The Value of Feedback: An Analysis of Reputation System

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Abstract

Online markets, as established by many authors, are prone to asymmetric information problems. Despite this observation, many online markets have thrived and grown over time primarily due to user experience rating systems, also known as reputation systems. In this paper, we analyze how such systems work, and specifically we turn our focus on eBay. We start by analyzing the feedback behavior of buyers and sellers over time. We use a key policy change, that sellers can no longer leave negative feedback for buyers, as an identifier. Our data analysis points to the existence of retaliation between buyers and sellers before the policy change. Furthermore, we develop a model of feedback behavior as a dynamic game between buyers and sellers and structurally estimate the model. The structural estimation further establishes the existence of retaliation incentives between buyers and sellers. Finally, we perform various welfare and counterfactual analysis.

Keyword: eBay, Reputation, Adverse Selection

JEL Classification: D8, L2

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1 Introduction

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

We focus on one such marketplace, eBay. As many authors have noted, eBay is a market prone to adverse selection.[2] When adverse selection hinders trade, reputation can be used as a possible mechanism in mitigating lemon problems.[3] At the center of the eBay reputation systems is the feedback system by buyers and sellers. Feedback by buyers affect sellers' future status as Powerseller as well as eBay Store and as shown in Saeedi [2011], these "tags" can significantly increase sellers' profits over time. Thus, an analysis of feedback behavior and its effect on market size is of utmost importance.

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

[1] Anderson and Magruder [2011] and Luca [2011] look at the effect of a higher rating on yelp on restaurant sale. Mayzlin et al. [2012] look at potential manipulation of online reviews on tripadvisor. Chevalier and Mayzlin [2006] argue that Amazon ratings leads to higher purchase from this website.

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

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

We start by analyzing the data on buyer and seller feedback over time. Examining the data shows sellers and buyers on eBay leave feedback for each other in more than 60% of the transactions. We also observe that users with a higher transaction volume on eBay leave and receive feedback more often. These evidences suggest that buyers and sellers put a strong emphasis on the reputation system implemented by eBay. Further, we consider the trend in feedback left by sellers and buyers when a new policy is put in place and study its effect on sellers and buyers of various characteristics. The evolution of the market, e.g. change in market share, price dispersion, and concentration, as a result of these policy changes will direct us to a better understanding of the role of reputation over time, across various characteristic groups. In addition the study of the changes of eBay policies, can help us to test different theories regarding reputation system and how different players in the market conceive the role of the reputation in this market.

Furthermore, we show evidence on the existence of retaliation before the policy change.[4] We observe that in more than a third of transactions that the sellers have received a negative feedback they retaliate with a negative feedback. This can also be a consequence of a mutual bad experience. In addition, we observe that the sellers will rarely leave any negative feedback for the buyers when they move first but this percentage increases by almost tenfold after the buyer has moved and left the seller a feedback.

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

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

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

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

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

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

The rest of the paper is organized as follows: in section 2, we give an overview of the market structure on eBay and the feedback system. We also explain the change in the eBay policy that happens during our data collection time period. In section 3, we explain the new policy in depth and we describe the data before and after the policy change. In section 4, we develop a model explaining sellers' and buyers' incentives for leaving feedback. Section 5 explains the identification strategy for the deep parameters of the model. Finally, section 7 concludes.

2 Background

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

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

The feedback system helps keep the very worst participants out of the market; sellers with very low feedback ratings are forced out of market because they usually cannot sell in the market.[5] However, some of low quality sellers would find ways to prevent getting negative feedback ratings. In a two-way feedback system a retaliatory approach may be used where poor quality sellers wait for buyers to leave their feedback before leaving a feedback, and if they receive a negative feedback then retaliate with a negative feedback, as noted by Dellarocas and Wood [2008], Masclet and Pénard [2008], Dellarocas [2002] and Resnick and Zeckhauser [2002]. The retaliation lowers the effectiveness and value of reputation system. To help remove this problem, eBay introduced detailed sellers rating and also has prevented sellers from leaving negative feedback for buyers.

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

[5] Cabral and Hortacsu [2009] show that the probability of a seller exiting eBay increases significantly after receiving the first negative feedback.

it is expected that buyers are more honest when leaving a detailed sellers' rating. This policy change has been studies in depth by Bolton and Ockenfels [2008].

