these assumptions to the returns of buyers and sellers.

The above is true given the Assumption 2.2. ∎

**Theorem 2.5** *Given Assumption 2.2, the percentage of time the buyer plays* $-1$ *is decreasing in the seller's action in period 1.*

**Proof.** Assume that $j < j'$ is the seller's actions in the two case, we show that the probability that the buyer plays $-1$ is higher for $z = j$.

$$\frac{\exp(\bar{\alpha}_{x,-1,j})}{\exp(\bar{\alpha}_{x,-1,j}) + \exp(\bar{\alpha}_{x0j}) + \exp(\bar{\alpha}_{x1j})} \geq \frac{\exp(\bar{\alpha}_{x,-1,j'})}{\exp(\bar{\alpha}_{x,-1,j'}) + \exp(\bar{\alpha}_{x0j'}) + \exp(\bar{\alpha}_{x1j'})}$$

$$\Rightarrow \exp(\bar{\alpha}_{x,-1,j} + \bar{\alpha}_{x0j'}) + \exp(\bar{\alpha}_{x,-1,j} + \bar{\alpha}_{x1j'}) \geq \exp(\bar{\alpha}_{x,-1,j'} + \bar{\alpha}_{x0j}) + \exp(\bar{\alpha}_{x,-1,j'} + \bar{\alpha}_{x1j})$$

The above is true given the Assumption 2.2. ∎

The intuition behind Theorems 2.4 and 2.5 is that the buyers' return from playing 1 increases in the sellers' action, and their return from playing $-1$ decreases in their opponents' actions. Therefore they would prefer to play 1 more often and $-1$ less often in the equilibrium. These two theorems leads to another result which stated in the Theorem 2.6:

**Theorem 2.6** *Given Assumptions 2.2 and 2.3, the sellers will not leave a negative feedback in the first period.*

**Proof.** I argue that it is always weakly better for the seller to leave no feedback at the first period rather than leaving a negative feedback. Given Theorem 2.4, the percentage of the time the buyer plays 1 is less if the seller plays $-1$ instead of 0. Moreover, Theorem 2.5 shows that buyers play $-1$ more often after the seller plays $-1$. Also note that by Assumption 2.3, sellers return in increasing in the buyers actions. ∎

**Theorem 2.7** *Given Assumptions 2.2 and 2.3, after the policy change, the sellers choose to leave positive feedback in the first period more often.*

**Proof.** Theorem 2.6 shows that before the policy change sellers would not choose to leave negative feedback in the first period. When comparing the before policy change and after policy change we should see if the incentive for leaving positive feedback in the first period has increased or not. The buyer's optimal action in the second period, given the seller's action in the first period, does not depend on the policy, since the buyer does not take into account the future behavior of the seller into account. The seller's expected utility from leaving no feedback before the policy change, on the left, is bigger than the expected utility of leaving no feedback after the policy change, on the right, as characterized below.

$$\frac{\sum_y \exp(\bar{\alpha}_{xyz}) \max\{\beta_{x,y,-1}, \beta_{xy0}, \beta_{xy1}\}}{\sum_y \exp(\bar{\alpha}_{xyz})} - \beta_{xy0} \geq \frac{\sum_y \exp(\bar{\alpha}_{xyz}) \max\{\beta_{xy0}, \beta_{xy1}\}}{\sum_y \exp(\bar{\alpha}_{xyz})} - \beta_{xy0}$$

This will decrease the incentive to leave no feedbacks while keep the level of incentives to leave a positive feedback at the same level which leads to more positive feedbacks left in the first period. ■

The above theorem is consistent with the data we observe in section 2.3, after the policy change sellers will move before the buyers more often. The intuition behind the proof is that after the policy change sellers' incentives to wait and leave feedback in the third period after the buyer has moved will decrease, because their options to move in the third period will decrease.

## 2.5 Identification Strategy

The identification of the model is possible when using both before and after the policy change data. We assume that the returns that the sellers and buyers receive does not change after and before the policy change: $\bar{\alpha}$ and $\bar{\beta}$ will stay fixed over time. The fact that we have two sets of observations from the seller and buyers actions will give us identification power.

We need to have information about the percentage of the transactions with a positive outcome: $P(x = 1)$, before and after the policy change. We assume that if the transaction has a undesirable outcome for the buyers they will report it through one of the mechanisms given by eBay, either through leaving negative feedback or by filing a dispute through eBay.[8]

- Step1. Start from an initial guess for $\alpha$ and $\beta$
- Step 2. Given $\alpha$ and $\beta$, find $\alpha'$ that satisfy the buyer's choice
- Step 3. Given $\alpha'$ and $\beta$, find $\beta'$ that satisfy the seller's choice
- Step 4. If the difference between the new parameters and starting parameters are bigger than $\epsilon$ go to step 2 using the new parameters.

This is a fixed point strategy. We start from an initial guess for the parameters and we find the true parameter for buyer, seller, and the economy in different steps. We stop the process when the new parameters are close to the old parameters. Each of the steps is explained in details below:

*Step 1.* Different initial values are chosen in this step.

*Step 2.* Given $\alpha$, $\beta$ and $P(x=1)$, $\alpha'$ is estimated as follows:
In the data, we observe the probability that the buyer plays $i$ after observing that the seller has played $j$. We do not observe $x$. Therefore, we can see:

$$P(Y=y, Z_1=z) = \sum_x \frac{\exp(\bar{\alpha}_{xyz})}{\sum_y \exp(\bar{\alpha}_{xyz})} P(X=x)P(Z=z|X=x)$$

By assuming that we have an estimate of $P(X=x)$ and $P(Z=z|X=x)$ can be estimated given $\alpha$ and $\beta$. For each value of $X=x$, $Y=y$, and $Z=z$, the above equation is valid for both before and after policy change. Which will result in a two equation two unknowns problem.

*Step 3.* Given $\alpha'$ and $\beta$, $\beta'$ is estimated using an optimization strategy:
$\alpha'$ estimated in *Step 2* gives us the optimal strategy of the buyers in $T=2$: $P(Y=y|X=x, Z=z)$. Having this values and starting from the $\beta$ as an initial value, we simulate the sellers strategies at $T=1$ and $T=3$ using random draws for $\gamma$. Doing so we can calculate

[8] We are working on the possible mechanism to identify this probability directly from the outcome of the game.

the simulated values for $P_s(Z_1 = z)$ and $P_s(Z_3 = z|Y = y)$. The next step is to get the distance between these values and the probabilities from the data.

$$d(P_s(Z_1 = z), P_s(Z_1 = z)) + d(P_s(Z_3 = z|Y = y), P_s(Z_3 = z|Y = y))$$

Where the function $d$ takes the quadratic difference between each component of the two matrix and adds these numbers together. Last step is to use an optimization mechanism to minimize the distance function by changing the value of $\beta$, the optimal value will give us $\beta'$.

*Step 4.* We take the distance between starting values of $\alpha$ and $\beta$ and the new estimates $\alpha'$ and $\beta'$ and if this distance is higher than an $\epsilon$ we try these steps again using the new estimates.

## 2.6 Results

In this section we first show the moments we used to do the estimation as explained in the previous chapter then we report the estimated values for $\bar{\alpha}$ and $\bar{\beta}$. Table 2.4 shows the percentage values for $P(Z_1 = z)$, probabilities that the sellers play different actions in period 1 before and after policy change. Table 2.5 shows the percentage of the time buyers play each action conditional on the sellers' actions in period 1, before and after policy change. Table 2.6 shows the percentage of the time sellers play each action after the buyer has moved, before and after policy change.

Table 2.4: Sellers' Actions in the First Period, Electronics

| | Before Policy Change | After Policy Change |
|---|---|---|
| Negative | 0.3% | – |
| No Feedback | 74.3% | 53% |
| Positive | 25.4% | 47% |

As mentioned before in order to identify $\bar{\alpha}$ and $\bar{\beta}$ we made some normalization assumption. First of all we assume that $\alpha_{x0z} = 0$ and also $\beta_{xy0} = 0$. Moreover, since after the policy change sellers can no longer leave negative feedback we only have one data point for the response of the buyers after a negative feedback from sellers. To be able to do

Table 2.5: Buyers' Actions in the Second Period
Before Policy Change

| | Negative | No Feedback | Positive |
|---|---|---|---|
| $Z_1 = -1$ | 10% | 87% | 3% |
| $Z_1 = 0$ | 2% | 32% | 66% |
| $Z_1 = 1$ | 1% | 31% | 68% |

After Policy Change

| | Negative | No Feedback | Positive |
|---|---|---|---|
| $Z_1 = 0$ | 1% | 37% | 62% |
| $Z_1 = 1$ | 0.8% | 37% | 62.2% |

Table 2.6: Sellers' Actions in the Third Period
Before Policy Change

| | Negative | No Feedback | Positive |
|---|---|---|---|
| $Y = -1$ | 37% | 58% | 5% |
| $Y = 0$ | 0.3% | 80.4% | 19.3% |
| $Y = 1$ | 0.04% | 10.49% | 89.47% |

After Policy Change

| | Negative | No Feedback | Positive |
|---|---|---|---|
| $Y = -1$ | – | 88% | 12% |
| $Y = 0$ | – | 57% | 43% |
| $Y = 1$ | – | 15% | 85% |

the identification we assume that when the sellers do not leave a negative feedback when $x = 1$: $\beta_{1y,-1}$ is a big negative number.[9]

Table 2.7 reports the values for $\bar{\alpha}$ and Table 2.8 reports the values for $\bar{\beta}$. These values are consistent with our observation from data, buyers leave more negative feedbacks when they have received a negative feedback but these values are much more drastically higher for sellers. Also we can separate sellers and buyers actions after a transaction with a good outcome and a bad outcome. Buyers tend to leave more positive feedback when the outcome of the transaction is good.

We can use the results in this section to the counterfactual estimations. There are few different potential policy analysis that we are planning to study in the future.

Table 2.7: Buyers' Utility Values

| $x = 1$ | $z = -1$ | $z = 0$ | $z = 1$ |
|---|---|---|---|
| $Y = -1$ | -2.15 | -3.32 | -3.15 |
| $Y = 0$ | 0 | 0 | 0 |
| $Y = 1$ | -3.24 | 0.52 | 0.79 |
| $x = 0$ | $z = -1$ | $z = 0$ | $z = 1$ |
| $Y = -1$ | -2.15 | 0.11 | -3 |
| $Y = 0$ | 0 | 0 | 0 |
| $Y = 1$ | -3.2 | 3.2 | -1.7 |

## 2.7 Conclusion

Online platforms and applications increasingly rely on user-generated content. Such platforms are prone to adverse selection. Typically some form of reputation mechanism is used to sustain the market and avoid deterioration. eBay is one of the earliest such commerce

[9] In the identification procedure we set this number to -100.

Table 2.8: Sellers' Utility Values

$x = 1$

| | $z=-1$ | $z=0$ | $z=1$ |
|---|---|---|---|
| $Y=-1$ | -100 | 0 | -0.02 |
| $Y=0$ | -100 | 0 | -1.17 |
| $Y=1$ | -100 | 0 | 2.74 |

$x = 0$

| | $z=-1$ | $z=0$ | $z=1$ |
|---|---|---|---|
| $Y=-1$ | 9.42 | 0 | -49.33 |
| $Y=0$ | -0.02 | 0 | -0.03 |
| $Y=1$ | 0.62 | 0 | 1.874 |

platform. With its adoption of a simple feedback mechanism eBay has thrived and expanded over years. Yet, we do not have a good understanding of the incentives behind the participation of buyers and sellers in the the reputation mechanisms on eBay. In this paper we develop a dynamic interaction of buyers and sellers after the end of transaction to capture these incentives.

