ABSTRACT

Title of Document: **RECIPROCITY IN ONLINE MARKETS: EMPIRICAL STUDIES OF AUCTION AND BARTER MARKETS**

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My dissertation seeks to understand how reciprocity affects transaction outcomes and mechanism design in online markets. The first essay examines negative reciprocity illustrated as feedback-revoking behavior in the eBay auction market, focusing on its impact and implications for reputation system design. I utilize the biggest policy change of eBay's reputation system in its history as a natural experiment setting to infer the causal impact of the reputation system on seller behavior. I find that strategic engagement in negative reciprocity enables low quality sellers to manipulate their reputations and masquerade as high-quality sellers. I further show that these sellers react strongly to eBay's announcement of a ban on revoking. Interestingly, disallowing negative reciprocity motivates these sellers to significantly improve their service quality. The second essay examines positive reciprocity in one of the leading online barter markets for books, focusing on participants' different reciprocity strategies and their impacts on transaction outcomes. I find that, whereas market participants who use the immediate reciprocity strategy are able to motivate higher service quality for the current transaction from the other partner, participants who use the delayed reciprocity strategy derive more benefits for future transactions by fulfilling their wishlists sooner. I further show that the market participants can be segmented into different reciprocity strategies based on their book avidness, breadth of interest, and psychographic profiles. Overall, the two studies provide important theoretical and practical implications for the design and regulation of online markets.

RECIPROCITY IN ONLINE MARKETS: EMPIRICAL STUDIES OF AUCTION AND BARTER MARKETS

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Table of Contents

List of Tables

Tables for Essay 1

Tables for Essay 2

List of Figures

Chapter 1: Introduction and Overview

Although every culture has its own unique ethical values, reciprocity, which can be defined as the norm of rewarding kind acts (i.e., positive reciprocity) and punishing hostile acts (i.e., negative reciprocity), stands as a universally embraced principle in virtually all cultures (Fon and Parisi 2005). The principles of “you scratch my back, and I’ll scratch yours’’ and “an eye for an eye, a tooth for a tooth’’ are two prototypical examples of reciprocity. Evolutionary biologists and economists argue that humans have successfully evolved an innate preference for fairness and reciprocity. In the early 1870s, Charles Darwin wrote in his *Descent of Men and Selection in Relation to Sex*:

“…as the reasoning powers and foresight…became improved, each man would soon learn from experience that if he aided his fellow-men, he would commonly receive aid in return. From this low motive he might acquire the habit of aiding his fellows; and the habit of performing benevolent actions certainly strengthens the feeling of sympathy, which gives the first impulse to benevolent actions. Habits, moreover, followed during many generations probably tend to be inherited.” (Darwin 1871)

The norm of reciprocity is deeply rooted in human nature and it plays an important role in nearly all economic or social interactions. Researchers have shown that reciprocity has a significant impact on human behavior and performance in a variety of traditional contexts, including bargaining (Guth et al. 1982), public good provision (Fehr and Gächter 2000), food transfer among civilians (Gurven et al. 2000), and garden labor exchange (Hames 1987), among others. With the growth of Internet and Web 2.0 technologies though, a majority of these social interactions have now moved online.

Whereas in traditional offline markets individuals are physically together in time and space for simultaneous exchanges, transactions in online markets are often characterized by asynchronous exchanges between total strangers from geographically dispersed locations. Because a vast majority of the interactions in online markets take place sequentially and one party endures costs before receiving benefits, there is no guarantee that future benefits will be fully delivered by another party. One theoretical solution to this uncertainty is formal contracts. However in practice, issues of information asymmetry in online markets and the lack of perfect monitoring mechanisms often make it costly or even impossible to enforce formal contracts. In such settings, reciprocity can serve as an effective implicit or informal contract (Seinen and Schram 2006).

In addition, the increased information availability, and the increased transparency and visibility of actions and behaviors make it conducive for fostering reciprocity in online markets. Since detailed histories of social interactions among participants are often publicly available, it requires less effort for an individual to recognize and reward cooperators and punish defectors. As noted by Pelapret and Brown (2010), reciprocity is one of the fundamental drivers of online behavior in a variety of contexts. For example, Wasko and Faraj (2005) show that reciprocity is one of the primary reasons why individuals share knowledge with each other in virtual communities, while Wang and Wang (2008) show that reciprocity drives players in online games to help each other.

Given individuals' strong reliance on reciprocity for online interactions, a good understanding of reciprocity-induced consumer behavior in online markets will not only help inform the design of online markets, but also provide guidelines for policies to improve individual interactions. Despite the documented importance of reciprocity in the online context, little is known about how reciprocity actually influences individuals' search and transaction-related behavior in online markets. My dissertation seeks to understand how individuals strategically utilize reciprocity and how reciprocity affects transaction outcomes and market efficiency in online markets. I propose two essays to examine reciprocity in two different online contexts.

Negative reciprocity is very common in human interactions. Contrary to positive reciprocity of which the emphasis is on the return of favors, negative reciprocity emphasizes on the return of injuries (Eisenberger et al. 2004; Friedman and Singh 2004; Helm et al. 1972). There is considerable evidence that humans take revenge in response to hostile acts even when it is costly. Some researchers argue that humans are disposed to give a greater role to negative reciprocity than to positive reciprocity (Friedman et al. 2004). The first essay in my dissertation examines negative reciprocity in online auction markets. To overcome the information asymmetry problem in online transactions, reputation systems have been widely implemented to communicate product/seller quality and foster trust among buyers and sellers by allowing them to share their opinions and experiences with other members. Typically a reputation system works as follows: after a transaction, both parties can rate the other party's performance; each participant has some publicly visible reputation metrics such as the running total of rating points received from other participants and the percentage of positive ratings. Although the goal of a reputation system is to elicit honest reports and ratings, its two-way nature opens the door for gaming through negative reciprocity: one party who receives a negative feedback can strategically reply with a negative feedback regardless of her actual performance in order to force the other party who cares about her reputation to mutually withdraw the negative ratings. My first essay examines this form of negative reciprocity which is called revoking and tries to answer two related questions: (1) do participants engage in negative reciprocity and how does it affect the effectiveness of the reputation system? (2) Do participants change their behavior if the potential for negative reciprocity is eliminated? Taking advantage of an exogenous change in eBay's reputation system design, the findings from the essay provide evidence that certain sellers in online markets utilize negative reciprocity to revoke the bad ratings they received, thus making the reputation mechanism less effective in distinguishing sellers of different qualities. I further find that sellers who engaged in negative reciprocity earlier significantly improve the quality of their transactions after negative reciprocity is made impossible. I discuss the implication of these findings for the design of reputation mechanisms in online markets.

The second essay examines positive reciprocity in the emerging online barter markets. Unlike transactions in money-based markets, barter transactions by definition are the exchanges of goods or services without using money and therefore are conducted under the norm of reciprocity. Because barter markets often specialize in a particular type of good, market participants typically share similar long-term interests in those goods and repetitive interactions are encouraged. Another significant difference between traditional money-based online markets and online barter markets is that, while the former is often characterized by one-shot interactions (Resnick and Zeckhauser 2002), the latter allows the potential for developing lasting reciprocal relationships among participants. Using a unique dataset from a leading barter market for books, I seek to understand the differential impacts of reciprocity-related search strategies on transaction outcomes as well as how individuals can be segmented into different search strategies. Specifically, I first use clustering techniques to unveil the predominant search strategies in the market. I find that there are three major search strategies used by the market participants: indirect reciprocity, immediate reciprocity, and delayed reciprocity. I next demonstrate that they have differential influences on transaction outcomes: whereas immediate reciprocity search strategy helps improve the service quality of the current transaction by encouraging faster delivery speed from the transaction partner, delayed reciprocity search strategy produces better match with an individual's actual transaction needs. I further find that individuals can be segmented into the different search strategy clusters based on their book avidness, breadth of interest, and psychographic profiles (rather than demographic profiles). The results provide guidance for barter market makes to segment the market participants.

Together the findings from my dissertation will help build a better understanding of how the norm of reciprocity affects individual behavior and transaction outcomes in various online markets and its implications for online market design. The following chapters provide more details about the two essays.

Chapter 2: Strategic Behavior in Online Reputation Systems: Evidence from eBay

2.1 Introduction

Reputation systems play a critical role in electronic markets due to significant information asymmetry between sellers and buyers (Ba and Pavlou 2002; Dellarocas 2003). A wide variety of reputation systems have been designed and implemented to mitigate problems arising from information asymmetry, with eBay's feedback mechanism being the most established and well-studied among them. Given the importance of reputation systems for online markets, it is not surprising that both practitioners and academic researchers have invested substantial efforts in examining the design of online reputation and feedback mechanisms as evidenced by the growing number of studies in recent years (e.g., Aperjis and Johari 2010; Bolton et al. 2004; Cabral and Hortacsu 2010; Dellarocas et al. 2006; Melnik and Alm 2002; Resnick et al. 2006; Resnick and Zeckhauser 2002). The importance of such feedback and ratings for transaction partners has been well documented, and prior studies have shown that a seller's reputation score has a significant impact on sales and price premiums (e.g., Houser and Wooders 2006; Resnick et al. 2006).

Clearly, the effectiveness of a reputation system critically depends on the behavior of the transacting partners (Dini and Spagnolo 2005). Given the importance of reputation, it is not surprising that opportunistic sellers try to "game" the system to boost their reputation scores. It has been inferred that a substantial percentage of buyers would rather remain silent than provide negative ratings to a seller due to fear of retaliation. Therefore, one critical mission for reputation system design is to promote desirable seller behavior. Up to this point, however, there have been few studies examining how sellers respond to changes in reputation system design. My study represents an effort to fill this gap in the literature. In particular, I focus on one strategic behavior within eBay's reputation mechanism – the revoking of negative buyer feedback. Before May 19, 2008, eBay allowed "revoking" – the ability to withdraw negative feedback subsequent to mutual agreement by the buyer and seller. While the ability to revoke negative feedback enables transacting partners to correct honest mistakes, it is also prone to abuse by strategic sellers. Specifically after receiving a negative rating from a buyer, the seller could retaliate by giving a negative rating to the buyer, and then suggest that both transaction partners withdraw their negative ratings. Since negative ratings are very rare (typically less than 1% of total ratings) and carry significantly more weight than positive ratings (Standifird 2001; Resnick and Zeckhauser 2002), such negative reciprocity-based revocations can be especially damaging to an online reputation system.

Starting in May of 2008, eBay banned the withdrawal of negative feedback, and disallowed sellers from leaving neutral and negative feedback for buyers – in essence eliminating the possibility of retaliation and revocation by opportunistic sellers. This policy change, the biggest in eBay's history, provides a "natural experiment" setting that allows me to infer the causal effect of reputation system design on seller behavior with greater confidence.

My study seeks to empirically examine how strategic sellers respond to this policy change in two periods: at the time of announcement, and in the post-implementation period. First, shortly after the announcement of the policy change, there was a week-long strike by some sellers. This provides a test-bed of sellers' reactions to the changes to reputation system. I would expect, especially given that this policy aims to curb the strategic seller behavior, that those opportunistic sellers who benefit from gaming the system would react more strongly to a ban on such revoking. Second, I analyze the changes in seller feedback after the implementation of the new policy by comparing it to feedback generated in the pre-change period. Using a “difference-in-differences” approach, I seek to infer the reactions of strategic sellers compared to other sellers.

This study makes several important contributions to the literature on reputation systems. To the best of my knowledge, there have been few studies on the explicit strategic behavior of sellers in the context of online reputation systems. Previous studies (e.g.: Dellarocas and Wood 2008) have inferred the threat of retaliation using statistical models. I build on these studies, and obtain direct and detailed measures of retaliation and revoking behavior, which allow us to obtain deeper insights into the operational details of the gaming behavior within a reputation system. Second, I advance the existing literature that reputation matters in eBay auctions (Dewan and Hsu 2004, Lucking-Reiley et al. 2007) by providing one of the first empirical evidence of seller reactions to changes in reputation mechanism design. Empirically, the natural experiment setting, as well as the use of a difference-in-differences approach, allows us to infer the causal effect more rigorously.

Theoretically, this study also provides important insights into the theory development of online reputation systems (Dellarocas 2005). In recent years, theoretical work on the design of reputation system has highlighted the significance of modeling how sellers respond to reputation mechanism design. There are three different ways to model a reputation system in a market wherein long-lived sellers interact with short-lived buyers: pure hidden information, pure hidden action, and mixed model (Barr-Issac and Tadelis 2008). In the pure hidden information model, sellers vary in their innate ability (or "type") to deliver a product/service, and the reputation system's goal is to reveal the seller's type (Cripps et al. 2004; Mailath and Samuelson 2006). On the other hand, the pure hidden action model assumes that sellers have control over the outcome of a transaction by deciding how much effort to put into it. In such a case the reputation system is designed to motivate the effort the seller exerts (Dellarocas 2005; Fan et al. 2005). The mixed model assumes that sellers differ in their innate abilities or qualities, but low quality sellers can increase the probability of a satisfactory transaction by exerting more effort (Aperjis and Johari 2010; Cabral and Hortacsu 2010; Li 2010). While various theoretical papers have adopted different models of reputation systems, there is little empirical evidence to verify these competing assumptions. My study examines the extent to which sellers change their behavior with the reputation system design, and generates valuable insights on the crucial behavioral assumption in these models.

The rest of the paper is structured as follows: in the next section, I provide an overview of existing literature; section 2.3 focuses on the analysis of seller reactions to the announcement of the policy change; section 2.4 examines the seller's response to the changes in the reputation mechanism design (i.e., the elimination of revoking); and section 2.5 concludes the paper.

2.2 Research Context and Theoretical Background

2.2.1 Online Reputation System

In online exchange markets like eBay sellers and buyers are often geographically separated. The buyer has few means to verify the quality of the seller or hold the seller responsible. This potential of seller opportunism is even more significant when buyers and sellers have infrequent interactions. Reputation systems, which disseminate information and past behavior of individual traders, are designed to facilitate trustworthy transactions among strangers on the Internet. Numerous online markets, such as Elance.com, vWorker.com, Amazon.com, and eBay have adopted reputation mechanisms to promote honesty and better efforts in traders' behavior.

Whereas an increasing number of studies have focused on designing different reputation mechanisms (e.g., Maslet and Penard 2012; You and Sikora 2011), eBay's reputation mechanism is arguably the most established and the most scrutinized by the popular press as well as by academics. On eBay, the primary source of information about the trustworthiness of a seller is his/her feedback profile. Upon the completion of a transaction, both buyers and sellers have the opportunity to leave feedback within 90 days. Resnick and Zeckhauser (2002) find that buyers leave feedback 52.1% of the time and sellers leave feedback 60.6% of the time.

The feedback has three levels of valence: positive, neutral, and negative. In addition, buyers and sellers can each provide detailed comments about the other party regarding the transaction. The feedback a seller or a buyer receives is aggregated with previous feedback to calculate his/her feedback score, which is one key metric indicating the user's reputation. A user's reputation score is calculated as the count of distinct users who gave positive feedback minus the count of those who left negative feedback, and it is displayed right next to the user's ID wherever it appears on eBay. In addition, the percentage of positive feedback amongst all distinct positive and negative ratings for each seller is also reported. Since examining each individual feedback comment would entail a huge investment of time by the buyer, the reputation score, together with the percentage of positive feedback, is displayed to signal a seller's quality. Given the importance of the feedback a user receives, eBay allowed buyers and sellers to negotiate to mutually revoke negative feedback ratings while unilateral attempts are disallowed. This policy has remained in place since eBay was founded in 1995, until the 2008 policy change that disallowed revoking.

Despite eBay's popularity and success, there has been evidence of inefficiencies in its reputation mechanism. Some sellers continue to peddle fraudulent items with misleading descriptions without being caught. For instance, it is estimated that over 70% of the Tiffany jewels sold on eBay are fakes (Hafner 2007). Furthermore, one would expect an effective reputation mechanism to reward good sellers. However researchers have failed to find consistent evidence for the impact of a seller's reputation on auction price. Resnick et al. (2006), for example, find that negative feedback seems to have no impact on buyers' willingness-to-pay. Cabral and Hortacsu (2010) examine sales of laptops, coins, and beanie babies on eBay and find that neither positive nor negative feedback influences the final auction price. Melnik and Alm (2002) find that even when a seller doubles his ratings, the consumer's willingness-to-pay for gold coin increases by only 18 cents. Similarly, Lucking-Reiley et al. (2007) find that positive ratings have a negligible impact on price. This is echoed by Eaton (2005) who finds that a seller's reputation has little or no impact on the actual bid prices.

One critical issue that is detrimental to eBay's reputation system is seller strategic behavior relating to feedback. On eBay, sellers and buyers may independently leave feedback within 90 days of the transaction and the feedback is available immediately to the other party. While the system is symmetric (two-way), allowing both buyers and sellers to rate each other, buyers are at a disadvantage because buyers face product uncertainty before payment and seller opportunism after payment. While the reputation system intends to facilitate buyers' reporting of dishonest sellers to warn others, the symmetric nature of the previous reputation system makes it convenient and nearly costless for sellers to retaliate against any buyer providing them a negative rating. Thus it was apt to say that for buyers, "a negative first feedback can never be given without the fear of retaliation" (Klein et al. 2009). This fear of retaliation reduces a buyer's propensity to leave negative feedback on the seller (Dellarocas and Wood 2008). As a result, this creates an incentive for one party to strategically withhold its feedback as a means of retaliation (Dellarocas and Wood 2008; Yamagishi and Matsuda 2002). In addition to these direct feedback retaliation, a seller can also threaten to report buyers as scammers or abusers of the feedback system as a way to discourage negative feedback. This happens through private messaging and is not directly observable.

Once a buyer leaves a negative rating, the seller can retaliate and then try to "fix" the feedback using eBay's revoking policy (Bolton et al 2009; Klein et al. 2009). In the vast majority of cases, revoking (the withdrawal of feedback based on mutual agreement) is preceded by a reciprocal negative feedback. When a seller responds to a negative rating with a negative rating, about 27% are later withdrawn through the revoking mechanism (Bolton et al. 2009).

In summary, the ability to retaliate and revoke feedback creates an incentive for opportunistic sellers to manipulate their reputations by nullifying negative feedback. Whereas Bolton et al. (2009) and Klein et al. (2009) have pointed out the possibility of such strategic revoking, no study has thus far empirically and systematically examined this phenomenon.

