From Lemon Markets to Managed Markets: The Evolution of eBay's Reputation System*

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Abstract

Asymmetric information potentially leads to adverse selection, market inefficiency, and possibly market failure. To mitigate these problems, market designers rely on different policies. Some adopt reputation policies, in which they certify high-quality users and help them signal their quality; others provide marketplace warranty policies to prevent low-quality users from participating. We have a unique opportunity to evaluate the reputation mechanism and then to analyze possible efficiency gains in light of the introduction of the buyer protection program to the existing reputation mechanism. We first demonstrate eBay's reputation signal raises the average sales price and the fraction of successful sales for certified sellers by 4% and 3%, respectively. Subsequently, we show adding the buyer protection provides an efficiency gain through two mechanisms that lead to fewer undesirable transactions: a reduction in moral hazard through an increase in sellers' quality, and a reduction in adverse selection through higher share of high-quality sellers. In addition, buyers' payoffs are higher in these transactions due to the buyer protection, leading to higher prices for all seller groups. The increase in prices is larger for low-reputation sellers which results in a decrease in the average markups for high-reputation sellers. Finally, our estimates suggest this policy increases the total welfare by 2.7% to 13.6% under different set-ups, which demonstrates a complementarity between the two mechanisms.

Keywords: Warranty, Reputation, Adverse Selection, e-Commerce

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1 Introduction

Asymmetric information potentially leads to adverse selection and market inefficiency, as noted in the seminal paper by Akerlof [1970]. Many markets are prone to asymmetric information problems: online shopping websites, e.g., eBay and Amazon, online recommendation systems, e.g., Yelp and TripAdvisor, and online room and house rentals, e.g., AirBnB.[1] To mitigate these problems, market designers rely on different policies. Some adopt reputation policies, in which they provide users' past histories and certify outstanding users. These policies mostly rely on contributions from individual participants. Others provide warranty policies to prevent low-quality users from participating, e.g., Grossman [1981]. We have a unique opportunity to evaluate the reputation mechanism and then to analyze possible efficiency gains in light of the introduction of the buyer protection program to the existing reputation mechanism.[2] Could adding this additional mechanism to a marketplace known for its reputation mechanism still increase efficiency, or would the added mechanism merely substitute for the previous mechanism?[3] Will reputation lose all its value in the presence of a warranty mechanism? Will buyers benefit from this policy? Which sellers benefit from this policy, low-reputation sellers and/or high-reputation sellers? Would this policy lead to an unraveling for low-quality sellers?

In this paper, we answer the above questions by using data from the eBay marketplace. We consider the eBay Top Rated Seller (eTRS) certificate as the main reputation signal. This signal incorporates various quality measures and is awarded to the best sellers on eBay.[4] Our empirical approach is based on regression discontinuity designs, similar to Einav et al. [2011]. We first show that the above signal is a measure of reputation and has positive value for buyers and sellers even after the introduction of the eBay Buyer Protection (eBP). To achieve this, we study the performance of sellers who become top-rated within a given period, controlling for different observable characteristics, and we demonstrate the reputation signal raises the average sales price and the

[1] Luca [2011] and Anderson and Magruder [2011] study the effect of star ratings on restaurant revenues on Yelp. Mayzlin et al. [2012] analyze users' behavior on TripAdvisor. Edelman and Luca [2011] investigate the effects of hosts' reputation and provide reasons for price variations on Airbnb.

[2] For details on this program, please refer to Section 2.

[3] Previous research has shown that adding warranty may have no effect on the reputation mechanism and prices, Roberts [2011], or it might even have negative effects on trust and consequently on prices, Cai et al. [2013].

[4] We perform a robustness check by using other definitions of reputation based on feedback ratings and number of feedbacks. Our main results go through using these alternative definitions. The disadvantage of using feedback ratings and number of feedbacks is that these measures are continuous and it is much harder to disentangle the signaling effect and the unobservable heterogeneity effect.

sales probability for badged sellers by 4% and 3%, respectively.[5] We perform multiple checks to ensure robustness.

Having established the signaling value of the eTRS badge, we study the effect of adding eBay Buyer Protection. Introduced in 2010, this program mandates that sellers must refund prices and shipping costs of items if they are not as described in the listings, or if buyers have not received them. We determine that this policy has two main effects. It increases buyers' willingness to pay and also decreases the average price premium for high-reputation sellers. These changes are due to buyers' lower probability of encountering undesirable outcomes through two main channels, and buyers' higher payoffs in these cases. The first channel is through a reduction in moral hazard, even among high-quality sellers: the instance of negative feedback ratings decreases by an average of 22.81% due to higher penalties.[6] The second channel is through a reduction in adverse selection: eBP leads to an increase in the exit rate of low-quality sellers and an increase in the share of high-reputation sellers. In our data, we observe that sellers with low performance exit the market with a higher probability and also the detrended number and share of eBay Top Rated Sellers increases by 10%. The reduction in moral hazard and adverse selection lead to a lower probability of undesirable outcome and given that buyers' payoffs are higher in those cases, their willingness to pay also rises. We observe its effect through an increase in prices for both groups of sellers, high-reputation and low-reputation ones. However, the increase in prices is higher for low-reputation sellers, which leads to a decrease in price premium for high-reputation sellers. We additionally provide some estimates of the change in total welfare due to the buyer protection. By assuming that the policy has not affected competition in the market, the total welfare rises by 2.7% to 13.6%, depending on different modeling assumptions. This increased welfare demonstrates a complementarity between the two mechanisms.

Two more effects of buyer protection are worth mentioning. First, the drop in the premium of reputation is the largest for the most expensive items, which is about 70%, but negligible for very cheap items;[7] even though buyers do not incur monetary costs if they decide to return the item

[5]Sales probability is defined as the ratio of successful listings to total listings by a seller. We use the word "successful" if a listing gets sold.

[6]Sellers' feedback ratings reflect buyers' overall experience with their transactions. Buyers can leave positive, negative, or neutral feedback for sellers after each transaction.

[7]We define the value for each product as the average sales price of the product in the posted price format. For more details, please refer to Section 3.

through buyer protection, they still incur intangible costs. However, these costs do not vary greatly with items' values; therefore, returning cheap items is relatively more costly for buyers. Second, before the introduction of the buyer protection, experienced buyers on eBay used to value the reputation badge more than novice buyers do, controlling for the value and condition of the items. Since the introduction of buyer protection, however, experienced buyers value the reputation badge less than novice buyers do. This difference can be explained by reduced costs related to filing disputes, as experienced buyers are more familiar with eBay rules and regulations.

In addition to our empirical findings, we develop a descriptive model of reputation to help us interpret our results. We are interested in finding the simplest setup that can generate our main findings. In our model, sellers can produce either a high-quality item or a low-quality item. The cost of producing a high-quality item varies among sellers and across time, and is higher than the cost of producing a low-quality item. Sellers who have produced high-quality items in the previous period are certified with a badge. This badge acts as a reputation signal, which can potentially increase sellers' sales prices, thereby giving sellers an incentive to produce high-quality items despite higher costs. Subsequently, we introduce warranty to this system, in which sellers who produce low-quality items must pay a penalty and buyers receive compensation. This simple model has three main predictions: first, the reputation signal has a positive value and this value can remain positive after adding warranty; second, this value can potentially decrease after introducing warranty; third, both types of sellers produce high-quality items more often, due to an increase in the cost of producing a low-quality item. This additionally results in higher prices for both seller types and a higher share of high-quality sellers.

Our work contributes to the reputation and e-Commerce literature in two respects. First, to the best of our knowledge, our paper is the first empirical work that identifies a robust complementarity between reputation and warranty mechanisms for the overall trust system. Added buyer protection does not completely replace the reputation system and the buyer protection increases the total welfare in the marketplace.

in terms of the allocation efficiency between site-wide buyer protection and a seller reputation system, in that buyers rely on both mechanisms to make purchasing decisions. Two other papers on buyer protection are related to our work. Cai et al. [2013] show that buyer protection could decrease the level of trust in a marketplace. In their setup , buyer protection increases buyers' expected utility from trading and could increase the entrance of low-quality sellers, thereby reducing the equilibrium level of trust. A more closely related paper is Roberts [2011], which studies the interaction between website-wide buyer protection and a reputation system in an online marketplace for tractors. He finds the added buyer protection does not change the value of reputation, either in terms of final prices or sales probability, with the exception being for sellers with very high feedback ratings. However, with access to the data of a broader set of products on eBay, we find a robust pattern that buyer protection affects the value of reputation badge across different item characteristics.

Second, our paper contributes to the literature by being among a few research works that empirically identify reputation-based badge effects in terms of price premium. A few other papers have taken similar approaches to estimating the values of reputation in online markets. Saeedi [2011] studies the effect of eBay Powerseller status and store status in the eBay marketplace.[8] She finds the reputation system significantly increases seller profit and consumer surplus. Fan et al. [2013] analyze the effect of badges on the leading e-Commerce platform Taobao.com in China. They find sellers offer price discounts to move up to the next reputation level. More recently, Elfenbein et al. [2013] study the signaling effects of eTRS in the eBay UK marketplace. They find the reputation badge leads to more sales and higher probabilities of sales, even after controlling for better positioning of badged sellers in search results. They also find that the badge effect is higher in categories where the share of badged sellers is lower.

The remainder of this paper is organized as follows. Section 2 explains the related eTRS and eBP rules and regulations; Section 3 describes our dataset; Section 4 provides benchmark analyses of the reputation badge in 2011 after the introduction of buyer protection; Section 5 analyzes the effects of adding buyer protection on the reputation badge; Section 6 provides welfare analysis; Section 7 reports various robustness checks; Section 8 constructs the descriptive model; Section 9 concludes the paper.

[8] Powerseller status was the previous signaling mechanism used by eBay before the introduction of the eTRS program in 2009.

2 Background

An important update for the eBay reputation system is the introduction of the eBay Top Rated Seller badge, which was announced in July 2009 and became effective in October 2009.[9] This status is awarded on a monthly base to sellers who have met the following requirements:

- 98% or higher positive feedback
- 4.6/5.0 Detailed Seller Ratings[10]
- 1% or less low Detailed Seller Ratings
- selling 100 items & $3000 in the past 12 months
- selling 100 items or $1,000 monthly for the past three consecutive months
- low dispute rates

The eTRS mechanism is comprehensive and combines various reputation signals for sellers: feedback ratings, Detailed Seller Ratings, and the number of disputes. The first two signals are observable to buyers, while the number of seller disputes are only observable to eBay. Therefore, the eTRS mechanism reduces buyers' costs of identifying good sellers. In our initial analysis, we include feedback measures and other reputation signals observed from listing pages, but these effects become insignificant once we control for the Top Rated Seller status.

The eBay Top Rated Seller status has potentially three benefits for sellers: first, they enjoy a 20% discount on the *final value fee* charged when items are sold; this fee does not change through the duration of our study. The standard average final value fee is about 10% of the sales price, which means eTRS sellers benefit from another 2% of the sales price besides price premiums. Note that this benefit is not related to the signaling value of the eTRS badge, hence we do not include this benefit in our analysis. The second benefit is that eTRS listings are generally better exposed in buyers' search results under eBay's default sorting order *Best Match*; this visibility advantage

[9] The badging mechanism is common in online communities where contents are user-generated. For instance, Amazon adopts badges like "#1 reviewer", "Top 10 reviewer", and "Vine Voice" (members of an early preview program); these badges are often seen on product review pages. Epinions offers similar badges such as "Category Leads", "Top Reviewer", and "Advisor."

[10] The Detailed Seller Ratings (DSR) system is a rating mechanism from buyers to sellers in the following four categories: item as described, communication, shipping time, and shipping and handling charges. Buyers can mark 1 to 5 stars after their transactions. The click data shows that less than 1% of buyers click on the DSR information of sellers when buying from them.

enhances buyers' visibility of eTRS listings. We control for higher visibility in the robustness analysis in Section 7. Finally, the gold-colored Top Rated Seller badge appears on all of the listings from Top Rated Sellers to signal their quality.

The introduction of the eBay Buyer Protection is another significant update related to the eBay trust mechanism.[11] In September 2010, eBay started the buyer protection to protect buyers' rights in cases where they may encounter purchase problems. This policy mandates sellers to fully refund buyers if the items received are not as described in the sellers' listings, or if the items have not been received at all.[12] This added feature constitutes free buyer insurance in the unfortunate event of receiving lemons or encountering dishonest sellers.