To identify the model we use a change regarding reputation mechanism: no negative feedback from the sellers. We first show the main effects of this policy change on the sellers and buyers behavior and then we show that the model is consistent with the observations from data.

The policy we study is a change to the symmetric two-sided feedback mechanism. This policy was implemented to remove the incentives to retaliate from seller side. We show that these policy changes, can cause buyers and sellers to significantly change their behavior on leaving feedback. The policy change has affected the rate at which buyer and sellers leave feedback and also the timing of it; sellers leave feedback more often while buyers leave feedback less often, and sellers leave their feedback sooner. This shows that the participants in the market take into account feedback ratings and they will actively react to the changes in rules.

Another noteworthy observation is the increase in positive feedback left by buyers after the first policy change. Buyers leave more positive feedback; both when they leave the feedback first and when they leave the feedback after the sellers. This observation can be explained by a better experience of buyers in the marketplace as a result of higher level of trust.

For future work, we want to use the estimated model to predict the effect of different counterfactuals on the market, the welfare implications of different changes on the users. One of the counterfactuals we want to study is the effect of eBay giving extra incentives to the participants in the market to leave a feedback. The other counterfactual is the effect of changing the rules to have anonymous feedbacks from users. A third counterfactual is the effect of having an automatic positive feedback for sellers if no feedback was received from buyers in the given time.

# Bibliography

[Aguirregabiria and Mira, 2007] Aguirregabiria, V. and Mira, P. (2007). Sequential estimation of dynamic discrete games. *Econometrica*, 75(1):1–53.

[Akerlof, 1970] Akerlof, G. (1970). The market for "lemons": quality uncertainty and the market mechanism. *The quarterly journal of economics*, pages 488–500.

[Anderson and Magruder, 2011] Anderson, M. and Magruder, J. (2011). Learning from the crowd: Regression discontinuity estimates of the effects of an online review database. *The Economic Journal*.

[Bajari et al., 2007] Bajari, P., Benkard, C., and Levin, J. (2007). Estimating dynamic models of imperfect competition. *Econometrica*, 75(5):1331–1370.

[Bajari and Hortaçsu, 2004] Bajari, P. and Hortaçsu, A. (2004). Economic Insights from Internet Auctions. *Journal of Economic Literature*, 42:457–486.

[Bar-Isaac and Tadelis, 2008] Bar-Isaac, H. and Tadelis, S. (2008). Seller reputation. *Foundations and Trends® in Microeconomics*, 4(4):273–351.

[Berry, 1994] Berry, S. (1994). Estimating discrete-choice models of product differentiation. *The RAND Journal of Economics*, pages 242–262.

[Board and Meyer-ter Vehn, 2010] Board, S. and Meyer-ter Vehn, M. (2010). A reputational theory of firm dynamics.

[Board and Meyer-ter Vehn, 2011] Board, S. and Meyer-ter Vehn, M. (2011). Reputation for quality. *UCLA Working Paper*.

[Bolton et al., 2009] Bolton, G., Greiner, B., and Ockenfels, A. (2009). Engineering trust-reciprocity in the production of reputation information. *Working Paper Series in Economics*.

[Bolton and Ockenfels, 2008] Bolton, G. and Ockenfels, A. (2008). *The Limits of Trust in Economic Transactions-Investigations of Perfect Reputation Systems*. CESifo, Center for Economic Studies & Ifo Institute for economic research.

[Brown and Morgan, 2006] Brown, J. and Morgan, J. (2006). Reputation in online auctions: The market for trust. *California Management Review*, 49(1):61–82.

[Cabral and Hortacsu, 2009] Cabral, L. and Hortacsu, A. (2009). The dynamics of seller reputation: Theory and evidence from eBay.

[Chari et al., 2010] Chari, V., Shourideh, A., and Zetlin-Jones, A. (2010). Adverse selection, reputation and sudden collapses in secondary loan markets.

[Chevalier and Mayzlin, 2006] Chevalier, J. and Mayzlin, D. (2006). The effect of word of mouth on sales: Online book reviews. *Journal of Marketing Research*, 43:345–354.

[Dellarocas, 2002] Dellarocas, C. (2002). Goodwill hunting: An economically efficient online feedback mechanism for environments with variable product quality. *Agent-Mediated Electronic Commerce IV. Designing Mechanisms and Systems*, pages 93–112.

[Dellarocas, 2005] Dellarocas, C. (2005). Reputation mechanisms. *Handbook on Economics and Information Systems*.

[Dellarocas and Wood, 2008] Dellarocas, C. and Wood, C. (2008). The sound of silence in online feedback: Estimating trading risks in the presence of reporting bias. *Management Science*, 54(3):460–476.

[Ericson and Pakes, 1995] Ericson, R. and Pakes, A. (1995). Markov-perfect industry dynamics: A framework for empirical work. *The Review of Economic Studies*, 62(1):53.

[Ganesan et al., 2008] Ganesan, K., Sundaresan, N., and Deo, H. (2008). Mining tag clouds and emoticons behind community feedback. In *Proceeding of the 17th international conference on World Wide Web*, pages 1181–1182. ACM.

[Holmström, 1999] Holmström, B. (1999). Managerial incentive problems: A dynamic perspective. *The Review of Economic Studies*, 66(1):169.

[Hopenhayn, 1992] Hopenhayn, H. (1992). Entry, exit, and firm dynamics in long run equilibrium. *Econometrica*, 60(5):1127–1150.

[Hopenhayn and Prescott, 1992] Hopenhayn, H. and Prescott, E. (1992). Stochastic monotonicity and stationary distributions for dynamic economies. *Econometrica: Journal of the Econometric Society*, pages 1387–1406.

[Hotz and Miller, 1993] Hotz, V. and Miller, R. (1993). Conditional choice probabilities and the estimation of dynamic models. *The Review of Economic Studies*, 60(3):497.

[Houser et al., 2006] Houser, D., Wooders, J., and Hall, M. (2006). Reputation in auctions: Theory, and evidence from eBay. *Journal of Economics & Management Strategy*, 15:353–369.

[Jovanovic, 1982] Jovanovic, B. (1982). Selection and the Evolution of Industry. *Econometrica: Journal of the Econometric Society*, pages 649–670.

[Kollock, 1999] Kollock, P. (1999). The production of trust in online markets. *Advances in group processes*, 16(1):99–123.

[Kreps and Wilson, 1982] Kreps, D. and Wilson, R. (1982). Reputation and imperfect information. *Journal of Economic Theory*, 27(2):253–279.

[Lewis, 2011] Lewis, G. (2011). Asymmetric Information, Adverse Selection and Online Disclosure: The Case of eBay Motors. *American Economic Review*. Forthcoming.

[Lu et al., 2009] Lu, Y., Zhai, C., and Sundaresan, N. (2009). Rated aspect summarization of short comments. In *Proceedings of the 18th international conference on World wide web*, pages 131–140. ACM.

[Luca, 2011] Luca, M. (2011). Reviews, reputation, and revenue: The case of yelp. com. *Harvard Business School Working paper 12*, 16:12–016.

[Lucking-Reiley et al., 2007] Lucking-Reiley, D., Bryan, D., Prasad, N., and Reeves, D. (2007). Pennies from ebay: The determinants of price in online auctions. *The Journal of Industrial Economics*, 55(2):223–233.

[Mailath and Samuelson, 2001] Mailath, G. and Samuelson, L. (2001). Who wants a good reputation? *Review of Economic Studies*, 68(2):415–441.

[Masclet and Pénard, 2008] Masclet, D. and Pénard, T. (2008). Is the eBay feedback system really efficient? An experimental study. *Economics Working Paper Archive (University of Rennes 1 & University of Caen)*.

[Melnik and Alm, 2002] Melnik, M. and Alm, J. (2002). Does a seller's ecommerce reputation matter? Evidence from eBay auctions. *Journal of Industrial Economics*, pages 337–349.

[Milgrom and Roberts, 1982] Milgrom, P. and Roberts, J. (1982). Predation, reputation, and entry deterrence. *Journal of economic theory*, 27(2):280–312.

[Pakes et al., 2004] Pakes, A., Ostrovsky, M., and Berry, S. (2004). Simple estimators for the parameters of discrete dynamic games (with entry/exit samples).

[Pesendorfer and Schmidt-Dengler, 2003] Pesendorfer, M. and Schmidt-Dengler, P. (2003). Identification and estimation of dynamic games.

[Reiley et al., 2007] Reiley, D., Bryan, D., Prasad, N., Reeves, D., Hall, M., Engines, K., Inc, T., and San Mateo, C. (2007). Pennies from eBay: The determinants of price in online auctions. *Journal of Industrial Economics*, 55(2):223–233.

[Resnick and Zeckhauser, 2002] Resnick, P. and Zeckhauser, R. (2002). Trust among strangers in Internet transactions: Empirical analysis of eBay's reputation system. *Advances in Applied Microeconomics: A Research Annual*, 11:127–157.

[Resnick et al., 2006] Resnick, P., Zeckhauser, R., Swanson, J., and Lockwood, K. (2006). The value of reputation on eBay: A controlled experiment. *Experimental Economics*, 9(2):79–101.

[Rust, 1987] Rust, J. (1987). Optimal replacement of gmc bus engines: An empirical model of harold zurcher. *Econometrica: Journal of the Econometric Society*, pages 999–1033.

[Saeedi, 2011] Saeedi, M. (2011). Reputation and Adverse Selection, Theory and Evidence from eBay. Working Paper.

[Shen and Sundaresan, 2011] Shen, Z. and Sundaresan, N. (2011). ebay: an e-commerce marketplace as a complex network. In *Proceedings of the fourth ACM international conference on Web search and data mining*, pages 655–664. ACM.

[Topkis, 1998] Topkis, D. (1998). *Supermodularity and complementarity*. Princeton Univ Pr.

[Weintraub et al., 2006] Weintraub, G., Benkard, C., and Van Roy, B. (2006). Oblivious equilibrium: A mean field approximation for large-scale dynamic games. *Advances in Neural Information Processing Systems*, 18:1489.

[Weintraub et al., 2008] Weintraub, G., Benkard, C., and Van Roy, B. (2008). Markov perfect industry dynamics with many firms. *Econometrica*, 76(6):1375–1411.

[Yamagishi and Matsuda, 2002] Yamagishi, T. and Matsuda, M. (2002). Improving the lemons market with a reputation system: An experimental study of internet auctioning. *University of Hokkaido, Tech. Rep., May*.

[Yin, 2003] Yin, P. (2003). Information Dispersion and Auction Prices.

# Appendix A

# Appendix to Chapter 1

## A.1 Proof of Proposition 1

**Proposition A.1** *Suppose that the solution to the functional equation (1.2) is unique. Then, the policy function $q^*(\eta, \gamma, \mathbf{q}_-)$ is increasing in quality $\eta$.*

**Proof.** Recall the functional equation (1.2) in the Section 1.3.3. 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 $\phi^s$ does not affect future values. Hence, I can define the following period profit function:

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

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 $(\eta, q)$ and in $(\eta, q_{-i})$ for $i = 1, 2, 3$.