2.2.2 eBay's Policy Change: Put An End to Seller Coercion

Given the potential problems of eBay's reputation system, scholars have suggested different ways to enhance the design of reputation systems. In a theoretical analysis, Ba et al. (2003) suggest that digital certificates issued by a trusted third party can motivate market participants to behave honestly. Others have also proposed that eBay should allow only the buyer to rate the seller (Chwelos and Dhar 2006) or that eBay should simultaneously reveal both partners' ratings (Reichling 2004). Eventually in January 2008, eBay announced dramatic changes to its reputation mechanism. Starting on May 19, 2008, sellers were no longer allowed to provide negative or neutral feedback to buyers. A seller now has only two choices: not leaving any feedback, or leaving a positive one to the buyer. Furthermore, revocation or mutual withdrawal of the feedback was disallowed. Any feedback that is left cannot be removed unless it is investigated and determined as a violation or abuse of eBay's feedback policy after a dispute is filed. Bill Cobb, CEO of eBay, made the following comments in his public announcement on the reputation mechanism changes:

"… the original intent of eBay's public feedback system was to provide an honest, accurate record of member experiences. …… But overall, the current feedback system

isn't where it should be. Today, the biggest issue with the system is that buyers are more afraid than ever to leave honest, accurate feedback because of the threat of retaliation. In fact, when buyers have a bad experience on eBay, the final straw for many of them is getting a negative feedback, especially of a retaliatory nature. Now, we realize that feedback has been a two-way street, but our data shows a disturbing trend, which is that sellers leave retaliatory feedback eight times more frequently than buyers do ... and this figure is up dramatically from only a few years ago. So we have to put a stop to this and put trust back into the system." (eBay 2008)

This change – from a symmetric to an asymmetric feedback system - removed a seller's ability to retaliate against a buyer providing negative feedback. This change serves as an exogenous event that enables us to investigate how sellers respond to the changes in the design of eBay's reputation system. After the change in the reputation system, since buyers are shielded from retaliation from the sellers, they should be more willing to express their negative opinions toward sellers. Since the policy change mostly affects strategic sellers who have used retaliation and revoking to "fix" their reputations, these sellers should be the most affected by the new policy. If these sellers continue to under-perform, they could easily attract more negative feedback than other sellers under the new (changed) reputation mechanism. Therefore this policy change offers a valuable opportunity to examine how strategic sellers respond to reputation system design, which I examine in Sections 2.3 and 2.4.

2.3 Data

eBay's radical overhaul of its reputation mechanism, described above to be effective on May 2008, was announced on January 30, 2008. The announcement caused outrage amongst some sellers and culminated in a week-long strike, from February 18 to February 25, 2008, to protest the changes (Zouhali-Worrall 2008). To allow enough time for the new reputation mechanism to take effect, I define a 3-month period – July 1, 2008 to September 30, 2008 – as the post-change period[1]. Correspondingly, I define July 1, 2007 to September 30, 2007 as the pre-change period for two reasons. First, the pre- and post- periods cover the same months of a year, which alleviates potential seasonal effects on seller behavior. Second, because the pre-change period ends four months before eBay's announcement, it is unlikely that buyers and sellers had changed their behavior in anticipation of the policy change. Comparing the pre- and post- periods allows us to examine the impact of the change in the reputation system design on buyer and seller behaviors. Figure 2.1 shows the timeline of the events.

I draw a random sample of 2890[2] sellers from the eBay marketplace (which I refer to as "general sellers"). To control for product categories, the sampling is stratified based on the distribution of product categories on eBay. As I argue, there are sellers who strategically exploit the revoking policy to manage their displayed reputations. If this were the case, then I would expect these sellers to respond most strongly to the

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[1] eBay instituted some other change later on in October, 2008. For example, eBay stopped allowing users to send checks or money orders as payment for items purchased on the US version of the site after October 20 2008. Buyers would only be able to pay using PayPal, ProPay, credit or debit cards (if the seller has an internet merchant account), or pay for the item upon pickup. These changes are beyond this study period, and thus they should not interfere with the effect of feedback policy change on seller behavior in this study.

[2] I restrict this sample to well-established sellers with total lifetime feedback of 500 or more at the time of data collection in the year 2008. This reduces the noise from casual sellers and allows for a more accurate measurement of seller behavior based on transaction volume. These sellers account for 69.98% of all active listings on eBay at the time of this data collection.

announcement of a ban on revoking. Therefore, examining the participation of strike provides an opportunity to test strategic sellers' reaction to the change in the reputation system design.

I use eBay's seller central forum to identify the sellers who participated in the strike. This forum is an online space for sellers to discuss a variety of issues related to eBay sellers, and it was established several years before the strike. Following the announcement of the policy change in January 2008, a thread on eBay's seller central forum was created with the title "Sign the pledge: No sales Feb 18-25!" From this thread I identify 398 unique IDs of sellers who signed the pledge, which I refer to as "strikers".

Since the strike was initiated in the eBay forum, one may argue that sellers active in the forum were more likely to strike merely because they knew about it. To control for this potential confounding factor and ensure the robustness of the results, I introduce a second control group: forum sellers who were active in the forum but did not participate in the strike. I create a random sample of 2280 such sellers (which I refer to as "forum sellers").

To confirm that the sellers who pledged in the strike thread were actually participating in the strike, I check their listing activities during the strike week. I do find that strikers reduced their listings very significantly during the one-week period whereas I observe no such trend for general sellers and forum sellers.

For all the sellers I collect two sets of data: sellers' feedback history and sellers' listing records. The data covers all listings (including sold and unsold items) for the years 2007-2008, as well as the feedback if received. Based on sellers' feedback history data, I calculate each seller's profiles, including their reputation scores and specific types of feedback ratings, which are dynamically updated at the time of each listing.

2.4 Data Analyses

2.4.2 Are Revokers More Likely to Be Strikers?

I first analyze the percentage of revoked feedback during the pre-change period for the three groups in Table 2.1.Idifferentiate between the cases of seller retaliated and revoked (SRR), buyer retaliated and revoked (BRR), and non-retaliated and revoked (NRR). SRR feedback refers to the situation wherein the buyer leaves the seller a negative rating followed by the seller retaliating with a negative rating, and then both parties mutually agreeing to revoke their negative feedback. BRR feedback refers to the situation wherein the seller leaves the buyer a negative rating followed by the buyer retaliating with a negative rating, and then both parties mutually withdrawing negative feedback. NRR feedback refers to the situation wherein the buyer gives the seller a negative rating and the seller directly asks for a withdrawal without any retaliation.

On average, strikers have 0.028% BRR feedback and 0.021% NRR feedback; general sellers have 0.015% BRR feedback and 0.043% NRR feedback; and forum sellers have 0.022% BRR feedback and 0.028% NRR feedback. The differences between strikers and other two types of sellers in terms of BRR and BRR feedback are not statistically significant. However, strikers do have a significantly higher SRR feedback percentage (0.445%) than general sellers (0.058%) and forum sellers (0.056%). To summarize the findings so far, the main difference between strikers and the two other categories of sellers is the frequency of SRR feedback. This indicates that strikers have engaged in significantly more retaliation and revoking: they strategically retaliated against buyers by providing them negative feedback after receiving negative feedback and then negotiated with buyers to mutually revoke the negative feedback.

The occurrence of the strike seems to suggest that sellers cared about changes to eBay's reputation mechanism. However, there are other factors that might drive participation in the strike. Specifically, at the same time eBay announced changes to its fee structure: lower listings fees (the price charged for each item listed to be sold on eBay) and higher final value fees (a percentage of the closing price extracted by eBay). Based on their listing and sales patterns, some eBay sellers believed that they would have to pay more because of these changes. Thus, potential financial loss under the new fee structure could have also motivated some sellers to join the strike.

To control for the potential impact of changes in the fee structure, I collect detailed listings of sellers in all three groups one month prior to the strike (from January 18, 2008 to February 17, 2008).I collect detailed information about each listing, including product category, auction style, starting price, final price, and usage of features such as gallery pictures and subtitles. This allows us to calculate the exact fee charged by eBay. To measure potential financial loss, I calculate, for each listing, the difference between fees actually charged by eBay under the old fee structure and fees that would be charged by eBay under the new fee structure. I then aggregate the differences at the seller level.

In addition to changes to the fee structure, several other factors could potentially influence participation in the strike as well. Sellers with a larger number of listings (logarithmized) would suffer more financially if they joined the strike and hence may have been less likely to participate. Powersellers[3] would also be less likely to join the strike because they would enjoy significant final value fee discounts under the new fee structure. The longer a seller has used eBay, the higher his/her switching cost due to the accumulated loyal customer base on eBay. These sellers should care more about the long-term interest and thus have a stronger reaction to the reduction of seller power under the new reputation mechanism. Therefore I include number of months on eBay as another control variable. Seller reputation is measured by both reputation score (log-transformed) and total negative feedback percentage (i.e., the sum of revoked negative feedback percentage and remained negative feedback percentage). The full specification of the model is:

$$Logit\ (strike) = \alpha + \beta_1 * num\_listing\_log + \beta_2 * power\_seller + \beta_3 * tenure + \beta_4 * fee\_diff + \beta_5 * score\_log + \beta_6 * total\_negative\_pct + \varepsilon$$

The descriptive statistics and correlation matrix of the variables in the regression are provided in Tables 2.2 and 2.3. The maximum VIF is 1.59, well below the threshold of 10, indicating that there is no multicollinearity among the independent variables.

The results of the logit regression model are shown in Table 2.4. Model 1 is the baseline model. The coefficient of fee difference is significantly positive, suggesting that sellers who stand to lose more (or save less) under the new fee structure are more likely to strike. Consistent with my prediction, sellers with a longer tenure on eBay are more likely to strike. Powerseller status and the volume of listings do not have a significant effect on a seller's propensity to strike.

[3] A Powerseller is an eBay seller who participates in the Powersellers program and maintains a high quality feedback profile and constant or growing trading volume. Powersellers enjoy a closer trading relationship with eBay, including increased attention, specialized tools, and discounts on final value fees.

The coefficient of total negative feedback percentage is significantly positive, suggesting that sellers with more negative feedback before revoking are more likely to strike. In Model 2, I divide total negative feedback percentage into remained negative feedback percentage and revoked feedback percentage in the regression. I find that the pseudo R2 increases by almost 160%, supporting the assertion that a seller's revoking behavior has significant explanatory power on his/her participation in the strike. The coefficient of the percentage of revoked feedback is positive and is significant at the $p<0.001$ level. This suggests that sellers with a history of revoking negative feedback are more likely to strike. In Model 3, I split revoked feedback into SRR feedback, BRR feedback, and NRR feedback. The Pseudo R2 further increases by about 100%. The coefficient of SRR feedback percentage is significant and positive, but the coefficients of BRR feedback percentage and NRR feedback percentage are insignificant. This indicates that the sellers who strategically retaliate and then revoke negative feedback are indeed more likely to strike. A 0.1% increase in SRR feedback percentage would lead to 18.07 percent increase in the odds of joining the strike.

The reputation profile comparison in the pre-change period and the logit regression analyses on the strike both provide empirical evidence that revoking after retaliation is a significant factor that motivates the participation in the one-week strike. This prompts us to examine the change on seller behavior after the implementation of the new policy, as detailed in Section 4.2.

2.4.2 Reputation System's Impact on Seller Behavior: A D-i-D Analysis

In this section, I focus on the impact of reputation system change on strategic sellers. To increase generalizability, I identify strategic sellers from the random sample of 2890 general sellers[4].

2.4.2.1 The Effect of Revoking on Seller Reputation

Before examining how the policy change affects strategic sellers' behavior, it is instrumental to assess the extent of the benefit these sellers derive from revoking. If revoking plays a major role in affecting these sellers' reputations, then it is more reasonable to assume that disallowing revoking should affect seller behavior in a substantial way. Therefore, I examine (1) how much revoking contributes to boosting the displayed reputation scores of revokers; and (2) how revokers' displayed and real reputation scores compare to the reputation of other non-revoking sellers.

Because only SRR feedback reflects sellers' strategic retaliation behavior, I define "revokers" as sellers who had SRR feedback in the pre-change period (before the announcement of the policy change). "Non-revokers" are sellers with zero SRR feedback (but they may have a small proportion of BRR or NRR feedback). This results in a sample of 221 revokers and 2669 non-revokers. Because SRR feedback is relatively rare, observing a higher percentage of SRR feedback for revokers requires that they have a significantly higher number of feedback ratings than non-revokers. Therefore, it is not surprising that the average reputation score for revokers (815.25) is higher than that of the non-revokers (156.66). This result is also consistent with the findings of Wood et al.

[4] I also conduct analysis using the strikers as the convenient sample of strategic sellers, and the rest of sellers as control group, and get similar findings.

(2002), which show that sellers with high reputation scores are more likely to engage in opportunistic behavior because buyers have a higher tolerance for them.

To confirm that My findings are not driven by the difference in the number of feedback ratings, I use the propensity score matching method to correct for potential sample selection bias due to the observable differences (Dehejia and Wahba 2002). I first predict propensity score based on a logit regression of the treatment (i.e., the status of revoker) on several key covariates, including the seller's reputation score, the seller's tenure on eBay, the seller's Powerseller status, and the average product price of the seller's listings. Then, for each revoker in the treatment group, I identify a matching seller in the control group (i.e., non-revokers) using nearest neighbor matching on the propensity score. Common support condition is imposed so that the treatment observations whose propensity scores are higher than the maximum or less than the minimum propensity score of the controls are dropped. This results in 198 revokers and 198 non-revokers.

On eBay, a seller's displayed reputation is reflected in his/her reputation score and in the percentage of positive feedback. Reputation score is defined as the number of unique positive feedback subtracted by the number of unique negative feedback[5]. The displayed percentage of positive feedback for a given seller is calculated by dividing the number of unique positive ratings by the total number of unique positive ratings and unique negative ratings. Once a feedback is revoked, it is not included in the calculation of reputation score and percentage of positive feedback. Therefore the displayed

[5] Consistent with eBay's approach to calculate reputations, I only consider unique feedback: multiple positive feedback ratings from the same buyer are counted as only one positive feedback rating. Other types of feedback ratings are treated similarly.

reputation is subject to gaming. I further calculate a seller's "true reputation" by taking into account neutral and revoked feedback.

Table 2.5 provides the comparison of both displayed reputation and true reputation profiles for revokers and non-revokers. For the displayed reputation, the average percentage of positive feedback for revokers and non-revokers is 99.42% and 99.56%, respectively. The difference is not significant at the 5% level, suggesting that the displayed reputation is similar between revokers and non-revokers.

I next compare the true reputations of revokers and non-revokers. Note that the revoked feedback was originally a negative feedback that had been withdrawn upon the mutual agreement of both the seller and the buyer. After adding in the original negative value of revoked feedback, I find that revokers actually have a much higher true negative feedback percentage than non-revokers (0.92%+0.57%=1.49% for revokers, and 0.06%+0.41%=0.47% for non-revokers, t-value=15.28, $p<0.001$). Combined with the comparison of the displayed reputations, the results indicate that while revokers have a much higher percentage of true negative feedback, the revoking mechanism helps these lower-reputation sellers masquerade as sellers with higher reputations. Therefore, one would expect that a ban on revoking should either help reveal the true reputation of these strategic sellers, or trigger behavioral change among these sellers – issues which I examine in-depth in the following sections.

2.4.2.2 Difference-in-Differences Analysis

To measure the impact of the 2008 policy change on seller behavior, I adopt a difference-in-differences model, which is commonly used to examine the causal effect of an intervention. One major advantage of the difference-in-differences model is that it circumvents many of the endogeneity issues that can arise when comparing heterogeneous individuals (Meyer 1995; Bertrand et al. 2004).

Denote Δ_r as the change in a revoker's propensity to receive negative feedback from buyers after the new policy, and Δ_n as that of non-revokers. Some unobserved factors can contribute to the change in seller reputation scores (e.g., changes in eBay's buyer population, competition from other market places, etc). However, since these factors are common to both the revokers and non-revokers, I can difference out their effects, and identify the extra impact of policy change on revokers by Δ_r - Δ_n (that is, beyond the impact received by non-revokers).

I delve deeper to identify these impacts. In my case, two major factors contribute to the change in feedback by buyers. First, because of the removal of seller retaliation, buyers are more likely to leave negative feedback, which I term as δ_b. Second, with less power in the reputation system, sellers are now likely to improve their efforts in servicing buyers, which could also lead to a reduction of negative feedback. I term this effect as δs. For revokers, the change in the propensity of receiving negative feedback from buyers, Δr, can be expressed as:

$\Delta r = \delta_{br} + \delta_{sr}$, where r denotes revokers.

Similarly, the change for non-revokers can be expressed as:

$\Delta n = \delta_{bn} + \delta_{sn}$, where n denotes non-revokers.

The difference-in-differences in the propensity of receiving negative feedback between revokers and non-revokers is:

$$\Delta r - \Delta n = (\delta_{br} + \delta_{sr}) - (\delta_{bn} + \delta_{sn})$$

$$= (\delta_{br} - \delta_{bn}) + (\delta_{sr} - \delta_{sn})$$

Therefore, I have $(\delta_{sr} - \delta_{sn}) = (\Delta_r - \Delta_n) - (\delta_{br} - \delta_{bn})$

In the above equation, $\delta_{sr} - \delta_{sn}$ reflects the extra effort exerted by a revoker to improve his/her behavior (which might be in the form of a more accurate description of items, faster delivery, better packaging, among other means), which leads to the reduction in negative ratings. A negative $\delta_{sr} - \delta_{sn}$ implies that revokers exert more efforts to reduce negative ratings from buyers in the post-change period.

Controlling for Buyer Behavior Change: $\delta_{br} - \delta_{bn}$ reflects the difference across revokers and non-revokers over the buyer's propensity to leave them negative feedback when holding seller service quality constant. Since the displayed reputation profiles of revokers and non-revokers are very similar, as I found in Section 2.4.2.1, I should not expect the buyers of revokers to be systematically different from buyers of non-revokers. Indeed I find that both revokers and non-revokers face similar groups of buyers. As shown in Table 2.6, the buyers of revokers are not statistically different from buyers of non-revokers in terms of how long they have been on eBay and their reputation scores both before the policy change and after the policy change. Furthermore, buyers of the revokers group and buyers of the non-revokers group have a similar propensity to leave negative feedback to sellers. Therefore, the difference-in-differences term, $\Delta_r - \Delta_n$, provides a good proxy for $\delta_{sr} - \delta_{sn}$, the additional efforts by revokers compared to non-revokers[6].