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

eBay has tens of minor markets like collectibles, stamps, electronics, toys, and so on. Each of these markets have different properties of user participation, use of trust mechanism, and adoption of sale formats like fixed price or auctions.[6] In this paper we consider three different categories on eBay: Electronics, Stamps, and Collectibles. Due to the diversity in the nature of these categories users may react differently to policy changes in each category. Considering multiple categories helps us determine whether the effect of a policy change is only restricted to a specific category or it is common across different categories. Stamps and collectibles are two categories which existed on eBay for a long time, these two categories have a lot of sellers and buyers that interact with one another over time. On the other hand, electronics is a category with a high growth in sales volume on eBay in recent years and has gone through many changes. Throughout the main body of the paper we discuss the data from the Electronics category and in the Appendix, we show the same graphs and data for Stamps and Collectible categories. The main results is consistent throughout these three categories, even though the extend of the effect varies from one to another.

3 Data

In this section, we illustrate actions of the sellers and buyers before and after the policy change. First, we show evidence of existence of retaliation from the sellers before the implementation of the no-negative-feedback from sellers' policy. Next, we show the response of the sellers and buyers to this change of the policy. One result that may appear counter intuitive at the beginning is that buyers tend to leave fewer negative feedbacks for sellers after the policy change. We argue that the reduction in power of the sellers in manipulating the market can be a cause of this change. We further show that the change in the policy has affected the feedback adoption rate and also the timing of leaving feedbacks.

[6] For a complete discussion refer to Shen and Sundaresan [2011].

Table 1: Sellers' Action, Electronics
Sellers' Actions After Receiving a Feedback from Buyers

Buyers' Feedback	Positive	Negative or Neutral	No Feedback
Negative or Neutral	5%	37%	58%
Positive	88.47%	0.04%	10.49%

We will use the guidance from this section for developing a model that fits the actions of sellers and buyers. We will also use this data to identify the model and to find the deep parameters of the model in Section 5.

3.1 Existence of Retaliation

We first investigate the feedback interactions between buyers and sellers before the policy was implemented. We show that before the change in policy, buyers and sellers were engaged in retaliation strategies: after leaving a negative feedback for sellers, buyers were very likely to receive a negative feedback from sellers. As shown in Table 1, after a negative feedback is received from a buyer, a seller will respond with a negative feedback in more than 30% of the transactions. This number is less 0.04% if a buyer leaves a positive feedback for a seller. Moreover, if the seller is the first party to leave a feedback, he will leave a negative feedback only in 0.3% of transactions.

Another evidence of sellers strategic behavior as of result of a negative feedback is illustrated in Figure 1(a). This figure represents the share of positive feedbacks among all feedbacks left from sellers for buyers. The x-axis shows the number of days the seller left the feedback before the buyer left a feedback; positive numbers correspond to transactions were the seller has moved first, and negative numbers are those that sellers left a feedback after the buyer has already left a feedback. When the sellers are moving first they rarely leave any negative feedback for the buyers, but when they move after the buyer the share of negative feedbacks increased about tenfold.

The above evidence can be in more details in Figure 1(b). Figure 1(b) shows the data in Figure 1(a) if sellers and buyers leave feedback for one another within a week. For cases in which seller and buyer left feedback on the same day, we separate them by the exact time that they left a feedback: 0.5 on the x-axis corresponds to the transactions in which the seller left a feedback first and then the buyer left a feedback for the seller in the same day, and -0.5 corresponds to the transactions in which the buyer left a feedback first and the seller respond in the same day after the buyer. Comparing these two data points, when the sellers and buyers leave feedback for each other in the same day, the percentage of negative feedback from sellers increases from 0.5% to 1.5%. This timing shows that the sellers will not show their disappointment in the quality of transaction before buyers have already left a feedback for them.