**Step 2.** I show that the solution to the functional equation (1.2) is supermodular in $(\eta, q_{-i})$ for $i = 1, 2, 3$.

**Step 3.** The policy function is increasing in quality $\eta$.

**Step 1.** Here I show that $\hat{\pi}(\cdot)$ is supermodular in $(\eta, q)$ and in $(\eta, q_{-i})$ for $i = 1, 2, 3$. To show it for $(\eta, q)$, I need to show that when $q' > q$ and $\eta' > \eta$ then:

$$\hat{\pi}\left(\eta', \gamma, q, \mathbf{q}_-\right) - \hat{\pi}\left(\eta, \gamma, q, \mathbf{q}_-\right) \leq \hat{\pi}\left(\eta', \gamma, q', \mathbf{q}_-\right) - \hat{\pi}\left(\eta, \gamma, q', \mathbf{q}_-\right)$$

To formulate the above differences, note that given the analysis in Section 1.3.5 and the formula (1.4), price for any seller is given by:

$$p\left(q, \phi^p, \phi^s, x\right) = f\left(q\right) + \beta_p \phi^p + \beta_s \phi^s + \beta_{ps} \phi^s \phi^p + \beta_x x$$

for some function of $q$, $f\left(q\right)$. This implies that:

$$\begin{aligned}
\hat{\pi}\left(\eta', \gamma, q, \mathbf{q}_-\right) \quad - \quad & \hat{\pi}\left(\eta, \gamma, q, \mathbf{q}_-\right) = \\
& \left[\beta_p \phi^p\left(\eta', \gamma, \mathbf{q}_-\right) + \beta_s \phi^s\left(\eta', q, \gamma, \mathbf{q}_-\right) + \beta_{ps} \phi^s\left(\eta', q, \gamma, \mathbf{q}_-\right) \phi^p\left(\eta', \gamma, \mathbf{q}_-\right)\right. \\
& \left. - \beta_p \phi^p\left(\eta, \gamma, \mathbf{q}_-\right) - \beta_s \phi^s\left(\eta, q, \gamma, \mathbf{q}_-\right) - \beta_{ps} \phi^s\left(\eta, q, \gamma, \mathbf{q}_-\right) \phi^p\left(\eta, \gamma, \mathbf{q}_-\right)\right] q \\
& - \left[\phi^s\left(\eta', q, \gamma, \mathbf{q}_-\right) - \phi^s\left(\eta, q, \gamma, \mathbf{q}_-\right)\right] c^s
\end{aligned}$$

Moreover, in the solution to the auxiliary problem (A.1),

$$\phi^s\left(\eta, \gamma, q, \mathbf{q}_-\right) = 1 \text{ iff } \left(\beta_s + \beta_{sp} \phi^p\left(\eta, \gamma, \mathbf{q}_-\right)\right) q \geq c^s \text{ and } \eta + \gamma \geq \mu^s$$

where $\phi^p(\cdot)$ is given by (1.3). Note that both of the function $\phi^p$ and $\phi^s$ are increasing in their arguments. I prove the supermodularity claim by showing the following inequalities:

$$\beta_p\left[\phi^p\left(\eta', \gamma, \mathbf{q}_-\right) - \phi^p\left(\eta, \gamma, \mathbf{q}_-\right)\right] q \leq \beta_p\left[\phi^p\left(\eta', \gamma, \mathbf{q}_-\right) - \phi^p\left(\eta, \gamma, \mathbf{q}_-\right)\right] q'$$

$$\begin{aligned}
& \phi^s\left(\eta', q, \gamma, \mathbf{q}_-\right)\left(\left[\beta_s + \beta_{ps} \phi^p\left(\eta', \gamma, \mathbf{q}_-\right)\right] q - c^s\right) - \\
& \qquad \phi^s\left(\eta, q, \gamma, \mathbf{q}_-\right)\left(\left[\beta_s + \beta_{ps} \phi^p\left(\eta, \gamma, \mathbf{q}_-\right)\right] q - c^s\right) \\
& \leq \phi^s\left(\eta', q', \gamma, \mathbf{q}_-\right)\left(\left[\beta_s + \beta_{ps} \phi^p\left(\eta', \gamma, \mathbf{q}_-\right)\right] q' - c^s\right) - \\
& \qquad \phi^s\left(\eta, q', \gamma, \mathbf{q}_-\right)\left(\left[\beta_s + \beta_{ps} \phi^p\left(\eta, \gamma, \mathbf{q}_-\right)\right] q' - c^s\right)
\end{aligned}$$

The top inequality is simply coming from the fact that $\phi^p(\eta,\gamma,\mathbf{q}_-)$ is increasing in $\eta$. Moreover, to show that the bottom inequality is satisfied I can only focus on a case where $\phi^s(\eta,q,\gamma,\mathbf{q}_-) < \phi^s(\eta',q,\gamma,\mathbf{q}_-)$ and $\phi^s(\eta,q',\gamma,\mathbf{q}_-) = \phi^s(\eta',q',\gamma,\mathbf{q}_-) = 1$. Note that the LHS of the bottom inequality is given by

$$\left(\left[\beta_s + \beta_{ps}\phi^p\left(\eta',\gamma,\mathbf{q}_-\right)\right]q - c^s\right)$$

Moreover, since $\phi^s(\eta,q,\gamma,\mathbf{q}_-) = 0$, I must have that $[\beta_s + \beta_{ps}\phi^p(\eta,\gamma,\mathbf{q}_-)]q - c^s < 0$. Therefore, the following expression is higher than the LHS of the bottom inequality

$$\begin{aligned}&\left(\left[\beta_s + \beta_{ps}\phi^p\left(\eta',\gamma,\mathbf{q}_-\right)\right]q - c^s\right) - \left(\left[\beta_s + \beta_{ps}\phi^p\left(\eta,\gamma,\mathbf{q}_-\right)\right]q - c^s\right)\\ &= \beta_{ps}\left[\phi^p\left(\eta',\gamma,\mathbf{q}_-\right) - \phi^p\left(\eta,\gamma,\mathbf{q}_-\right)\right]q\end{aligned}$$

Moreover, since $\phi^s(\eta,q',\gamma,\mathbf{q}_-) = \phi^s(\eta',q',\gamma,\mathbf{q}_-) = 1$, the RHS of the inequality is given by

$$\beta_{ps}\left[\phi^p\left(\eta',\gamma,\mathbf{q}_-\right) - \phi^p\left(\eta,\gamma,\mathbf{q}_-\right)\right]q'$$

and hence the inequality is satisfied by the fact that $\phi^p(\eta,\gamma,\mathbf{q}_-)$ is an increasing function of $\eta$. Hence, I have shown that $\hat{\pi}(\eta,\gamma,q,\mathbf{q}_-)$ is supermodular in $(\eta,q)$.

To show supermodularity in $(\eta,q_{-i})$, note that $\hat{\pi}(\cdot)$ is only a function of $q_{-1}+q_{-2}+q_{-3}$ and therefore, I only need to show supermodularity with respect to $q_{-1}$. That is, I need to show that if $\eta' > \eta$ and $q'_{-1} > q_{-1}$

$$\begin{aligned}&\hat{\pi}\left(\eta,\gamma,q,q'_{-1},q_{-2},q_{-3}\right) - \hat{\pi}\left(\eta,\gamma,q,q_{-1},q_{-2},q_{-3}\right)\\ &\leq \hat{\pi}\left(\eta',\gamma,q,q'_{-1},q_{-2},q_{-3}\right) - \hat{\pi}\left(\eta',\gamma,q,q_{-1},q_{-2},q_{-3}\right)\end{aligned}$$

The argument will be similar to the previous case. Any changes in profits, as a result of a change in $q_{-1}$, come from changes in $\phi^p$. That is for the above differences not to be zero, I need to have $q_{-1}+q_{-2}+q_{-3} < 3Q \leq q'_{-1}+q_{-2}+q_{-3}$. Moreover, since all of the rules specified above for becoming powerseller and store are cutoff rules for $\eta+\gamma$, whenever $\phi^p\left(\eta,\gamma,q,q'_{-1},q_{-2},q_{-3}\right) > \phi^p\left(\eta,\gamma,q,q_{-1},q_{-2},q_{-3}\right)$, I must have $\phi^p\left(\eta',\gamma,q,q'_{-1},q_{-2},q_{-3}\right) > \phi^p\left(\eta',\gamma,q,q_{-1},q_{-2},q_{-3}\right)$. Hence, the above inequality must hold. This concludes our proof of supermodularity of $\hat{\pi}$.

**Step 2.** Here I show that the solution to the functional equation above is supermodular. To do so, since the set of continuous supermodular functions is closed, it is sufficient to show that the transformation associated with the Bellman equation preserves supermodularity. That is for any function $v(\eta, \gamma, \mathbf{q}_-)$ that is supermodular in $(\eta, q_{-i})$, the following function is also supermodular in $(\eta, q_{-i})$:

$$\hat{v}(\eta, \gamma, \mathbf{q}_-) = \max_q \hat{\pi}(\eta, \gamma, q, \mathbf{q}_-) + \beta \int v\left(\eta, \gamma', (q, q_{-1}, q_{-2})\right) g(\gamma)\, d\gamma$$

To show this, note that the function

$$\tilde{v}(\eta, \gamma, q, \mathbf{q}_-) = \hat{\pi}(\eta, \gamma, q, \mathbf{q}_-) + \beta \int v\left(\eta, \gamma', (q, q_{-1}, q_{-2})\right) g(\gamma)\, d\gamma$$

is supermodular. Therefore, by Lemma 1 in [Hopenhayn and Prescott, 1992], the function $\hat{v}(\eta, \gamma, \mathbf{q}_-)$ is also supermodular. This concludes step 2.

**Step 3.** Given the steps above, I know that the objective function in the above Bellman equation is supermodular in $(\eta, q)$ and $(\eta, q_{-i})$. Now suppose to the contrary to the proposition , that there exists $\eta' > \eta$ such the optimal solution under $(\eta', \gamma, \mathbf{q}_-)$, $q'$, is lower than the optimal solution under $(\eta, \gamma, \mathbf{q}_-)$, $q$. Given $\gamma, \mathbf{q}_-$, define the following function

$$f(\eta, q) = \hat{\pi}(\eta, \gamma, q, \mathbf{q}_-) + \beta \int v\left(\eta, \gamma', (q, q_{-1}, q_{-2})\right) g(\gamma)\, d\gamma$$

which is supermodular in $(\eta, q)$. Hence,

$$f(\eta, q) - f\left(\eta, q'\right) \leq f\left(\eta', q\right) - f\left(\eta', q'\right)$$

By optimality of $q$ under $\eta$ and uniqueness of the policy function, the LHS of the above inequality is positive. Hence, so is the RHS. This contradicts with the fact that $q'$ is optimal under $\eta'$. Hence, the policy function $q^*(\eta, \gamma, \mathbf{q}_-)$ must be increasing in $\eta$. Similarly, I can show that it is increasing in $q_{-i}$. ■

## A.2 Regression Discontinuity Design for Powerseller Status

eBay has used powerseller status as a signaling method and to certify some sellers over the rest. This status shows the sellers' ability for high volume of trade on the website and

Table A.1: Reasons for Removal from Powerseller Program

| Reasons for Removal | | Percent |
|---|---|---|
| Low Sales | 788084 | 75.56 |
| Poor Feedback | 65808 | 6.31 |
| Business Account Violation | 839 | 0.08 |
| Past Due Account | 74415 | 7.13 |
| Below Specific Standard | 87291 | 8.37 |
| TOTAL REMOVAL | 1043054 | |

their consistent positive track record over time. To qualify for the powerseller program as mentioned in the data section, sellers need to have a high feedback score and also a high volume of sales, in addition to following eBay rules to qualify for powerseller status.