I estimate the following specification:

[6] Still, one might argue that buyers of revokers respond differently to the policy change than buyers of non-revokers. If this were the case, then δ_{sr} should be greater than δ_{sn}, given the historical higher retaliation rate of revokers. Since $(\delta_{sr} - \delta_{sn}) = (\Delta_r - \Delta_n) - (\delta_{br} - \delta_{bn})$, this means that $(\Delta_r - \Delta_n)$ is underestimating $(\delta_{sr} - \delta_{sn})$. Therefore, revokers' behavioral improvement could be even greater than what is reported here.

$$Logit\ (ifNegative_{it}) = \alpha + \beta_1 * P_t + \beta_2 * G_i + \beta_3 * P_t * G_i + \beta_4 * month\_dummy_t + \beta_5 * duration_{it} + \beta_6 * price_{it} + \beta_7 * s\_tenure_{it} + \varepsilon_{it}$$

where i indexes the sellers and t indexes the feedback. The dependent variable, $ifNegative_{it}$, is a dummy that equals 1 if the feedback received by the seller is negative[7]. P_t is a dummy variable indicating whether the time of the feedback is within the pre-change period or the post-change period (P_t=1). The coefficient of P_t reflects the general change in the possibility of receiving negative feedback by sellers. G_i is a dummy variable indicating whether the seller is a revoker (G_i=1) or not. As discussed above, the coefficient of $P_t * G_i$ captures δ_{sr} - δ_{sn}. I also include the $month\_dummy_t$ variables to control for possible time fixed effects. Finally, three control variables are added to control for transaction heterogeneity: duration of the transaction, final price, and the seller's tenure at the time of transaction. As detailed in Section 2.4.1, the pre-change period is defined as July-September 2007, and the post-change period is July-September 2008.

2.4.2.3 Empirical Findings

For the 198 revokers and 198 non-revokers, I collect 240,990 feedback ratings in the pre-change period and 215,802 feedback ratings in the post-change period.

The estimates are reported in Table 2.7. In the random effects logit model, the coefficient of P_t is significantly positive, indicating that sellers generally are more likely to receive negative feedback after the change in the reputation system. This is consistent with my prediction: since sellers are no longer able to use retaliation to prevent buyers

[7] Revoked feedback in the pre-change period is converted to their original values and count as negative feedback.

from providing negative feedback, or eliminate negative feedback by revoking, they are expected to have more negative feedback displayed in their profiles under the new reputation mechanism. The significantly positive coefficient of G_i suggests that revokers are more likely to receive negative feedback than non-revokers in the pre-change period, as expected.

Interestingly, the coefficient of P_t*G_i is significantly negative across various specifications. This indicates that the increase in negative feedback percentage is much smaller for revokers than for non-revokers after revoking is disallowed. This result still holds after I control for possible seller fixed effects in the fixed effects logit model.

Because negative feedback is extremely rare on eBay, I also estimate a rare-event logit model to correct for the potential underestimation bias, as suggested by King and Zeng (2001). I once again observe a significantly negative coefficient of the interaction term P_t*G_i as shown in Model 2.

As a further robustness check, I add transaction-related variables such as the duration of the transaction (i.e., the interval between the listing date and the transaction closing date) and the final price into the conventional logit regression analyses. The estimates are reported in Model 4 and Model 5.While the sample size is reduced due to missing values in these two variables in the raw data, I find that all major results hold.

In the formal difference-in-differences model, I assume that the error term ε_{it} follows an independent and identically distributed (i.i.d.) standard logistic distribution. However, as Bertrand et al. (2004) suggests, serial correlation between ε_{it} and $\varepsilon_{it}+1$ can lead to an underestimation of the standard error and an overestimation of t-statistics and significance levels. One way to circumvent this issue without making any specific assumption about the autocorrelation form is to aggregate the time series information. Therefore as a robustness check, I aggregate the data at two levels for further robustness checks.

First, I aggregate each seller's performance by month. The dependent variable now is the seller's monthly aggregated percentage of negative feedback, a ratio whose predicted value should also fall between 0 and 1, requiring the use of a generalized linear model (Papke and Wooldridge 1996). As shown in Model 6 of Table 2.7, the coefficient of P_t*G_i is consistently significantly negative.

Second, I aggregate each seller's overall performance in the pre-change and the post-change period. As shown in Figure 2.2, the displayed negative feedback percentage increases for all sellers (1.49% to 1.54% for revokers, and 0.47% to 0.87% for non-revokers). However, the 0.05% increase in actual negative feedback percentage for revokers is much lower than the 0.40% increase for non-revokers, and the difference is statistically significant at the 10% level (t-value=-1.90).

Overall, I find that while both revokers and non-revokers experience a higher percentage of negative ratings in the post-change period, the magnitude of the increase is much smaller for revokers. Prior literature (e.g, Pavlou and Dimoka 2006) has suggested that feedback can be a proxy for the effort exerted by a seller in a transaction. The difference-in-differences estimate therefore provides supporting evidence that revokers exert extra efforts (compared to non-revokers) to improve service quality. This indicates that retaliators changed their behavior in a positive way to mitigate the increase in negative feedback caused by the change in the reputation mechanism.

<u>Broadening the Definition of Strategic Sellers:</u> while revokers are defined here as sellers who had successfully convinced a buyer to revoke negative feedback, there are also 57 sellers in the sample who retaliated but with no success in revoking. These cases might be caused by the inadequate effort the seller made to negotiate with the buyer. Despite the fact that a revocation outcome was not reached in these cases, retaliation nonetheless reflects a seller's endeavor to game the reputation system under the old policy. Therefore, it is reasonable to assume that not only revokers but also sellers who retaliated (even though did not successfully revoke), would be affected by the change in the feedback policy. Accordingly, I use "retaliators" to denote the combination of revokers and sellers who retaliated but did not succeed in revoking. In total, I have 255 retaliators. Using propensity score matching method based on reputation score, tenure on eBay, and average product price, I construct a matched sample of 255 non-retaliators who had never retaliated against any negative feedback and who did not involve in revoking. The results of the difference-in-differences model are shown in Table 2.8.Iconsistently find that retaliators improve their efforts more compared to non-retaliators after the policy change. This suggests that my findings are applicable to a broader range of strategic sellers in addition to pure revokers.

2.4.2.4 Falsification Test and Additional Robustness Checks

<u>Falsification Test:</u> as discussed earlier, the focus of above analysis is how the behavior of strategic sellers is affected by the changes to the reputation system. I find evidence that there are sellers who previously attempted to fix their reputations by retaliating against buyers and revoking negative feedback. After revoking is banned these sellers began making more efforts to improve their services. To further verify this inference, I also conduct a falsification test. Specifically, there are sellers who, upon receiving negative feedback, did not retaliate against the buyer. Rather, they admitted their mistakes and take action of remedies, and then asked the buyers to withdraw the negative feedback. To further corroborate that these sellers were behaving honestly, I examine the communications between buyers and sellers through text replies to negative feedback. I find that these sellers typically did not retaliate because they committed a genuine error and were attempting to fix it (for instance replies include “Would be happy to give a full refund” and “Sorry for the confusion, I guarantee quality and delivery, will get enough back!”). I call these sellers “honest revokers”. Since this group of sellers do not strategically retaliate buyers with negative feedback, they should be less affected by the policy change. In other words, this group of “revokers” should behave differently from strategic revokers.

I identify a total of 98 honest revokers in the sample. Using similar propensity score matching method based on reputation score, tenure on eBay, and the average product price of the seller’s listings, 98 non-revokers are matched as the control group. The comparison of reputation profiles between these two groups is shown in Table 2.9.

Even though honest revokers initially receive more negative feedback than non-revokers, they look similar to non-revokers after correcting their mistakes and removing the negative feedback. This suggests that revoking is a useful tool for honest sellers to remedy their mistakes, perhaps the primary reason why eBay introduced this policy initially. However, the existence of strategic retaliators who abuse the policy dampens its effectiveness.

As shown in Model 1 and Model 2 of Table 2.10, the interaction term P_t*H_i (H_i is a dummy variable for being an honest revoker) is not significant. This result strengthens the finding that only retaliators who used to behave strategically are incentivized to perform better after the policy change.

Examining Changes in Positive Feedback: In the above analyses, I focus on the negative feedback received by sellers. As another robustness test, I examine the positive feedback received by the strategic sellers after the policy change.

If my finding is correct that retaliators exert more efforts than non-retaliators after the policy change, this should be reflected in the positive feedback they receive as well. In other words, because of their improved service quality in the post-period, these retaliators should also experience a greater increase in the likelihood of receiving positive feedback than non-retaliators when compared to the pre-change period. The empirical finding confirms this conjecture. As shown in Model 3 and Model 4 of Table 2.10, the coefficient of P_t*G_i is consistently positive and significant in both random effects logit model and fixed effects logit model. These tests give us greater confidence that the reputation system change does motivate strategic sellers to improve their efforts to serve buyers.

I further carefully examine and rule out alternative explanations why retaliators are less likely to receive negative feedback in the post-change period, other than improving efforts[8], as detailed below.

(1) Switching product categories. One alternative explanation for retaliators' "improved" feedback scores compared with non-retaliators is that retaliators simply switch to safer product categories instead of improving their services. To rule out this

[8] I conduct all of these checks for revokers vs. non-revokers and obtain consistent results.

possible alternative explanation, I first calculate the distribution of listings among product categories for retaliators and non-retaliators in the pre-change period and the post-change period. I then compare the change in each product category for retaliators and non-retaliators. As shown in Figure 2.3, no significant difference is detected between retaliators and non- retaliators in terms of changes in the total number of product categories they are selling and the percentage of listings in the top 5 product categories sold[9].

Researchers have argued that different product categories might inherently have different potentials for receiving negative feedback. For example, MacInnes et al. (2005) find that in eBay online auctions, transactions in services are more likely to result in disputes than transactions in physical goods. Scott and Gregg (2004) propose that, when purchased online, high sensory products such as clothing and furniture are more likely to generate negative feedback compared with low sensory products. Product categories may differ in their inherent riskiness and, consequently, in the number of complaints received by their sellers (MacInnes et al. 2005). This product category risk is aligned with the consumers' beliefs regarding whether the products will perform according to their expectations (Bhatnagar et al. 2000). Product category risk increases with greater technical complexity, price, and needs of feel and touch (Bhatnagar et al. 2000, Chang et al. 2006; Finch 2007). I then examine whether retaliators have switched to low-risk product categories more than non-retaliators after the change in the reputation mechanism. I consider only the top 5 product categories: clothing, collectibles, books, jewelry, and electronics. These top 5 categories account for about half of all listings. Clothing is considered a high-risk product category because of the sensory nature of the

[9] This result also holds for the rest of the 26 product categories.

product and the difficulty in describing its features accurately (Bhatnagar et al. 2000). Collectibles are considered a high-risk product category because they have many attributes and a complex description is required (Scott and Gregg 2004). Books, which are typically lower priced items, are considered a low-risk product category. Jewelry is considered a high-risk product category as sellers who cheat stand to benefit more from higher price items. Electronics are considered to be a high-risk product category because, in general, electronic items are technically and descriptively complex. According to Bhatnagar et al. (2000)'s rank of product category risk, electronics are much riskier than clothing and books.

Figure 2.4 presents the percentage of listings in high-risk and low-risk product categories for retaliators and non-retaliators. Retaliators and non-retaliators show similar proportion of listings in high-risk products and low-risk products respectively in both the pre-change and the post-change periods. Also, the magnitudes of change for retaliators and non-retaliators are not significantly different.

(2) Buying reputation. Another potential alternative explanation for retaliators' smaller increase in negative feedback is that retaliators strategically buy more positive feedback through selling very low-value items to buyers and engaging in reciprocally positive feedback exchange (Dini and Spagnolo 2009). Typically the title of such listings clearly states "100% positive feedback." However, an examination of the product listings by both retaliators and non-retaliators suggest that no such feedback-buying behavior exists.

(3) Sell-through rates. In the above analysis, I focus on seller reputation profiles. Another important measure of seller performance is the sell-through rate, which has

important implications for market liquidity and efficiency. As shown in Figure 2.5, retaliators and non-retaliators do not differ in their sell-through rates for both high-risk and low-risk products. Also, there is no difference in the magnitudes of change in sell-through rates between the two groups of sellers (t-value=-1.13). This indicates that the smaller increase in negative feedback for retaliators is not driven by successfully selling more low-risk product categories but in instead largely due to their quality improvement in selling.

(4) Product price. It is possible that retaliators might be likely to intentionally reduce the product price to lower buyers' expectations of service quality in order to get less negative feedback in the post-change period. Therefore I compare the average change in product price from the pre-change period to the post-change period for both retaliators and non-retaliators. As shown in Figure 2.6, I do not find any significant difference between retaliators and non-retaliators for both high-risk products and low-risk products. This helps rule out the alternative explanation.

To summarize, my results consistently show that the reputation system design has a meaningful and significant impact on seller behavior. After the power balance shifts in favor of buyers, retaliators improve their efforts more than non-retaliators in the post-change period, and therefore have smaller increase in negative feedback.

2.5 Discussion and Implications

Reputation mechanisms are vital to the success of online marketplaces such as eBay. However, the efficacy of these mechanisms depends crucially on how robust they are to potential gaming by participants. My s is among the first studies to examine strategic gaming behavior in the context of online reputation systems. I utilize the policy change on eBay – banning revoking – to examine the impact of reputation system design on seller behavior. My analysis of the protest/strike following the new policy announcement provides supporting evidence that strategic sellers do react strongly to the reputation system change: those who have revoked before are much more likely to participate in the online strike. After the new policy is implemented, I find that in general, buyers are more likely to leave negative feedback after the seller loses the power to retaliate. More interestingly, I find that those strategic sellers have indeed acted opportunistically as they exert more efforts to improve the quality of their transactions.

The current findings make significant contributions to the literature on online reputation mechanism design (see Dellarocas 2005; Fan et al. 2005; Qu et al. 2008; Zhou et al.2008). A reputation mechanism should facilitate market transactions by separating good players (either sellers or buyers) from bad ones and inducing honest behavior. I provide the first empirical evidence that sellers do respond to the design of the reputation mechanism. Allowing revoking of feedback facilitates sellers' strategic gaming behavior. After revoking is disabled, the more opportunistic sellers "behave better". This finding has important implications for the theoretical work on reputation systems as well, as it is a crucial assumption to what degree the models can assume that sellers be motivated to behave by a reputation system (Barr-Issac and Tadelis 2008). I find support to both hidden information and hidden efforts: strategic sellers improve their services after the policy change, but the reputation scores are now revealed as worse than average, as reflected in Figure 2.2 (1.54% negative feedback for revokers and 0.87% negative feedback for non-revokers, t-value=2.05). Therefore, the mixed model is likely closer to reality.

Furthermore, by examining the buyer-seller interactions before and after a fundamental change this study contributes to the understanding of reputation system design by shedding light on the importance of the power balance between the buyer and the seller on the effectiveness of a reputation mechanism. This study also contributes to the understanding of the emerging influence of users' actual interactions with feedback systems and other information systems on market mechanism design, as noted by Bapna et al. (2004) and Adomavicius et al. (2011).

The paper also contributes to the growing literature on ways that retailers can strategically influence buyer reviews. Whereas Stephen et al. (2012) show that monetary incentives offered by sellers can lead buyers to leave more helpful reviews, Cabral and Li (2012) find that monetary rewards can only increase the likelihood of buyers leaving unbiased ratings but not the values of the ratings. Abeler et al. (2010) examine sellers' response to negative buyer reviews by comparing private apology to monetary compensation and find the former more effective in motivating buyers to withdraw negative ratings. Similarly, Gu and Ye (2011) find that a public management response can increase the future satisfaction of buyers who leave negative ratings. Jiang and Guo (2012) argue that retailers should allow more rating scales for popular products and fewer rating scales for niche products in order to induce more positive ratings. This study makes contributions to this line of literature by studying sellers' strategic gaming behavior with reputation systems.

This paper is also part of the growing literature on gaming behavior in online marketplaces. Kauffman and Wood (2005) examine the shilling behavior of sellers to artificially raise bidding prices. Cabral and Hortacsu (2010) find that roughly one-third of sellers built their reputations by acting as a buyer first. Jin and Kato (2006) find that some eBay sellers make non-credible claims of quality and mislead buyers. Stephen and Toubia (2010) find that sellers can strategically increase revenues by creating incoming links from other sellers who are dispersed. I contribute to the above literature by introducing a new way to study seller strategic behavior. This work is also related to the question of how consumers should interpret sellers' online reputations. Zhang (2006) finds that reputations as a seller and as a buyer have different impacts on closing price. My findings imply that reputation system should make consumers aware of seller strategic behavior to better differentiate their qualities.

Managerially, this study has two implications. First, the finding that revoking elicits strategic behavior in sellers suggests that, when revoking is available to sellers, online market makers should adopt other measures to reveal more quality information to buyers. One potential way to do this is to take revoked feedback into account when calculating overall reputation and to display the percentage of revoked feedback to buyers. Currently there is no easy and straightforward way of getting this information from eBay or other similar markets. Second, while banning revoking and the possibility of retaliation by sellers might help mitigate the retaliation problem, such a change could unduly shift the balance of power in favor of buyers. Providing more detailed and granular feedback and reputation scores (for instance, their reputation in their role as a buyer versus seller) could help alleviate such a power imbalance, making the market participants less vulnerable to strategic transaction partners.

I acknowledge several limitations in this study. First, in order to ensure that I examine active sellers with substantial number of transactions, who account for the majority of the transactions on eBay, I restrict my investigation to sellers with lifetime total feedback of 500 or more. Second, eBay made some other changes in October of 2008 (e.g. no checks or money order as payment methods, as detailed in footnote 4). While I have limited my sample period to July-September, which is ahead of these changes, the announcement effect may potentially influence selling behavior. Since these changes are not related to the reputation mechanism, I believe the confounding effects of these other changes, should be trivial or nonexistent. Third, while I have controlled for change in buyer feedback-leaving behavior in the difference-in-differences model, direct investigation of buyer behavior using detailed buyer-side data would provide further support for my findings. Finally, I infer the seller behavioral change using buyer feedback. Future research could strengthen the findings by seeking more direct measures of seller efforts and service quality.

