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

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Abstract

The absence of perfectly symmetric information potentially leads to adverse selection, market inefficiencies, 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 investigate the interaction of these two policies and the possible efficiency gains in light of the introduction of the eBay Buyer Protection program. We first demonstrate eBay's reputation system raises the average sales price and the fraction of successful sales for certified sellers by 4% and 3%, respectively; this result is robust for various specifications. Adding buyer protection provides an efficiency gain as buyers do not solely rely on the reputation system. In addition, it decreases the markup reputable sellers receive compared to low-reputation sellers. However, it increases the value of purchasing from eBay for buyers, leading to higher prices for all groups of sellers. Furthermore, adding eBay Buyer Protection increases the number and market share of reputable sellers by increasing the cost of dishonest behavior. We develop a model to interpret these results and to get an estimate for change in social welfare: this policy increases the total welfare from 12.4% to 19.6%.

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

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1 Introduction

Asymmetric information potentially leads to adverse selection and market inefficiencies, 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] Most of such markets adopt reputation policies, in which they provide users' past histories and certify outstanding users. Others provide marketplace warranty policies to prevent low-quality users from participating. We have a unique opportunity to investigate the interaction of these two policies and the possible efficiency gains in light of the introduction of eBay Buyer Protection. 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?[2] Would it only benefit sellers with low levels of reputation or also reputable sellers? Would this yield a lower market share for reputable sellers? Would this policy increase social welfare? Would the marketplace unravel in some ways?

To answer these questions, we first develop a descriptive model of reputation. In the model, sellers who have produced high-quality items in the previous period are certified with a badge. This badge gives them incentive to produce high-quality items despite higher costs. Subsequently, we introduce warranty to this system, in which sellers who produce a low-quality item must pay a fine if they are reported by buyers. This added warranty has three main effects: first, it increases the price for both badged and non-badged sellers; second, it increases the share of badged sellers; third, the premium of becoming a badged seller can change in different directions depending on the prevalence of reputation, as well as the generosity of the warranty mechanism, both of which lead to lower premiums.

Afterwards, we examine the implications of the model using data from the eBay platform. We first show the eBay reputation system has positive value. We consider the eBay Top Rated Seller (eTRS) mechanism as the main signal for seller reputation.[3] Our empirical approach is based

[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 the hosts' reputation and provide reasons for price variations on Airbnb.

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

[3] We have considered the feedback ratings and the number of feedback at the first stages of this research, but they have been proven to have very small or insignificant effects on prices when we control for Top Rated Seller status. As it will be explained in detail, sellers should a maintain high level of feedback ratings in order to become and remain

on regression discontinuity designs, similar to Einav et al. [2011]. We partition observations into groups of listings with the same Product ID–eBay's internal catalog system that is finely defined. Subsequently, we study the performance of sellers who become Top Rated within a given period, controlling for different observable characteristics. We demonstrate the reputation system raises the average sales price and the sell-through rate for badged sellers by 4% and 3%, respectively.[4] We perform multiple checks to ensure robustness.

Next, we empirically study the interaction of eBay reputation mechanism and eBay Buyer Protection. eBay introduced the site-wide buyer protection in 2010. This program mandates that sellers must refund item prices plus shipping costs if items received are not as described, or if buyers do not receive the items. This program affects buyers' welfare through two main channels. The first is the risk reduction effect in that eBay Buyer Protection decreases buyers' losses for unsatisfactory transactions. The second is the unravelling effect, since the quality of sellers has increased after the introduction of this program. In particular, we see about 30% more reputable sellers, and about 11% less negative feedback and detailed seller ratings after the buyer protection is implemented. In addition, average final sales price has increased, even for auction listings, which indicates an increases in buyers' valuation towards the same products.[5]

Consistent with the model prediction, buyer protection increases the average sales price of items for all sellers, after controlling for time trends. Thus, buyer protection benefits high-quality sellers regardless of their reputation status. Additionally, we show it increases the percentage of badged sellers among all sellers by 30%. Furthermore, we find that buyer protection lowers the badge effects by 19% in terms of the average sales price and by 21% in terms of the conversion rate. Finally, our results show buyer encounter more positive experience after the introduction of buyer protection. All evidence suggests buyer protection provides a reasonable complement for the reputation program, as buyers shop with confidence and shop beyond badged sellers. In other words, buyer protection increases competition by increasing the substitutability of items sold by badged and non-badged sellers.

eTRS.

[4] Conversion rate is the probability of sales, which is defined as the ratio of successful listings to total listings.