After becoming a powerseller, a seller's volume of trade and quality get checked every month. If any of the sellers' characteristics, volume of trade or quality, is below the threshold set by eBay, the seller gets either a warning from eBay or get removed from the program. Table A.1 shows the reasons that powersellers got removed from powerseller program according to eBay. In 75% of occasions the reason for removal from the program was related to the low volume of trade; the other reasons for removal usually relates to quality of sellers, for example, low feedback score, business account violation.

To observe the effects of powerseller status on sellers' volume of trade and profit, I track sellers who became powersellers for the first time in their life cycle in the eBay marketplace. I look at all sellers who became powersellers for the first time in January 2008 and also all the sellers who lost their powerseller status during the same period of time.

I follow these sellers from a year before they became powersellers and a year after they became powerseller and I get all the listings they have during this two year period. I normalize the time period that sellers gained powerseller status or lost their powerseller status to period 0 and I assume each period is a 15-day interval. Negative periods represent the time periods before the change and positive periods represent the time periods after the change.

I expect to observe an increase in sale and revenue for sellers when they become powersellers. Graph A.1 shows the average prices of items sold by sellers who became powerseller for the first time. Each point in the graph shows the average prices of all sales done by sellers in the study during that period. Period 0, as mentioned, is the date that these sellers became powersellers and the graph tracks sellers one year before and after the change. We cannot observe a definitive increase in price as a result of becoming a powerseller in Graph A.1. It may be because sellers will try to sell more items to meet the requirements; therefore, the powersellers may try to sell cheaper items to stay above threshold. To study the effect of powerseller status on price further I control for the value of the objects which is hard to do when we look at all the items on the eBay website.[1]

Figure A.2 shows the total number of transactions in each period for sellers who become powersellers. The total number of transactions has a positive trend with a break at period zero. Figure A.3 shows the average revenue for these sellers. The revenue for the sellers increase after they became powersellers. So overall the powerseller status has a positive effect on sellers' revenue after they enroll in the program.

Figure A.4 shows the average price of items sold by sellers who lost their powerseller status in January 2008. There is a decreasing trend for price of sellers who lose their powerseller status. The effect of decreased price will magnify for these sellers when we add the effects of losing powerseller status on the quantity of items they can sell on the market. Figure A.5 shows s sharp decline on the the average number of items these sellers can sell each period after they lose their powerseller status. The combination of the two effects is shown in Figure A.6 as an even sharper decline in revenue of these sellers.

[1] The items on the eBay dataset usually do not have a good measure for value, they are not very well categorized at this point.


Figure A.1: Average Final Price, Sellers Who Became Powersellers in Period 0

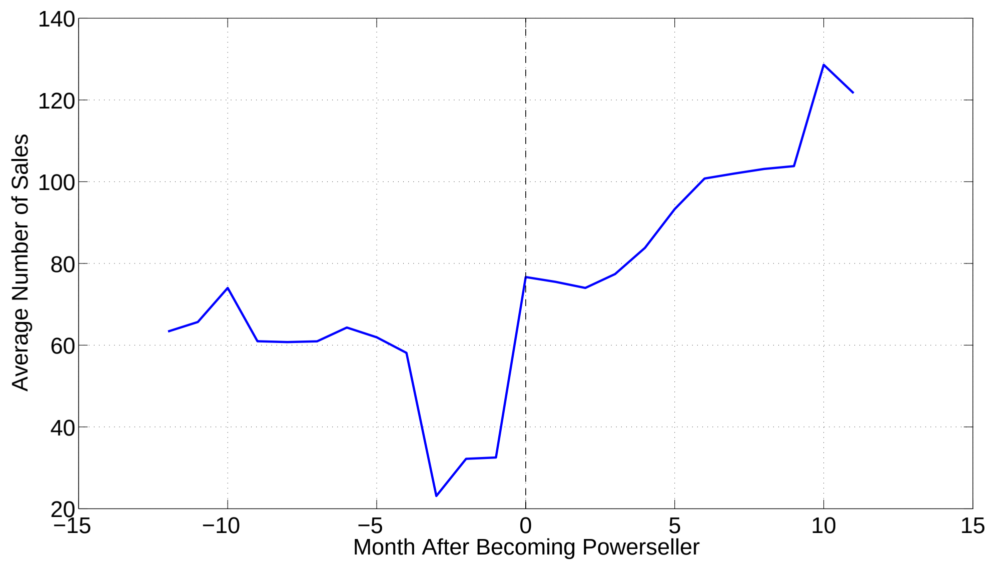



Figure A.2: Number of Sales, Sellers Who Became Powersellers in Period 0

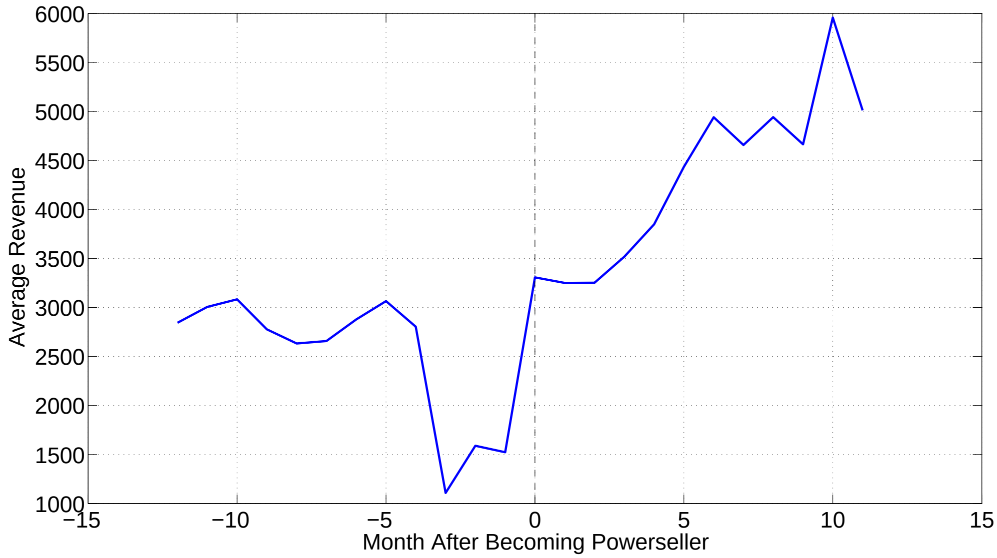



Figure A.3: Average Revenue, Sellers Who Became Powersellers in Period 0


Figure A.4: Average Prices, Sellers Who Lost Their Powerseller Status in Period 0


Figure A.5: Number of Sales, Sellers Who Lost Their Powerseller Status in Period 0

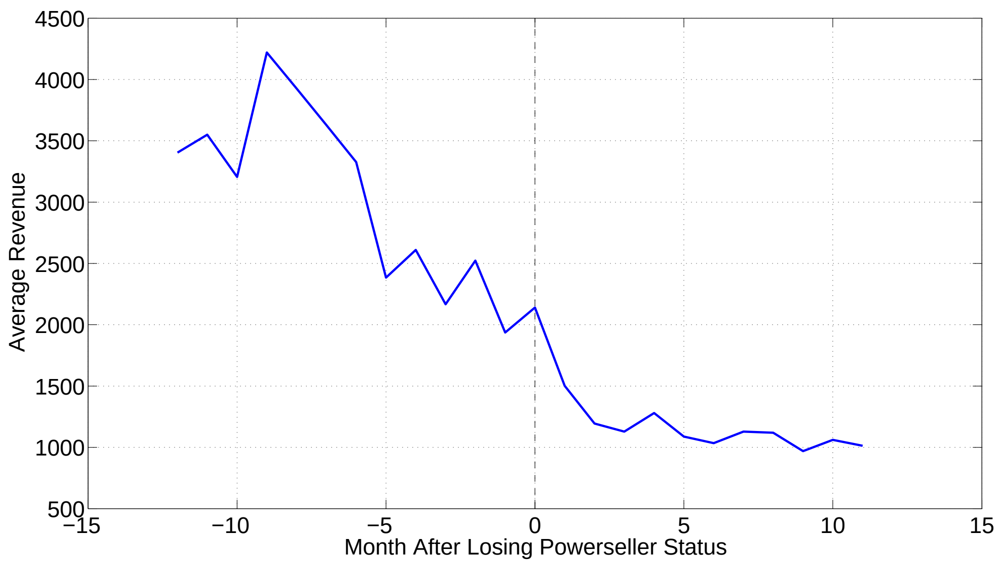



Figure A.6: Average Revenue, Sellers Who Lost Their Powerseller Status in Period 0

## A.3 Demand Function Estimation Robustness

As mentioned in the data section, I estimate a structural demand function based on the buyers' utility function. In this section I run a simple OLS regression of price over additional characteristics of sellers and characteristics of items sold by them to show the robustness of the results when it comes to the effect of powerseller status and store status. The results in this section shows that when we control for the sellers with a high levels of sales we still see the positive effect of powerseller and store status. Moreover, when we control for the condition of the items sold, if they are new or used, we see that the powerseller and store still have a positive effect with a higher effect when we are only looking at used items.

Table A.2 reports the OLS results. The first column includes only the seller characteristics. In addition to powerseller status and store status, I also include other sellers' characteristics– number of days a seller has being active in the market which I will call age, amount of information entered by sellers on the listing page, if sellers have provided their phone number in their listing page, existence of "About-me" page,[2] and if the listing was in a fixed price format: "Buy in Now."

Table A.2 shows that being a powerseller or a registered store on eBay has a positive effect on the price. The coefficient of variable age shows that being on the eBay website for one additional year will give a seller about a three-dollar boost in the final price. Additionally, having more text has a positive effect on the price.[3] The "About-me" coefficient has a negative effect on the price. The reason behind this effect is that the option of having an "About-me" web page was more popular during the starting days of eBay. However, iPod is a newer sub category on eBay and most of the big sellers in this category are newer sellers; therefore, the coefficient on the "About-me" variable picks up the effect of older sellers versus newer sellers.

---

[2] Sellers can enter a web page called "About-me" and explain their business on this page for buyers to see.

[3] Note that the two variables, text and description size, represent different measures of information entered on the web page. They are highly correlated and having only one of them in the regression results in a positive coefficient.

Column II represents the coefficients when we only consider the characteristics of the items sold on eBay. As expected, if the condition of the iPod is new or refurbished, it results in a price premium. Also a higher level of internal memory, gigabyte of internal memory, of the iPods results in higher prices. I also added dummy variables for different brands of iPods which also have the expected coefficients.

Column III of Table A.2 includes both seller and item characteristics. The effect of powerseller status and store status is lower compared to the results in column I. This shows that powersellers and stores tend to sell better quality products and when we control for item characteristics the effect of powerseller status and store status diminish. However, the effect of these reputation related variables is still very high; the premium on powerseller status is 29 dollars which is about 15% of the price of the items sold in this category, iPods. The premium on Store status is about $8.6 which is about 5% of the price of items in this category.

Column IV represents only sellers with more than 25 sales in my sample. The effect of store and powerseller status declines when we only focus on this sample of data. This change in the effect of the reputational signals arises because we are in a pool of sellers with a higher volume of sale, and therefore higher experience. So the signal for these sellers is less important than for smaller sellers with lower volume of sales.