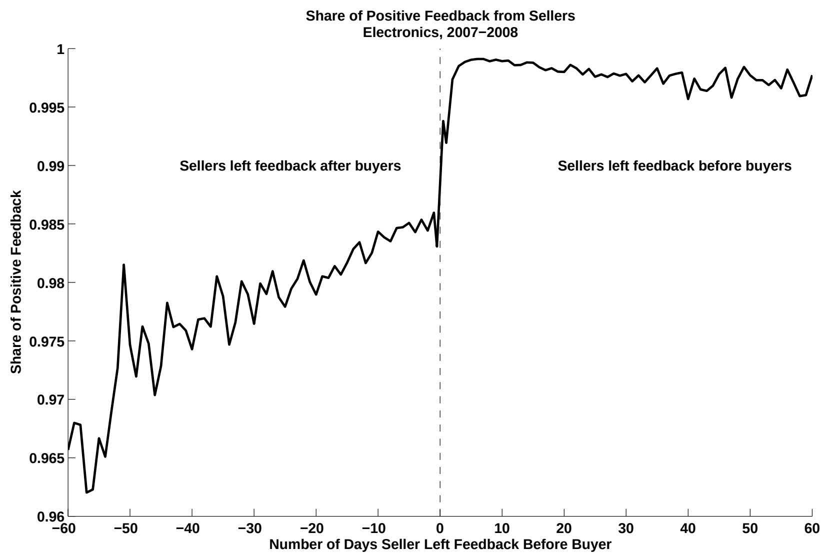
Figure 2 demonstrate additional evidence of existence of retaliation. In this figure, the share of positive feedbacks for buyers from sellers is shown conditional on different buyers feedbacks: positive, negative, and neutral. When the seller is leaving feedback first most of the feedbacks left are positive even if the buyer leaves a negative or neutral feedback for the seller. But when the buyer has left feedback first, the sellers' feedback is strongly correlated with the buyers' feedback. These figures show that the data in Table 1 is not just because if the buyer is not satisfied with the transaction then that implies sellers are also not satisfied with the transaction as well. There are many transactions that the seller has left a positive feedback for the buyer but then the buyer has left left a negative or neutral feedback for the seller, and the probability that sellers will leave a negative feedback after the buyer has left a feedback for them increases sharply only if the buyers' feedbacks are negative or neutral. We will explore this more in Section 4.

3.2 Buyers' Response

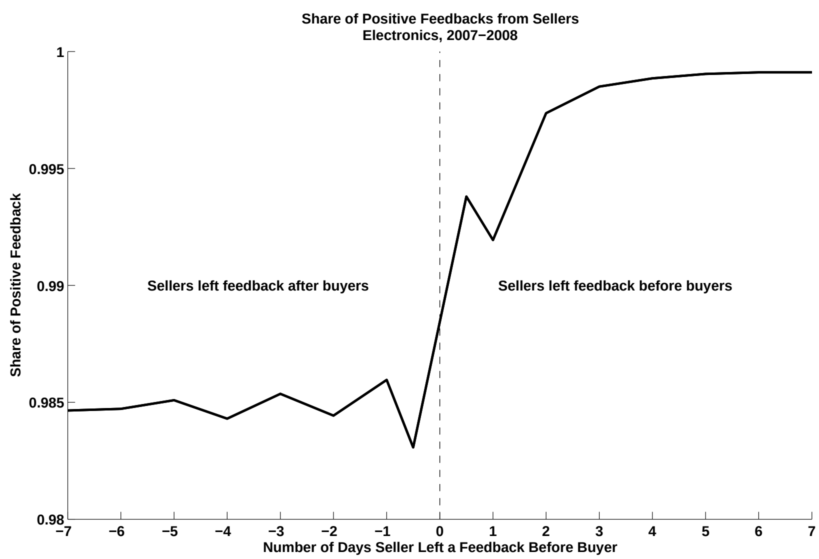
One of the main observations that we want to emphasize is the behavior of buyers as a result of the change in policy. One would expect that buyers should be more honest in their feedbacks and therefore leave negative feedback for sellers more often since they are not threatened by retaliation any more. However, we observe that the buyers leave positive feedback for sellers more often after the policy change. On average the buyers tend to leave a negative or neutral feedbacks for the sellers in 2% of the transactions and this number has dropped to 1% after the policy change.

Figure 3 shows a consistent change in the behavior of buyers throughout the time span they leave a feedback to sellers. This graph shows the share of the negative or neutral feedbacks for the sellers as a function of the number of days buyers wait from the end of the transaction to leave a feedback for the seller. It clearly illustrates that the buyers are leaving fewer negative or neutral feedbacks and it is not a function of the timeline they decide to leave a feedback for the seller. This is puzzling because retaliation incentives are removed by the new policy change and it is expected for buyers to be more honest and emphasize their true experience on the marketplace, which as argued by Bolton et al. [2009], Dellarocas and Wood [2008], Masclet and Pénard [2008], Dellarocas [2002], and Resnick and Zeckhauser [2002] should be toward more negative feedbacks from buyers to sellers.