The study can be extended in a number of interesting ways. For instance, one might conduct a more detailed analysis of how the process of revoking unfolds by looking at both sellers' and buyers' detailed feedback behavior. It is also important to understand how the changes in reputation mechanism influence market efficiency. A detailed comparison of final auction prices between retaliators and non-retaliators may shed light on this. Finally, it would be interesting to examine whether banning revoking in the new system benefits eBay or not. Prior to the policy change, eBay's reputation mechanism was more symmetric with both buyers and sellers being allowed to post positive, neutral, or negative feedback about their transaction partners. However, the inherent asymmetry in the value of reputations (i.e. a good reputation is more valuable to a seller than it is to a buyer), made revoking more attractive to sellers. The change in the design of the reputation mechanism from a symmetric to an asymmetric one is likely to be in line with the asymmetric value of reputation to sellers and buyers, and therefore optimal. On the other hand, it is possible that these changes make buyers more powerful and induce them to behave opportunistically. For example, buyers may slow down their payment speed without worrying about negative feedback from the sellers, or buyers may make fraudulent claims of product defects or return products for senseless reasons. In more extreme cases, bad buyers might make excessive demand on sellers by threatening to leave negative feedback. Further research is needed on the costs and benefits of a symmetric versus an asymmetric feedback mechanism. Also, I find supporting evidence that sellers improve their services as reflected in buyer feedback. Future research could look at more direct measures of seller efforts, and provide a deeper understanding of how these efforts lead to better reputation portfolios.

Chapter 3: Truck, Barter and Exchange: An Empirical Investigation of Reciprocity in Online P2P Bartering

"The propensity to truck, barter, and exchange one thing for another... is common to all men, and to be found in no other race of animals... Nobody ever saw a dog make a fair and deliberate exchange of one bone for another with another dog."

-Adam Smith (1776)

3.1 Introduction

Barter, defined as the exchange of goods or services without money changing hands, has been used throughout the world for centuries since introduced in the pre-historic times. This most primitive form of transaction incurs higher transaction costs than monetary transactions for three major reasons. First, in a direct barter market, a trader who has apples but wants bananas must wait until someone willing to give up bananas for apples shows up. This search for "double coincidence of wants" is costlier than the combination of a search for a buyer who will pay money for apples and a search for a seller of bananas (Heller and Starr 1976; Jevons 1985). Second, fiat money has virtually zero storage and transfer cost, making its exchange for goods less costly than the exchange of goods for goods (Freeman 1989). Third, each trader has private information about own-produced goods due to social specialization. This information asymmetry can incentivize the trader to produce low-quality products and take advantage of uninformed trading partners (Kim 1996). Fiat money, whose value is identifiable by every trader, reduces the information acquisition cost needed to mitigate the moral hazard and adverse selection problem in exchange of goods (Banerjee and Maskin 1996; Brunner and Meltzer 1971). As a result, money arises endogenously from an evolutionary process as the predominant medium of exchange in modern society.

However, recent developments of Internet and Web 2.0 technologies have greatly reduced transaction costs associated with barter transactions. Electronic marketplaces overcome the geographic constraint, connect individuals from all over the world, and allow them to search for potential trade partners easily and at a nearly zero cost (Bakos 1997). Virtual currency, which usually has all of the characteristics of fiat money such as zero storage and transfer cost (Yamaguchi 2004), can be used as the medium of exchange in online barter market. Online reputation systems, which help communicate product and trading partner quality and promote trust among buyers and sellers, have proved to be effective in reduce information asymmetry and the “lemons” problem (Dellarocas 2003). Due to reduced transaction costs, the past four years have witnessed the growth of various online peer-to-peer (P2P) barter marketplaces. For example, there are barter marketplaces focused on books such as Paperbackswap.com and Swap.com, marketplaces focused on clothes such as thredUp.com, marketplaces focused on music and movies such as SwapaCD.com and SwapaDVD.com, marketplaces focused on housing such as HomeExchange.com, and marketplaces open to anything such as BarterQuest.com.

This study is among the first to systematically examine the emerging trading model--online P2P barter markets. Traditional electronic marketplaces are based on the monetary system that operates under the maxim “money buys goods and goods buy money; but goods do not buy goods” (Davidson 1972). Because money is a universally accepted medium of exchange, sellers can use the money from selling goods or services outside the electronic marketplace. However, in barter markets typically no real money is involved. There are two major forms of barter: direct barter and indirect barter (Oh 1989; Rice 2003). Direct barter is the exchange of one good from one party for another good from the other party. Indirect barter involves the use of an intermediary good such as virtual point. In indirect barter marketplaces, one good from one party is given to the second party in exchange for the intermediary good, and afterwards the intermediary good can be used by the first party to exchange for another good from a third party. To increase the efficiency of transactions, nowadays most barter markets are indirect barter markets, which are different from traditional money-based online markets in three aspects. First, because the intermediary good gained from giving a good is usually valuable only in the same marketplace, it helps increase market participants' loyalty and commitment to the market (Ji et al. 2008). Second, whereas traditional online market is often characterized by one-shot interactions (Resnick and Zeckhauser 2002), online barter markets allow the potential for developing lasting relationships over time among participants as they are devoted to the market, especially given that participants are often like-minded individuals when the barter market is focused on a particular type of good such as books. Third, whereas in traditional money-based online markets formal contracts are often involved to govern transactions, online barter markets more reply on norms of reciprocity and implicit contracts (Kaikati 1976).

The above distinct natures of online barter markets imply that participants seem to exhibit more needs for developing long-term relationships in the market, and this might affect how they search for and choose transaction partners. Despite the growing literature on online markets, few studies have focused on the relationship between market participants and how it might influence transaction process and outcomes. To bridge the gap, this study seeks to understand how individuals search for transaction partners given the needs for relationship building and how different search strategies might affect transaction outcomes and market efficiency in online P2P barter marketplaces. More specifically, I try to answer the following three questions:

- What are the predominant search strategies in P2P barter markets?
- How do different search strategies affect transaction outcomes in P2P barter markets?
- How can P2P market makers effectively identify user segments of different search strategies?

Drawing upon literature on buyer-seller relationships and reciprocity and using detailed transaction level data from a leading online P2P indirect barter marketplace, I show that there are three dominant search strategies in P2P barter markets: indirect reciprocity, immediate reciprocity, and delayed reciprocity. I further show that these three search strategies have differential impacts on transaction outcomes: compared to the baseline of indirect reciprocity search strategy, immediate reciprocity search strategy increases service quality for the current transaction and delayed reciprocity search strategy provides better match for transaction needs. Based on the existing secondary data as well as survey results, I further show that individuals with different transaction needs and psychographic profiles adopt different search strategies in the market. As the first study to systematically examine online P2P barter markets using real transaction data, my study also make significant contributions to the existing literature on reciprocity by examining the differential impacts of different forms of reciprocity on transaction outcomes and how different individuals choose different reciprocity strategies.

The rest of the paper is organized as follows. Section 3.2 presents the theoretical motivation and review of relevant literature. Section 3.3 describes the research context. Section 3.4 presents the data analyses and results. Section 3.5 concludes.

3.2 Literature Review

3.2.1 Literature on Barter

Previous research on bartering falls into two major streams. The first stream of research focuses on macroeconomics of the barter market and consistently concludes that barter markets are in general less efficient compared with the monetary market (e.g., Banerjee and Maskin 1996; Brunner and Meltzer 1971; Freeman 1989). Nevertheless, barter is still widely used in this monetary economy. According to the U.S. Department of Commerce, barter accounts for about 30 percent to 40 percent of the world's total business. In the U.S., over 250,000 businesses actively participate in barter (Rice 2003). The second stream of research focuses on barter practice between firms and provides theoretical justifications for the use of bartering by firms. For example, Magenheim and Murrell (1988) show that barter can serve as a hidden price discrimination device by helping not reveal the firm’s type to future customers. Prendergast and Stole (2001) show that barter helps firms to generate liquidity and segment the market into high-demand and low-demand customers when liquidity constraints do not allow firms to discriminate through money. Guriev (2004) shows that barter can emerge as a means of screening high quality buyers from low quality buyers even when there are no financial constraints. Marin and

Schnitzer (2005) show that barter can be used by a firm to collateralize a trade credit to maintain production when the firm faces a severe creditworthiness problem.

Despite the justification of barter practice among firms, little research has been done on barter exchange among individuals. As best as I know, my study is the first to examine barter exchange among individuals using large scale transaction data.

3.2.2 Literature on Transactional vs. Relational View

As discussed earlier, market participants in online barter markets might have a stronger need for establishing ongoing relationships in the market. In the marketing literature, an exchange between the buyer and the seller can be viewed as discrete (or transactional) or relational (Macneil 1980). The discrete transaction view treats exchanges as characterized by very little communication between the buyer and the seller, one-time interaction and sharp ending of the buyer-seller relationship. In this view, the exchange between the buyer and the seller is pure transaction and it excludes relational elements. The relational view treats exchange between the buyer and the seller as ongoing relationships that transpire over time. In this view, the buyer and the seller may develop obligations and norms to facilitate future collaboration. Exchanges built from the relational view are often repeated as the buyer and the seller engage in social exchange. Researchers like Dwyer et al. (1987) argue that some elements of a "relationship" underlie all transactions and the exchange between the buyer and the seller should be treated as a continuum, ranging from discrete to relational.

Whereas discrete transactions are often governed by full written contracts, relational exchanges heavily rely on the enforcement of "relational contracts" which are implicitly stated (Lambe et al. 2000). Even though there are no formal contracts guiding transactions in the online barter markets, market participants may still develop implicit contracts with each other to govern the exchange relationships. One type of such implicit contracts can be psychological contracts. Barter can be seen as a subtype of gift exchange (Bell 1991), which gives rises to psychological contracts between the giver and the receiver (Davis 2009; Schein 1965). A psychological contract is an individual's belief in mutual obligations between himself/herself and another party and is formed under the norm of direct reciprocity (Coyle-Shapiro and Kessler 2002; Dabos and Rousseau 2004). Psychological contracts exist between buyers and sellers in online markets and affect their transaction decisions (Pavlou and Gefen 2005). These prior studies suggest that transactions in online barter markets might also have relational elements.

One of the observable relations between market participants over time is reciprocal relationship. In indirect barter markets, the transaction between two individuals can become bi-directional and repeatedly bi-directional over time, giving birth to reciprocity.

3.2.3 Literature on Reciprocity

The study on reciprocity traces back to earlier evolutionary biology research on cooperation in humans and other species. Several theories have been proposed to explain the evolution of cooperation behavior. The theory of reciprocal altruism posits that species engage in bilateral cooperation in pursuit of net benefits (Trivers 1971). The theory of indirect reciprocity posits that species helping others build a reputation or image score for themselves. This positive signal allows them to benefit from others in larger groups in the future (Nowak and Sigmund 2005; Zahavi 1995).

The theory of reciprocity to explain human behavior by evolutionary biologists is echoed by behavior experiments in economics. Berg et al. (1995) design an investment game to study reciprocity among individuals. In the investment game, subjects in room A decided how much of their $10 in hand to send to an anonymous counterpart in room B. Subjects were informed that the amount being sent would be tripled when it reaches room B. Then the anonymous counterpart in Room B decided how much of the tripled endowment to give back to the donor in room A. Whereas standard economic theory assuming self-interest and rationality predicts that subjects in room A should send zero amount, Berg et al. (1995) find that over 90% of the subjects in room A sent some money in the expectation of a positive return. Fehr et al. (1998) and Kirchler et al. (1996) design a gift-exchange experiment in which the subject representing the firm makes a wage offer to the subject representing the worker and then the worker decides how much effort to provide. Contrary to what standard money-maximizing theory would predict, they find strong social norm of reciprocity—a positive correlation between effort level and wage level. Their findings are further supported by the bilateral gift-experiments in Charness (2004). The conflict between observed direct reciprocation behavior and the hypotheses of self-interest and rationality can be explained by evolutionary game theory. According to evolutionary game theory, more successful strategies and behavior will survive and less successful ones will be washed out (Sethi and Somanathan 2003). Although self-interested individuals can gain more by defecting (i.e., not reciprocate), humans have evolved mental algorithms for identifying and punishing cheaters (Hoffman et al. 1998). Guth et al. (1982) and Ochs and Roth (1989) find that individuals are willing to punish opportunists even when it is costly. Therefore, self-regarding cheating is unstable in the presence of preference towards reciprocal cooperation in the long run and reciprocity dominates as a norm during the evolution process (Sethi and Somanathan 2001).

Besides direct reciprocity in bilateral interactions (if you scratch my back, I will scratch yours), indirect reciprocity (if I scratch your back, somebody else will scratch mine) also proves to be important in explaining helping and cooperation. Indirect reciprocity is implemented via image scoring and is also evolutionarily stable (Nowak and Sigmund 2005). Individuals build image score by helping others and high image score leads to higher probability of being helped by a third party. Seinen and Schram (2006) designed a repeated helping game in which two subjects were randomly matched and randomly assigned the role of donor and recipient followed by the donor's decision to whether help the recipient or not. They find that the probability that the donor helps increases as the recipient's image score built from her behavior as a donor increases, providing support for indirect reciprocity. Engelmann and Fischbacher (2009) posit that indirect reciprocity can be either strategic or pure. Image scoring provides incentives for individuals to strategically build publicly visible reputation and image scores by helping others in the expectation of net positive benefits in the long run. In pure indirect reciprocity, donors are more willing to help recipients with a higher image score even when image scoring on the donor's side is disallowed. Engelmann and Fischbacher (2009) further conduct a modified version of the repeated helping game and find support for both pure indirect reciprocity and strategic indirect reciprocity.

Several other studies compare the direct reciprocity mechanism with the indirect reciprocity mechanism to see which one induces more cooperation. Dufwenberg et al. (2001) conduct a revised version of Berg et al. (1995)'s investment game and find that the average amount of donation under indirect reciprocity is only insignificantly smaller than the donation under direct reciprocity. However, Guth et al. (2001) show that compared with direct reciprocity mechanism, indirect reciprocity induces substantially reduced amount of donations. Stanca (2009) conduct similar experiments and find that indirect reciprocity has a significantly stronger effect on donation than direct reciprocity.

In the sociology literature, reciprocity is regarded as one of the fundamental norms underlying social exchange wherein resources are transacted among individuals (Gouldner 1960). Network exchange theory and social exchange theory are two complementary theories that have been proposed to explain individual behaviors and interpersonal relations in social exchange processes. Whereas network exchange theory primarily focuses on individuals' positions and power issues in a network context, social exchange theory primarily focuses on individuals' actual interactions and the consequences of relationships (Faraj and Johnson 2010). According to network exchange theory, individuals deliberately choose partners by carefully evaluating their resources and the possibility of reciprocation before engaging in an exchange relationship (Willer 1999). According to social exchange theory, indirect reciprocity involves higher risk than direct reciprocity, because individuals are dependent on the actions of multiple others from whom they cannot directly benefit, with risk increasing in proportion to the length of the chain (Molm et al. 2007). In addition, due to the lack of ability to directly reward or punish a trusting or non-trusting partner in indirect reciprocity, the quality of reciprocation is expected to be lower in indirect reciprocity than in direct reciprocity (Buchan et al. 2002). However, other researchers like Bearman (1997) and Takahashi (2000) argue that the value of reciprocity should not be sensitive to its form: once an individual takes resources, she is obligated to return them to someone in the future. In this study, I will empirically examine whether direct reciprocity and indirect reciprocity lead to differential outcomes in online P2P barter markets.

Whereas many of the existing studies treat reciprocity as a behavior, reciprocity can also be treated as a relationship shared between one individuals and his/her partner which is consumed in the future and gives both of them utility (Leidner et al. 2009). This corresponds to the relational view of exchange or social exchange theory. More specifically in online indirect barter markets, three types of reciprocity relation could happen: (1) an individual A gives some goods to individual B but receives other goods from a third individual C and never meet with A again. This is indirect reciprocity. Because the transaction between A and B is only one-time, and A and B do not develop relations over time, this exchange is similar to the discrete transaction scenario; (2) an individual A gives some goods to individual B and later on after some time ask for other goods back from individual B. Later on, A and B start to have repeated transactions with each other. This case is a direct reciprocal relationship between A and B, and it is similar to the relational transaction scenario; (3) an individual A gives some goods to individual B and ask for other goods back from individual B immediately or within a very short time period. This is a case in between discrete transaction and relational exchange as A and B develops some extent of direct reciprocal relationship which might not be long-lived. To differentiate between (2) and (3), I call (2) delayed reciprocity and (3) immediate reciprocity. Because the three types of reciprocal relation reflect how an individual search for and choose a transaction partner, I also call this the search strategy for the individual.

Existing studies on transactional vs. relational views of exchange have shown that individuals may strategically engage in relational exchange (Gomes-Casseres 1987). Given the three possible different types of relationship, I next examine how these different search strategies have influences on transaction outcomes and how different individuals choose different search strategies.

3.3 Research Context

I collect data from a leading online P2P barter marketplace for books. Although most of the market participants are from the United States, the site is open to individuals from all over the world. More than 1000 books are bartered every day. The market is an indirect barter market based on an intermediary good called “point”. Every book request costs the requestor 1 point (or 3, if book owner resides in another country). Every book given away earns the giver 1 point (or 3, if it is sent overseas). Book owners add books they have to their inventory lists. Individuals can also add books they want into their wishlists. Both the inventory list and the wishlist of an individual are available for others to see.

Similar to eBay, the market allows book requesters and book givers to rate each other. Each market participant has an overall feedback score equal to the number of positive feedbacks minus the number of negative feedbacks. A user can also give her partner additional special praise -- publicly visible thanks plus 1 point donated to the partner--after a satisfactory transaction. In addition, a number of other indices regarding the user’s giving and receiving history such as the number of books reported by the book requester as lost in the mail, and the number of rejections to others’ requests, are also publicly displayed in every participant’s profile page. These serve to signal each participant's image score reflected in previous barter performance. This provides a basis for indirect reciprocity, wherein one person's kind or hostile acts to another person are rewarded or punished by a third party.

I first take a snapshot of all individuals' data on November 1^{st} 2010. Then I collect detailed transaction data for each individual from November 1st 2010 to May 1st 2011 in the barter marketplace. 245191 transactions involving 19261 users were traded during the period.