Buyers take reputation of sellers more into account when they are buying an item with a less pre-determined value, i.e. used goods versus new goods. Table A.3 shows the regression results for used versus new items. Powerseller status and store status have remarkably higher effects for a used item versus a new item. The market value of a new iPod is pre-determined. In this case buyers may be more confident to buy from a more trustworthy seller because they expect better shipping experience and better communications, or in the extreme cases: fear of receiving a used iPod as a new one from a less reputable seller. On the other hand, when buying a used iPod there are many aspects of the item quality that can be misrepresented by a fraudulent seller; therefore, the value of reputation in the market becomes very high.

In the last column of Table A.3, I include feedback score and feedback percentage to the regressors in the third column. After the end of a transaction seller and buyer can leave each other feedback. These feedback can be positive, negative, or neutral. Feedback percentage is percentage of positive feedback among all feedback that a seller has received. Feedback score is number of positive feedback received minus number of negative feedback received by a seller. Many of the papers written about the effects of reputation of eBay only focus on feedback scores and feedback percentage of the sellers. This regression shows that, controlling for powerseller status and store status, these two variables do not have a high effect on final price. Feedback percentage is a number between 0 and 100, with an average of 99% for the active sellers' on the market. When comparing a seller with perfect feedback percentage, 100% feedback percentage, and a seller in 25% percentile, 98% feedback percentage, the effect of feedback percentage on price is $0.75. The coefficient on feedback score is negative when we control for the size of the sellers.

Table A.2: Regression Result for iPod

| | Price | | | |
|---|---|---|---|---|
| | I | II | III | IV |
| Powerseller | 80.04 | | 29.26 | 9.29 |
| | (0.75) | | (0.81) | (0.31) |
| Store | 40.67 | | 8.62 | 4.31 |
| | (0.65) | | (0.42) | (0.36) |
| Age | 0.01 | | 0.008 | 0.005 |
| | (0.00) | | (0.0002) | (0.0001) |
| Phone | 21.19 | | 0.68 | -5.39 |
| | (0.72) | | (0.50) | (0.40) |
| Text | -0.003 | | -0.001 | -0.0004 |
| | (8.0E-05) | | (4.3E-05) | (4E-05) |
| Description | 0.001 | | 0.0004 | 0.0002 |
| | (2.4E-05) | | (1.4E-05) | (1.2E-05) |
| About Me | -14.89 | | -15.07 | -5.69 |
| | (0.91) | | (0.53) | (0.37) |
| Buy it Now | 26.20 | | 36.62 | 5.38 |
| | (3.26) | | (2.09) | (0.54) |
| New | | 31.02 | 29.43 | 48.27 |
| | | (0.52) | (0.55) | (0.34) |
| Refurbished | | 11.04 | 3.32 | 12.42 |
| | | (0.39) | (0.45) | (0.32) |
| Internal Memory | | 1.43 | 1.40 | 1.41 |
| | | (0.02) | (0.02) | (0.008) |
| Nano | | 87.72 | 46.16 | 64.89 |
| | | (0.34) | (1.05) | (0.30) |
| Mini | | 52.02 | 3.62 | 34.02 |
| | | (0.60) | (1.25) | (0.46) |
| Classic | | 44.33 | 2.50 | 24.94 |
| | | (1.80) | (1.98) | (0.70) |
| Shuffle | | 27.82 | -14.37 | 7.07 |
| | | (0.31) | (1.05) | (0.34) |
| Touch | | 195.66 | 152.11 | 179.61 |
| | | (0.52) | (1.17) | (0.41) |
| Video | | 58.99 | 19.69 | 43.63 |
| | | (1.16) | (1.50) | (0.58) |
| $R^2$ | 0.72 | 0.93 | 0.94 | 0.92 |

I: Only Sellers' Characteristics
II: Only Item Characteristics,
III: Both Sellers' and item Characteristics,
IV: Both Sellers' and item Characteristics, Sellers > 25 Sales
Standard errors in parentheses
* $p<0.05$ ** $p<0.01$ *** $p<0.001$

Table A.3: Regression Result for iPod, New vs. Used Items

| | Price | | | |
|---|---|---|---|---|
| | Original | New Items | Used Items | Feedback |
| Powerseller | 29.27*** | 6.37*** | 35.95*** | 17.41*** |
| | (0.82) | (1.51) | (0.91) | (0.80) |
| Store | 8.62*** | 0.36 | 11.53*** | 15.49*** |
| | (0.42) | (1.09) | (0.45) | (0.42) |
| Age | 0.008*** | 0.01*** | 0.006*** | 0.008*** |
| | (0.0002) | (0.0007) | (0.0002) | (0.0002) |
| Phone | 0.68 | -7.84*** | 5.58*** | -3.95*** |
| | (0.49) | (1.28) | (0.58) | (0.46) |
| Description Size | 0.0004*** | -0.0001* | 0.0006*** | 0.0005*** |
| | (0.00001) | (0.00004) | (0.00002) | (0.00001) |
| Text | -0.001*** | 0.001*** | -0.002*** | -0.001*** |
| | (0.00004) | (0.0001) | (0.00004) | (0.00004) |
| About me | -15.07*** | -1.16 | -13.75*** | -15.77*** |
| | (0.53) | (1.59) | (0.55) | (0.48) |
| Buy it Now | 36.62*** | -31.29*** | 66.24*** | 24.95*** |
| | (2.09) | (3.24) | (2.33) | (2.07) |
| New | 29.43*** | | | 36.96*** |
| | (0.55) | | | (0.54) |
| Refurbished | 3.31*** | | 0.51 | 15.13*** |
| | (0.44) | | (0.47) | (0.41) |
| Internal Memory | 1.40*** | 1.55*** | 1.36*** | 1.48*** |
| | (0.017) | (0.07) | (0.08) | (0.02) |
| Nano | 46.16*** | 101.40*** | 41.17*** | 38.79*** |
| | (1.051) | (2.67) | (1.14) | (0.99) |
| Mini | 3.62** | | -4.41** | -1.76 |
| | (1.25) | | (1.35) | (1.28) |
| Classic | 2.50 | 45.35*** | -0.23 | -12.87*** |
| | (1.98) | (8.16) | (2.05) | (1.98) |
| Shuffle | -14.37*** | 19.41*** | -14.00*** | -15.40*** |
| | (1.06) | (2.37) | (1.15) | (0.98) |
| Touch | 152.1*** | 209.0*** | 147.6*** | 147.1*** |
| | (1.17) | (3.28) | (1.26) | (1.09) |
| Video | 19.69*** | 106.8*** | 16.17*** | 15.63*** |
| | (1.49) | (4.56) | (1.54) | (1.43) |
| Feedback Percentage | | | | 0.37*** |
| | | | | (0.006) |
| Feedback Score | | | | -0.00006*** |
| | | | | (0.000002) |
| $R^2$ | 0.94 | 0.96 | 0.94 | 0.95 |

Standard errors in parentheses
* p<0.05 ** p<0.01 *** p<0.001

# Appendix B

# Appendix to Chapter 2

Appendix includes graphs related to the Collectibles and Stamps categories. The results here are very similar to the data presented in the main body of the paper and is presented as a robustness check. Also some additional graphs related to our work are left in this section.

## B.1 Data: Collectibles and Stamps

Table B.1: Sellers' Actions, Collectibles and Stamps

Sellers' Actions After a Negative Feedback from Buyers

| | Positive | Negative | Neutral | No Feedback |
|---|---|---|---|---|
| Collectibles | 6% | 38% | 1% | 55% |
| Stamps | 7% | 33% | 1% | 59% |

Table B.2: Timing of Feedback
Sellers Left Feedback before Buyers

| | Before Policy Change | After Policy Change |
|---|---|---|
| Collectibles | 38.00% | 46.00% |
| Stamps | 53.00% | 59.00% |

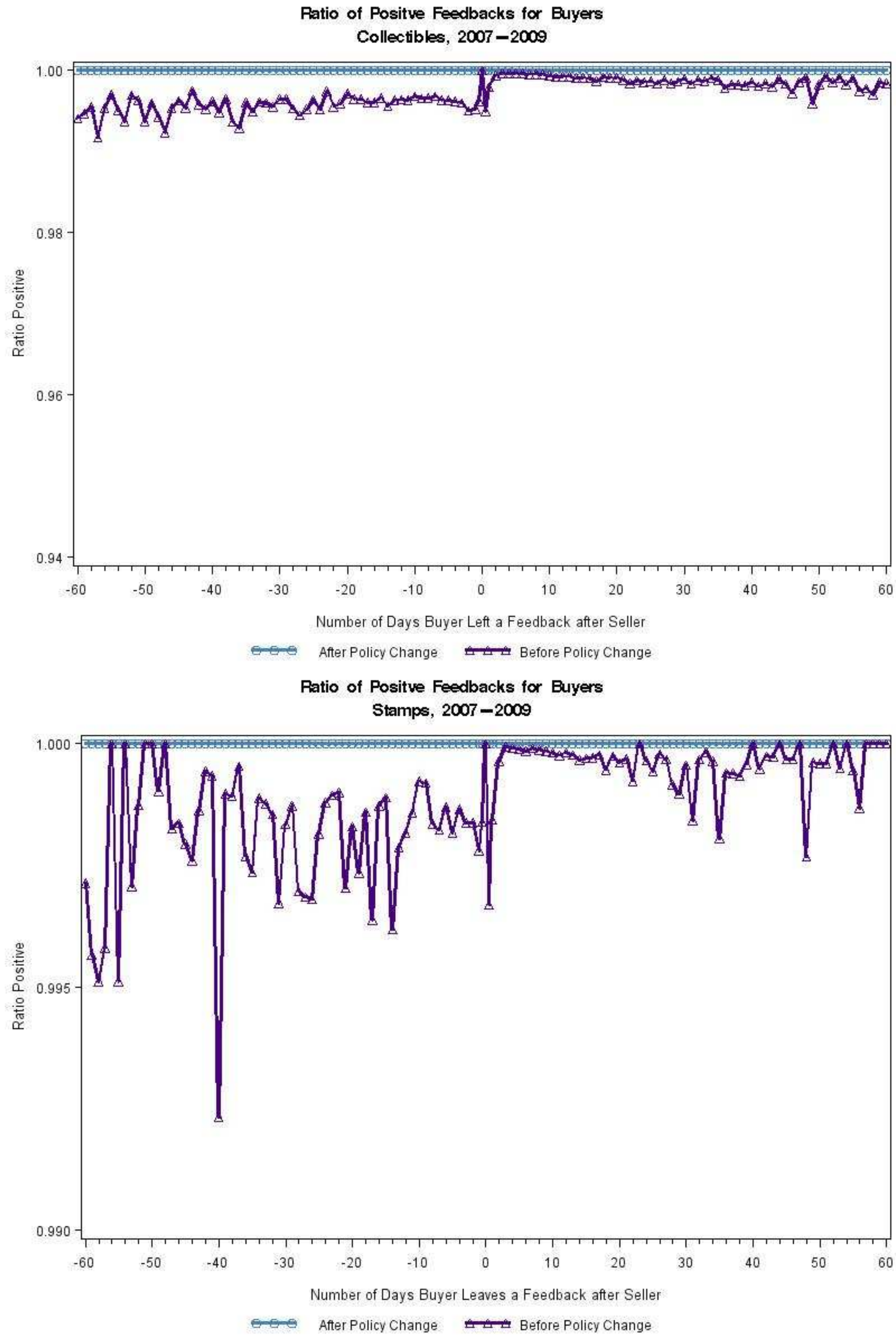
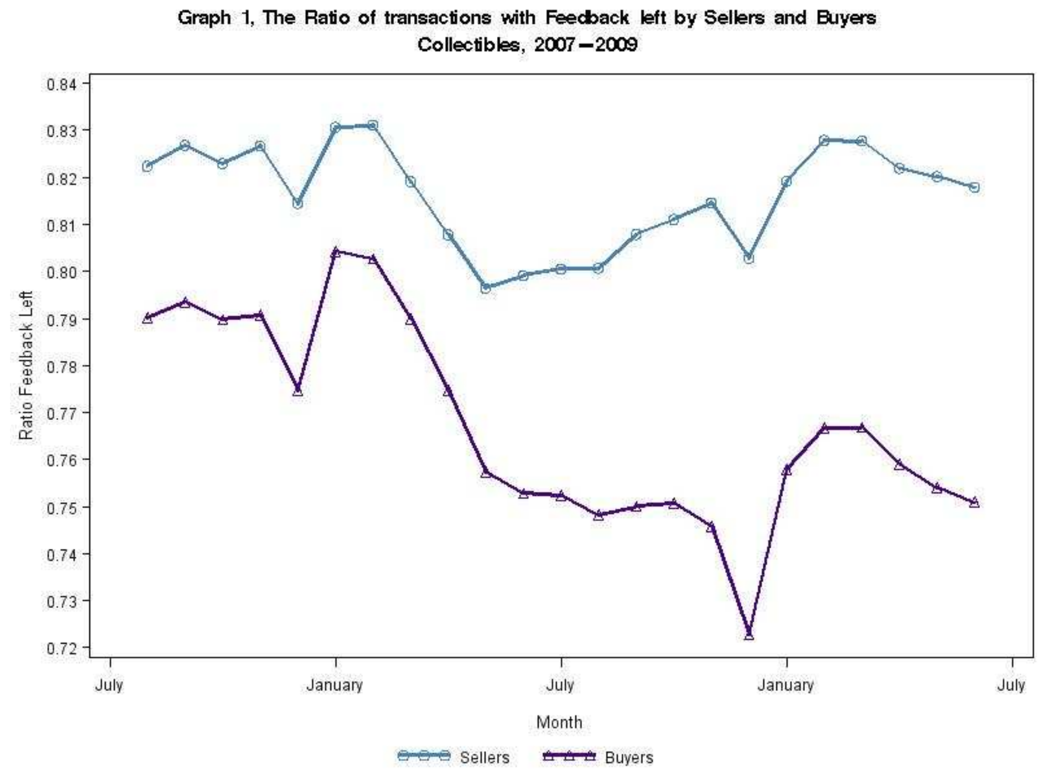