3 Data and Empirical Approaches

Our dataset consists of posted price and auction listings with determined Product IDs within eBay's catalog, and accounts for about 10% of total listings between 2009 and 2012 on the eBay U.S. marketplace.[13] We observe several listing attributes, such as listing titles with their conditions, the dates that listings are posted, the number of page views on listings, and sellers' eTRS status. We have information on whether the listings result in sales and what their sale prices are, as well as buyer characteristics. Our analyses are mainly based on single-item listings data.[14] We choose 2011 as the benchmark year to estimate the badge effect of eTRS, as no reputation policy change took place in this year, and it is the earliest year from which item conditions data are available to us.

Sales prices in our data vary from less than $1 to more than $10,000. Among different listing formats, Buy It Now (BIN) and auction formats account for more than 80% of the total sales,

[11] Before the introduction of this program, buyers could dispute transactions to eBay, but they had much lower chance of getting their money back and would not get the shipping fee back.

[12] eBay holds the sales revenue and transfer it to sellers only if buyer receives the item and does not complain.

[13] eBay has an internal catalog in which distinct Product IDs are assigned to different products. Product IDs are finely defined and two items with the same Product ID are usually exactly the same type. For example, a 4GB Silver 3rd-generation iPod Nano has a unique Product ID that is different from iPods with different generations, colors, or memories; for books or CDs, these IDs represent their ISBN codes. The drawback of using Product IDs is that products that are too heterogeneous, such as collectibles or apparel, do not have Product IDs; therefore, these samples are not considered in our study.

[14] Our early analyses were done with single-item listings. We later incorporated multi-unit listings in Section 4, but found no qualitative differences in the estimates. Therefore, we keep results from single-unit listings in Section 5.

which justifies the focus on these two formats in the literature.[15] We consider these two formats separately, as outcomes of auction listings reflect buyers' perceptions of items more closely, given that most items have very low starting bids and very few have secret reserve prices; BIN prices reflect sellers' pricing strategies more closely, as the price is fixed and posted by sellers. In addition, we study sales probabilities to analyze buyers' reaction to BIN prices. In our dataset, auction listings on average result in higher sales probability and lower sales prices, which is consistent with findings from previous literature. Furthermore, about 3% of sellers are badged, but they make approximately 50% of the sales in the marketplace.

We are interested in estimating the badge effect of the eTRS status on seller performance, both in terms of increases in average sales price and sales probability. Our analysis exploits the variations in sellers' eTRS status and their performance variables in different product groups, distinguished by their Product IDs.[16] Our key regression specification is given as

$$Y_{ijp} = \beta ETRS_{ijp} + \eta_p + \epsilon_{ijp}, \tag{1}$$

where Y_{ijp} is the outcome variable of item i from seller j with Product ID p, such as sales price, relative price, and sales probability; $ETRS_{ijp}$ is a dummy variable that equals to 1 if seller j is badged when item i with Product ID p is sold; η_p is a product-specific unobservable effect; lastly, ϵ_{ijp} is a conventional error term that captures any additional variations in Y_{ijp}.

It is important to note that the estimated β contains not only the signaling value of the badge, but also other factors that affect sales prices. However, we show in Section 7 that the positive effects of eTRS are persistent even after including additional observable characteristics and seller fixed effects. Specifically, regression 1 yields qualitatively the same results as those from the following

[15] Buy It Now is eBay's term for the posted price mechanism. eBay uses a proxy bidding system for auctions: a bidder enters his/her maximum willingness to pay on the listing page, and eBay will automatically bid a small and exogenous amount, so that he/she remains the highest bidder, up to his/her maximum willingness to pay, which sellers and other bidders do not know. In the literature, eBay auctions are commonly modeled as second-price auctions with sealed bids.

[16] There is a small chance that items with the same Product ID will be different, as reported in a recent working paper by Dinerstein et al. [2013]. They study consumers' price search behaviors on eBay and find there are some mis-specifications within a Product ID. This is not a big problem for our study because these errors seem to be independent of the sellers' eTRS status and therefore do not systematically bias our results.

regression:

$$Y_{ijpt} = \beta_1 ETRS_{ijpt} + \beta_2 X_{ijpt} + \beta_3 X_{ijpt} * ETRS_{ijpt} + \beta_4 t + \eta_p + \nu_j + \epsilon_{ijpt},$$

where X_{ijpt} represents characteristics of item i with Product ID p listed by seller j at time t, such as item conditions and page views of this item; η_p and ν_j represent product and seller fixed effects, respectively; t is a linear time trend for the outcome variable Y_{ijpt}. We use regression 1 as our key regression, since we are more interested in the direction of the badge effect after different policy changes have been made. Another reason for this adoption is that, besides estimating the eTRS signaling values, we are also interested in how Top Rated Sellers were affected by the eBP in general, and the key regression specification allows for a comprehensive comparison of seller performance before and after the policy change.

In Section 5, to study the effect of eBay Buyer Protection, we first perform regression 1 separately on sales in ten months before and ten months after the eBP introduction, and compare these two estimates. Another approach is to use sales from the entire 20-month period and perform the following regression:

$$Y_{ijpt} = \beta_1 ETRS_{ijpt} + \beta_2 EBP_t + \beta_3 ETRS_{ijpt} * EBP_t + \beta_4 X_{ijpt} * EBP_t + \beta_5 X_{ijpt} + \beta_6 t + \eta_p + \nu_j + \epsilon_{ijpt},$$

where EBP_t is the dummy variable for whether the buyer protection is introduced.

eBay merchants sell a wide variety of products with different values. Following Einav et al. [2011], we define the value of a product to be the average successful Buy It Now price of items within its product ID category in each time frame. We also tried alternative definitions of value, such as the average successful price across both formats, or monthly fitted values to adjust for monthly depreciation in product values.[17] Our results are robust to changes in the definition of values; these robustness checks will be discussed in Section 7.

[17] The reason that we cannot get reference value for products through another website, e.g. Amazon, is because we have 3,257,454 distinct products in our dataset for 2011. Even if we assume getting a reference point takes only one minute, getting price data for these entire products will take 6.2 years without any break.

4 Value of the Reputation Badge: Year 2011 as the Benchmark

The year 2011 serves as the benchmark year where the badge effect is estimated using multiple specifications and various robustness checks are performed. This year is chosen due to the absence of any change to the eBay reputation mechanism and the availability of item condition data. In addition, more items were categorized into eBay's catalog in 2011 compared to prior years, which helps us measure product values more accurately. Furthermore, since the introduction of eBay Buyer Protection happened in 2010, we show that the value of eTRS remains positive. In this section, we begin by analyzing the summary statistics among different seller groups and across different listing formats, followed by the key regression analysis to identify the badge value. Next, we incorporate more regressors and extra controls to show that our key regression 1 is able to capture most of the badge value.

4.1 Summary Statistics in 2011

We begin by taking the average of sales prices and sales probabilities for different seller groups and listing formats.[18] It is important to emphasize a profound difference between auction and Buy It Now formats: item prices in BIN format are set by sellers, and buyers face a take-it-or-leave-it option at the posted price; on the other hand, final prices in auction format are demand-driven and determined by the second highest valuation among the participating bidders. Therefore, final prices from auction listings resemble the buyers' willingness to pay more closely, as the price cannot be directly controlled by sellers.[19]

Table 1 shows the overall performances of badged and non-badged sellers, using listings with Product IDs.[20] Somewhat counter-intuitive, the average sales prices received by badged sellers in auction and BIN transactions are both lower, compared to those by non-badged sellers: \$49.31 and \$41.79, compared to \$65.87 and \$49.80. However, we should be cautious in interpreting the data, since the composition of items sold by different sellers could be different. As explained in Section 3,

[18] In this paper only auction and Buy It Now (BIN) listings are studied, as they account for more than 80% of the sales on eBay. The conventional listing format used to be auction on eBay, but in recent years, Buy It Now has become more popular. BIN is a fixed price format on eBay where the price is set by sellers and is non-negotiable. (Einav et al. [2013] study possible reasons behind this change.)

[19] As documented by Einav et al. [2011], most starting prices are very low on eBay and most sellers do not use secret reserve prices.

[20] Throughout this paper, we use the phrase "with Product IDs" as a shorthand for items that are in the eBay's internal catalog, i.e., have well-specified Product IDs.

Table 1: Summary Statistics: 2011

	Top Rated Seller		Non-Top Rated Seller	
	Auction	BIN	Auction	BIN
Price	49.31	41.79	65.87	49.80
Relative Price	0.87	1.02	0.78	0.98
Sales Probability	0.38	0.14	0.36	0.08

Notes: This table uses BIN and auction listings with Product IDs in 2011 in the eBay U.S. marketplace. Relative price is defined to be the sales price over the product value, where the product value is the average successful BIN price within a given Product ID. Sales probability is defined as the share of the successful listing among total listings.

we define the value of an item as the average BIN price of items sold within a given Product ID. Subsequently, we define value-normalized sales price, or relative price, as the price over the product value. In our dataset, we find consumers are willing to pay 9% and 4% more to badged sellers for auctions and BIN listings, respectively.

Our dataset shows badged sellers also have an advantage on sales probabilities in both listing formats. They sell 38% of their auction listings, compared to 36% from non-badged sellers. The gap in the sales probability is as big as 6% for BIN listings, even though badged sellers charge 4% more. These results suggest that the badge has some signaling value. The results are also consistent with two patterns on eBay: auction listings sell with higher probabilities, but at lower prices.

The above analysis indicates that Top Rated Sellers receive price and sales probability premiums, compared to non-Top Rated Sellers. However, these differences might stem from discrepancies in seller quality, rather than from the signaling value of the badge. In other words, high-quality sellers may have received these premiums even if they are not badged, given their superior quality of products and services. To disentangle these two causes, we study the changes in average (relative) sales prices in the vicinity of the sellers' badge certification date. In particular, we consider sellers who become top-rated in 2011 and analyze the daily average (relative) sales price within two 30-day intervals of their badged date.[21]

Figure 1a plots the daily average sales prices of new items with Product IDs sold by sellers who become top-rated in 2011 in our dataset. Negative (positive) numbers on the x-axis represent the

[21] Note that the change in average price could be due to sellers' endogenous response to gaining the badge; however, in Section 7 we will show this does not drive our results.

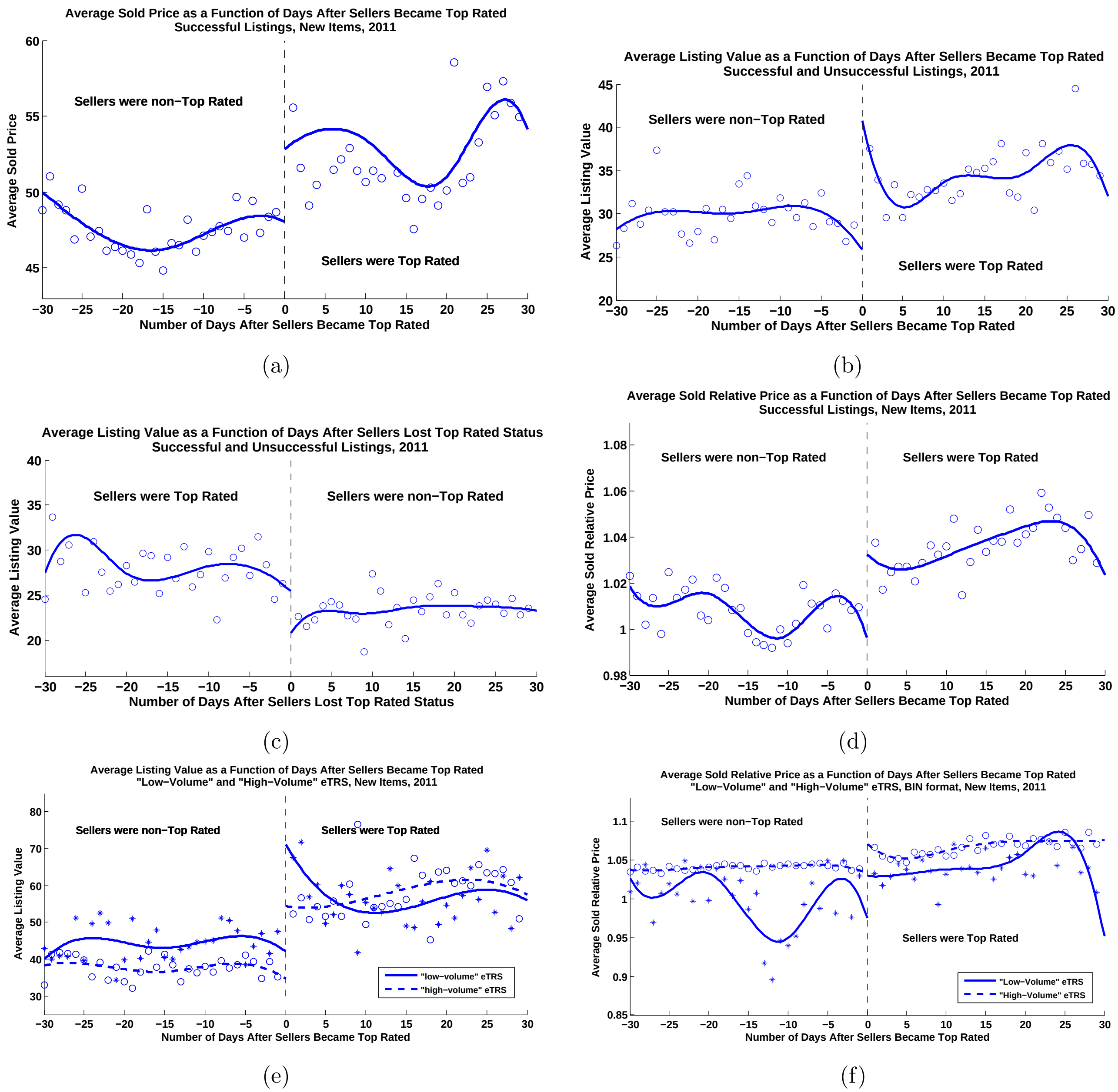

Figure 1: Average Sales (Listings) Variable as a Function of Days After Sellers Become (Lose) eTRS