We examine the possibility of few justification for this puzzling observation. First, forcing sellers not to leave a negative feedback eliminates retaliation from buyers side as well. Buyers will no longer



(a)



(b)

Figure 1: Share of Positive Feedback for Buyers, Electronics

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

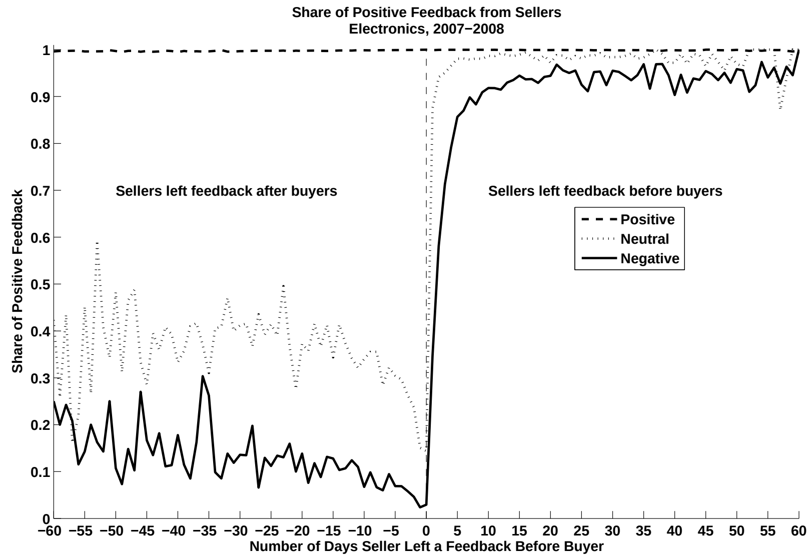


Figure 2: Share of Positive Feedback for Buyers Conditional on Buyers' Feedback, Electronics

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

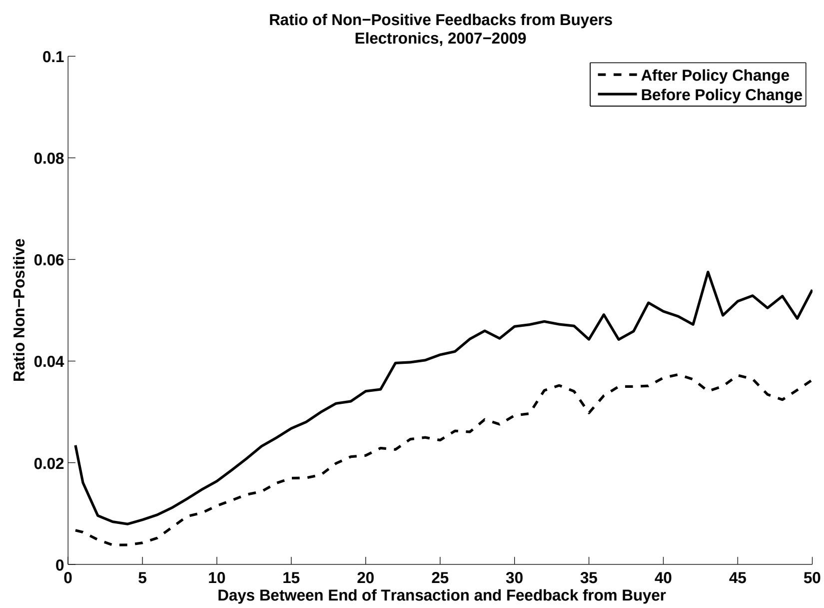
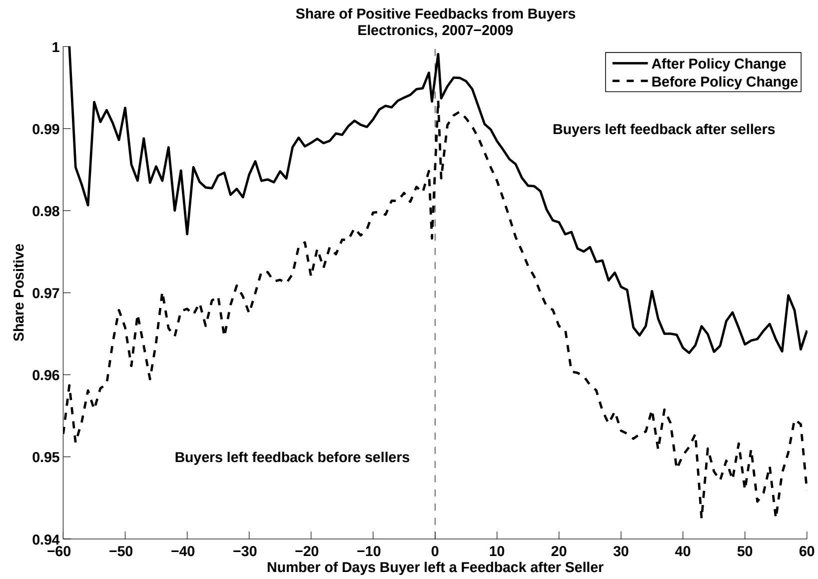
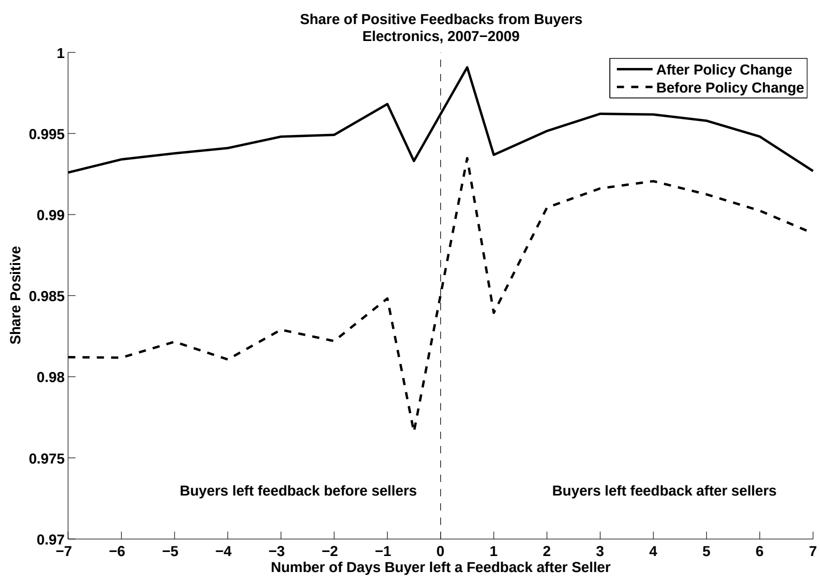