3.4 Data Analyses

3.4.1 The Impact of Search Strategy: Individual-Level Analysis

To examine the impact of different search strategies on transaction outcomes, I first have to uncover the distinct search strategy patterns in the market, I use a two-step cluster analysis approach with complementary methods as suggested by prior studies (e.g., Ketchen and Shook 1996; Viswanathan et al. 2007). Each individual is represented by his/her distribution of transactions among the three search strategies (*indirect_pct*, *immediate_pct*, *delayed_pct*)[10] by November 1^{st} 2010. First, I employ the hierarchical clustering technique with Ward's minimum variance method, which minimizes the total within-cluster variance and is relatively insensitive to outliers (Jobson 1992). The stopping rule from Calinski and Harabasz index is used to determine the appropriate

[10] Transactions initiated by indirect reciprocity are defined as transactions wherein the book requester A requests a book from book owner B whom he/she has not given a book to after he has given a book to at least another individual C. Transactions initiated by immediate reciprocity are defined as transactions wherein the book requester A requests a book from book owner B whom he/she has just given a book to in the past 7 days. Transactions initiated by delayed reciprocity are defined as transactions wherein the book requester A requests a book from book owner B whom he/she has given a book to more than 7 days ago. I have tried different thresholds for defining immediate reciprocity (e.g., within 1 day; within 2 days; within 5 days, etc) but get consistent results across all analyses. For simplicity, all the results for immediate reciprocity are based on the 7-day window definition.

number of clusters because it provides the best results in Monte Carlo evaluations (Milligan and Cooper 1985). As shown in Table 3.1, the 3-cluster solution produces the highest value of the Calinski and Harabasz index and therefore is preferred to other solutions.

Next, I use k-means clustering, which generally produces more homogenous clusters, to confirm the three clusters (Sireci, Robin, and Patelis 1999). The three distinct clusters indicate distinct search strategy patterns as shown in Table 3.2: cluster 1 represents individuals who mainly use the indirect reciprocity strategy; cluster 2 represents individuals who mainly use the immediate reciprocity strategy; and cluster 3 represents individuals who mainly use the delayed reciprocity strategy.

Given the above cluster analysis results, I define the three groups of users with different search strategies directly from their past transaction histories. "Indirect reciprocity search users" are defined as individuals who have not engaged in any immediate reciprocity or delayed reciprocity. "Immediate reciprocity search users" are defined as individuals of whom at least 60% of all transactions are based on immediate reciprocity. "Delayed reciprocity search users" are defined as individuals of whom at least 60% of all transactions are based on delayed reciprocity. These three search strategies are mutually exclusive. As shown in Table 3.3, I identify 9156 users in the indirect reciprocity cluster, 317 users in the immediate reciprocity cluster, and 608 users in the delayed reciprocity cluster. Whereas the total number transactions by users in the indirect reciprocity cluster count for almost 80% of all transactions, on average each user in the delayed reciprocity cluster or immediate reciprocity cluster engage in more transactions.

I then examine whether using different search strategies results in differences in overall transaction outcomes, including rejection rate, service quality measured by the partner's speed of delivery, wishlist fulfillment rate. As indicated by the following three estimations, I control for individual characteristics such as whether they have a bio, how long they have stayed in the market, their feedback score, etc.

(1)

$$Rejection\_rate = \alpha_1^1 + \beta_1^1 * Immediate\_dummy + \beta_2^1 * Delayed\_dummy + \beta_{3-14}^1 * Individual\_Controls + \varepsilon$$

(2)

$$Delivery\_speed = \alpha_1^2 + \beta_1^2 * Immediate\_dummy + \beta_2^2 * Delayed\_dummy + \beta_{3-14}^2 * Individual\_Controls + \varepsilon$$

(3)

$$Wishlist\_rate = \alpha_1^3 + \beta_1^3 * Immediate\_dummy + \beta_2^3 * Delayed\_dummy + \beta_{3-14}^3 * Individual\_Controls + \varepsilon$$

The descriptive statistics of all variables are shown in Table 3.4, and the correlation matrix is shown in Table 3.5. Because the three estimations may have contemporaneous cross-equation error correlations, I use the seemingly unrelated regression estimation (SURE) model to estimate the three equations simultaneously. For equation (4) and (6), the dependent variable is a ratio whose predicted value should also fall between 0 and 1, requiring the use of a generalized linear model (Papke and Wooldridge 1996). The results of the SURE estimation are shown in Table 3.6.

Whereas there is no difference among the three strategies in terms of ensuring transactions successes[11], the usage of immediate reciprocity search strategy leads to the fastest delivery speed and the usage of delayed reciprocity search strategy results in a

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[11] In general, the rejection rate in the marketplace is pretty low (less than 5%).

little bit faster delivery speed. Among the three strategies, immediate reciprocity search strategy results in much smaller wishlist fulfillment rate.

3.4.2 The Impact of Reciprocity: Transaction-Level Analysis

The above cross-sectional individual-level analyses suggest that different search strategies lead to different transaction outcomes. However, the cross-sectional analysis does not reflect the decision process made by individuals in the market. In this section, I examine whether individuals make different decisions for transactions initiated by different search strategies using transaction-level panel data.

First, I examine how book givers make decisions of whether to accept or reject a transaction request as well as how sooner to mail the book if he/she accepts the request based on the following model:

(4) $if\_reject_{it} = \alpha_1^4 + \beta_1^4 * if\_immediate_{it} + \beta_2^4 * if\_delayed_{it} + \beta_{3-11}^4 * Receiver\_Controls_{it} + \beta_{12-14}^4 * Book\_Characteristics_{it} + \beta_{15-17}^4 * Similarity_{it} + \beta_{18}^4 * if\_same\_country_{it} + \varepsilon$

(5) $Delivery\_Speed_{it} = \alpha_1^5 + \beta_1^5 * if\_immediate_{it} + \beta_2^5 * if\_delayed_{it} + \beta_{3-11}^5 * Receiver\_Controls_{it} + \beta_{12-13}^5 * Book\_Characteristics_{it} + \beta_{14-16}^5 * Similarity_{it} + \beta_{17}^5 * Selection\_Bias_{it} + \beta_{18}^5 * Num\_to\_Send + \varepsilon$

In equation (4) for estimating the propensity of a transaction to happen, I also control for book characteristics such as book price, demand-to-supply ratio based on past transactions, as well as the number of alternative book owners who have the book at the time of the transaction. Book owners might be expecting for reciprocation when deciding to accept a transaction request or not. As a result, they are more likely to accept requests from users who will possibly in the future have books they want. People with similar tastes are more likely to exchange books with each other simply because one party is more likely to have the book the other party wants. I use several similarity measures of book tastes between two individuals. *Taste_similarity* is calculated using the cosine similarity measure based on the books in users' inventory lists. I first calculate each individual's percentages of books in each of the 36 topics (e.g., Action & Adventure, Arts & Photography, Business & Investing, etc) and store them as a vector to represent the individual's book taste. I then measure the similarity of book tastes using the following formula:

$$similarity(A,B) = \cos(\theta) = \frac{A \bullet B}{\|A\|\|B\|} = \frac{\sum_{i=1}^{n} A_i * B_i}{\sqrt{\sum_{i=1}^{n} A_i^{\ 2}} * \sqrt{\sum_{i=1}^{n} B_i^{\ 2}}}$$

The resulting similarity ranges from 0 to 1, with 0 indicating totally different book tastes, 1 indicating sharing exactly the same book taste, and in-between values indicating some level of similarity. The *shared_genre* variable measures the count of common genres of books the two individuals are both interested in. The *r_focalgenre_depth* variable measures how many other books in the genre of the requested book the book requester has at the time of the request as seen by the book owner.

For equation (5) to estimate delivery speed, because the dependent variable depends on whether the transaction request is accepted or not, there might be some unobservable characteristics of the transaction that simultaneously make it successful and lead to faster delivery speed. If regressions are on only transactions that are accepted, I might have a selection bias problem. Therefore, I employ the Heckman two-stage model to overcome this issue. The first stage is a logit model in equation (4) which models whether a transaction is accepted or not. The second stage is an OLS regression that uses the estimated inverse mills ratio from the first stage to account for selection bias in estimating the delivery speed.

In equation (4), *if_same_country* is a dummy variable indicating if the book requester and the book giver are in the same country. Theoretically, a request from a user in a different country is less likely to be accepted by the book owner due to higher shipping cost endured by the book giver. However, *if_same_country* should have no impact on the delivery speed once the request is accepted. There, I use *if_same_country* as an instrument variable in estimating the likelihood of a transaction of being rejected or not.

Individuals might send books in batches. To capture this possible batch-sending habit, I introduce another explanatory variable *num_to_send*, which measures how many other books the book owner is to send by the time of request. If the book owner has only a few books to be sent, he/she might wait for more requests from others before dropping by the post office and mailing all the books at once.

When estimating equation (4) independently, I try both random effects model and fixed effects logit model. Hausman test is conducted to decide which model is more appropriate (chi-square=353.79, p-value=0.000). I reject the null hypothesis that the random effects model is preferable over the fixed effects model. Therefore, fixed effects logit model is used and the results are reported in Table 3.7. An individual's past performance in the market has a significant impact on the likelihood of success for his/her request: the request from an individual who used to reject others' requests or who has a low feedback score is more likely to be rejected. Also, requests for high value books are more likely to be rejected. However, how the transaction is initiated (i.e., whether by indirect reciprocity, immediate reciprocity or delayed reciprocity) does not influence the possibility of rejection.

As expected, the coefficient of *if_same_country* is significantly negative, suggesting that requests from overseas countries are more likely to be rejected. The coefficient *selection_bias* is significant in the estimate results for delivery speed. These results suggest that *if_same_country* is a good instrument variable and it is reasonable to employ the Heckman 2-stage model to overcome the potential selection bias problem. The batch-sending habit is supported by the significantly negative coefficient of *num_to_send*. Overall, the estimation results for delivery speed indicate that compared to transactions initiated by indirect reciprocity, transactions initiated by delayed reciprocity on average have a slightly faster delivery speed and transactions initiated by immediate reciprocity have the fastest delivery speed.

I next employ the following model to examine how likely a book requested is in the book requestor's wishlist.

(6) $if\_wishlist_{it} = \alpha_1^6 + \beta_1^6 * if\_immediate_{it} + \beta_2^6 * if\_delayed_{it} + \beta_{3-11}^6 * Receiver\_Controls_{it} + \beta_{12-13}^6 * Book\_Characteristics_{it} + \beta_{14-16}^5 * Similarity_{it} + \varepsilon$

Both random effects model and fixed effects logit model are conducted and Hausman test suggests that the fixed effects model should be used (chi-square=2267.50, p-value=0.000). As shown in Table 3.7, the coefficient of *if_immediate* is significantly negative. This indicates that a book requested by using the immediate reciprocity strategy is less likely to be on an individual's wishlist compared to a book requested by using either the indirect reciprocity strategy or delayed reciprocity strategy. Meanwhile, if the book requested is more wanted, it is also more likely to be on the book requester's wishlist. In addition, when the book requester and the book owner share high similarity in book tastes, the book is more likely to be on the book requester's wishlist.

Overall, the transaction-level data analysis produces consistent results with cross-sectional individual-level data analysis: a transaction request using the immediate reciprocity strategy enjoys faster delivery speed but seems to be improvised, whereas a transaction request using the delayed reciprocity strategy has a better match with the book requester's wishlist.

3.4.3 The Transaction Partner Choice by Individuals

The analyses so far consistently suggest that transactions initiated by different search strategies have differential outcomes and individuals who belong to different search strategy clusters overall derive different benefits. However, the observe search strategy cluster might be purely caused by the lack of choices: one individual might choose a transaction partner who happens to make the transaction immediate or delayed reciprocal only because there is no third person to request the book. To show that individuals belong to different search strategy clusters purposefully choose transaction partners differently, I examine how individuals initiate a transaction when there are multiple alternative choices using the following model:

(7) $if\_chosen_{it} = \alpha_1^7 + \beta_1^7 * if\_immediate_{it} + \beta_2^7 * if\_delayed_{it} + \beta_{3-11}^7 * Giver\_Controls_{it} + \beta_{12-14}^7 * Similarity_{it} + \beta_{15-18}^7 * Other\_Controls + \varepsilon$

In the marketplace, a transaction is initiated by a request from the book seeker to the book owner. In the estimation, I control for giver characteristics and similarity measures. I also control for one confounding factor, *position*, which is the ranking position of the focal alternative in the choice list. In addition, individuals may want to help new members or do not trust new members much. As a result, I control for the tenure of the giver (*g_tenure_in_month*) in the estimation. Finally, book givers who have not been active recently might not be chosen because the book requester is not sure if the book giver would respond to his/her request or not. Therefore, I control for how many months has passed since the potential giver's last login time (*g_last_login_month*).

Multinomial logit model assumes that everybody faces the same choice set and the decision is only dependent on individual characteristics. It is inappropriate here because different book seekers face different choice sets and the decision is dependent on the attributes of choices. Therefore, conditional logit model is used to estimate the marginal effect of each attribute of choices given an individual's specific choice sets.

I restrict the estimate to be on transactions wherein at least one of the potential book owners has a received a book from the book requester in the past. I then run the estimation for each cluster separately to examine how the book requester deliberately chooses which strategy for the transaction. The results are shown in Table 3.8.

In all three clusters, users are more likely to choose the book owner who resides in the same country to save his/her mailing cost. For users in the indirect reciprocity cluster, both the coefficients of *if_immediate* and *if_delayed* are not significant. This indicates that these users do not purposefully utilize immediate reciprocity or delayed reciprocity even though they could. Rather, book requesters choose book owners based on their overall performance in past transactions: book owners who reject others' requests more are less likely to be chosen; book owners who have received more special thanks are more likely to be chosen; book owners who have a higher feedback score are more likely to be chosen; book owners who request more books than they give out books are less likely to be chosen. For users in the immediate reciprocity cluster, the coefficient of *if_immediate* is significant whereas the coefficient of *if_delayed* is not significant. This indicates that users in this cluster do intentionally choose partners to whom they have given a book in the past 7 days. Interestingly, most of the variables related to the book giver's past performance measures become insignificant. This strengthens the finding that users in the immediate reciprocity clusters do care about immediate reciprocation very much. For users in the delayed reciprocity cluster, the coefficient of *if_delayed* is significant whereas the coefficient of *if_immediate* is insignificant. This indicates that in contrast to users in the immediate reciprocity cluster, users in the delayed reciprocity cluster are not looking for immediate reciprocation. Rather, they patiently wait until they find a book they really want in the reciprocal partner's inventory list.

Overall, the analyses results suggest that individuals who are identified as belonging to different search strategy clusters do intentionally choose transaction partners in ways that are consistent with their pre-defined search strategy.

3.4.4 The Segmentation of Individuals

Given that individuals who use different search strategies intentionally derive differential benefits, I next examine how these users segments can be identified through main user characteristics. A post hoc analysis of whether the usage of different search strategies is associated with significantly different user characteristics is conducted. To accomplish this, I use the following generalized linear model to test the effects of belonging to different search strategy groups on the means of the joint distribution of dependent variables:

(8) $(if\_bio, if\_homepage, if\_photo, if\_librarything, tenure\_in\_month,$
$interest\_breadth,\ avidness) = f(immediae\_dummy, delayed\_dummy)$

The results in Table 3.9 show that individuals who use different search strategies significantly differ from each other in user characteristics. I find that users who use the immediate or delayed reciprocity search strategy disclose more personal information to other users. Compared to users of the indirect reciprocity strategy who adopt the transactional view of the interaction, the other two groups of users have the inclination to build relationships in the market and therefore are more willing to provide information to promote trust from others (Olson and Olson 2000). In addition, users of the delayed reciprocity strategy tend to be significantly more avid and have a much broader interest than the other two groups.

I also examine how these users segments can be identified through their psychographic profiles. A targeted survey was designed and emailed to 300 randomly chosen users of the barter market (100 users in each strategy group) and 67 full responses were received. In the survey, users answered questions about their age, gender, education level, annual household income, and other psychographic characteristics including altruistic orientation, exchange orientation, long-term relationship orientation, disposition to trust and online self-disclosure. All the measures for the psychographic constructs were adapted from previous literature, as listed in Table 3.10. Another general survey with the same questions, which also asked respondents to voluntarily disclose their user names, was advertised in the marketplace with the help of the market owner. This helped elicit 445 more responses. I restrict the analysis to be on 205 users who belong to the pre-specified strategy groups and who completed all the questions except for the question about annual household income in the survey.

As shown in Table 3.10, all the Cronbach's alpha values are above the recommended threshold of 0.70, suggesting good reliability for all construct scales (Fornell and Larker 1987). One way to evaluate the convergent and discriminant validity of each construct is to examine the factor loadings of each indicator. Each indicator should have higher loadings on the construct of interest than on any other construct (Chin 1998). Table 3.11 shows the factors loadings and cross-loadings for all the constructs. An inspection of this table suggests that the measurement model of all constructs provides adequate discriminant and convergent validity.

I then test the effects of belonging to different search strategy groups on the means of the joint distribution of all psychographic characteristics as well as demographic profiles using the following generalized linear model:

(9)

$$(gender, age, education, household\_income, altruistic\_orientation, exchange\_orientation, long\_term\_orientation, disposition\_to\_trust, online\_disclosure) = f(immediae\_dummy, delayed\_dummy)$$

The results of the above model are shown in Table 3.12. Except for that users who mainly use the delayed reciprocity strategy are a little bit older in age, there are no other significant differences in demographic profiles among the three groups of users. However, users who belong to different search strategy clusters differ significantly in their psychographic profiles. In particular, I find that users who use the delayed reciprocity search strategy have a higher disposition to trust others, are more forward-looking. Users who use the immediate reciprocity strategy tend to trust others less, and are inclined to ensure equality by reciprocation in the short-term. Users who belong to the indirect reciprocity cluster care about equality less. Interestingly, all three groups of users are equally comfortable with sharing personal information online. However as shown earlier, users who use the delayed reciprocity strategy disclose more personal information. One possible explanation is that these users are more willing to put efforts to disclose themselves as an investment in the market since they are more forward-looking and try to build long-term relationships with others in the market.

Overall, my results suggest that user differences in information search behavior are more driven by differences in their psychographic profiles and transaction needs than in their demographic profiles.