Notes: These figures use listings of new items with Product IDs in 2011. Positive (Negative) integers on the x-axis represent the number of days after (before) sellers' status change. Integers on the y-axis represent the variables of interest, which are averaged across all sellers who become (or lost) eTRS for the corresponding number of days after/before they become (or lose) eTRS. In Figure (a), (d), and (f), only sold listings are used to compute the average (relative) prices. In Figure (b), (c), and (e), all listings are used to compute the average listing values. The value of a product is defined to be the average sold BIN price. In Figure (e) and (f), we define "low-volume" eTRS to be the Top Rated Sellers whose annual GMV and sales quantity were no more than 10% of the minimum eTRS annual GMV and sales quantity on the certification date. "High-volume" eTRS are those who are at least 20% above the minimum eTRS requirements in GMV and sales quantity.

numbers of days before (after) sellers become badged. Sellers receive higher average sales prices after they become top-rated, suggesting a signaling value of the badge; however, higher prices could also be due to listing more expensive items after their badge certification. To investigate possible changes in sellers' listing behaviors, we study the average *value* of items they listed before and after becoming top-rated. As shown in Figure 1b, sellers start listing more expensive items, as expected, starting on the day after they become top-rated, and the jump in the value of items listed is as high as 30%. Note that one subtle but crucial difference between Figure 1b and Figure 1a is that the x-axis in Figure 1a indicates dates that items are sold, whereas in Figure 1b, it represents dates that items are listed. Figure 1c plots an analogue of the above behavior for sellers who lose their signaling badge. These sellers tend to start listing less valuable items, even though the drop is only around 15%. We control for this change in value of items by using relative prices. To further control for change in the quality of items, we examine only *new* items in Figure 1d. Consistent with Figure 1a, the average relative sales price received by these sellers also increases after they become top-rated. In Appendix A, Figure A.1a and Figure A.1b are analogously produced with only auction listings. Examining sellers who lost their top-rated status also confirms that they receive lower relative price after losing the status.

Figure 1d shows another notable feature, that the average relative price of items sold has a drop within the last two weeks of becoming badged. On eBay, sellers are (re-)examined for the eTRS badge on the 20th of each month and they get notified if they are in the vicinity of becoming top-rated but have not met all of the requirements yet. To examine the effect of these notifications, we study two groups of sellers based on their Gross Merchandize Value (GMV) and sales quantity levels on the day they become eTRS. "High-volume" eTRS are those who are above 20% of the GMV and sales quantity threshold, and "low-volume" eTRS are those within 10% of the GMV and sales quantity threshold. We first study the average *value* of items they list before and after becoming eTRS, as shown in Figure 1e. The average value of items sold by "low-volume" sellers has not changed, i.e., the second-order fitted spline is fairly flat in the month before eTRS certification date in Figure 1e. However, "low-volume" sellers provide discounts on their items by as much as 10% in the two weeks before the certification date to reach the thresholds, as indicated by Figure 1f. On the other hand, Figure 1f illustrates that "high-volume" eTRS do not encounter this decrease. Our finding here is consistent with Fan et al. [2013]'s finding, suggesting that sellers consider the badge to be valuable and are willing to give up some short-term profits in order to become top-rated and gain profit later.

4.2 Regression Results in 2011

In this section, we apply the key regression 1 to successful BIN and auction sales with Product IDs in 2011 in the eBay U.S. marketplace. The aim is to identify the effect of the eTRS badge for sellers in terms of receiving higher sales prices and relative sales prices. Table 2 reports the estimated value $\hat{\beta}$, the coefficient on the effect of eTRS, for different data subsamples. Panel A shows the estimates of the badge effect by using our complete subsample of transactions in 2011, controlling for product or seller characteristics. In the key specification 1, the badge effect is positive and significant in terms of receiving higher (relative) prices across both listing formats. In our dataset, badged sellers receive a 15% higher average markup in both formats and 10% in auction listings. Subsequently, we control for Seller ID fixed effects instead of Product ID fixed effects. Note that by using relative prices, we control for product characteristics by normalizing a product's sales price by its value. The estimates suggest the signaling badge effect is 3% for BIN and auction listings and 2% for auction sub-samples in terms of relative prices.

Buyer valuations of the eTRS badge may vary with items' values. When buyers purchase expensive items on eBay, they face the possibility of losing a large sum of money; this concern should lead to a higher effect for the reputation badge for more expensive items. Similar arguments hold for items with different conditions: purchasing used items involves more risk, since a used item may have flaws that sellers do not report. Therefore, we expect to see higher reputation effects for such items.

To test the above hypotheses, the key regression has been performed on subsamples of items with different value ranges and conditions. Panel B in Table 2 displays the results for different product value ranges. Low, medium, and high value ranges run from \$0.01 to \$10, from \$10 to \$100, and from \$100 to \$500, respectively.[22] We find that for items with higher values, the badge value is higher in terms of sales prices but lower in terms of relative prices. Intuitively, items with high values are expensive so the markup from carrying the badge is higher in the absolute sense; but when we normalize these absolute markups with high item values, the effects in terms of relative price

[22]The estimates for the value range from \$500 to \$1000 are omitted as they are consistent with the observed pattern.

Table 2: Regression Results, 2011

Panel A. BIN and Auction Sales with Product IDs				
Dependent Variable	BIN+Auction	Auctions Only		Controls
Price	3.93***	0.35***		Product
	(0.02)	(0.03)		Characteristics
R^2	0.91	0.91		
Rel. Price	0.15***	0.10***		Product
	(4.7E-4)	(1.9E-3)		Characteristics
R^2	0.62	0.81		
Observations	28,279,096	16,783,646		
Rel. Price	0.03***	0.02***		Seller
	(9.6E-4)	(1.9E-3)		Fixed Effect
R^2	0.50	0.54		
Observations	28,279,096	16,783,646		

Panel B. Items with Different Value Ranges				
Dependent Variable	Low Value	Med Value	High Value	Controls
Price	1.13***	3.55***	10.22***	Product
	(0.01)	(0.01)	(0.08)	Characteristics
R^2	0.93	0.62	0.70	
Rel. Price	0.22***	0.13***	0.05***	Product
	(1.2E-3)	(3.6E-4)	(3.9E-4)	Characteristics
R^2	0.70	0.22	0.21	
Observations	10,853,792	12,294,778	4,174,947	

Panel C. Different Conditions				
Dependent Variable	New Items	Refurb Items	Used Items	Controls
Price	4.06***	6.77***	0.77***	Product
	(0.02)	(0.13)	(0.03)	Characteristics
R^2	0.95	0.95	0.92	
Rel. Price	0.09***	0.06***	0.13***	Product
	(6.4E-4)	(1.1E-3)	(6.2E-4)	Characteristics
R^2	0.84	0.90	0.60	
Observations	10,223,129	620,057	13,068,809	

Notes: Coefficients are estimated from regression 1 on different subsamples. The regressions are based on successful BIN and auction listings with Product IDs in 2011 in the eBay U.S. marketplace. The reported coefficients are estimated from regressing the dependent variables on the eTRS dummy with different controls. The dependent variables are either sales price or relative sales price of items sold. The numbers in parentheses represent standard errors. Low, medium, and high value ranges run from $0.01 to $10, from $10 to $100, and from $100 to $500, respectively.

***Significant at the 1 percent level.

**Significant at the 5 percent level.

*Significant at the 10 percent level.

become lower.[23] The estimated badge value for different conditions are reported in Table 2, Panel C. Note that refurbished items could be both manufacturer-refurbished and seller-refurbished; used items include conditions ranging from “like new” to “for parts/not working”. Our results show that the badge effect in terms of relative prices is the highest for used items and lowest for refurbished items. The reason for the latter result is that most refurbished items in our dataset are expensive. The badge effect in terms of price is different from that in terms of relative price. However, note that sales price does not incorporate the value of items, i.e. a small increase in price is equal to a large increase in relative price if the value of the item is small.

5 eBay Buyer Protection

In September 2010, eBay introduced a new website-wide buyer protection for most items listed on the website. eBay's website states:

> eBay Buyer Protection covers items purchased on eBay with eligible payment methods that are not received (INR) or not as described (SNAD) in the listing. Our internal research shows that a very significant portion of listings on eBay is covered by eBay Buyer Protection. Some purchases aren't covered, such as items eligible for protection under eBay's Business Equipment Purchase Protection, items listed or that should be listed in the Motors (except for Parts and Accessories) and Real Estate categories, and most prohibited or restricted items. Most Business and Industrial categories are covered by eBay Buyer Protection.

eBay Buyer Protection (eBP) covers the vast majority of transactions on eBay, regardless of the sellers' statuses and experience on the website. This program affects buyers' welfare through three main channels: first, through a reduction in moral hazard by giving incentives to sellers to exert more effort; second, through a reduction in adverse selection by increasing the exit rate of low-quality sellers and by increasing the market share of high-quality sellers; and third, through a reduction in buyers' losses decrease for unsatisfactory transactions. Note that after the introduction of the buyer protection, the eTRS badge still has a positive value for buyers, as indicated in the previous chapter. The reason is that the process of filing eBP claims has other intangible costs and

[23] Note that the median value for MED and HIGH value groups are 55 and 300, respectively. Therefore, a 5% markup in relative price for high value items is in fact higher in dollars than a 13% markup for medium value items.

buyers prefer not to encounter any problems.

5.1 Overall Effects of eBay Buyer Protection

We begin by analyzing the summary statistics of our dataset for the period consisting of ten months before and ten months after the introduction of the eBay Buyer Protection program.[24] Table 3 utilizes single-item BIN and auction listings in the eBay U.S. marketplace for the 20-month period. In our dataset, the number of listings has increased by 19% after the introduction of the buyer protection, but the probability of sales has declined by 9%. The percentage of eTRS and percentage of items sold by badged sellers both have risen by about 30%. This increase is not entirely driven by the new policy, but is also a result of an upward trend on the number of top-rated sellers on eBay, which is mostly driven by the entry of young sellers on eBay. When we detrend the growth rate of the number of eTRS sellers on eBay, the effect of eBP on the number of badged sellers is roughly reduced to 10%. This increase is driven by an increase in the cost of dishonest behavior from sellers.