Figure B.1: Share of Positive Feedback for Buyers, Collectibles and Stamps

X axis: The number of days the seller has left a feedback before the buyer.
Y axis: Percentage of positive feedbacks over the total feedback left at the same day.



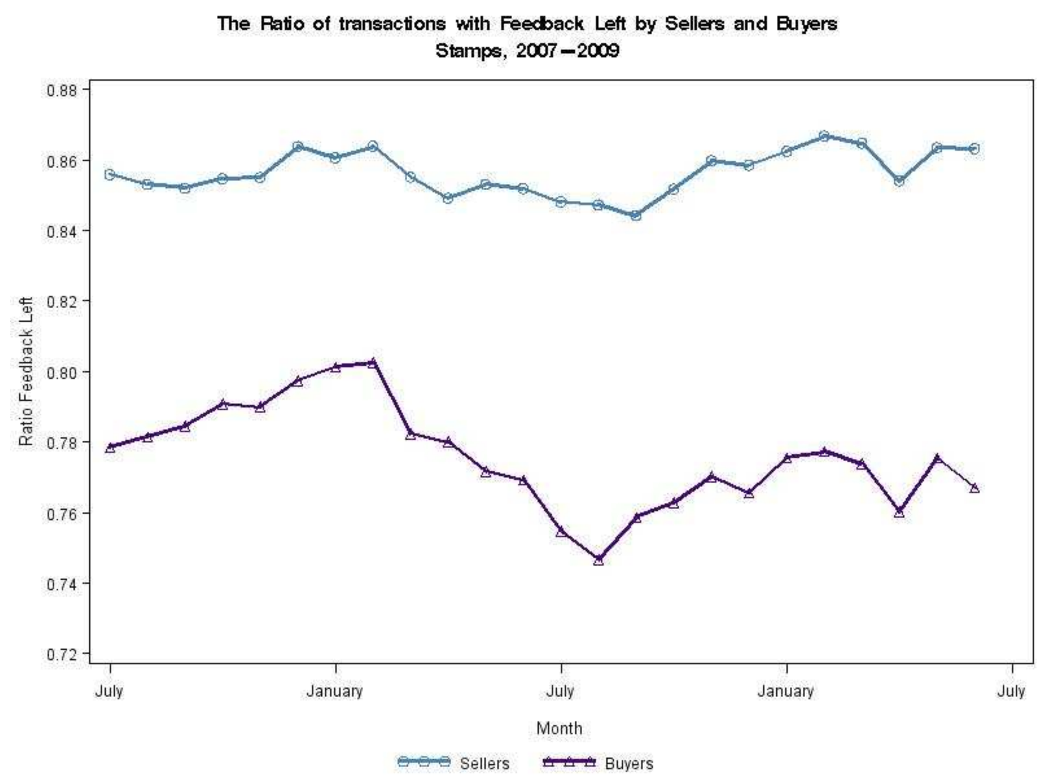
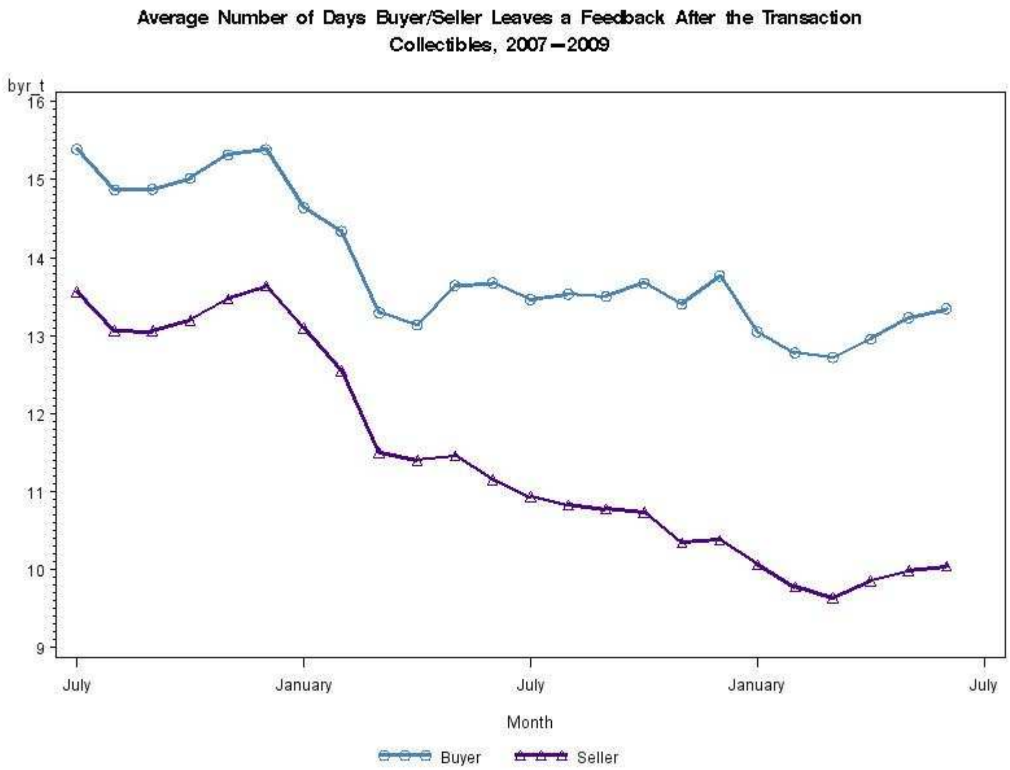




Figure B.2: Adoption Rate for Feedbacks, Collectibles and Stamps

X axis: Time period. The policy Change happens in May 2008.
Y axis: Share of transactions with a feedbacks from the sellers and buyers.



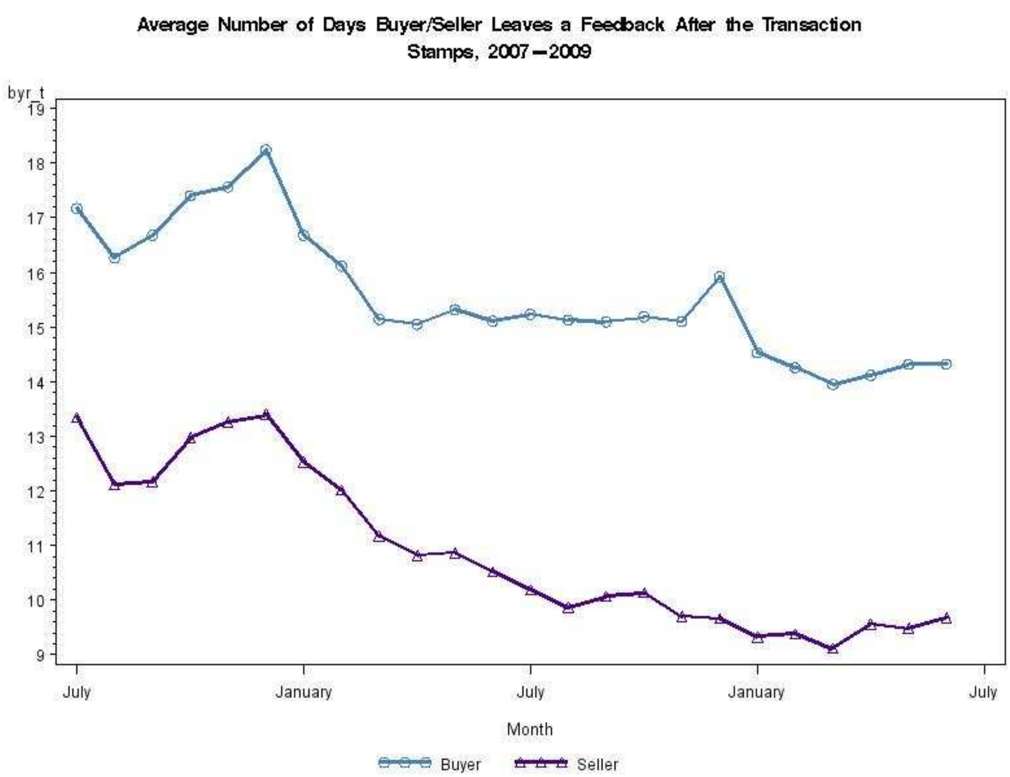




Figure B.3: Timing of the Feedback, Comparing to The End of Transaction, , Collectibles and Stamps

X axis: The time period. The policy Change happens in May 2008.
Y axis: The number of days participants in the market wait before leaving a feedback.