3.5 Discussion

The developments in Internet and Web 2.0 technologies have brought about significant transformation in how business transactions are conducted as well as in the day-to-day lives of individuals. The emergence of P2P bartering serves as one vivid example that highlights such transformation. This study is one of the very first attempts to examine this emerging market. I find that participants in P2P barter markets use three different search strategies to initiate transactions. More interestingly, I find that the three different search strategies lead to differential transaction outcomes. Whereas the indirect reciprocity strategy is the predominant form of search in the market, the usage of immediate reciprocity strategy improves delivery speed of the current transaction and the usage of delayed reciprocity strategy benefits future transactions by ensuring better wishlist fulfillment. Furthermore, I demonstrate that the usage of different search strategies is associated with different transaction needs and psychographic profiles.

The findings of this study make significant contributions to the broad literature on buyer-seller relationships. Existing research on buyer-seller relationships argues that the transactions between a buyer and a seller should not be just treated as discrete events. Instead, transactions are relational exchanges that reflect the ongoing relationships between buyers and sellers (e..g, Dwyer et al. 1987; Ganesan 1994; Wilson 1995). Whereas most of the existing studies focus on relational exchange between buyers and sellers in the presence of availability of hard contracts in offline contexts, this study examines the relational exchange between market participants in barter markets wherein no formal contracts are available. Some of the existing research has examined buyer-seller relationships in online contexts. For example, Pavlou and Gefen (2005) study the relationship between buyer and sellers on eBay through the transactional view. In this study, I examine the relationship between users in barter markets using the relational view. The findings of the study suggest that the lens of relational exchange also applies to transactions in online markets even without the presence of formal contracts. In addition, this study contributes to the existing literature by showing that individuals with different characteristics adopt different views of exchange relationships.

The study also contributes to the literature on reciprocity. Whereas many studies have examined direct reciprocity and indirect reciprocity separately in experimental settings or offline field settings (e.g., Berg et al. 1995; Engelmann and Fischbacher 2009; Fehr et al. 1998; Nowak and Sigmund 2005), this study is among the first to empirically examine how indirect reciprocity and direct reciprocity might coexist and be utilized by individuals differently in large online settings. The findings of the study imply that certain individuals with certain characteristics value and pursue for direct reciprocity even when indirect reciprocity is designed to be the predominant form of exchange.

Whereas the study complements the existing literature on bartering by examining the microeconomics of bartering between individuals, it also adds to the literature on information asymmetry in online marketplaces. Like traditional online marketplaces, P2P barter marketplace suffers from the issue of information asymmetry: trading partners are not familiar with each other and there is no guarantee that one party will sacrifice his/her good to help the other party. The essay provides some new evidence that individuals rely on reciprocity to mitigate the “lemons” problem proposed by Akerlof (1970).

The study provides important implications for the design of P2P barter marketplaces. For example, the observed reliance of individuals on reciprocity to select partners and make transaction decisions indicates that it is crucial to increase the visibility of reciprocal relations. Exemplary measures to achieve this might include tracking, recording and publicly displaying every participant’s past interactions. The findings that individuals of different search strategies can be segmented based on their transaction needs and psychographic profiles suggest that any new design features might only be valuable to certain users in the market. The market maker need to carefully evaluate which group of users might be embracing a new design feature before implementing it.

I acknowledge several limitations in this study. First, the current analyses mainly focus on dyads. Future research could examine the different transaction network patterns using social network analysis techniques to help unveil new search and transaction strategies. Second, I do not examine how the relationship between two individuals changes over time. Future research on the evolution patterns of relationships could help better understand the formation and maintenance of ongoing relationships in the markets.

Third, a field experiment in the barter marketplace to examine how individuals in different search strategy clusters respond to different design features might be worthwhile.

Chapter 4: Conclusion

The rapid growth of Internet and Web 2.0 technologies has significantly changed the way individuals interact with each other in today's digital economy. The norm of reciprocity, which is embedded in all human offline interactions, also plays an important role in the online context. Seeking to understand the impact of reciprocity on individual behavior and transaction outcomes in online markets, my dissertation will make significant contribution to both theory and practice.

On the theoretical side, the first essay in my dissertation is among the first to examine the implications of feedback-revoking behavior enabled by negative reciprocity in online markets. The findings make significant contributions to the literature of online reputation system design (ex: Dellarocas 2005; Fan, Tan and Whinston 2005; Qu, Zhang and Li 2008; Zhou, Dresner, and Windle 2008). A reputation system should facilitate market transactions by separating good players (either seller or buyer) from bad ones and inducing honest behavior. This essay provides one of the first empirical evidence that sellers do respond to the design of the reputation system. Allowing revoking in feedback mechanism will lead to sellers' strategic gaming behavior. After revoking is disabled, the more opportunistic sellers increase their efforts to behave better. The findings also provide empirical evidence for a fundamental assumption in the theory work of reputation system: whether sellers should be modeled as intrinsically bad or not. This second essay is also related to the growing literature of gaming behavior in online marketplace. Kauffman and Wood (2005) study the shilling behavior of sellers to artificially raise bidding prices. Cabral and Hortacsu (2004) find that about one third of sellers build up their reputations by being a buyer first. Jin and Kato (2006) find that some eBay sellers make non-credible claims of quality and mislead buyers. I contribute to the above literature by introducing a new way of studying seller's strategic behavior—negative reciprocity-enabled revoking. The work is also related to how consumers should interpret sellers' reputation. Zhang (2006) finds that reputation as seller and buyer has different impact on closing price. My findings suggest that consumers should take into account the negative reciprocation behavior to better differentiate seller quality.

My second essay is among the first to systematically examine an emerging trading model--online P2P barter markets. Whereas many studies have examined direct reciprocity and indirect reciprocity separately in explaining cooperative behavior among humans (e.g., Berg et al. 1995; Engelmann and Fischbacher 2009; Fehr et al. 1998; Nowak and Sigmund 2005), this study is among the first to empirically examine how indirect reciprocity and direct reciprocity might coexist and be utilized by individuals differently. It also complements the existing literature on bartering by examining the microeconomics of bartering between individuals. In addition, this essay also adds to the literature on information asymmetry in online marketplaces. Like traditional online marketplaces, P2P barter marketplace suffers from the issue of information asymmetry: trading partners are not familiar with each other and there is no guarantee that one party will sacrifice his/her good to help the other party. The essay provides some new evidence that individuals rely on reciprocity to mitigate the "lemons" problem proposed by Akerlof (1970).

On the theoretical side, the first essay in my dissertation is among the first to examine the implications of feedback-revoking behavior enabled by negative reciprocity in online markets. The findings make significant contributions to the literature of online reputation system design as it provides one of the first empirical evidence that sellers do respond to the design of the reputation system. The findings that strategic sellers improve their efforts after negative reciprocity is disallowed also provide empirical evidence for a fundamental assumption in the theory work of reputation system: whether sellers should be modeled as intrinsically bad or not.

The finding of sellers' strategic revoking behavior in the first essay suggests that the reputation system should reveal more quality information to buyers when negative reciprocity is allowed. Second, the finding that seller behavior is a mixture of both moral hazard and adverse selection suggests that online market makers should carefully estimate the magnitude of each and strive for a balance between sanctioning (i.e., promoting truthful behavior) and signaling (i.e., driving out low-quality sellers) through the design of their reputation systems.

The second essay is among the first to systematically examine an emerging trading model--online P2P barter markets. Whereas many studies have examined direct reciprocity and indirect reciprocity separately in explaining cooperative behavior among humans (e.g., Berg et al. 1995; Engelmann and Fischbacher 2009; Fehr et al. 1998; Nowak and Sigmund 2005), this study is among the first to empirically examine how indirect reciprocity and direct reciprocity might coexist and be utilized by individuals differently. It also complements the existing literature on buyer-seller relationships by validating the relational view of exchange in online markets when formal contracts are not available.

As for practitioners, this essay provides important implications for the design of online markets. For example, given that only avid users use delayed reciprocity a lot, market makers with a financial constraint might need to carefully evaluate the percentage of these users and their contributions to the overall transaction volume before introducing new features such as social networking support that only appeal to them.

Overall, the findings from my dissertation suggest that reciprocity plays an important role in shaping user behavior in online markets. It could have positive or negative impact on the efficiency of the market depending on its nature (i.e., whether it is positive or negative). . It is shown from my first essay that negative reciprocity, albeit harmful to the traditional online market, is partly driven by the seller' lack of effort. Online markets should implement policies that incentivize sellers to exert more efforts, such as rewarding high quality sellers with considerable discounts and priorities in the search results, among others. One major obstacle to the sustainability of P2P barter markets is the "adverse selection" problem: everyone might have the incentive to shed from his/her responsibility to help others after he/she has got a book from others. The findings from my second essay suggest that positive reciprocity helps mitigates this problem. For an individual to ensure higher transaction quality for both the current and the future, he/she might need to use reciprocity as an incentive tool. Therefore, policies that help facilitate the norm of positive reciprocity, such as requiring participants to maintain a minimal give-to-receive ratio and encouraging participants to establish friendships in the markets, among others, will be beneficial to the governance of online barter markets. To conclude, online markets should carefully evaluate the influence of reciprocity and make optimal structures, designs and policies to promote transactions and increase market efficiency.

Appendices for Essay 1

Table 2.1 Pre-Change Revoked Feedback Profile Comparison

	SRR	**BRR**	**NRR**	**Revoked=SRR+BRR+NRR**
Strikers	0.445%	0.028%	0.021%	0.49%
General Sellers	0.058%	0.015%	0.043%	0.12%
(Forum Sellers)	(0.056%)	(0.022%)	(0.028%)	0.11%
T-value	20.80*** (17.26***)	1.26 (0.44)	-0.85 (-0.54)	10.52*** (13.11***)

Numbers for forum sellers in parentheses, *p<0.05, **p<0.01, ***p<0.001

Table 2.2 Summary Statistics for the Strike Analysis

Variable	**Number of Observations**	**Mean**	**Std. Dev.**	**Min**	**Max**
(1) log(Number of Listings)	5568	4.00	2.15	0.00	9.19
(2) Powerseller Status (Dummy)	5568	0.43	0.50	0.00	1.00
(3) Number of months on eBay	5567	76.77	30.58	5.73	145.83
(4) Fee Difference ($)	5568	-21.38	89.66	-699.02	1715.68
(5) log(Reputation Score)	5568	4.46	1.19	0.00	9.61
(6) Total Negative%	5568	0.27%	0.10%	0.00%	28.57%
(7) Remained Negative%	5568	0.26%	0.96%	0.00%	25.00%
(8) Revoked Negative%	5568	0.14%	0.61%	0.00%	25.00%
(9) SRR%	5568	0.08%	0.39%	0.00%	10.00%
(10) BRR%	5568	0.02%	0.20%	0.00%	6.67%
(11) NRR%	5568	0.04%	0.42%	0.00%	25.00%
(12) Strike (Dummy)	5568	0.07	0.26	0.00	1.00

Note: there is one missing value for number of months on eBay.

Table 2.3 Correlation Matrix

Variable	**VIF**	**(1)**	**(2)**	**(3)**	**(4)**	**(5)**	**(6)**	**(7)**	**(8)**	**(9)**	**(10)**	**(11)**	**(12)**
(1)	1.39	1											
(2)	1.29	0.36*	1										
(3)	1.04	0.02*	-0.07*	1									
(4)	1.16	-0.28*	-0.16*	0.07*	1								
(5)	1.59	0.45*	0.45*	-0.18*	-0.19*	1							
(6)	1.01	0.01*	0.04*	-0.05*	-0.01	0.00	1						
(7)	1.01	0.03*	0.01	-0.03*	-0.00	-0.02	0.86*	1.00					
(8)	1.01	0.06*	0.06*	-0.04*	-0.02	0.04*	0.58*	0.07*	1.00				
(9)	1.01	-0.02	0.05*	-0.03*	-0.03*	0.08*	0.38*	0.07*	0.63*	1.00			
(10)	1.00	-0.00	-0.01	-0.02	0.01	-0.01	0.19*	0.02	0.33*	-0.00	1.00		
(11)	1.00	0.01	0.03*	-0.02	-0.01	-0.02	0.38*	0.03*	0.69*	0.00	-0.00	1.00	
(12)		0.03*	-0.02	0.05*	0.04*	-0.04*	0.07*	-0.01	0.16*	0.27*	0.01	-0.01	1.00

Note: Pair-wise Spearman correlation is reported. * indicates p<0.05.

Table 2.4 Logit Regression Analyses of Strike Propensity

	Dependent Variable: Strike		
	Model 1	**Model 2**	**Model 3**
Independent Variable	coefficient (std. err.)	coefficient (std. err.)	coefficient (std. err.)
Intercept	-2.768*** (0.273)	-2.767*** (0.278)	-2.607*** (0.286)
Number of Listings	0.005 (0.029)	0.009 (0.030)	0.000 (0.031)
Powerseller Status	-0.006 (0.121)	-0.011 (0.122)	0.017 (0.126)
# of Months on eBay	0.007*** (0.002)	0.007*** (0.002)	0.007*** (0.002)
Fee Difference	0.002* (0.001)	0.002** (0.001)	0.002** (0.001)
Reputation Score	-0.088 (0.053)	-0.108* (0.055)	-0.158* (0.057)
Total Negative%	13.958*** (3.029)		
Remained Negative%		-15.667* (7.791)	-24.764* (9.469)
Revoked Feedback%		69.149*** (7.098)	
SRR%			166.126*** (11.073)
BRR %			15.029 (19.976)
NRR %			-52.169 (33.837)
Pseudo R^2	0.017	0.045	0.098

*p<0.05, **p<0.01, ***p<0.001

Table 2.5 Pre-Change Overall Reputation Profile Comparison: Revokers vs. Non-Revokers

		Displayed Reputation[12]		**True Reputation**				
	Score	Positive	Negative	Positive	Negative	Neutral	Revoked	eBay-Withdrawn
Revokers	844.24	99.42%	0.58%	97.29%	0.57%	1.12%	0.92%	0.10%
Non-Revokers	754.24	99.56%	0.44%	98.90%	0.41%	0.54%	0.06%	0.09%
T-value	0.72	-1.63	1.63	-8.36***	2.62*	5.80***	10.72***	0.72

$^{+}p<0.10$, $*p<0.05$, $**p<0.01$, $***p<0.001$

Table 2.6 Buyers of Revokers vs. Buyers of Non-Revokers

	Pre-Change			**Post-Change**		
	Feedback Score	Tenure on eBay in month by May 8th 2008	Propensity of Leaving Negative Feedback	Feedback Score	Tenure on eBay in month by May 8th 2008	Propensity of Leaving Negative Feedback
Buyers of Revokers	170.53	49.74	1.46%	173.64	49.83	1.66%
Buyer of Non-Revokers	190.80	49.98	1.32%	192.14	50.20	1.70%
T-test	-0.44	-0.45	0.26	-0.38	-0.20	-0.14

$*p<0.05$, $**p<0.01$, $***p<0.001$

[12] eBay displays the percentage of positive feedback as the key metric of a seller's reputation. Percentage of negative feedback is simply 1 minus the percentage of positive feedback. To be consistent with eBay's practice, I only report the percentage of positive feedback and the percentage of negative feedback for "Displayed Reputation", which is what a buyer observes.

Table 2.7 The Impacts of Removal of Revoking: Revokers vs. Non-Revokers

	Model 1 (Random Effects Logit)	**Model 2 (Fixed Effects Logit)**	**Model 3 (Rare Event Logit)**	**Model 4 (Random Effects Logit)**	**Model 5 (Fixed Effects Logit)**	**Model 6 (Generalized Linear Model)**
Dependent Variable	ifNegative (dummy)	ifNegative (dummy)	ifNegative (dummy)	ifNegative (dummy)	ifNegative (dummy)	monthly negative percentage
	coefficient (std. err.)	coefficient (std. err.)	coefficient (std. err.)	coefficient (std. err.)	coefficient (std. err.)	coefficient (std. err.)
Intercept	-5.990*** (0.153)		-4.844*** (0.065)	-5.970*** (0.303)		-5.410*** (0.152)
P_t	0.265** (0.081)	0.278* (0.124)	0.259** (0.090)	0.483* (0.206)	0.506* (0.256)	0.673* (0.278)
G_i	1.389*** (0.136)		0.742*** (0.054)	0.839*** (0.263)		1.373*** (0.179)
P_t*G_i	-0.187* (0.084)	-0.205* (0.101)	-0.244** (0.094)	-0.460* (0.193)	-0.482* (0.205)	-0.458* (0.216)
s_tenure	-0.003 (0.002)	0.034 (0.026)	-0.005*** (0.000)	-0.004 (0.003)	0.032 (0.l26)	-0.003 (0.003)
m_Aug07 (dummy)	0.150* (0.048)	0.032 (0.029)	0.032 (0.048)	0.064 (0.106)	0.048 (0.092)	0.191+ (0.114)
m_Sept07(dummy)	0.201*** (0.050)	0.025 (0.076)	0.033 (0.050)	0.198+ (0.105)	0.053 (0.150)	0.173 (0.146)
m_Jul08 (dummy)	0.008 (0.058)	0.128 (0.080)	0.117* (0.058)	-0.007 (0.133)	0.146 (0.240)	-0.133 (0.290)
m_Aug08 (dummy)	0.108+ (0.058)	0.151 (0.092)	0.206*** (0.058)	0.108 (0.130)	0.138 (0.096)	-0.161 (0.292)
duration				0.001 (0.001)	0.001 (0.001)	
log(price)				0.254*** (0.034)	0.255*** (0.030)	
# of obs.	456792	456792	456792	97330(a)	97330(a)	2376(b)

+p<0.10, *p<0.05, **p<0.01, ***p<0.001

Note: m_Sept08 is dropped from the model due to collinearity with P_t; (a) 359462 feedback instances are removed from the regression because of missing data on duration and price, either due to non-US transactions or missing transaction ID in the feedback history data; (b) The total number of data points is 198*2*6=2376.