The first effect of adding the buyer protection is through alleviation in moral hazard. To study it, we examine changes in conventional measures of sellers' performance on eBay, namely feedback ratings and Detailed Seller Ratings. Detailed Seller Ratings, as mentioned before, is a rating mechanism from buyers to sellers. Buyers give one to five stars to sellers in four categories: 1) Item as described; 2) Communication; 3) Shipping time; and 4) Shipping and handling charges. eBay has implemented another policy close to the introduction of eBay Buyer Protection that affects the last two DSRs directly; therefore, we do not report the changes on these DSRs.[25] Considering sellers who are active both before and after implementing eBP, Table 3 shows that the share of negative feedback has decreased for both Top Rated Sellers and non-Top Rated Sellers by 14.56% and 26.35%, respectively. To study eBP's effect on DSRs, we report the change in proportions of the ratings of 1 and 2 for sellers. The drops in low DSR ratings in "item as described" and "communication" for non-eTRS are 11.96% and 10.65%, respectively. For Top Rated Sellers, the changes in low DSRs are -2.75% and 2.54%, respectively. Overall, our findings suggest an allevia-

[24] The eBay Buyer Protection program was introduced in September 2010; the ten months before the eBP run from November 2009 to August 2010 and the ten months after the buyer protection run from October 2010 to July 2011. The reason we study a ten-month period is that eTRS was not introduced until October 2009 and the longer time period enables us to control for seasonal effects.

[25] In August 2010, eBay implemented a policy that if sellers offer free shipping, they get 5 stars for the fourth DSR automatically. Later in October 2010, a similar policy was implemented that if an item is shipped within two business days and tracking information is uploaded, then sellers automatically receive 5 stars for the DSR on shipping time.

tion in moral hazard in that sellers exert more efforts, which can be seen from higher performance ratings from buyers.

Another main effect of adding the buyer protection is through a reduction in adverse selection. As established in regression results in the second part of Table 3, sellers' future sizes decrease as they get more complaints from buyers. A complaint from buyers could be a non-positive feedback, a low Detailed Seller Rating, or a dispute. The number of complaints is the total number of complaints received by a seller in a month. Our result shows that prior to the introduction of the eBay Buyer Protection, having a complaint in one month reduces seller sizes in terms of sales volume in the next month by about 2 units; after the eBP introduction, there is an additional reduction in size of 0.03 units. This result suggests that eBP adds a cost for sellers in the cases of unsatisfactory transactions and reduces future sales from lower-quality sellers. This is consistent with the findings of Cabral and Hortacsu [2010] that negative feedback increases seller exit rates.

The rest of Table 3 shows that non-badged sellers on average receive a higher average sales price but a lower average relative price than do badged sellers, similar to the pattern we have seen earlier. Average sales probability decreases for both types of sellers, but the decline is larger for non-badged sellers on both listing formats. Finally, the average relative sales price decreases slightly for badged sellers, but rises for non-badged sellers after the introduction of the buyer protection. This information suggests that the buyer protection increases the reliability of non-badged sellers relative to badged sellers, which contributes to lower price premiums for eTRS.

5.2 Regression Analysis on the Effects of the Buyer Protection

Adding eBay Buyer Protection has affected the premium that Top Rated Sellers receive after becoming badged. Figure 2 illustrates this change. In each month, we identify sellers who gain the badge, and sample their transactions in the 30 days before and the 30 days after their certification dates. Then for each month, we perform regression 1 by regressing relative prices for these sellers on their eTRS status, controlling for Product IDs. Figure 2 shows a sudden decline in badge effect after the buyer protection has been introduced, and this value remains at lower levels for the entire ten months after this introduction.

Table 3: Adding Buyer Protection

Single-Item BIN and Auction Listings in eBay U.S. Marketplace with Product IDs	% Change: 10M Before to 10M After
Number of Listings	18.71%
Number of Successful Listings	8.33%
Sales Probability	-8.75%
Number of Active Buyers	3.14%
Percentage of eTRS	30.49%
Percentage of Quantity Sold by eTRS	30.94%
Percentage of Negative Feedback for non-eTRS	-26.35%
Percentage of Negative Feedback for eTRS	-14.56%
Percentage of Low Item as Described Score for non-eTRS	-11.96%
Percentage of Low Item as Described Score for eTRS	-2.75%
Percentage of Low Communication Score for non-eTRS	-10.65%
Percentage of Low Communication Score for eTRS	2.54%

Seller's Future Size

FUT_SIZE	SIZE	#CMPLNT	#CMPLNT*EBP	R^2
	0.78***	-2.12***	-0.03***	0.93
	(0.2E-3)	(4.8E-3)	(5.0E-3)	

Top Rated Sellers

	Buy It Now			Auction		
	Price	Rel. Price	Conv. Rate	Price	Rel. Price	Conv. Rate
10M Before	37.22	1.30	0.2051	45.58	1.04	0.4473
10M After	37.75	1.28	0.1892	50.56	1.03	0.4206
Pct. Change	1.42%	-1.54%	-7.75%	10.92%	-0.96%	-5.97%

Non-Top Rated Sellers

	Buy It Now			Auction		
	Price	Rel. Price	Conv. Rated	Price	Rel. Price	Conv. Rated
10M Before	41.73	1.12	0.1730	54.95	0.91	0.4742
10M After	64.16	1.13	0.1438	66.85	0.92	0.4025
Pct. Change	53.76%	0.89%	-16.88%	21.65%	1.10%	-12%

Notes: This table uses single-item BIN and auction listings with Product IDs on the eBay U.S. marketplace. The time intervals for these two samples are from November 2009 to July 2011, excluding September 2010, which is the month when eBP was introduced. In the table, 10M before refers to the period from November 2009 to August 2010 and 10M after refers to the period from October 2010 to July 2011. For statistics on the percentage change of negative feedbacks and of low DSRs, we only consider sellers who are active both before and after implementing eBP. We do not report the changes in shipping DSRs because eBay started to auto-fill these DSRs under some circumstances around September 2010 and this raises the number of these two DSRs left, which is not due to the eBP. In the regression, sellers' sizes in terms of number of sales in the following month are regressed upon their sizes this month, the number of complaints they have received this month, and the interaction of this number with whether buyer protection is implemented. A complaint from buyers is either a non-positive feedback, a low detailed seller rating, or a dispute. Relative price is defined to be the sales price over the product value, where the product value is the average successful BIN price within a given Product ID. Sales probability is defined to be the share of successful listings among a seller's all listings. eTRS and eBP are dummies for sellers' eTRS status and whether eBay Buyer Protection was implemented, respectively.

Table 4: Regression Results, Adding Buyer Protection

Price Regressions With Product Fixed Effects

Panel A. Single-Item BIN and Auction Listings in eBay U.S. Marketplace with Product IDs						
	BIN+Auctions			*Auctions Only*		
Dependent Variable	10M Before	10M After	Pct. Change	10M Before	10M After	Pct. Change
Price	4.34***	2.80***	-35.70%	3.54***	1.23***	-65.40%
	(0.02)	(0.02)		(0.03)	(0.03)	
R^2	0.91	0.90		0.91	0.90	
Rel. Price	0.21***	0.17***	-19.04%	0.16***	0.13***	-18.76%
	(0.5E-3)	(0.4E-3)		(0.5E-3)	(0.5E-3)	
R^2	0.56	0.61		0.71	0.76	
Observations	14,771,765			15,983,708		
Panel B. Low Value Ranges						
Price	1.32***	1.35***	2.27%	0.68***	0.64***	-5.47%
	(0.01)	(0.01)		(0.02)	(0.02)	
R^2	0.35	0.33		0.56	0.58	
Relative Price	0.28***	0.28***	-1.34%	0.11***	0.11***	-4.61%
	(1.1E-3)	(1.5E-3)		(2.1E-3)	(2.1E-3)	
R^2	0.57	0.45		0.64	0.66	
Observations	5,884,725	5,310,539		3,857,839	4,036,924	
Panel C. Medium Value Ranges						
Price	4.34***	2.85***	-34.33%	3.62***	1.88***	-48.11%
	(0.02)	(0.02)		(0.02)	(0.02)	
R^2	0.64	0.58		0.66	0.59	
Relative Price	0.16***	0.12***	-24.37%	0.12***	0.09***	-28.26%
	(0.4E-3)	(0.4E-3)		(0.7E-3)	(0.6E-3)	
R^2	0.15	0.20		0.24	0.29	
Observations	6,186,406	6,695,011		4,793,189	5,401,471	
Panel D. High Value Ranges						
Price	16.91***	4.97***	-70.61%	11.29***	1.44***	-87.26%
	(0.16)	(0.13)		(0.18)	(0.14)	
R^2	0.65	0.66		0.67	0.68	
Relative Price	0.09***	0.02***	-74.84%	0.07***	0.01***	-88.84%
	(0.7E-3)	(0.5E-3)		(0.9E-3)	(0.7E-3)	
R^2	0.16	0.15		0.22	0.21	
Observations	1,905,666	12,647,997		1,590,369	2,224,076	

Notes: Coefficients are estimated from regression 1 on different sub-samples. This table uses successful single-item listings with Product IDs within the eBay U.S. site from November 2009 to July 2011, excluding September 2010, when buyer protection was introduced. In addition, we only use products that are sold at least twice before and also after the September policy change. 10M before refers to the period from November 2009 to August 2010, and 10M after refers to the period from October 2010 to July 2011. Relative price is defined to be the sales price over the product value, where the product value is the average successful BIN price within a given Product ID. The coefficients are estimated from regressing (relative) prices on the eTRS dummy after controlling for product characteristics. Standard errors are the numbers in parentheses. The low value range is from \$0.01 to \$10; the medium price range is from \$10 to \$100; the high price range if from \$100 to \$500. The result for the value higher than \$500 is as expected and therefore omitted.

***Significant at the 1 percent level.

**Significant at the 5 percent level.

*Significant at the 10 percent level.

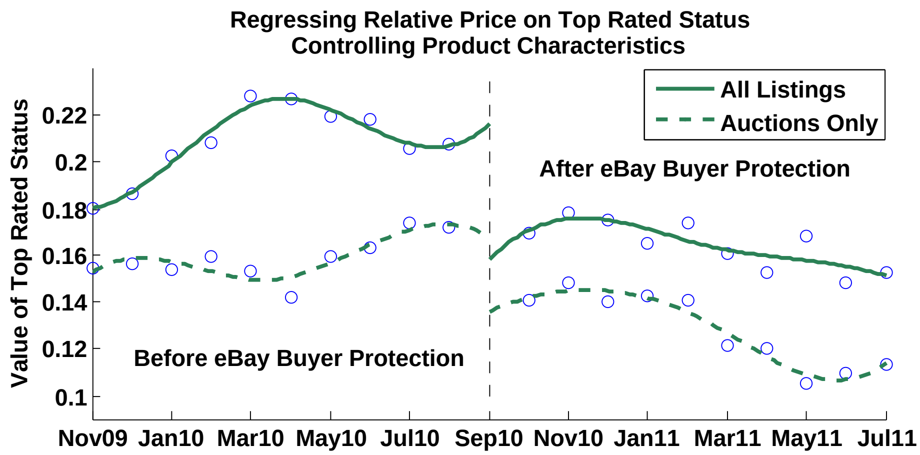

Figure 2: Monthly Badge Effect of Being Top-Rated

Notes: This figure uses single-item BIN and auction sales with Product IDs from sellers who earned the badge during the ten months before and the ten months after the introduction of the buyer protection. Each circle in the graph represents the average badge value in a given month. These monthly values are the estimated coefficients from regressing the relative price on eTRS dummy by controlling for product fixed effects. This figure shows the decline in the value of eTRS is not a result of a long-run downward trend in this value.

To further investigate the change in the badge effect for different item values, we perform regression 1 on the transactions in the ten months before and the ten months after the introduction of eBP. Panel A in Table 4 reports the results with all single-item listings with Product IDs on the eBay U.S. marketplace. Consistent with earlier discussions, being a badged seller raises both prices and relative prices that sellers receive. In addition, the estimated badge effect in terms of relative price decreases by 19% after adding the buyer protection. Essentially, the buyer protection reduces buyers' costs of encountering unsatisfactory transactions, and lowers their reliance on the eTRS badge for good outcomes, thereby decreasing the badge effect. In auctions, the estimated coefficient from the price regression decreases much more than that from the relative price regression. This indicates the composition of items sold may have changed.