Figure 3: Share of Positive Feedback for Sellers, Electronics

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



(a)



(b)

Figure 4: Share of Positive Feedback from Buyers, Electronics

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

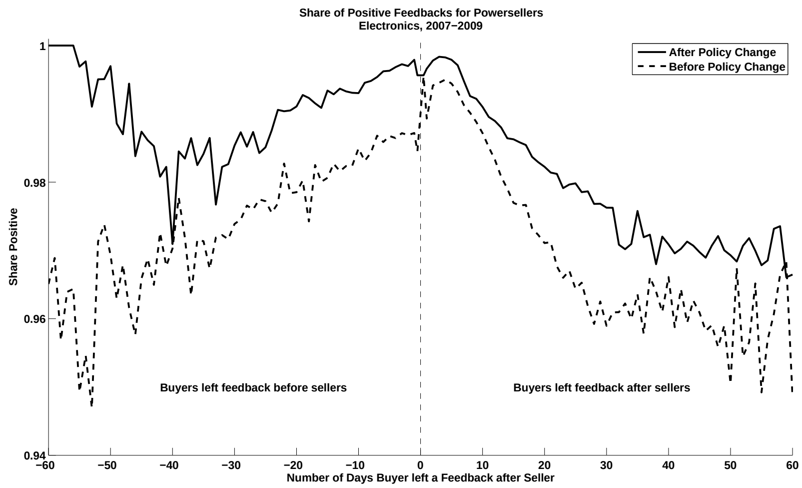


Figure 5: Share of Positive Feedback for Powersellers .

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

leave a negative feedback in response to a negative feedback from sellers which can increase the share of positive feedback. This justification implies that before the policy change buyers and sellers were involved in tit-for-tat type strategies and the policy change takes this option away from them.

Figure 4(a) and 4(b) illustrate the above cannot explain all the changes in the data. Figure 4(a) shows the share of positive feedbacks among all feedbacks left for sellers as a function of the time difference between the time that sellers and buyers left feedback. It can be seen that independent of the time difference, buyers are consistently leaving more positive feedback after the policy change comparing to their actions before the policy change. A puzzling observation is that when buyers leave feedback earlier than sellers, i.e., negative values on the x-axis, they leave positive feedback more often.

Fig 4(b) shows the details when the buyers leave feedback within a week of the sellers. In this case we can see that there is a slight increase in percentage of negative feedbacks left from the buyers when they move after the sellers, however the difference is lower than the effect for the sellers. These two figure show that the buyers leave fewer negative or neutral feedback for the sellers even when they are the party who moves first, therefore the first justification cannot explain all the changes in the data.

A second justification can be that buyers get a positive benefit by receiving a positive feedback, the only choice for sellers after the policy change, but this effect does not as well explain the actions of the buyers when they are leaving feedback first. Figure 4(a) also shows that they leave more positive feedbacks before they receive a positive feedback.

A third explanation can be the change in the market share of business sellers, or powerseller in

Table 2: Sellers' Performance, Electronics

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

the market over time.[7] The bigger sellers tend to perform better on eBay and they tend to get higher percentage of positive feedbacks. Figure 5 shows the percentage of the positive feedbacks for powersellers in the market as a function of number of days buyers left a feedback after they have received feedback from the seller. Comparing Figure 5 and 4(a) demonstrates powersellers tend to receive slightly fewer negative or neutral feedbacks but the pattern does not change for them.