Table 2.8 The Impacts of Removal of Revoking: Retaliators vs. Non-Retaliators

	Model 1 (Random Effects Logit)	**Model 2 (Fixed Effects Logit)**	**Model 3 (Rare Event Logit)**	**Model 4 (Random Effects Logit)**	**Model 5 (Fixed Effects Logit)**	**Model 6 (Generalized Linear Model)**
Dependent Variable	ifNegative (dummy)	ifNegative (dummy)	ifNegative (dummy)	ifNegative (dummy)	ifNegative (dummy)	monthly negative percentage
	coefficient (std. err.)	coefficient (std. err.)	coefficient (std. err.)	coefficient (std. err.)	coefficient (std. err.)	coefficient (std. err.)
Intercept	-5.905*** (0.134)		-4.982*** (0.056)	-5.880*** (0.292)		-4.764*** (0.284)
P_t	0.241*** (0.061)	0.288* (0.143)	0.343*** (0.054)	0.329** (0.126)	0.346* (0.156)	0.677* (0.272)
G_i	1.304*** (0.116)		0.859*** (0.040)	0.804*** (0.225)		0.569** (0.189)
P_t*G_i	-0.220** (0.084)	-0.243* (0.121)	-0.285** (0.106)	-0.302** (0.120)	-0.332* (0.164)	-0.367* (0.180)
s_tenure	-0.004* (0.002)	0.041 (0.032)	-0.005*** (0.000)	-0.001 (0.003)	0.036 (0.l20)	-0.004 (0.003)
m_Aug07 (dummy)	0.137** (0.048)	0.042 (0.044)	0.021 (0.047)	0.046 (0.099)	0.045 (0.087)	0.191 (0.138)
m_Sept07 (dummy)	0.193*** (0.049)	0.015 (0.086)	0.028 (0.048)	0.165 (0.099)	0.056 (0.140)	0.057 (0.148)
m_Jul08 (dummy)	0.010 (0.057)	0.118 (0.090)	0.119* (0.056)	-0.016 (0.126)	0.145 (0.242)	-0.064 (0.263)
m_Aug08 (dummy)	0.098 (0.057)	0.130* (0.052)	0.194*** (0.056)	0.098 (0.123)	0.167+ (0.086)	0.117 (0.295)
duration				0.001 (0.001)	0.001 (0.001)	
log(price)				0.234*** (0.032)	0.233*** (0.026)	
# of obs.	499589	499589	499589	112250[(a)]	112250[(a)]	3060[(b)]

+p<0.10, *p<0.05, **p<0.01, ***p<0.001

Note: m_Sept08 is dropped from the model due to collinearity with P_t; (a) 387339 feedback instances are removed from the regression because of missing data on duration and price, either due to non-US transactions or missing transaction ID in the feedback history data; (b) The total number of data points is 255*2*6=3060.

Table 2.9 Pre-Change Overall Reputation Profile Comparison: Honest Revokers vs. Non-Revokers

		Displayed Reputation		**True Reputation**				
	Score	Positive	Negative	Positive	Negative	Neutral	Revoked	eBay-Withdrawn
Honest Revokers	447.52	99.47%	0.53%	96.31%	0.51%	0.88%	1.25%	1.05%
Non-Revokers	453.09	99.73%	0.27%	99.11%	0.27%	0.54%	0.00%	0.08%
T-value	0.05	-1.77^{+}	1.77^{+}	-2.25*	1.71^{+}	2.38*	3.91***	1.06

$^{+}p<0.10$, *$p<0.05$, **$p<0.01$, ***$p<0.001$

Table 2.10 Falsification Test and Robustness Test

	Model 1 (Random Effects Logit)	**Model 2 (Fixed Effects Logit)**	**Model 3 (Random Effects Logit)**	**Model 4 (Fixed Effects Logit)**
Dependent Variable	ifNegative (dummy)	ifNegative (dummy)	ifPositive (dummy)	ifPositive (dummy)
	coefficient (std. err.)	coefficient (std. err.)	coefficient (std. err.)	coefficient (std. err.)
Intercept	-5.858*** (0.239)		4.838*** (0.107)	
P_t	0.432** (0.164)	0.458* (0.230)	0.086* (0.035)	0.090* (0.045)
Hi	1.148*** (0.211)			
P_t*Hi	-0.243 (0.154)	-0.261 (0.284)		
G_i			-1.032*** (0.094)	
P_t*G_i			0.169*** (0.045)	0.172*** (0.048)
s_tenure	-0.005 (0.003)	-0.005 (0.003)	0.003* (0.001)	-0.002 (0.002)
m_Aug07 (dummy)	0.172 (0.105)	0.154 (0.142)	-0.112*** (0.033)	0.034 (0.047)
m_Sept07 (dummy)	-0.048 (0.116)	0.105 (0.127)	-0.163*** (0.034)	0.018 (0.032)
m_Jul08 (dummy)	-0.120 (0.113)	-0.114 (0.095)	-0.02 (0.042)	0.152 (0.143)
m_Aug08 (dummy)	-0.238^{+} (0.126)	-0.184 (0.167)	-0.058 (0.042)	0.158^{+} (0.085)
# of obs.	131419	131419	499589	499589

$^{+}p<0.10$, $*p<0.05$, $**p<0.01$, $***p<0.001$

Note: m_Sept08 is dropped from the model due to collinearity with P_t

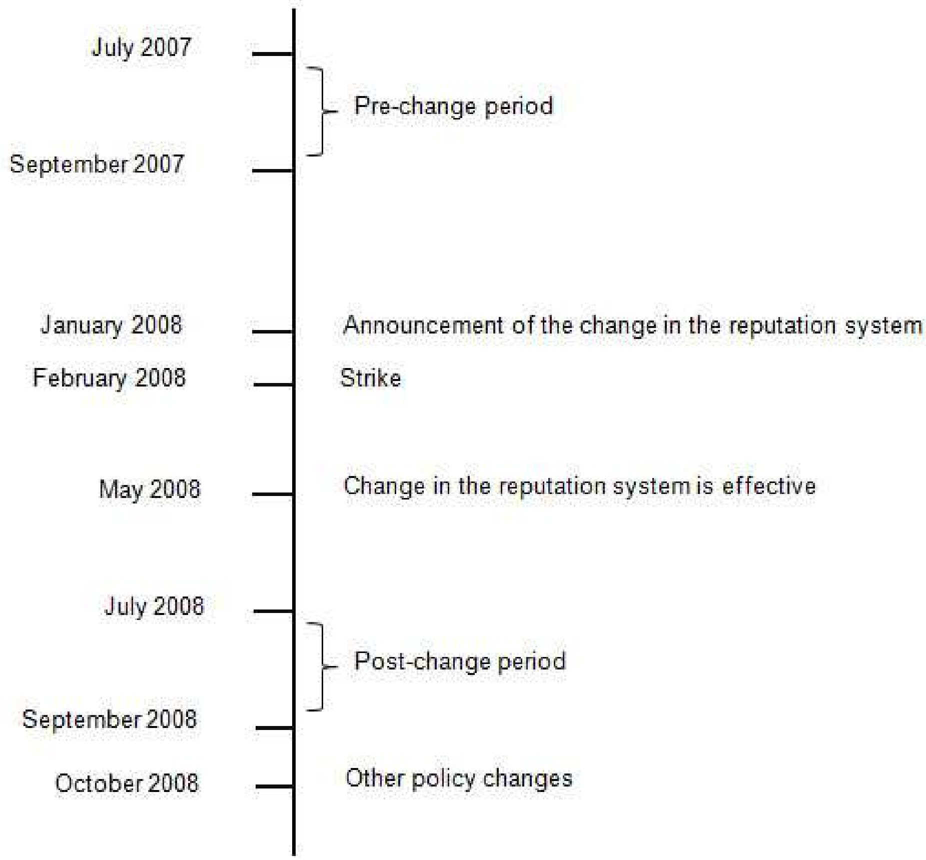

Figure 2.1 Timeline of eBay’s Reputation Change

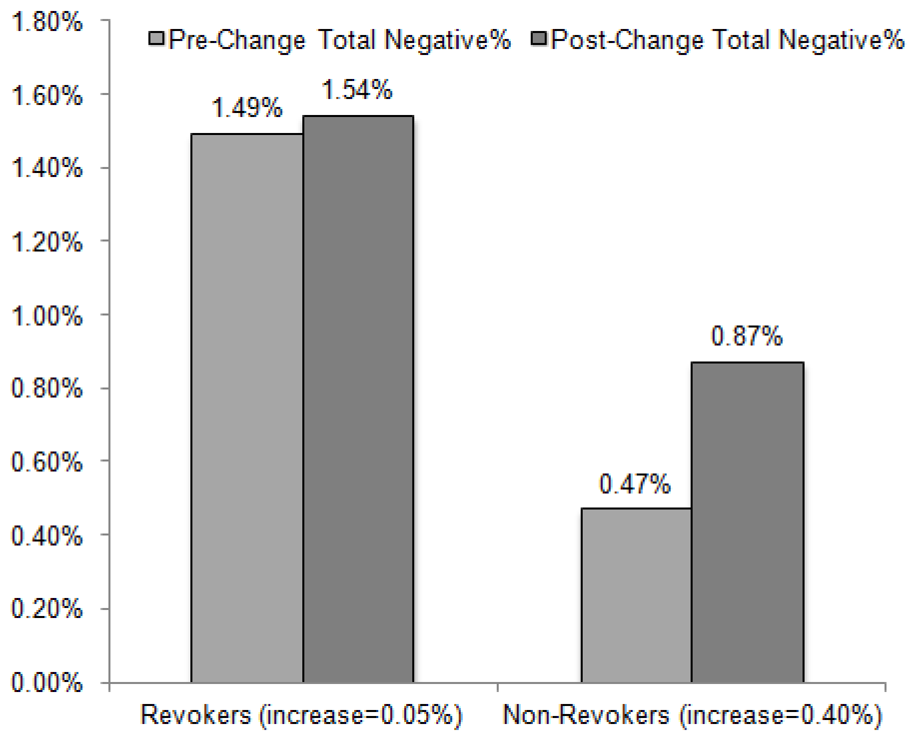

Figure 2.2 Comparison: Change in Negative Feedback Percentage

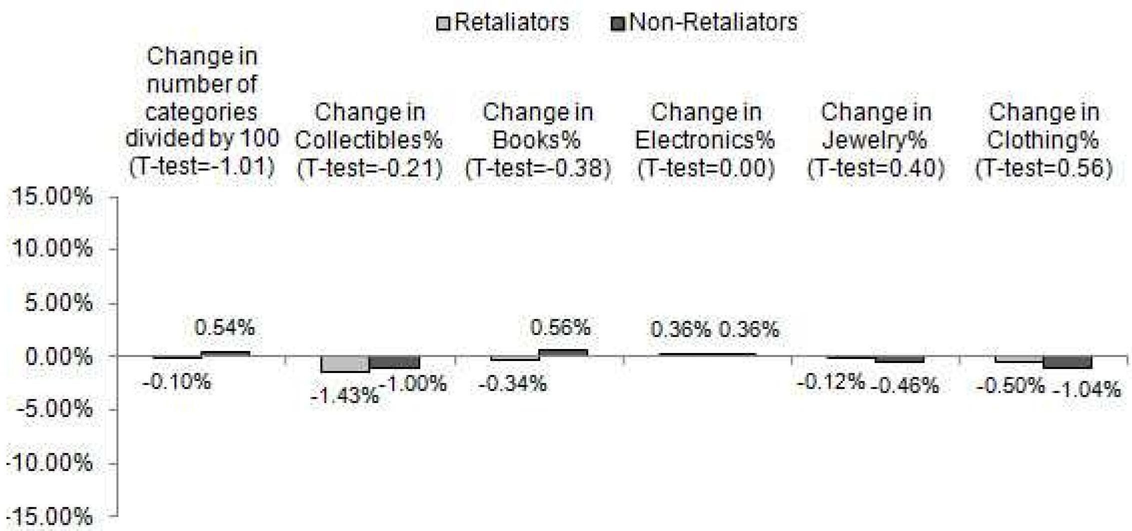

Figure 2.3 Comparison: Change in Distribution of Product Categories

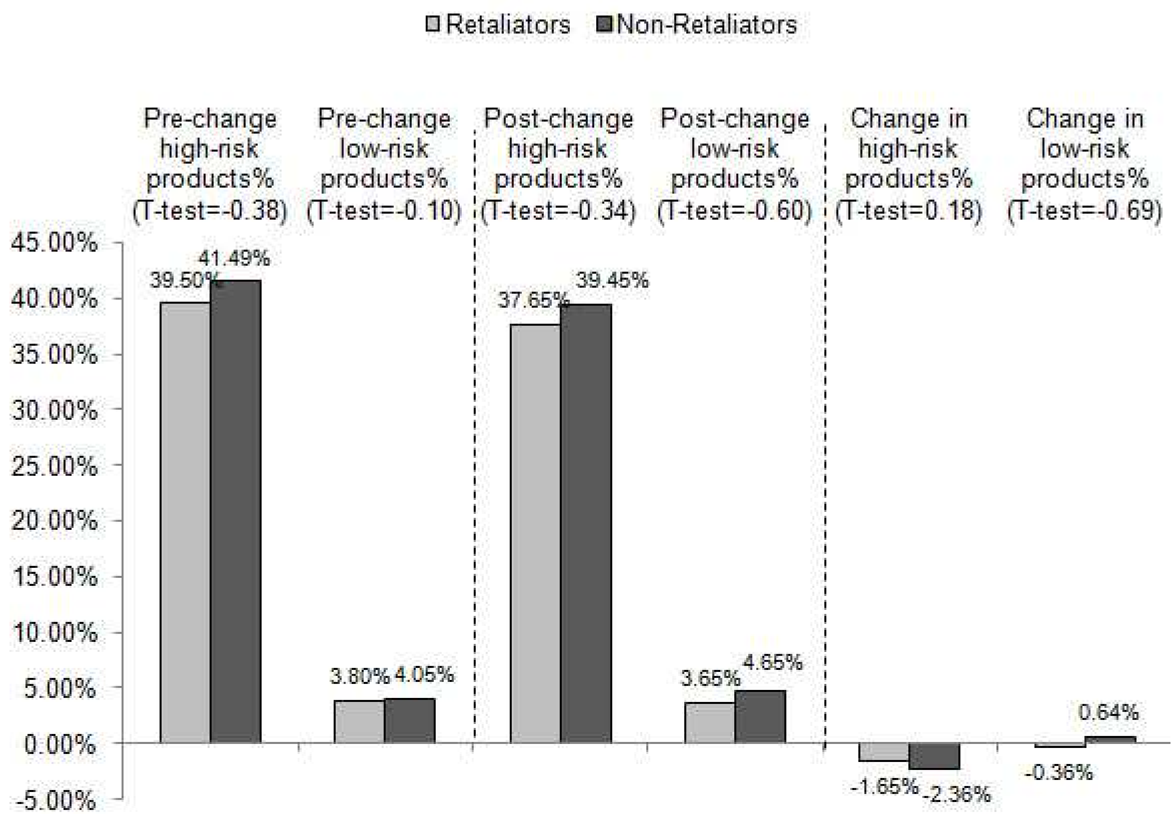

Figure 2.4 Comparison: Change in Distribution of Product Categories by Risk

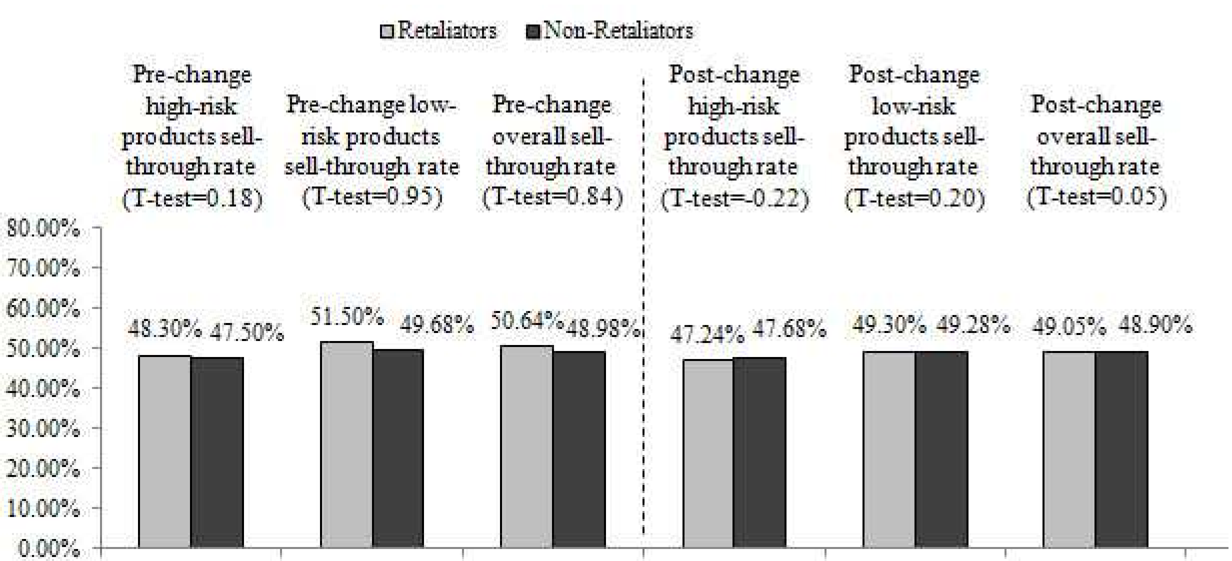

Figure 2.5 Comparison: Sell-Through Rate

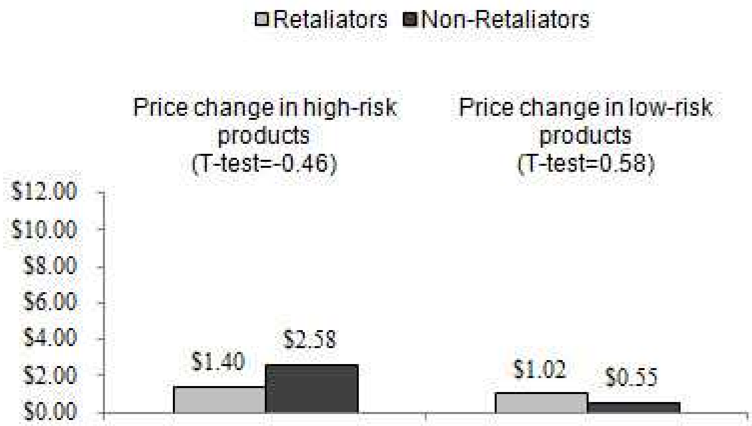

Figure 2.6 Comparison: Change in Product Selling Price

Appendices for Essay 2

Table 3.1 The Caliński and Harabasz Index for Clustering

Number of Clusters	Calinski and Harabasz index
3	2522.19
4	1760.15
5	1457.51
6	1167.33
7	988.13
8	871.49
9	762.66
10	713.90
11	670.93