To control for potential changes in product composition in the marketplace, we control for different product value ranges. The regression results with subsamples for different value ranges are reported in Panel B, C, and D in Table 4. In both pre- and post- buyer protection periods, the badge effect is smaller for cheaper items in terms of price, but larger in terms of relative price, consistent with our results from Section 4. Most of the estimated values decrease after the introduction of buyer protection; the drop in the badge value for inexpensive items is only about 2%,

Table 5: Quantity Regressions, Adding Buyer Protection

	10 Months Before		10 Months After	
Explanatory Variable	log(1+QTY_SOLD)	SUCCESS	log(1+QTY_SOLD)	SUCCESS
ETRS	0.027***	0.035***	0.022***	0.027***
	(0.4E-3)	(0.4E-3)	(0.4E-3)	(0.4E-3)
LOG_PRICE	-0.064***	-0.073***	-0.066***	-0.073***
	(0.2E-3)	(0.2E-3)	(0.2E-3)	(0.2E-3)
ETRS*LOG_PRICE	-0.001***	-0.001***	0.001***	-0.001***
	(0.1E-3)	(0.2E-3)	(0.1E-3)	(0.2E-3)
QTY_AVAIL_IN_2_10	0.076***	0.040***	0.105***	0.057***
	(0.3E-3)	(0.3E-3)	(0.2E-3)	(0.2E-3)
QTY_AVAIL_IN_11_100	0.153***	0.078***	0.153***	0.053***
	(0.3E-3)	(0.3E-3)	(0.3E-3)	(0.3E-3)
QTY_AVAIL_IN_101_UP	0.182***	0.078***	0.152***	0.047***
	(0.7E-3)	(0.7E-3)	(0.7E-3)	(0.7E-3)
Product-Seller FE	✓	✓	✓	✓
R^2	0.74	0.72	0.80	0.79
Observations	50,051,383	50,051,383	54,905,995	54,905,995

Notes: This table uses all Buy It Now sales with Product IDs within the eBay U.S. site from November 2009 to July 2011, excluding September 2010 where eBay Buyer Protection was introduced. 10 months before refers to the period from November 2009 to August 2010, and 10 months after refers to from October 2010 to July 2011. SUCCESS is a dummy variable that equals to 1 if the listing results in at least one sale. QTY_AVAIL_IN_2_10 is an indicator function for listings with product availability between 2 and 10 units; QTY_AVAIL_IN_11_100 and QTY_AVAIL_IN_101_UP are similarly defined. The regressions are performed with product-seller fixed effects controls.

***Significant at the 1 percent level.

**Significant at the 5 percent level.

*Significant at the 10 percent level.

whereas it is as large as 70% for items with high values. The reason is that, even though buyers do not incur monetary costs if they decide to return items through the buyer protection, they still encounter other intangible costs, such as communicating with sellers, comprehending regulations, filing disputes, or bringing the item to the post office. However, these costs are fairly fixed and do not depend on item values. Therefore, returning cheap items is more costly for buyers relative to the value of the item, which leads to lower impact of eBP on the eTRS value for these items. For expensive items, however, buyers use the new policy in case of lemons since the benefit exceeds the cost of disputing. One must note that Figure 2 shows the decline in the value of eTRS is not a result of a long-run downward trend in this value.

5.3 Effects of the Buyer Protection on Quantity and Sales Probability

The benefits of becoming badged are multi-dimensional: having analyzed the change in benefits sellers receive in terms of price, the next step is to study the change in badge value in terms of sales quantities and sales probabilities. To study this question, we regress the logarithm of one plus quantity sold in a listing and the sales indicator on the sellers' badge statuses with proper controls. In this exercise, our sample contains single-item and multi-item BIN listings, as all auction listings are single-item. In the regressions, we also include dummy variables for the number of quantities available in different listings, since the total amount sold, if there exists any, obviously cannot exceed the available units in each listing.[26] In Table 5, QTY_SOLD is the total quantity sold in a listing; SUCCESS is a dummy variable that equals to 1 if there is at least one sale in a listing; QTY_AVAIL_IN_i_j is an indicator for whether the total available items in a listing are between i and j units. Prior to the buyer protection, the badge raises the percentage of quantity sold in listings by 2.7%, but this number drops slightly to 2.2% afterwards; the badge used to increase the sales probability by 3.5%, but decreases to 2.7% afterwards. Indeed, the decline in the badge effect of eTRS is also found in quantities sold and sales probabilities after the introduction of the buyer protection. The levels of the badge effects are reasonably close to those reported in Elfenbein et al. [2013], which are based on data from eBay's UK site.

5.4 Different Buyer Experience

Buyers in the eBay marketplace differ in their levels of experience and their familiarity with eBay's rules and regulations. Therefore, they may conceive the value of reputation differently and may be affected by the buyer protection differently. We partition buyers based on their spending in the year prior to the observed purchases. In particular, we define EXPERIENCED as the dummy variable for buyers who have spent at least $2500 in the past year. We then perform regression analysis on our dataset, which contains BIN and auction sales with Product IDs from November 2009 to July 2011, excluding September 2010 when eBP was introduced.

Table 6 reports estimation results for buyers with different levels of experience on eBay and for different value ranges. LOW, MED, and HIGH are dummies for item value ranges from $0.01 to

[26] On the listing page, potential buyers can see the total quantity available in this listing and decide to buy one or more units from it.

Table 6: Effects of Buyer Protection for Buyers with Different Experience

	10 Months Before		10 Months After	
	Price	Relative Price	Price	Relative Price
ETRS*EXPERIENCED	2.57***	0.03***	-0.57***	-0.02***
	(0.08)	(0.2E-2)	(0.08)	(0.3E-2)
ETRS*LOW	0.80***	0.25***	1.35***	0.25***
	(0.06)	(0.2E-2)	(0.07)	(0.3E-2)
ETRS*MED	4.10***	0.15*	3.81***	0.14***
	(0.06)	(0.2E-2)	(0.06)	(0.3E-2)
ETRS*HIGH	23.75***	0.12***	10.26***	0.06***
	(0.12)	(0.2E-2)	(0.12)	(0.3E-2)
PRODUCT FE	✓	✓	✓	✓
R^2	0.85	0.59	0.83	0.51
Observations	23,965,507	23,965,507	23,965,507	23,965,507

Notes: This table uses BIN and auction sales with Product IDs in the eBay U.S. marketplace from November 2009 to July 2011, excluding September 2010, when eBay Buyer Protection was introduced. 10 months before refers to the period from November 2009 to August 2010, and 10 months after refers to from October 2010 to July 2011. ETRS is the dummy variable for seller's eTRS status. EXPERIENCED equals to 1 if a buyer has spent more than $2500 in the year prior to her purchase. LOW, MED, and HIGH are dummies for item value ranges from $0.01 to $10, from $10 to $100, and from $100 to $500, respectively.

***Significant at the 1 percent level.

**Significant at the 5 percent level.

*Significant at the 10 percent level.

$10, from $10 to $100, and from $100 to $500, respectively. Consistent with our previous findings, the badge effect weakly decreases for all experience-value range combinations in terms of relative price as indicated by coefficients in front of interaction terms of eTRS and the experience dummy.

The first two columns of Table 6 show that, before the introduction of eBP, experienced buyers were willing to pay higher prices, relative to novice buyers, to buy from high-reputation sellers. After the introduction of eBP, experienced buyers pay lower prices, as indicated by a negative coefficient on the interaction term between ETRS and EXPERIENCED in columns 3 and 4. Note that this effect is not driven by changes in the composition of items or buyers, as we control for both of these parameters. This observation indicates that experienced buyers understand the marketplace mechanism better: before the buyer protection, they place a larger value on the badge for higher valued items, since they understand that their costs in cases of lemons would be large; after the introduction of eBP, their valuation decreases, since experienced buyers know that transactions with bad outcomes will be covered by the buyer protection. Novice buyers are, in contrast, not as responsive to changes in market rules, since they may be skeptical about the new rules or unaware of the details.

Note that our results are robust to different definitions of experience. In particular, we have checked different threshold levels for experience and also having four experience levels instead of two. In the second check, the group with the highest experience level values reputation the most before the introduction of eBP and the group with the lowest experience level values reputation the least. After the policy introduction, this relationship is reversed.

6 Welfare Analysis: Adding Buyer Protection

As mentioned earlier, adding buyer protection can improve market efficiency. In this section, we attempt to find an estimate for the change in welfare. To do this, we need to make additional assumptions on the market structure and on changes in cost parameters for sellers. We use data on the highest bids for auctions, together with sales prices for Buy It Now transactions in the month before and the month after adding the buyer protection to construct our estimates. We focus on the month before and the month after this policy change for various reasons. First, there are no other important policy changes during this period. Second, the market values of items listed on eBay do not change greatly. Third, the market size in terms of active buyers and sellers is fairly fixed; otherwise, the market structure can change.[27]

Total welfare equals to total buyers' willingness to pay minus total sellers' cost. We do not directly observe buyers' willingness to pay, but we can observe highest bids for all auction transactions. eBay auctions are hybrids of second-price and first-price auctions, in which the bidder with the highest valuation should pay either the second highest bid plus an increment (proxy) that is exogenous to bidder, or his own bid, whichever is smaller. The proxy can potentially lead buyers to bid values that are different from their willingness to pay.[28] We assume the bid function remains the same across time and can be approximated by a linear function:

$$bid = a * willingness\_to\_pay,$$

where a is a function of the market structure, bidders' expectations of other bidders' valuations and strategies, and the number of bidders per auction. We assume these two parameters have not changed as a result of the policy change.[29] Therefore, any percentage change in the highest bids will translate to the same percentage change in the buyers' willingness to pay. Table 7 uses transaction data in the month before and after the introduction of eBP and shows the results of regressing the relative highest bids, i.e., the highest bids over product values, on the eBP dummy in columns 1 and 2. The value of a product is defined as the average BIN sales prices of items in each Product ID category in the two-month period considered in this study. In these regressions, we control for a weekly time trend to capture exogenous changes in the value of products. Auction listings in which the highest bids are 100 times larger than the final sales prices (0.3% of all auctions) have been removed from our dataset, as they may be mistakenly recorded.

Regression 1 shows a 14.4% increase in the average relative highest bid for non-eTRS sellers and a 12% increase for eTRS sellers, which equals to a 13.6% increase in the weighted (by the proportion of eTRS and non-eTRS) average relative highest bid received. In regression 2, we control for differ-

[27]Even though we control for weekly price changes with a linear time trend, large changes in price may not be captured linearly.

[28]In the literature, eBay auctions are commonly assumed to be second-price auctions, in which bidders' weakly dominant strategy is to bid their willingness to pay.

[29]We observe the number of bidders and number of bids per auction do not vary before and after eBP, nor does the number of active sellers or buyers.

Table 7: Welfare Changes: Adding Buyer Protection

	Auction Rel. Highest Bid		Auction Rel. Price		BIN Rel. Price		Auction+BIN Rel. Price	
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
ETRS	0.062*	0.062*	0.074*	0.075*	0.095***	0.094***	0.099***	0.099***
	(0.036)	(0.036)	(0.041)	(0.041)	(0.003)	(0.003)	(0.035)	(0.035)
EBP	0.144	0.035	0.239**	0.134	0.033***	0.001	0.119	0.060
	(0.093)	(0.094)	(0.107)	(0.108)	(0.008)	(0.008)	(0.094)	(0.094)
ETRS*EBP	-0.024	-0.026	-0.023	-0.025	0.029***	0.030***	-0.089*	-0.089*
	(0.050)	(0.050)	(0.058)	(0.058)	(0.004)	(0.004)	(0.048)	(0.048)
LOW		2.639***		2.422***		0.921***		1.539***
		(0.522)		(0.599)		(0.056)		(0.583)
MED		1.635***		1.612***		0.904***		1.268***
		(0.452)		(0.518)		(0.052)		(0.527)
HIGH		0.101		0.135		0.274***		0.257
		(0.413)		(0.474)		(0.049)		(0.491)
Week	-0.002	-0.003	-0.013	-0.013	-0.4E-3	-0.4E-3	-0.002	-0.002
	(0.009)	(0.009)	(0.010)	(0.010)	(0.001)	(0.001)	(0.009)	(0.009)
Product FE	✓	✓	✓	✓	✓	✓	✓	✓
R^2	0.951	0.951	0.926	0.926	0.706	0.708	0.706	0.706
Observations	308,570	308,570	308,570	308,570	346,587	346,587	655,157	655,157

Notes: This table uses single-item listings with Product IDs that have the keyword "new" in their listing titles. Transactions in the month before the introduction of eBP and the month after are included in the sample. Relative price is defined to be the sales price over the product value, where the product value is the average successful BIN price within a given Product ID; relative highest bids are the highest bids of transactions divided by product values. The value of a product is defined as the average BIN sales prices of items in each Product ID category in the two-month period considered in this study. The value of a product is defined as the average BIN sales prices of items in each Product ID category in the two-month period considered in this study. ETRS and EBP are dummies for sellers' eTRS statuses and whether eBay Buyer Protection was implemented, respectively. LOW, MED, and HIGH are dummies for item value ranges from \$0.01 to \$10, from \$10 to \$100, and from \$100 to \$500, respectively. In the estimation of welfare changes, we control for a linear trend for weeks of sales and Product IDs.