Another justification is that, when sellers are unable to leave negative feedback, the sellers loose a tool that helped them in staying in the market and staying successful, for example low quality sellers can no-longer sustain in the market. This will force sellers to spend more effort when dealing with the buyers, which further implies that the market shifts toward higher quality sellers and as a result the number of positive feedback would increase. Section 4 introduces a model consistent with the observation in this section.

3.3 Sellers' Performance

If our claim in the past section is correct and the change in the feedback policy leads sellers to be higher quality sellers, we should see the effects in other determinants of the market performance. There are few other variables that show sellers' performance in the market: disputes, detailed sellers' ratings, and charge backs. Buyers can dispute a transaction directly to eBay when they are not happy with the transaction and they cannot resolve the issue with the sellers between themselves. Detailed sellers' rating works the same way as feedback but it is anonymous and sellers cannot see what the buyers have left them, therefore it cannot get affected directly by the the change in the policy but it can get affected indirectly by a change in the sellers' behavior. Buyers can rate sellers in five different sections and in each of them they should give sellers a rating from 1 to 5. Buyers can get a charged back from their credit card company, bank, and/or PayPal if they argue the item was not as described or was not shipped to them. Table 2 shows the frequency of each of these actions.

As it is shown in the Table 2 the sellers performance has improved in all of these categories and the market has moved to a less prone to adverse selection market.

[7]Powersellers are more reputable sellers on eBay which get a badge on the website, the tend to be bigger sellers in the market.

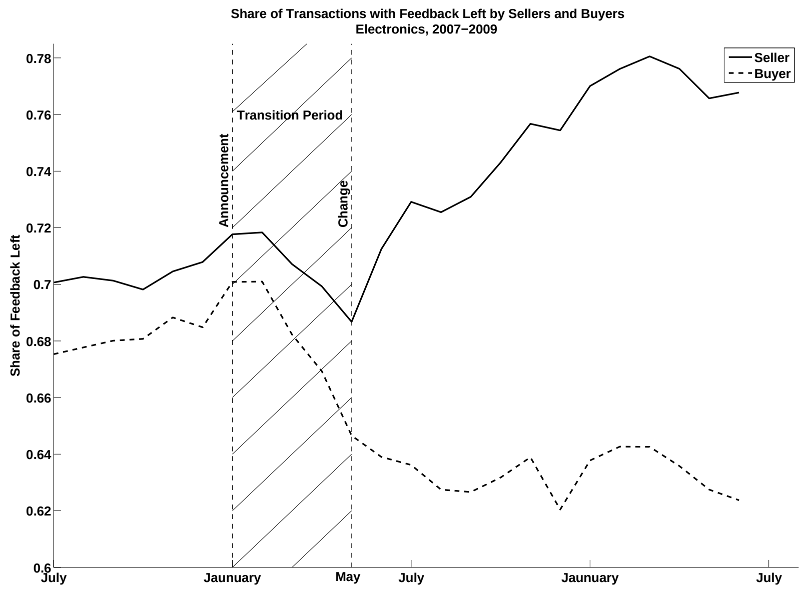


Figure 6: Adoption Rate for Feedbacks, Electronics

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

Table 3: Timing of Feedback
Sellers Left Feedback before Buyers

	Before Policy Change	After Policy Change
Electronics	29%	51%

3.4 Feedback Adoption and Timing of Feedback

In addition to addressing the retaliation problem, the policy change has other interesting and noteworthy effects on buyers and sellers behavior. One observation is that sellers are leaving feedback for buyers more often, as shown in Figure 6. Specifically, data on electronics shows that following May 2008 policy change, the likelihood of sellers leaving feedback has increased from 70% to 78%. In addition, buyers are leaving feedback less often, from 68% to 62%.

Before the policy change a lot of the sellers would wait for the buyers to move first in order to have the power of retaliation if the buyers would leave a negative feedback for them. After the policy change they do not have this incentive to wait for the buyers to leave a feedback first and they, in many cases, leave a feedback for buyers right after the payment has received. This has an implication on the timing of the the feedback as well.