Table 3.2 The 3-Cluster Solution

	Indirect_Pct	Immediate_Pct	Delayed_Pct
Cluster 1	99.06%	0.26%	0.69%
Cluster 2	19.98%	60.67%	19.35%
Cluster 3	20.06%	19.75%	60.19%

Table 3.3 The Defined Three Search Strategy Clusters Based on Past Transaction

	# of Users	**# of Transaction Per User**	**Overall Transaction Percentage**
Indirect Reciprocity Cluster	9156	30.88	79.83%
Immediate Reciprocity Cluster	317	47.54	4.26%
Delayed Reciprocity Cluster	608	92.68	15.91%

Table 3.4 Summary Statistics

Variable	Description	N	Mean	SD	Min	Max
(1) Immediate_dummy	if immediate reciprocity cluster	10081	0.03	0.17	0	1
(2) Delayed_dummy	if delayed reciprocity cluster	10081	0.06	0.24	0	1
(3) if_bio	if provides bio	10081	0.24	0.43	0	1
(4) if_photo	if provides photo of self	10081	0.16	0.37	0	1
(5) if_homepage	if provides linkage to personal website	10081	0.10	0.29	0	1
(6) if_librarything	if indicated as a librarything user	10081	0.12	0.32	0	1
(7) tenure_in_month	How long in the market in month	10081	22.26	14.05	0.07	51.03
(8) interest_breadth[(a)]	Number of genres the individual is interested in	10030	16.19	9.37	1	34
(9) avidness	Number of books requested per month	10081	1.54	2.24	0	48.61
(10) books_in_category	Number of books in inventory list	10006	21.70	27.32	1	632
(11) log(feedback_score)	logarithmized feedback score	10081	3.32	0.85	0	6.62
(12) log(rejected)	logarithmized rejections to others' requests	10081	0.59	0.72	0	4.62
(13) log(praise_received)	logarithmized special thanks from others	10081	0.24	0.49	0	3.82
(14) log(praise_given)	logarithmized special thanks given to others	10081	0.11	0.40	0	4.33
(15) receive_give_ratio	Number of books received per books given	10063	0.75	0.45	0	9
(16) rejection_rate	Percentage of rejected requests from others	10081	0.07	0.19	0	1
(17) delivery_speed	Intervals between request date and mail date	9691	8.71	14.75	0	571.66
(18) wishlist_rate	Percentage of books requested that belongs to wishlist	10081	0.16	0.29	0	1

Note: (a): it is calculated based on an individual's inventory list and wishlist. The maximum number of book genres is 36;

Table 3.5 Correlation Matrix

Variable	**(1)**	**(2)**	**(3)**	**(4)**	**(5)**	**(6)**	**(7)**	**(8)**	**(9)**	**(10)**	**(11)**	**(12)**	**(13)**	**(14)**	**(15)**	**(16)**	**(17)**	**(18)**
(1)	1.00																	
(2)	**-0.05**	1.00																
(3)	**0.07**	**0.07**	1.00															
(4)	**0.06**	**0.08**	**0.37**	1.00														
(5)	**0.05**	**0.05**	**0.33**	**0.29**	1.00													
(6)	**0.03**	**0.06**	**0.20**	**0.20**	**0.20**	1.00												
(7)	**0.06**	**0.12**	**0.05**	**0.10**	**0.10**	**0.16**	1.00											
(8)	**0.04**	**0.21**	**0.14**	**0.12**	**0.07**	**0.10**	**0.12**	1.00										
(9)	**0.06**	**0.32**	**0.16**	**0.12**	**0.03**	**0.06**	**-0.15**	**0.35**	1.00									
(10)	**0.05**	**0.44**	**0.13**	**0.13**	**0.05**	**0.11**	**0.25**	**0.48**	**0.53**	1.00								
(11)	**0.10**	**0.35**	**0.19**	**0.17**	**0.09**	**0.16**	**0.48**	**0.52**	**0.41**	**0.68**	1.00							
(12)	**0.03**	**0.19**	**0.03**	**0.07**	**0.05**	**0.09**	**0.29**	**0.29**	**0.17**	**0.46**	**0.43**	1.00						
(13)	**0.04**	**0.25**	**0.17**	**0.17**	**0.09**	**0.11**	**0.14**	**0.26**	**0.36**	**0.41**	**0.37**	**0.19**	1.00					
(14)	**0.04**	**0.21**	**0.18**	**0.19**	**0.08**	**0.14**	**0.12**	**0.22**	**0.24**	**0.36**	**0.32**	**0.15**	**0.38**	1.00				
(15)	**0.05**	**0.12**	**0.11**	**0.13**	**0.08**	**0.08**	**0.21**	**0.13**	**0.36**	**0.16**	**0.13**	**0.11**	**0.25**	**0.11**	1.00			
(16)	-0.00	-0.01	-0.01	0.00	-0.01	-0.01	0.01	-0.01	-0.01	-0.01	-0.01	0.01	0.00	-0.00	-0.01	1.00		
(17)	**-0.03**	**-0.02**	0.00	-0.00	-0.01	-0.00	-0.01	-0.01	**-0.02**	**-0.03**	**-0.04**	-0.00	-0.01	-0.01	0.00	-0.01	1.00	
(18)	**0.02**	**0.03**	**0.04**	0.02	**0.03**	**0.06**	**0.03**	**0.07**	**0.04**	**0.06**	**0.09**	**0.05**	**0.03**	**0.05**	-0.02	-0.11	-0.06	1.00

Note: Pair-wise Spearman correlation is reported. Numbers in bold indicates $p<0.05$.

Table 3.6 The Impacts of Search Strategy on Transaction Outcomes: Individual-Level

Variables	Dependent Variables: SURE Estimation		
	Rejection_rate	Delivery_speed	Wishlist_rate
	Coefficient (std. err.)	Coefficient (std. err.)	Coefficient (std. err.)
Intercept	0.091*** (0.011)	5.387*** (0.225)	-2.230*** (0.125)
Search Strategy			
Immediate_dummy	-0.003 (0.010)	-2.551*** (0.347)	-0.174*** (0.015)
Delayed_dummy	-0.004 (0.008)	-0.808* (0.358)	0.027 (0.082)
Individual Controls			
if_bio	-0.002 (0.005)	0.353 (0.479)	0.050 (0.054)
if_homepage	-0.010 (0.007)	-0.308 (0.461)	0.084 (0.075)
if_photo	0.006 (0.006)	0.237 (0.461)	-0.094 (0.062)
if_librarything	-0.004(0.006)	0.010 (0.503)	0.278 (0.265)
tenure_in_month	0.000 (0.000)	0.008 (0.013)	-0.001 (0.002)
interest_breadth	0.000 (0.000)	0.030 (0.020)	0.008** (0.003)
avidness	0.023 (0.010)	-0.038 (0.054)	0.023* (0.010)
books_in_inventory	-0.000 (0.000)	0.002 (0.006)	-0.001 (0.001)
log(feedback_score)	-0.006 (0.004)	-1.048*** (0.247)	0.169 (0.142)
log(rejected)	0.004 (0.003)	0.304 (0.247)	0.041 (0.033)
log(praise_received)	0.004 (0.004)	0.301 (0.388)	-0.034 (0.048)
log(praise_given)	0.001 (0.005)	-0.352 (0.261)	0.127 (0.151)
receive_give_ratio	-0.004 (0.010)	0.193 (0.283)	-0.244 (0.254)
N(LISTWISE) = 9989, System-Weighted R^2=0.725			

*p<0.05, **p<0.01, ***p<0.001

Table 3.7 The Impacts of Search Strategy on Transaction Outcomes: Transaction-Level

Variables	Dependent Variables Heckman Two-Stage Model if_reject	 Delivery_speed	 if_wishlist
	Coefficient (std. err.)	Coefficient (std. err.)	Coefficient (std. err.)
Intercept		10.769*** (0.374)	
Search Strategy			
if_immediate	-0.742 (0.539)	-2.700*** (0.294)	-0.726*** (0.101)
if_delayed	-0.141 (0.183)	-0.585*** (0.123)	-0.156 (0.136)
Receiver Controls			
r_if_bio	0.119 (0.105)	-0.072 (0.067)	-
r_if_homepage	0.074 (0.049)	0.075 (0.095)	-
r_if_photo	-0.039 (0.037)	0.020 (0.070)	-
r_if_librarything	-0.083(0.050)	0.147 (0.075)	-
log(r_feedback_score)	-0.051* (0.023)	-0.113* (0.046)	-3.235 (3.116)
log(r_rejected)	0.066*** (0.017)	0.038 (0.033)	-0.276 (0.184)
log(r_praise_received)	0.004 (0.020)	0.139 (0.138)	0.106 (0.157)
log(r_praise_given)	-0.007 (0.017)	0.032 (0.031)	0.247 (0.251)
r_receive_give_ratio	0.000 (0.001)	-0.001 (0.001)	-1.385 (0.127)
Book Characteristics			
log(price)	0.280*** (0.026)	-0.022 (0.056)	-0.145*** (0.016)
log(d_s_ratio)	0.025 (0.026)	-0.331*** (0.048)	1.326*** (0.014)
num_choices	0.001* (0.000)		
Receiver-Giver Similarity			
taste_similarity	-0.167 (0.113)	-0.155 (0.214)	0.151* (0.071)
shared_genre	0.003 (0.003)	-0.001 (0.006)	0.004** (0.001)
log(r_focalgenre_depth)	-0.012 (0.013)	-0.068 (0.065)	0.055 (0.085)
Instrument Variables & Other Variables:			
if_same_country	-0.737*** (0.053)		
selection_bias		3.778* (1.693)	
# of Observations	69560	147148	106110
Chi Square	386.60	205.17	13144.98

*p<0.05, **p<0.01, ***p<0.001

Table 3.8 Search Strategy and Transaction Partner Choice: Transaction-Level

	Dependent Variable: if_chosen		
	Indirect Reciprocity Cluster	Immediate Reciprocity Cluster	Delayed Reciprocity Cluster
Variables	Coefficient (std. err.)	Coefficient (std. err.)	Coefficient (std. err.)
Search Strategy			
if_immediate	0.482 (0.846)	3.653** (1.262)	2.044 (1.423)
if_delayed	-1.274 (1.137)	0.275 (0.288)	0.513*** (0.066)
Giver Controls			
g_if_bio	0.124* (0.047)	0.376* (0.176)	0.082 (0.058)
g_if_homepage	0.063 (0.074)	-0.269 (0.292)	-0.139 (0.094)
g_if_photo	0.036 (0.051)	0.210 (0.190)	0.296*** (0.060)
g_if_librarything	-0.109 (0.055)	-0.592 (0.437)	-0.289 (0.171)
log(g_feedback_score)	0.125* (0.048)	-0.052 (0.187)	-0.047 (0.057)
log(g_rejected)	-0.191*** (0.022)	-0.087 (0.083)	-0.195*** (0.026)
log(g_praise_received)	0.138*** (0.032)	0.050 (0.118)	0.192*** (0.036)
log(g_praise_given)	-0.073 (0.054)	0.045 (0.088)	-0.032(0.025)
g_receive_give_ratio	-0.436*** (0.043)	-0.498*** (0.164)	-0.532*** (0.056)
Receiver-Giver Similarity			
taste_similarity	0.063 (0.165)	0.486 (0.630)	0.276 (0.212)
shared_genre	0.035 (0.045)	0.040* (0.016)	0.032*** (0.005)
log(r_focalgenre_depth)	-0.042 (0.030)	-0.059 (0.116)	0.041 (0.033)
Other Variables:			
if_same_country	2.147*** (0.126)	3.280*** (0.913)	2.211*** (0.173)
position	-0.003 (0.003)	-0.002 (0.002)	-0.005 (0.003)
g_tenure_in_month	-0.006*** (0.000)	-0.011*** (0.003)	-0.006*** (0.001)
g_last_login_month	-0.002*** (0.000)	-0.001 (0.001)	-0.001*** (0.000)
# of Observations	210699	11474	62994
Pseudo R^2	0.06	0.07	0.09

*p<0.05, **p<0.01, ***p<0.001

Table 3.9 User Characteristics and Search Strategy

	Mean of Dependent Variables: Multivariate Regression Analysis						
Dependent Variable	if_bio	if_homepage	if_photo	if_librarything	tenure	interest_breadth	avidness
Delayed_dummy (1)	0.400	0.179	0.284	0.194	21.52	23.90	4.38
Immediate_dummy (2)	0.355	0.147	0.276	0.173	21.22	18.12	2.24
Indirect_dummy (3)	0.229	0.090	0.152	0.111	21.61	15.61	1.33
F(p)	46.346*** (0.000)	21.490*** (0.000)	48.478*** (0.000)	22.889*** (0.000)	0.581 (0.320)	241.144*** (0.000)	606.519*** (0.000)
Scheffe differences[(a)]	(3;1,2)	(3;1,2)	(3;1,2)	(3;1,2)	n.s.	(1;2,3)	(1;2,3)
Overall effect: Wilks' Lambda = 0.8442, F = 126.49, p = 0.000							

*p<0.05, **p<0.01, ***p<0.001

Note: (a): (x; a, b) means that group x is significantly different from groups a and b.

Table 3.10 Construct Operationalization [a]

Altruistic Orientation (adapted from Webb et al. (2000) and Smith 2003)		Cronbach's α	Mean [b]	S.D.
ALT1:	People should be willing to help others who are less fortunate.			
ALT2:	[+]Those in need have to learn to take care of themselves and not depend on others.	0.773	3.97	0.64
ALT3:	Personally assisting people in trouble is very important to me.			
Exchange Orientation (adapted from Vanyperen and Buunk 1991)				
EXO1:	When I give something to another person, I generally expect something in return.			
EXO2:	[+]I do not think people should feel obliged to repay others for favors.	0.715	3.19	0.80
EXO3:	I do not bother to keep track of benefits I have given others.			
Long-Term Relationship Orientation (adapted from Ganesan 1994)				
LRO1:	I believe that over the long run, a relationship with someone else on the website will be beneficial.			
LRO2:	Maintaining a long-term relationship with someone else on the website is important to me.			
LRO3:	I focus on long-term goals in the relationship with someone else on the website.	0.737	3.13	0.63
LRO4:	I am willing to make sacrifices to help another individual on website from time to time.			
Disposition to Trust (adapted from Ridings et al. 2002)				
DOT1	I generally have faith in humanity			
DOT2	I feel that people are generally reliable	0.700	3.73	0.61
DOT3	I generally trust other people unless they give me reason not to.			
Online Self-Disclosure (adapted from Ledbetter 2009)				
OSD1	I feel like I can sometimes be more personal during Internet conversations.			
OSD2	It is easier to disclose personal information online.			
OSD3	I feel like I can be more open when I am communicating online.	0.845	2.87	0.75
OSD4	I feel less shy when I am communicating online.			
OSD5	I feel less embarrassed sharing personal information with another person online.			

[+]: reverse coded item

(a): all the items are measured on a 5-point Likert scale.

(b): an individual's score on each construct is measured as the average of agreement (five-point scale) with statements for all items corresponding to the construct.

Table 3.11 Factor Loading and Cross-Loadings

	Altruistic Orientation	Exchange Orientation	Long-Term Relationship Orientation	Disposition to Trust	Online Self-Disclosure
ALT1	**0.861**	-0.136	0.109	0.075	-0.144
ALT2	**0.797**	-0.105	0.075	0.017	-0.159
ALT3	**0.834**	-0.175	0.221	0.107	-0.169
EXO1	-0.152	**0.734**	0.187	-0.059	0.129
EXO2	-0.160	**0.835**	0.013	-0.110	0.043
EXO3	-0.096	**0.819**	0.268	-0.084	0.142
LRO1	0.224	0.040	**0.772**	0.265	0.156
LRO2	0.054	0.217	**0.862**	0.211	0.172
LRO4	0.087	0.203	**0.837**	0.141	0.156
LRO4	0.248	-0.039	**0.640**	0.333	-0.056
DOT1	0.098	-0.037	0.297	**0.829**	-0.020
DOT2	-0.004	-0.162	0.190	**0.792**	0.104
DOT3	0.089	-0.072	0.133	**0.746**	0.064
OSD1	-0.121	0.087	0.153	0.105	**0.870**
OSD2	-0.160	0.032	0.079	0.006	**0.661**
OSD3	-0.192	0.107	0.183	0.058	**0.874**
OSD4	-0.105	0.110	0.154	0.014	**0.786**
OSD5	-0.178	0.168	0.119	0.033	**0.754**

Table 3.12 User Demographics, Psychographic Characteristics and Search Strategy

	Mean of Dependent Variables: Multivariate Regression Analysis								
Dependent Variable	gender[(a)]	age[(b)]	education[(c)]	household_ income[(d)]	altruistic_ orientation	exchange_or ientation	long_term_o rientation	disposition _to_trust	online_ disclosure
Delayed_dummy (1)	1.2	3.66	4.97	5.47	4.17	3.46	3.61	3.89	3.00
Immediate_dummy (2)	1.17	3.24	5.17	5.22	3.83	3.53	2.79	3.58	2.80
Indirect_dummy (3)	1.22	3.21	5.20	5.33	3.91	2.58	2.98	3.74	2.80
F(p)	0.342 (0.710)	3.05* (0.05)	1.298 (0.275)	0.088 (0.916)	5.299** (0.006)	39.301*** (0.000)	43.934*** (0.000)	4.471* (0.012)	1.984 (0.140)
Scheffe differences[(e)]	n.s.	(1;2,3)	n.s.	n.s.	(1;2,3)	(3;1,2)	(1;2,3)	(2;1,3)	n.s.
Overall effect: Wilks' Lambda = 0.8442, F = 126.49, p = 0.000									

*p<0.05, **p<0.01, ***p<0.001

(a): 1=Male; 2=Female;

(b): 1 = 18-24; 2 =25-34; 3 =35-44; 4 = 45-54; 5 = 55 or above;

(c): 1 = 98th grade or less; 2 = some high school but did not graduate; 3 = high school graduate or GED; 4 =some college or 2-year degree; 5 = 4-year college graduate; 6 = more than 4-year college degree.

(d): 1 = $0 to $24,999; 2 = $25,000 to $49,999; 3 = $50,000 to $74,999; 4 = $75,000 to $99,999; 5 = $100,000 to $124,999; 6 = $125,000 to $149,999; 7 = $150,000 to $174,999; 8 = $175,000 to $199,999; 9 = $200,000 and up.

(e): (x; a, b) means that group x is significantly different from groups a and b.

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