***Significant at the 1 percent level.

**Significant at the 5 percent level.

*Significant at the 10 percent level.

ent value ranges and find a 3.5% increase in the average relative highest bid for non-eTRS sellers and a 0.9% increase for eTRS sellers, yielding an increase in the weighted average relative highest bid of 2.7%. The reason for including dummies for value ranges is to take care of potential changes in item composition. Columns 1 and 2 show that buyers' willingness to pay has increased by 2.7% to 13.6%, depending on the regression specifications. Note that we keep both regressions since one might consider the change in composition of items offered as a potential welfare gain.

We do not observe and neither can we identify the cost parameters directly. However, the BIN prices are set by sellers and these prices are a function of sellers' costs. To examine the relationship between price and cost, we need to make an assumption on sellers' strategy. A wide range of pricing models can be addressed by a revenue sharing model, namely choosing prices that maximize the following weighted welfare function:

$$\max_{p}(u-p)^{\alpha}(p-c)^{\beta},$$

where α and β are buyers' and sellers' welfare weight, u is buyers' utility, and c is sellers' cost parameter. Note that this model is a more general case of the one in Section 8 and different values for α and β can generate different equilibrium assumptions.[30] We cannot identify α, β, and c directly, but we can find upper bounds on changes in cost parameters. This maximization problem leads to the following pricing strategy:

$$p = \frac{\beta u + \alpha c}{\alpha + \beta}, \tag{2}$$

which implies

$$c = \frac{\beta}{\alpha}(p-u) + p. \tag{3}$$

Assuming the change in u is the average change in highest relative bids from auction listings, and the change in p is the average change in BIN prices, we obtain an upper bound for changes in sellers' marginal cost. Columns 5 and 6 show a lower increase in the average relative sales price of BIN transactions relative to buyers' willingness to pay; therefore, the change in $p-u$ in equation 3 is negative, which implies that the change in sale prices, p, is an upper bound for changes in the marginal cost. Therefore, we find a lower bound on the changes in welfare by estimating the change in $u-p$. In our dataset, u has gone up by 13.6% — 2.7% and p has increased by 4.1% — 1.0%. Therefore, a lower bound on the increase in welfare, namely $u-p$, is 13.6% — 2.7%, depending on whether we take into account changes in composition of items or not. In Table 7, we also include regression results on the sales price of auctions and of all transactions. The results on changes in prices are consistent with the changes in highest bids and therefore support our estimates.

7 Robustness Analysis

In this section, we perform various robustness checks to verify the validity of our key regression design. In particular, we show that the estimated effect of eTRS is not driven by omitted variables,

[30]In our model, we implicitly assume $\beta = 0$ and $\alpha = 1$, which has the same weights as in the Bertrand model. In the Cournot Model with N sellers, we have $\alpha = \frac{N}{N+1}$ and $\beta = \frac{1}{N+1}$.

unobserved heterogeneity, or exogenous changes in the value of items. We incorporate alternative definitions for product value and additional regressors, i.e., page views, start prices, interactions between eTRS and condition/value dummies, and control for the product-seller pair fixed effects. Additionally, we study the effects of eTRS for the group of sellers who have lost and later re-gain the badge in 2011 to eliminate the possibility of learning. Furthermore, we consider sellers who are very close to the GMV and sales quantity thresholds of the eTRS requirements and compare sellers who are just above and below the threshold. Finally, we investigate alternative definitions of reputation.

Recall that we define the value of an item to be the average successful BIN price of items listed under a given product ID in 2011. We have also considered an alternative definition that calculates the average price from both listing formats, but found no qualitatively different estimates. Another concern is that if product values change significantly within a year, our estimates of the badge effect would be biased. We therefore define monthly fitted values for different products to account for possible depreciation in product values. For tractability, we assume linear depreciation in values, and the monthly fitted values for each product are fitted by a category-level depreciation rate.[31] All except for two categories have depreciation rates that are less than 1% of their estimated intercepts. The two exceptions are: Computer & Network whose monthly depreciation rate is 1.7% and Cell Phones & PDA whose monthly depreciation rate is 1.5%. For these two categories, we define the adjusted relative price to be the sales price over the depreciation-adjusted monthly fitted value and perform our key regression. The results are shown in columns 1 and 2 in Table 8. The badge effects in terms of relative prices are 0.04 and 0.06 for the above-mentioned categories, comparing to 0.03 and 0.04 if we do not incorporate monthly value depreciation. This shows that we may underestimate the badge effect of eTRS when we do not account for depreciation in product values. The reason is that even though we consider all sellers with status changes, in our dataset more sellers gain, than lose the eTRS badge over time.[32]

eBay's default search ranking is *Best Match*. Being a badged seller increases the probability that

[31]We have more than three million distinct products in our dataset; and given that we have very few observations for some of the groups, the estimates for the time trend become very noisy. In contrast, we only have 30 categories for these products. The top five most popular categories in our data are DVDs & Movies, Books, Video Games, Cell Phones & PDA, and Consumer electronics.

[32]In cases where sellers lose their eTRS status, not including a decreasing trend in product values overestimates the eTRS value. Conversely, in cases where sellers gain the status, not including such a trend underestimates the eTRS value. In our dataset, the number of sellers who gain eTRS exceeds those who lose the status over time. Therefore, our estimate on the eTRS value is lower, compared to if we had controlled for the time trend in product values.

his/her listings appear on the first page in buyers' query search results. If we do not account for this factor, our estimated parameters will not only capture the signaling effect of the badge, but also its visibility effect. In column 3, we include the number of page views as a control for visibility for BIN transactions. The effect of eTRS remains positive and significant. Another concern is that, in an auction listing, eTRS may be more likely to set lower starting prices to attract more bidders, which leads to increased competition and higher sales prices. Therefore, we include the number of page view and start price of a listing in our key regression. Column 4 shows that the effect of the reputation badge remains positive and significant after controlling for the two new parameters. Next, we verify that changes in composition of the items listed do not drive the differences in sales prices. To do this, we include different interaction terms between eTRS status, item conditions, and items' value range, controlling for Seller ID fixed effects. Results under this specification are displayed in column 7: the positive effects of eTRS still exist for almost all of the condition-value combinations.

Our earlier analyses show sellers may list cheap (expensive) items in the two weeks before (after) they become badged. Therefore, we examine whether the badge effect of eTRS is driven by sellers' extreme behaviors close to the certification date. In particular, we consider the subsample of transactions from sellers whose statuses have changed in 2011 and remove transactions within two weeks of sellers' status change. The key regression 1 is then performed on this subsample with and without the removal of transactions in those two weeks, and the estimated results are 7.1% and 7.3% increase in price, respectively. Therefore, it seems that the badge effect in terms of increase in relative price is not largely driven by the inclusion of these extreme behaviors.

To eliminate the possibility of omitted variables in terms of seller experience or learning, we perform a few robustness checks. We first employ the regression discontinuity design that investigates sellers in our dataset who are "just below" the eTRS threshold and those who are "just above" the threshold, in terms of the annual GMV requirement ($3000) and the annual quantity requirement (100 items). In particular, these sellers qualify for the quality requirements for badge certification and they differ only in meeting the minimum GMV or quantity requirements. In columns 5 and 6 in Table 8, the 10% band includes "just-below" eTRS sellers whose annual GMV is between $2700 and $2999.99 or whose annual sales quantities are between 90 and 99; "just-above" eTRS who were sellers whose annual GMV is between $3000 and $3299.99 with annual sales quantities

Table 8: Robustness Check, 2011

Panel A: Multiple Robustness Regressions

	Cellphone	Computer	BIN Only	Auctions Only	10% Band	20% Band	
	(1)	(2)	(3)	(4)	(5)	(6)	(7)
	Adj_Rel_Price	Adj_Rel_Price	Rel_Price	Rel_Price	Rel_Price	Rel_Price	Rel_Price
ETRS	0.06***	0.04***	0.14***	0.12***	0.04***	0.05***	0.10***
	(0.9E-3)	(0.7E-3)	(0.5E-3)	(0.6E-3)	(0.3E-2)	(0.3E-2)	(0.01)
VIEW_COUNT			0.4E-3***	5.2E-3***			-6.7E-7***
			(0.1E-4)	(0.3E-3)			(1.2E-7)
START_PRICE				0.2E-2***			
				(0.9E-4)			
ETRS*NEW							-0.01***
							(1.5E-3))
ETRS*REFURB							-0.01**
							(3.9E-3)
ETRS*LOW							-0.07***
							(5.6E-3)
ETRS*MED							-0.09***
							(5.6E-3)
ETRS*HIGH							-0.04***
							(5.5E-3)
PRODUCT FE	✓	✓	✓	✓	✓	✓	
SELLER FE							✓
Observations	2,327,469	979,775	11,495,450	16,783,646	415,240	839,995	27,705,329
R^2	0.88	0.89	0.51	0.81	0.92	0.88	0.498

Panel B: Performances of Sellers Who Have Lost and Later Re-Gain the Badge

	Sellers Are eTRS		Sellers Lost eTRS		Sellers Re-Gain eTRS	
	Auction	BIN	Auction	BIN	Auction	BIN
Price	38.30	28.00	36.17	19.61	49.36	30.65
Relative Price	1.02	1.07	0.87	1.03	1.02	1.03
Sales Probability	0.41	0.15	0.38	0.11	0.32	0.18

Notes: Regressions in Panel A are based on successful BIN and auction listings with Product IDs in 2011 in the eBay U.S. site. ETRS is a dummy variable indicating the seller's eTRS status. In regressionss 1 and 2, Adj_Rel_Price is the adjusted relative price defined as price over monthly depreciation-adjusted values for a product, which is obtained by fitting a line through monthly average successful BIN prices for each product at the category level. We include only cell phone and computer categories in the table because the percentage depreciations in dollar values for these two categories are the largest ($3 and $5 decrease per month) among all categories. In regressions 3 and 4, VIEW_COUNT is the number of page views for a product; START_PRICE is the auction starting (reservation) price. Low, medium, high, and highest value ranges run from $0.01 to $10, from $10 to $100, from $100 to $500, and from $500 to $1000, respectively, where the value of a product is defined to be the average successful BIN price. In regression 5 and 6, the sample being used contains transactions from sellers who are "just-below" eTRS and those who are "just-above" eTRS, in terms of the annual Gross Merchandise Value requirement ($3000) and the annual quantity requirement (100 items) for eTRS. In particular, all of these sellers qualify for the eTRS quality requirements and they differ only in meeting the minimum GMV or quantity requirements. The 10% band includes "just-below" eTRS sellers whose annual GMV was between $2700 and $2999 or whose annual sales quantities were between 90 and 99, and "just-above" eTRS sellers were those whose annual GMV was between $3000 and $3299 with annual sales quantity between 100 and 109. In regression 7, we also control for conditions and value dummy variables. The statistics in Panel B are based on successful BIN and auction sales with Product IDs in 2011 from sellers who have lost their badge for some time but later re-gain it in 2011. We have about 5000 such sellers.

***Significant at the 1 percent level.

**Significant at the 5 percent level.

*Significant at the 10 percent level.

between 100 and 109. The 20% band is similarly defined. The coefficients are estimated by applying regression 1 to this sub-sample. With this approach, the results from our dataset indicate that the badge effect is 4% in terms of the relative price for the 10% band and 5% for the 20% band.

In addition to the above check for seller learning, we investigate behaviors of sellers in our dataset who lost and re-gained their eTRS badges. If sellers receive higher prices just as they become more experienced, the subsequent changes in status should not have much impact on price premiums. However, results in Panel B from Table 8 suggests sellers who lost and later re-gain their status have enjoyed higher prices for the second time they become top-rated as well. In particular, the average relative price that sellers receive in auctions decreases from 1.02 to 0.87 after they lose the eTRS status, but bounces back to 1.02 after they re-gain this status. In another exercise, we study sellers who have lost and re-gained the eTRS status for 1 time, 2-3 times, or more than 4 times, and find that they receive 8%, 6%, and 8% increase in price, respectively, when they are eTRS; these changes do not diminish for their consecutive re-gaining of the badge.