As a result of change in the policy, the number of days sellers and buyers would wait to leave a feedback has change, as well as the party who leaves feedback first. After the policy change, sellers

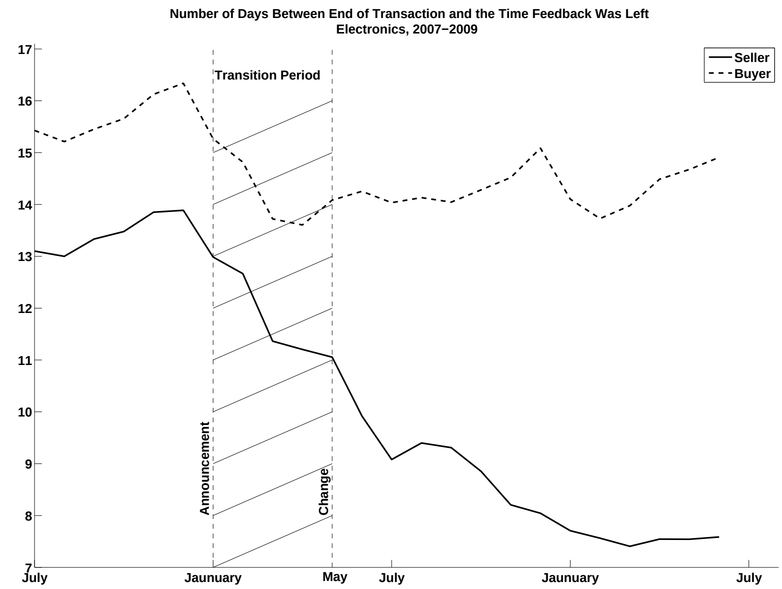


Figure 7: Timing of the Feedback, Comparing to The End of Transaction, Electronics

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

tend to feedback before buyers in more instances. This observation is shown in Table 3. In%51 of the transactions sellers leave feedback for the buyers before the buyers have moved. This number was only %29 before the policy change. This data also includes transactions in which the seller is the only party who leaves the feedback.

Additionally, as shown in Figure 7, both buyers and sellers leave feedback faster as a result of the policy change. The number of days a seller will wait to leave a feedback for a buyer has significantly reduced after the announcement of the change in the policy. The average number of days a seller will wait to leave a feedback for buyer used to be around 13 days and after the policy change it is down to around 7 days. The effect on the buyer is similar, even though less significant. The number of waiting days has gone down for buyers about two days.

Note that in Figure 7 the average number of days buyers will wait to leave feedback for buyers is higher than the average number for buyers. This may at first look contradictory with the number in Table 3. The reason is first higher variance on the number of days buyers will wait to leave feedback for sellers. Second, sellers that are waiting for the buyers to leave feedback first tent do leave a feedback to buyers right after they have received a feedback, often in the same day. Third, Table 3 also includes the transactions that the buyer never leaves a feedback, but in Figure 7 both parties should leave a feedback to be included in the data.

4 Model

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

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

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

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

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

and for sellers we similarly have:

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

where:

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

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

4.1 Timing

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

4.2 Buyers' Problem

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

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

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

4.3 Sellers' Problem

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

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

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

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

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

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

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

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

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

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

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

4.4 After Policy Change

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

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

4.5 Characterization of Equilibrium

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

Assumption 1 *Buyers' average return from the feedback is supermodular.*

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

Assumption 2 *Buyers' and sellers' return are increasing with their rivals' action.*

Assumption 1 implies the increasing differences on the returns for buyers. This assumption is similar to concavity. Assumption 2 implies that players benefit from a positive feedback while they do not like a negative feedback from their opponent.[8]

Theorem 2 *Given Assumption 1, the probability that the buyer plays* 1 *is increasing in the seller's action in period 1.*

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

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

The above is true given the Assumption 1. ■

Theorem 3 *Given Assumption 1, the percentage of time the buyer plays* -1 *is decreasing in the seller's action in period 1.*

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

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

The above is true given the Assumption 1. ■

The intuition behind Theorems 2 and 3 is that the buyers' return from playing 1 increases in the sellers' action, and their return from playing -1 decreases in their opponents' actions. Therefore they would prefer to play 1 more often and -1 less often in the equilibrium. These two theorems leads to another result which stated in the Theorem 4:

Theorem 4 *Given Assumptions 1 and 2, the sellers will not leave a negative feedback in the first period.*

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

Proof. I argue that it is always weakly better for the seller to leave no feedback at the first period rather than leaving a negative feedback. Given Theorem 2, the percentage of the time the buyer plays 1 is less if the seller plays -1 instead of 0. Moreover, Theorem 3 shows that buyers play -1 more often after the seller plays -1. Also note that by Assumption 2, sellers return in increasing in the buyers actions. ■

Theorem 5 *Given Assumptions 1 and 2, after the policy change, the sellers choose to leave positive feedback in the first period more often.*

Proof. Theorem 4 shows that before the policy change sellers would not choose to leave negative feedback in the first period. When comparing the before policy change and after policy change we should see if the incentive for leaving positive feedback in the first period has increased or not. The buyer's optimal action in the second period, given the seller's action in the first period, does not depend on the policy, since the buyer does not take into account the future behavior of the seller into account. The seller's expected utility from leaving no feedback before the policy change, on the left, is bigger than the expected utility of leaving no feedback after the policy change, on the right, as characterized below.