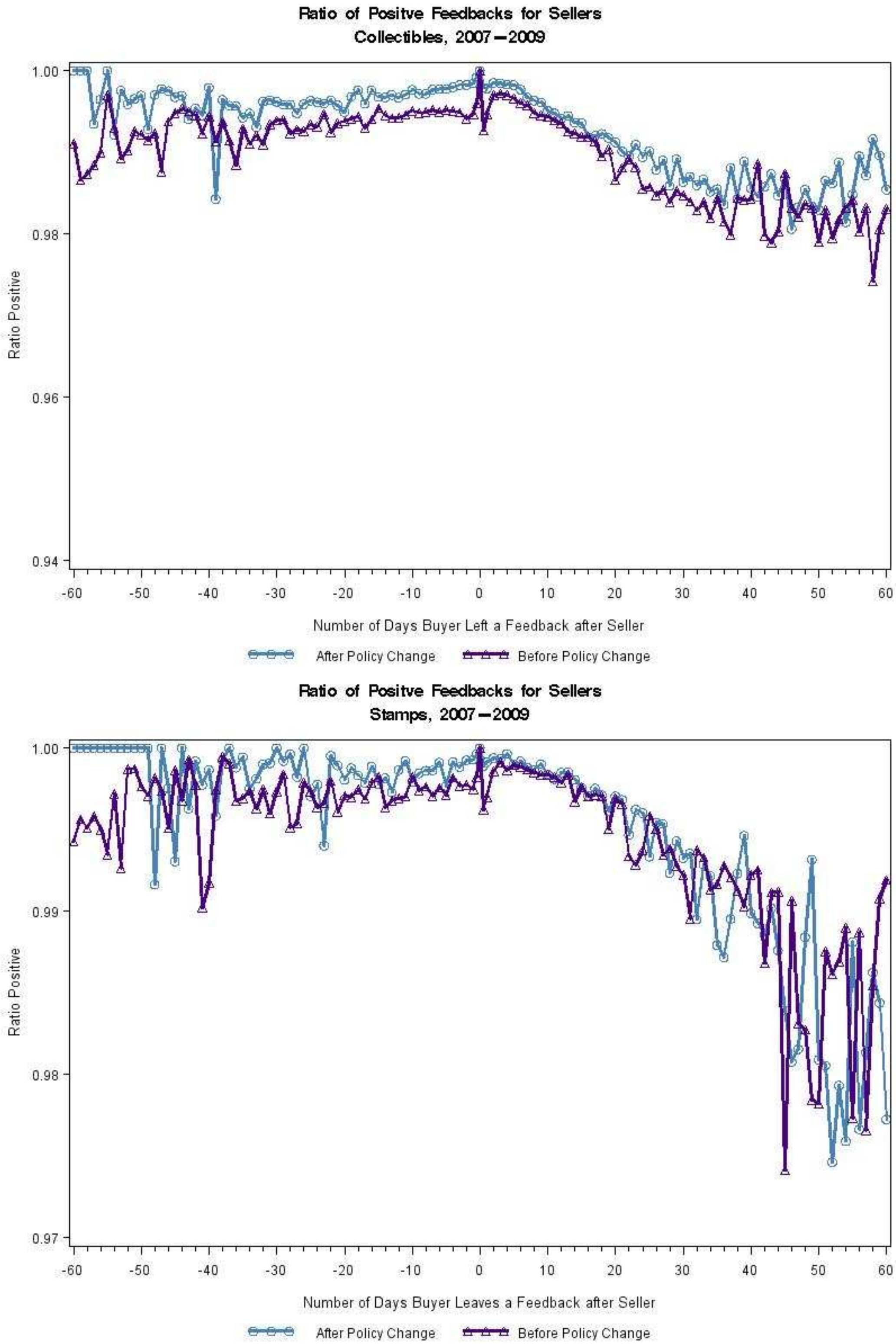
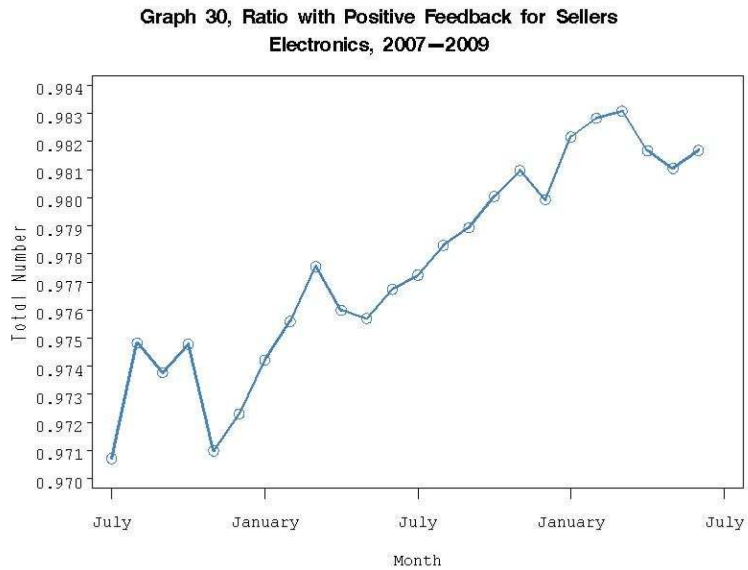
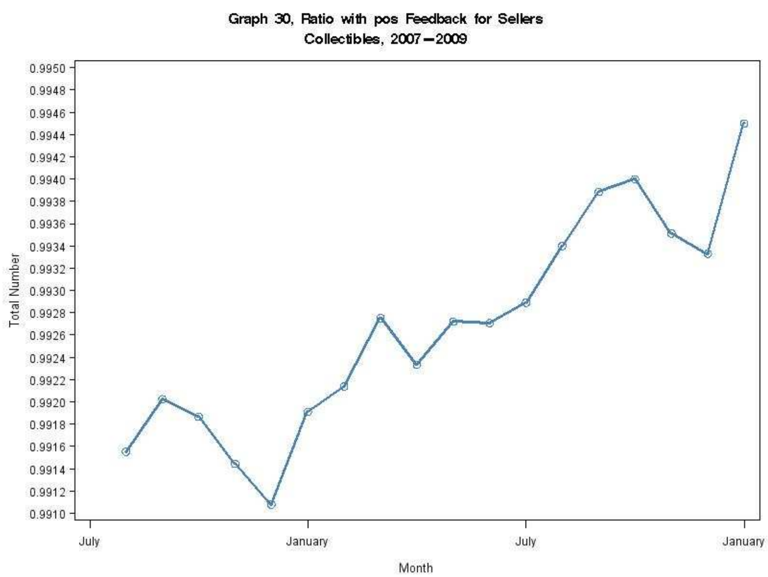



Figure B.4: Share of Positive Feedback for Sellers, Collectibles and Stamps

X axis: The number of days the buyer has left a feedback after the seller.
Y axis: Percentage of positive feedbacks over the total feedback left at the same day by buyers for sellers.



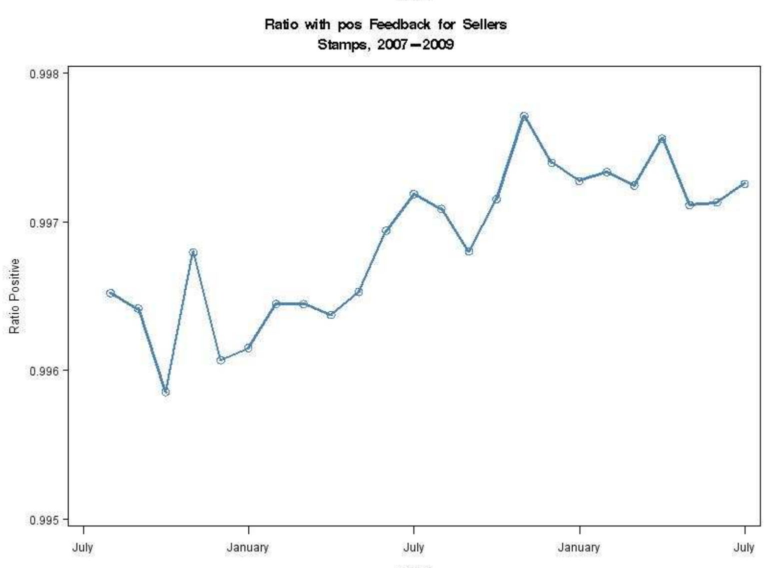




Figure B.5: Share of Positive Feedback for Sellers.

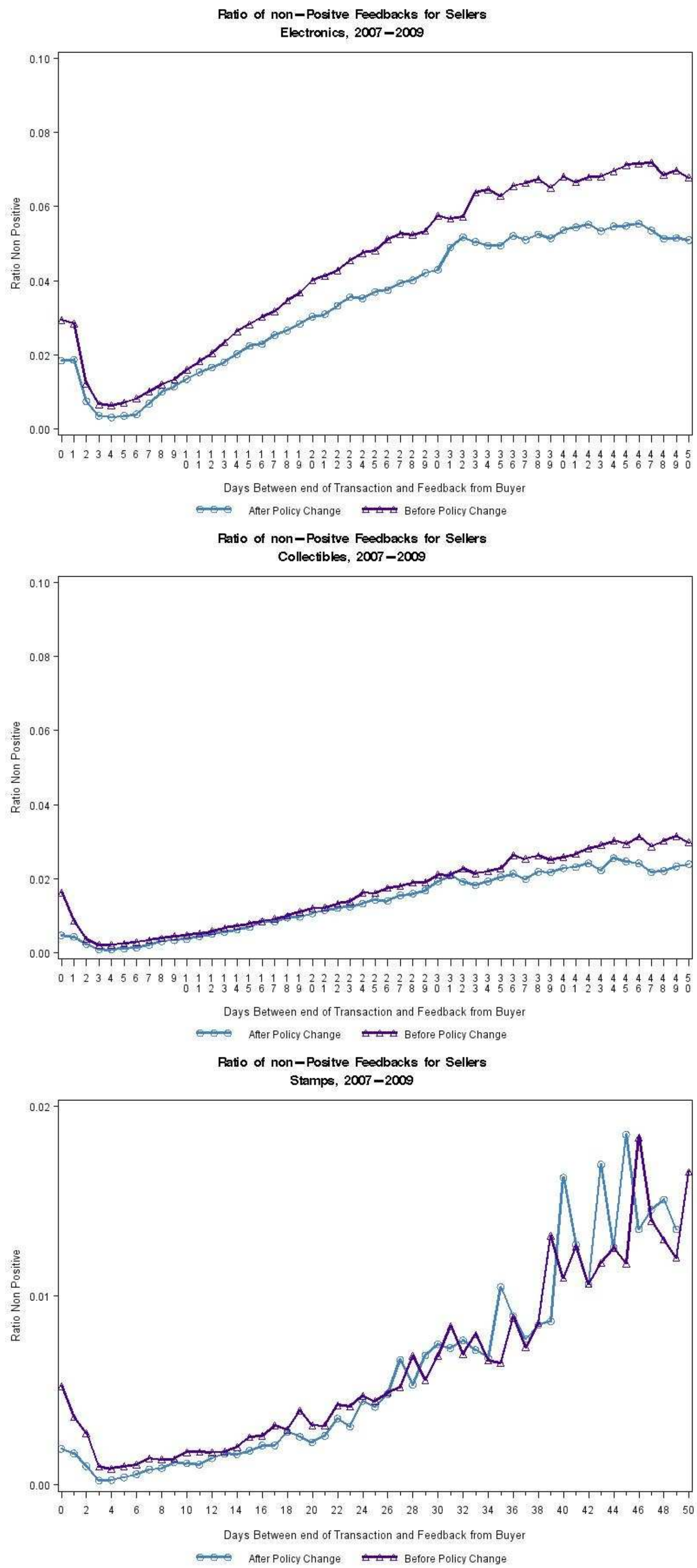



Figure B.6: Share of non-Positive Feedback for Sellers vs. Timing of Feedback.