The last robustness check we perform is to consider the effect of adding the buyer protection on other measures of reputation to test the robustness of our findings on the definition of reputation. We construct new reputation status based on sellers' feedback scores.[33] In particular, we consider sellers who meet eBay's minimum selling standard and have feedback scores of at least x, where $x \in \{100, 500, 1000, 2000, 5000\}$.[34] Note given that feedback scores change gradually over time for sellers and we cannot disentangle signaling value and unobservable heterogeneity among sellers. Therefore, we do not take a stand on what share of the effect is the signaling effect. Panel A in Table 9 shows the effect of being in each feedback score group. The price premiums that sellers in most of these groups receive drop after the change in policy, which is consistent with our earlier results. Panel B and C in Table 9 report the welfare results based on these alternative reputation signals, using the method in Table 7. It turns out that the lower bounds on the change in welfare are between 7% and 8% for all reputation signals. These results suggest our previous results do not depend heavily on the definition of reputation and can therefore be applied to more general cases.

[33]Seller's feedback score is a cumulative score, which changes by 1, 0, or -1 if the seller receives a positive, neutral, or negative feedback, respectively. Since the number of negative feedback on eBay is small, the feedback score is essentially the number of feedback sellers received.

[34]eBay's minimum selling standard requires a seller to have at most 1% low DSR scores in "item as described" and at most 2% low scores in other DSRs. In addition, eBay requires the percentage of closed dispute cases without seller resolution to be no more than 0.3%.

Table 9: Alternative Reputation Signals

Panel A: Alternative Reputation Signals						
Dependent Var: Relative Price	eTRS	100Fdbk	500Fdbk	1000Fdbk	2000Fdbk	5000Fdbk
10M Before	0.21***	0.09***	0.12***	0.12***	0.11***	0.07***
10M After	0.17***	0.07***	0.10***	0.10***	0.10***	0.08***
Percentage Change	-19.04%	-26.79%	-15.91%	-11.94%	-1.66%	18.20%

Panel B: Welfare Analysis with Alternative Reputation Signals: Auction Listings					
Dependent Var: Rel. Highest Bid	100Fdbk	500Fdbk	1000Fdbk	2000Fdbk	5000Fdbk
FDBK	0.002	0.013	0.019	0.023	0.039
	(0.033)	(0.028)	(0.028)	(0.028))	(0.031)
EBP	0.083	0.086	0.087	0.086	0.086
	(0.096)	(0.096)	(0.096)	(0.095)	(0.095)
FDBK*EBP	0.075	0.070*	0.068*	0.069*	0.068*
	(0.048)	(0.040)	(0.038)	(0.037)	(0.037)
Product FE	✓	✓	✓	✓	✓

Panel C: Welfare Analysis with Alternative Reputation Signals: BIN Listings					
Dependent Var: Relative Price	100Fdbk	500Fdbk	1000Fdbk	2000Fdbk	5000Fdbk
FDBK	0.060***	0.041***	0.035***	0.034***	0.25***
	(0.004)	(0.003)	(0.003)	(0.003)	(0.003)
EBP	0.054***	0.033***	0.026***	0.022***	0.015**
	(0.008)	(0.008)	(0.008)	(0.007)	(0.008)
FDBK*EBP	0.019***	0.043***	0.052***	0.055***	0.063***
	(0.005)	(0.004)	(0.003)	(0.003)	(0.003)
Product FE	✓	✓	✓	✓	✓

Notes: In Panel A, coefficients are estimated from regressing relative sales prices on eTRS or other reputation signals based on feedback scores, controlling for product fixed effects. Dummy variable #Fdbk equals to 1 if the total number of seller feedback is bigger than # and the seller is not below eBay's selling standard at the time when transactions take place; this dummy equals to 0 otherwise. 10M before refers to the period from November 2009 to August 2010, and 10M after refers to from October 2010 to July 2011. In Panel B and C, we replicate our welfare analyses in Table 7 by using other reputation signals based on feedback scores. Relative price is defined to be the sales price over the product value, where the product value is the average successful BIN price within a given Product ID; relative highest bids are the highest bids of transactions divided by product values. The value of a product is defined as the average BIN sales prices of items in each Product ID category in the two-month period considered in this study. FDBK are dummy variables for the corresponding #Fdbk groups; for example, FDBK=1 in the 1000Fdbk group if the number of feedback for a seller is at least 1000 and the seller is not below eBay's selling standard. EBP is the dummy for whether eBay Buyer Protection has been implemented. LOW, MED, and HIGH are dummies for item value ranges from $0.01 to $10, from $10 to $100, and from $100 to $500, respectively. In the estimation of welfare changes, we control for a linear trend for weeks of sales, as well as the Product IDs.

***Significant at the 1 percent level.

**Significant at the 5 percent level.

*Significant at the 10 percent level.

8 A Descriptive Model

In this section, we propose a simple model that can explain the economic forces that generate our empirical findings. While this model is a stylized simplification of features in the eBay marketplace, it can capture important properties of the interaction of the reputation and warranty mechanisms. In particular, the model can explain the following main features: first, the reputation signal has value even after the introduction of warranty. Second, this value can potentially go down after the introduction of warranty. Third, adding warranty can increase prices for both groups of sellers, i.e., sellers with high-reputation and low-reputation levels; in addition, we can get an increase in the share of high-reputation sellers. The last result leads to a welfare gain due to an increase in allocative efficiency in the presence of a reputation mechanism and a warranty mechanism.

Our model builds on Mailath and Samuelson [2001] and Holmström [1999] by modeling reputation as buyers' uncertainty about sellers' types and adding a warranty mechanism. Our model shares some features with Cai et al. [2013]. The main difference is that we explicitly model a reputation signal which leads to different predictions.

In our model, time is discrete, $t = 0, 1, 2, ...$ There is a unit measure of buyers in the market. The buyers are short-lived and receive a normalized utility level of 0 from consuming a low-quality item, while they receive u units of utility from consuming a high-quality item. A crucial assumption for our analysis is that buyers can only observe the reputation badge and do not observe sellers' past behavior.[35] While this assumption is restrictive, it is consistent with the fact that the buyers do not have access to full history of sellers' actions. In particular, one explanatory factor that affects price dispersion is the number of past disputes for sellers, which is not directly observable to the consumers, but can be inferred from the Top Rated Seller status.

There is a unit measure of sellers who produce a single item in each time period, which can be of

[35]The lack of recall assumption makes the model tractable. Additionally, it also provides a positive value for reputation in the long-run. Recent theoretical papers such as Liu [2011], Ekmekci [2011], and Jehiel and Samuelson [2012] demonstrate that the value of reputation can be positive in the long-run, if the market designer reveals only partial information on seller performance, or if buyers have limited memory; these results hold even when sellers' qualities are fully persistent. This is in contrast to the result of Mailath and Samuelson [2001] where with fully persistent types and full recall, reputation has no value in equilibrium.

high or low quality, $a_{jt} \in \{H, L\}$. The cost function for sellers is $c_j(a_{jt}, \epsilon_{jt})$. The cost of producing a low-quality item for all sellers at any time period is $c_j(L, \epsilon_{jt}) = c_l$; the cost of producing a high-quality item for seller j at time period t is $c_j(H, \epsilon_{jt}) = c_l + c_j + \epsilon_{jt}$, where $c_j, \epsilon_{jt} > 0$, ϵ_{jt} is distributed from CDF function $G(\epsilon)$ and is i.i.d. across time and sellers; c_j is distributed from CDF function $F(c)$ and is fixed for each seller across time. The additional cost of producing a high-quality item has two components: a fixed and persistent component, c_j, and a variable component, ϵ_{jt}, that is i.i.d over time.[36] This cost information is privately known to each seller and is unobservable to buyers, other sellers, or eBay. At the beginning of each period sellers receive their cost for that period and can then decide on the type of item to produce; this type is unobservable to buyers. Buyers only observe the reputation status of sellers when we have a reputation mechanism in place.

8.1 Benchmark Model without Reputation and Warranty

When buyers receive no information about sellers' quality and past behavior (which can be interpreted as the absence of a reputation mechanism and a warranty mechanism, and with no recall), sellers find it optimal to always produce low-quality items in equilibrium. This is because the cost of producing a high-quality item is always higher for all sellers, and there is no short-term or long-term benefit that could compensate sellers for producing high-quality items. In equilibrium, buyers' belief on the type of items produced will coincide with sellers' choice, therefore their belief will be that all the items are of low quality. Given that low-quality items give them 0 utility, the price will be zero in equilibrium.

8.2 Reputation and Warranty

We defined a simple reputation system, in which buyers observe a single signal for the sellers: the type of item they produced in the last period. Note that buyers are short lived and do not observe any other information on sellers' history. This reputation signal will serve as sellers level of reputation, $\phi \in \{H, L\}$. We think that this assumption captures, to a great extent, key features of the eBay Top Rated Seller status. In particular, in order for a seller to become top-rated, only sale data from the last year is taken into account with special emphasis on observations in the past three months.[37]

[36] The higher cost of providing a good with high quality in the context of eBay can be interpreted as an increase in the cost of providing detailed descriptions of the item, communicating effectively with the buyers, shipping the item promptly, and using good packaging. These actions increase the cost of selling an item on eBay, while increasing the utility of buyers. Note that in the data sections we control for the item type, item condition, and the differences in quality to make sure that the differences in price are not a result of changes in item types.

[37] On the eBay website, buyers can observe the feedback rating of a seller. We do not consider the feedback rating to be the main measure of the reputation, as the correlation of feedback percentage and price is not large. The

Buyers form a belief about the distribution of sellers' types, persistent levels of cost, conditional on sellers' reputation signal, $\mu(c_j|\phi)$. The difference between the belief for the two reputation signal can lead to different prices for different sellers, i.e., $p(\phi = L) \neq p(\phi = H)$. We additionally assume the equilibrium is stationary; hence, price is only a function of the sellers' reputation level and not the time period.

We assume that price is determined as an outcome of a second-price auction or equivalently a Bertrand competition among buyers. Both setups yield a price equal to buyers' expected utility from purchasing the good from each type of sellers, as there is no heterogeneity among buyers. The basic results stay the same if we assume that the outcome is determined by a Nash bargaining game with varying bargaining weight for buyers and sellers, in this paper we have assumed that sellers have much higher negotiation power. In this scenario, price will be a value between buyers willingness to pay and sellers' cost, and the exact number will be a function of their respective Nash bargaining weights. Note that by assuming Nash bargaining, the directional effects for prices or share of high-reputation sellers do not change.

After implementing buyer protection in the system, buyers receive compensation of γ units of utility in case the item is of low quality. γ can be interpreted as combining various effects: the probability that buyers report the seller, the probability that they are successful in proving the item is of low quality, the monetary compensation they receive, and the cost of filing a dispute.[38] For simplicity, we assume buyers are truthful and do not misreport an item's quality. Sellers pay a one-time penalty of τ if they offer low-quality items. τ can also be interpreted as combining various effects: the probability that buyers report the bad outcome, the probability they can prove the item is of low quality, the monetary penalty sellers must pay, and intangible costs of going through the disputing process.[39] τ and γ do not need to be the same; i.e., the dispute process may have different

feedback system works as a mechanism to prevent entry of the worst sellers into the market, Cabral and Hortacsu [2010]. Even though buyers can get more detailed information about the seller by going through their past feedback ratings and reviewing descriptions of feedback left for them, the click data on eBay shows less than 0.1% of buyers use this data. Also as a theoretical note, if the full history of the sellers is available, the value of reputation would go to zero, Mailath and Samuelson [2001].

[38] We can explicitly model this stage by assuming buyers incur different costs in filing a dispute and make their decision endogenous.

[39] Strictly speaking, even sellers who produce high-quality items could incur higher cost through fraudulent behaviors from buyers. However, eBay checks for these behaviors frequently; these users will be removed and are forbidden to register on eBay again; therefore, the share of these buyers is very small and negligible and hence we ignore this

levels of cost for buyers and sellers. For example, sellers should pay for the shipping cost both ways.