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

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

The above theorem is consistent with the data we observe in section 3, after the policy change sellers will move before the buyers more often. The intuition behind the proof is that after the policy change sellers' incentives to wait and leave feedback in the third period after the buyer has moved will decrease, because their options to move in the third period will decrease.

5 Identification Strategy

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

We need to have information about the percentage of the transactions with a positive outcome:

$P(x = 1)$, before and after the policy change. We assume that if the transaction has a undesirable outcome for the buyers they will report it through one of the mechanisms given by eBay, either through leaving negative feedback or by filing a dispute through eBay.[9]

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

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

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

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

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

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

Step 3. Given α' and β, β' is estimated using an optimization strategy: α' estimated in *Step 2* gives us the optimal strategy of the buyers in $T = 2$: $P(Y = y|X = x, Z = z)$. Having this values and starting from the β as an initial value, we simulate the sellers strategies at $T = 1$ and $T = 3$ using random draws for γ. Doing so we can calculate the simulated values for $P_s(Z_1 = z)$ and $P_s(Z_3 = z|Y = y)$. The next step is to get the distance between these values and the probabilities from the data.

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

Where the function d takes the quadratic difference between each component of the two matrix and

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

Table 4: Sellers' Actions in the First Period, Electronics

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

Table 5: Buyers' Actions in the Second Period

Before Policy Change

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

After Policy Change

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

adds these numbers together. Last step is to use an optimization mechanism to minimize the distance function by changing the value of β, the optimal value will give us β'.

Step 4. We take the distance between starting values of α and β and the new estimates α' and β' and if this distance is higher than an ϵ we try these steps again using the new estimates.

6 Results

In this section we first show the moments we used to do the estimation as explained in the previous chapter then we report the estimated values for $\bar{\alpha}$ and $\bar{\beta}$. Table 4 shows the percentage values for $P(Z_1 = z)$, probabilities that the sellers play different actions in period 1 before and after policy change. Table 5 shows the percentage of the time buyers play each action conditional on the sellers' actions in period 1, before and after policy change. Table 6 shows the percentage of the time sellers play each action after the buyer has moved, before and after policy change.

As mentioned before in order to identify $\bar{\alpha}$ and $\bar{\beta}$ we made some normalization assumption. First of all we assume that $\alpha_{x0z} = 0$ and also $\beta_{xy0} = 0$. Moreover, since after the policy change sellers can no longer leave negative feedback we only have one data point for the response of the buyers after a negative feedback from sellers. To be able to do the identification we assume that when the sellers do not leave a negative feedback when $x = 1$: $\beta_{1y,-1}$ is a big negative number.[10]

Table 7 reports the values for $\bar{\alpha}$ and Table 8 reports the values for $\bar{\beta}$. These values are consistent

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

Table 6: Sellers' Actions in the Third Period

Before Policy Change

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

After Policy Change

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

Table 7: Buyers' Utility Values

$x = 1$

	$z = -1$	$z = 0$	$z = 1$
$Y = -1$	-2.15	-3.32	-3.15
$Y = 0$	0	0	0
$Y = 1$	-3.24	0.52	0.79

$x = 0$

	$z = -1$	$z = 0$	$z = 1$
$Y = -1$	-2.15	0.11	-3
$Y = 0$	0	0	0
$Y = 1$	-3.2	3.2	-1.7

with our observation from data, buyers leave more negative feedbacks when they have received a negative feedback but these values are much more drastically higher for sellers. Also we can separate sellers and buyers actions after a transaction with a good outcome and a bad outcome. Buyers tend to leave more positive feedback when the outcome of the transaction is good.

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

7 Conclusion

Online platforms and applications increasingly rely on user-generated content. Such platforms are prone to adverse selection. Typically some form of reputation mechanism is used to sustain the market and avoid deterioration. eBay is one of the earliest such commerce platform. With its adoption of a simple feedback mechanism eBay has thrived and expanded over years. Yet, we do not have a good understanding of the incentives behind the participation of buyers and sellers in the the reputation mechanisms on eBay. In this paper we develop a dynamic interaction of buyers and sellers after the

Table 8: Sellers' Utility Values

$x = 1$

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

$x = 0$

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

end of transaction to capture these incentives.

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

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

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

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

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