Figures B.7, B.8, and B.9 plot the number of positive, negative, neutral feedback from buyers to sellers, respectively, as a function of the time between the transaction and feedback. It can be observed that the number of positive feedback has slightly increased while the number of neutral feedback has decreased and number of negative feedback has stayed at the same level. A possible explanation for this is that buyers were used to leave neutral feedback, instead of negative ones, in fear of retaliation before the policy change.

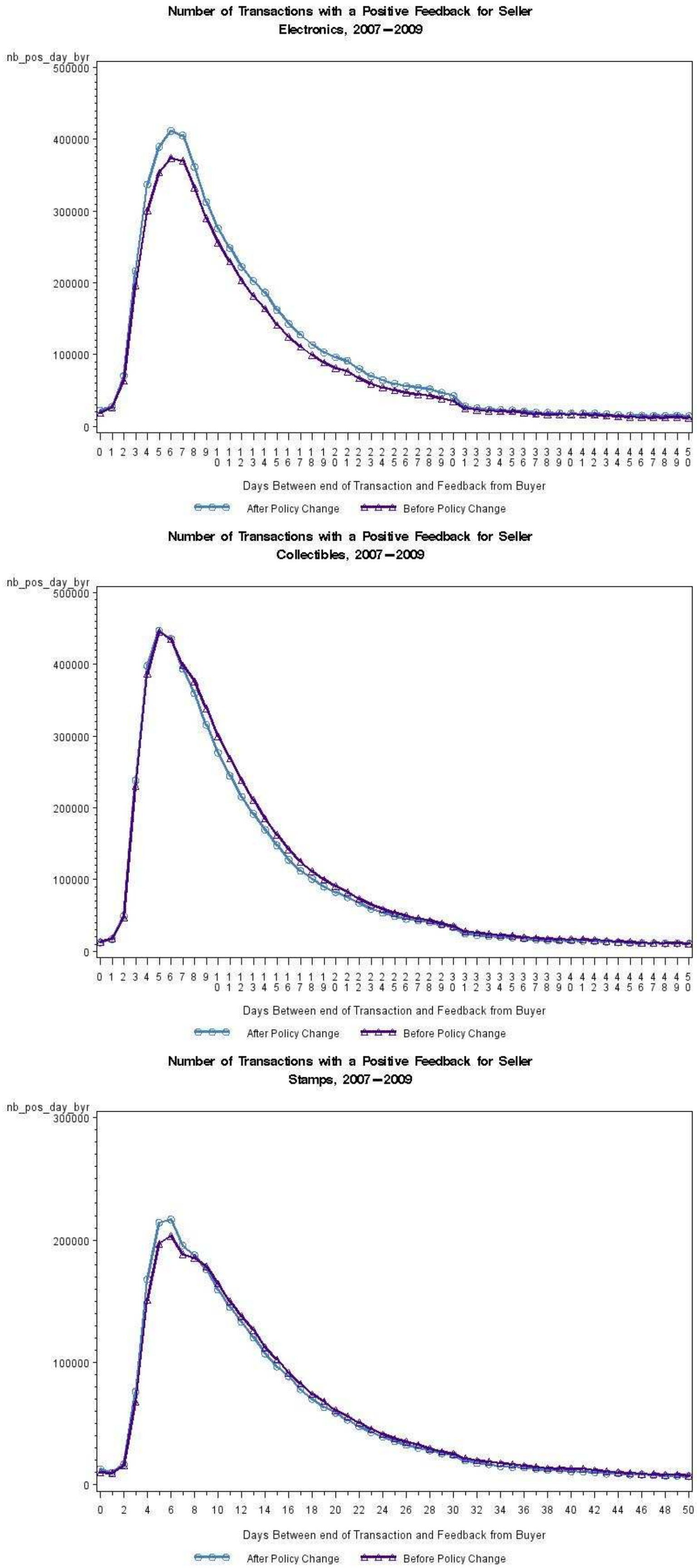



Figure B.7: Number of Positive Feedback for Sellers, Before and After Policy Change

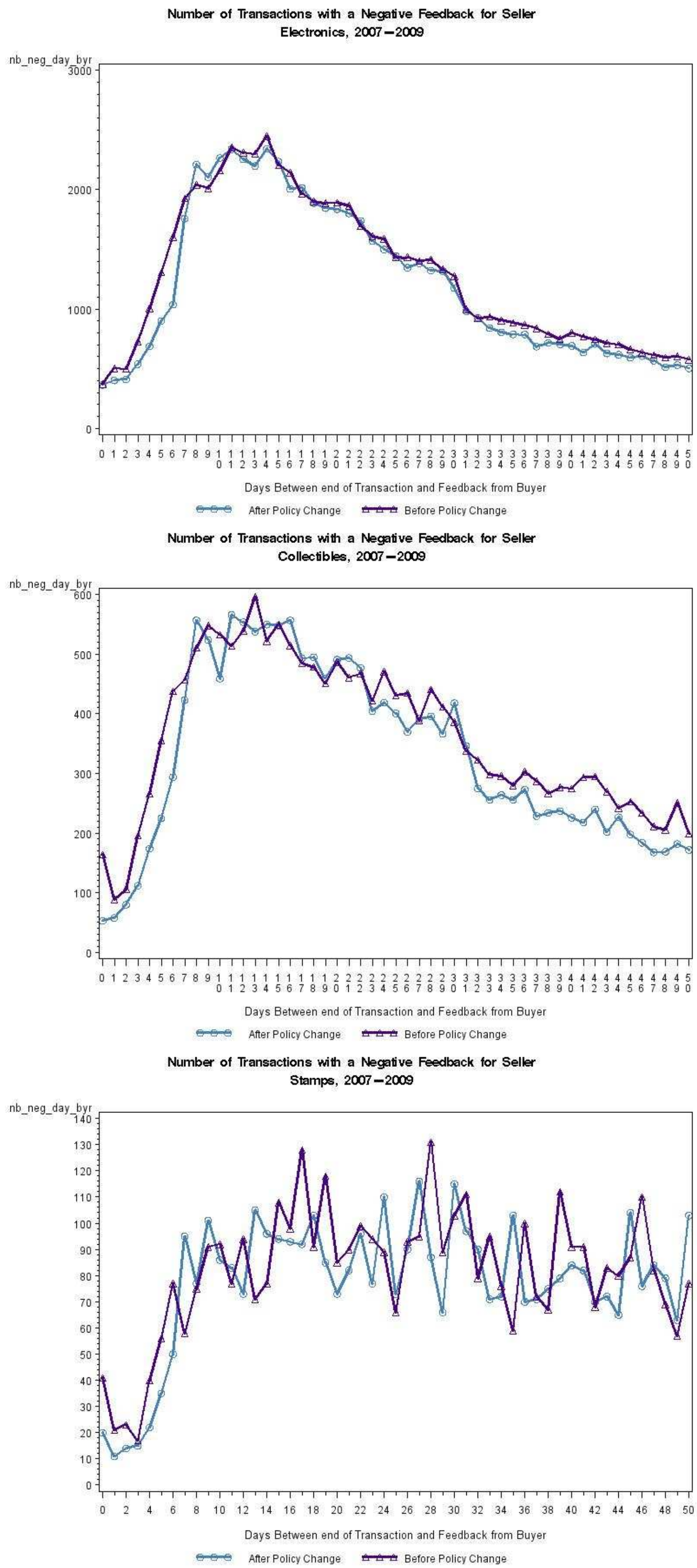



Figure B.8: Number of Negative Feedback for Sellers, Before and After Policy Change

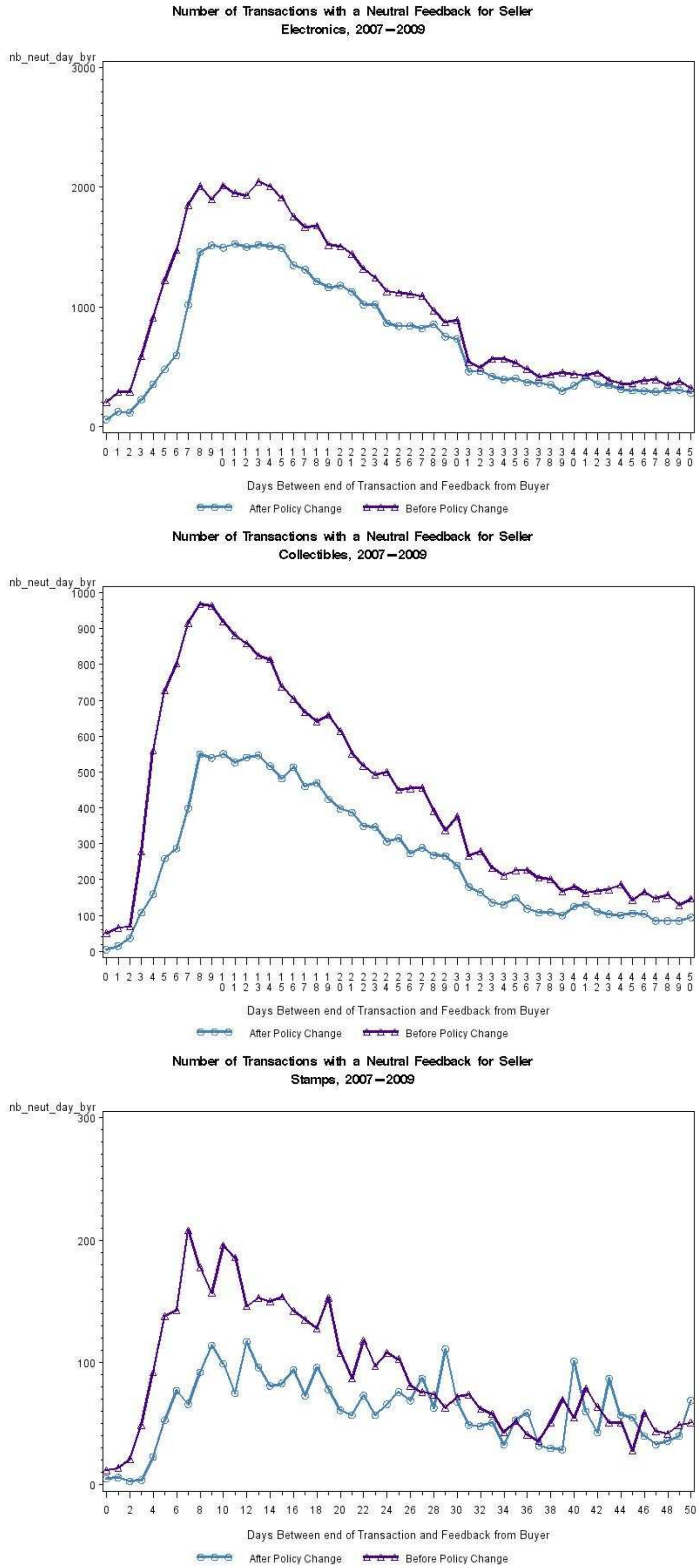



Figure B.9: Number of Neutral Feedback for Sellers, Before and After Policy Change