At the beginning of each time period, t, seller j with persistent level of cost, c_j, receives an i.i.d. shock to the cost of producing a high-quality item, ϵ_{jt}. This seller has a reputation signal $\phi_t \in \{L, H\}$, and given this signal, she will get a price, $p(\phi)$, for producing any type of item. If she chooses to produce a good of low-quality, she should pay the cost and penalty of producing a low-quality item: $c_l + \tau$. In addition, her reputation signal next period will be $\phi_{t+1} = L$. On the other hand, if she chooses to produce a high-quality item, the cost will be: $c_l + c_j + \epsilon_{jt}$. In addition, her reputation signal next period will be $\phi_{t+1} = H$. The above problem of seller can be written as the following value function:

$$V(c_j, \phi) = \int \max_{a_j} \{p(\phi) - c(a_j, \epsilon) + \beta V(c_j, \phi')\} dG(\epsilon)$$

where $\phi' = a_j \in \{H, L\}$, the action of seller j. Note that $\tau = 0, \gamma = 0$ represent the special case with a reputation mechanism, but no warranty mechanism in the market. In the absence of warranty, the only force that gives incentive to sellers to offer a high-quality item is receiving higher prices in the next period. Adding warranty will increase sellers' static cost of producing a low-quality item by adding the fine τ. The sellers problem after observing ϵ_{jt} can be simplified as producing high-quality item iff:

$$\begin{aligned} -c_j - \epsilon_{jt} + \beta V(c_j, H) &\geq -\tau + \beta V(c_j, L) \\ \Rightarrow \epsilon_{jt} &\leq \beta(V(c_j, H) - V(c_j, L)) + \tau - c_j \end{aligned}$$

The above strategy does not depend on the current value of ϕ; thus, two sellers with the same level of c_l and different levels of ϕ will act exactly the same, which gives them the same cost levels in this period and also the same continuation value. The only difference between these two sellers is the price they receive this period. Hence: $V(c_j, H) - V(c_j, L) = p(H) - p(L)$. We can simplify sellers action further; sellers produce high-quality item iff:

$$\epsilon_{jt} \leq \beta(p(H) - p(L)) + \tau - c_j$$

effect.

To make the problem more tractable, we define a new parameter $b = \beta(p(H) - p(L)) + \tau$ as the sum of dynamic and static incentives for sellers to produce high-quality items. The first term is the dynamic benefit, by producing high-quality items sellers receive higher prices in the next period; the second term, τ, is the static benefit of not paying the penalty for warranty mechanism at the current period. With the new notation, sellers produce H iff:

$$\epsilon_{jt} \le b - c_j \Rightarrow Pr(a_{jt} = H|c_j) = G(b - c_j)$$

In equilibrium, buyers' belief about sellers' type, $\mu(c_j|\phi)$, is consistent with sellers' actions:

$$\mu(c_j|H) = \frac{G(b - c_j)}{\int G(b - c)dF(c)},$$

where $\mu(c_j|H)$ is the pdf for sellers' types if they have produced a high-quality item in the last period. The above equation and our assumption on the price mechanism will characterize the equilibrium as a function of b, as specified in the following theorem.

Theorem 1 *In equilibrium,* $\frac{b-\tau}{\beta(u-\gamma)} = K(b)$*, where*

$$K(b) := Pr(a = H|\phi = H) - Pr(a = H|\phi = L) = \int G(b-c)\{\frac{G(b - c)}{\int G(b - c)dF(c)} - \frac{1 - G(b - c)}{1 - \int G(b - c)dF(c)}\}dF(c).$$

Proof. Given that buyers' belief is consistent with sellers' actions, $p(H)$ and $p(L)$ can be written as:

$$\begin{aligned}
p(H) &= u * Pr(a = H|\phi = H) + \gamma * Pr(a = L|\phi = H) \\
&= (u - \gamma)Pr(a = H|\phi = H) + \gamma \\
&= (u - \gamma)\int Pr(a = H|c)\mu(c|H)dF(c) + \gamma \\
&= (u - \gamma)\frac{\int G(b - c)^2 dF(c)}{\int G(b - c)dF(c)} + \gamma
\end{aligned}$$

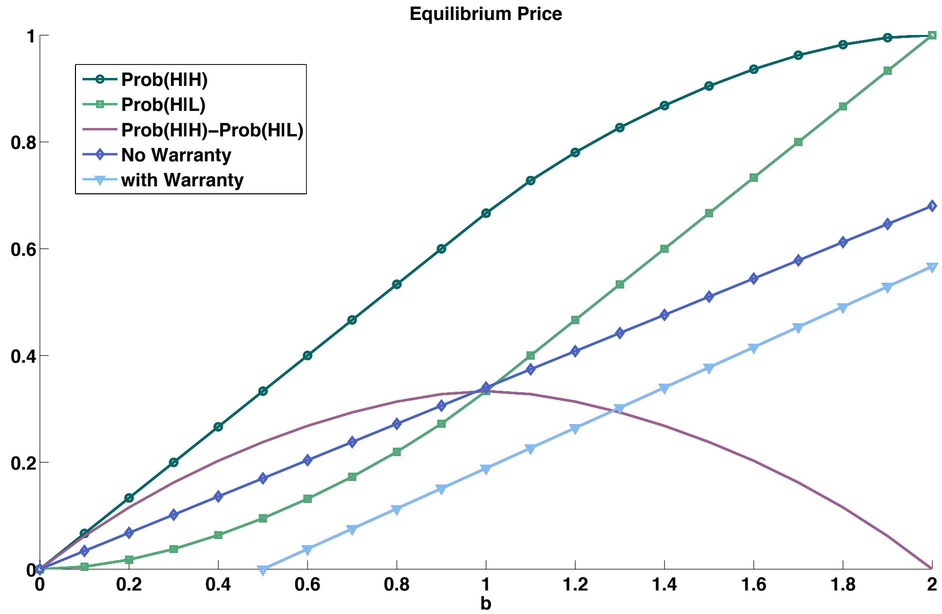

Figure 3: Equilibrium Price

Notes: The x-axis shows benefit that sellers get from producing H in a period. The inversed u-shaped curve shows the function $K(b)$. For $\beta = 0.98$ and $u = 3$, and no warranty, equilibrium level of b is the intersection of line noted as "No Warranty" and the u-shaped curve. For warranty case, we use parameter values $\gamma = 0.5$ and $\tau = 0.5$.

$$\begin{aligned} p(L) &= u * Pr(a = H|\phi = L) + \gamma * Pr(a = L|\phi = L) \\ &= (u - \gamma)Pr(a = H|\phi = L) + \gamma \\ &= (u - \gamma)\int Pr(a = H|c)(\mu(c|L))dF(c) + \gamma \\ &= (u - \gamma)\frac{\int G(b - c)(1 - G(b - c))dF(c)}{\int (1 - G(b - c))dF(c)} + \gamma \end{aligned}$$

Recall that u is buyers' utility from consuming a high-quality item, and γ is the utility of consuming a low-quality item in presence of warranty. Using definition of b and subtracting the above two equations give us the result. ■

Solving the above equation in terms of b will give us the equilibrium. Let b_w denote the equilibrium value of b in the presence of warranty mechanism and let b_{nw} denote the equilibrium value of b with no warranty mechanism. After finding the equilibrium level of b, we can solve for the value for $p(\phi)$ using the above two equations. We can solve the above equation for various functional assumptions on G and F. Assuming that G and F comes from uniform distribution between 0 and 1, Figure 1 plots $K(b)$. We have checked multiple distribution functions, e.g., Normal, extreme value, and uniform with different supports, and in all of these cases the function $K(b)$ is a inversed u-shaped function similar to Figure 3. The intuition is that when the benefit is zero, $b = 0$, no seller produces high-quality items, and when benefit goes to infinity, all the sellers always produce high-quality items, which gives the same price for all seller groups at the two extremes. Therefore, the differences in prices at the two extreme are always zero. The nice feature of the K function is that it is independent of τ and γ after controlling for b. Therefore, the K function does not change with or without warranty. The equilibrium level of b is found at the intersection of k and $(b-\tau)/(\beta(u-\gamma))$. When there is no warranty, τ and γ are zero.

Let $0 \leq \gamma \leq u$, buyers' utility is lower when the item is of low quality even in the presence of warranty. In addition to the above assumption, a necessary condition for $b_{nw} < b_w$ is: $\gamma < \tau$.[40] The intuition behind the condition is that warranty mechanism should be designed so that the cost to the seller is at least as big as benefit to buyers. Otherwise, we might have a situation that more low-quality items would be produced after adding warranty. Recall that the probability that a seller of type j produce high-quality item is $G(b - c_j)$.

Assuming the necessary condition holds, we conclude $b_{nw} < b_w$, which leads more of H and L sellers to produce high-quality items, which results in higher prices for both seller groups and higher share of sellers with high reputation signal. But the difference in prices of the two groups, or the premium of reputation, will depend on the value of $K(b)$ function, which is not monotone in b. Note that $p(H) - p(L) = K(b)(u - \gamma)$. By adding warranty, $K(b)$ can go up or down; If γ is big enough, we can always get to lower gap in prices regardless of the change in K.

The model shows the premium of reputation, $P(H) - P(L)$, can remain positive after adding warranty, even though this premium may go down. Moreover, with a higher value of b, after adding warranty, we get bigger proportion of sellers who produce high-quality items and thus an efficiency gain. All these three effects are seen in the example depicted in Figure 3.

[40] The necessary condition ensures that the intersection of the two lines, with and without warranty, lies outside of the $K(b)$ cure which will be for sure less than 1.

9 Conclusion

Asymmetric information potentially leads to adverse selection, market inefficiency, and possibly market failure. Market designers commonly develop seller reputation policies and warranty policies to overcome these problems. In this paper, we have a unique opportunity to evaluate the reputation mechanism and then to analyze possible efficiency gains in light of the introduction of the buyer protection program to the existing reputation mechanism.

In this paper, we first show that the value of reputation is positive for sellers; certified sellers receive a price premium. We then demonstrate that after introduction of the buyer protection, the premium goes down but remains positive. The added cost of buyer protection policy on sellers when they provide a low-quality service, induce sellers to provide a better service, alleviation in moral hazard; it also forces low-quality sellers to quit more often, alleviation of adverse selection. These two leads to lower instances of bad outcome and an efficiency gain in the marketplace. Furthermore, buyers receive compensation when they encounter a bad outcome, which leads to higher willingness to pay for goods produced by both types of sellers. By assuming that the policy has not affected competition in the market, the total welfare rises by 2.7% to 13.6%, depending on different modeling assumptions. This increased welfare demonstrates a complementarity between the two mechanisms.

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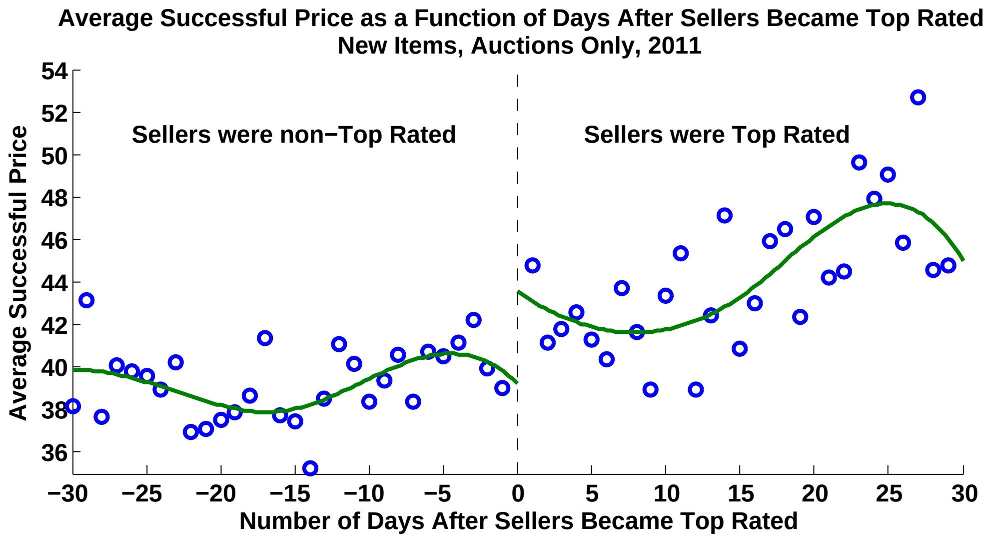
A Additional Figures



(a)

(b)

Figure A.1: Average Auction (Relative) Price as a Function of Days After Sellers Became eTRS

Notes: These figures use successful auction listings of new items with Product IDs in 2011. Positive/negative integers on the x-axis represent the number of days after/before sellers became top-rated. Integers on the y-axis represent (relative) prices that are averaged across all sellers who become eTRS for the corresponding number of days before and after they became top-rated.