[5] The number of auction listings has increased, so the lift in average sales price is not due to lower levels of competition.

Another interesting finding is that buyers rely more on buyer protection, rather than on the badge for more expensive items: the drop in badge effect is largest for the most expensive items by 70%, and it is negligible for inexpensive items. A potential reason is that, even though buyers do not incur monetary costs if they decide to return the item through buyer protection, they still incur intangible costs. However, these costs do not vary much with the value of the items. Therefore, returning cheap items is relatively more costly for buyers who might choose not to exercise their rights, even if they are guaranteed a refund through buyer protection.

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 in terms of allocation efficiency between site-wide buyer protection and 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. Buyer protection in their setup 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 the 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 conversion rates, 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 provides a reasonable complement for the reputation badge in terms of allocation efficiency across different item characteristics.

Our paper is also among a few research works that empirically identify reputation-based badge effects in terms of price premiums. A few other papers have taken similar approaches in estimating the values of reputation in online markets. Saeedi [2011] studies the effect of eBay Powerseller status and store status on the eBay marketplace.[6] She finds that 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 that sellers offer price discounts to move up to the next reputation level. More recently, Elfenbein et al. [2013] look at the signaling

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

effects of eTRS in eBay UK marketplace. They find that the reputation badge leads to more sales and higher conversion rates, 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 rest of this paper is organized as follows. Section 2 explains the related eTRS and eBP rules and regulations; Section 3 constructs the model; Section 4 describes our dataset; Section 5 provides benchmark analyses of the reputation badge in 2011 after the introduction of buyer protection; Section 6 analyzes the effects of adding buyer protection on the reputation badge; Section 9 concludes the paper.

2 Background

An important update for the eBay reputation system is the introduction of the eBay Top Rated Seller (eTRS) badge, which was announced in July 2009 and became effective in October 2009.[7] This status is awarded monthly to *PowerSellers* that have met extra requirements:[8] they need to make at least 100 transactions and $3,000 in sales over the past 12 months and maintain low dispute rates from buyers.

The most direct benefit of being an eTRS is enjoying 20% discount on the *final value fee* charged when items are sold. Another crucial benefit is that listings from eTRS are generally better exposed in buyers' search results under eBay's default sorting order *Best Match*; this "informational" advantage enhances buyers' visibility of eTRS listings. Last, the gold-colored Top Rated Seller badge appears on all of the listings from Top Rated Sellers, signaling their quality and helping their listings stand out.

Introduction of the eBay Buyer Protection (eBP) is another significant update for the eBay reputa-

[7] 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".

[8] *PowerSeller* is one of the oldest reputation badges on eBay; however, it losts its importance after the introduction of the eTRS badge and removal of PowerSeller badge of the listing page and search page. To qualify for PowerSeller status, sellers need to sell at least 100 items or at least $1,000 worth of items every month for three consecutive months. Sellers also need to maintain at least 98% positive feedback and 4.6/5.0 Detailed Seller Ratings

tion system. Starting in September 2010, eBay announced this buyer protection to protect buyers' rights in cases where they encounter a purchase problem. This policy mandates sellers to fully refund buyers if the received items are not as described in the sellers' listings, or if the items were not received at all. This added feature constitutes free buyer insurance in the unfortunate event of receiving lemons or encountering dishonest sellers.

3 Model

In this section, we propose a descriptive model to point out different economic forces that can increase allocative efficiencies in presence of reputation mechanism and warranty mechanism. While the model is a stylized simplification of features in eBay marketplace, it can capture certain properties about the interaction of reputation and warranties. In particular, it can explain why introduction of a warranty mechanism can lead to the following observations:

1. The increase in share of high-reputation sellers
2. The increase in prices for both high-reputation and low-reputation sellers
3. The possibility of lower mark-up for high-reputation sellers,
4. The increase in welfare.

The model builds on Mailath and Samuelson [2001] and Holmström [1999] by modelling reputation as uncertainty about sellers' types and explicitly allowing for existence of a warranty mechanism. The model shares some features with Cai et al. [2013]. The main difference is that we explicitly model the reputation mechanism which leads to different predictions.

Time period t is descrete and in $\{0, \inf\}$. There is a unit measure of buyers in the market. The buyers are short-lived and receive a utility 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 and do not observe sellers' past behavior.[9] While this assumption is restrictive, it captures the idea that in eBay, buyers do not have access to certain information

[9]The lack of recall assumption makes the model tractable. Additionally, it also provides 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 in Mailath and Samuelson [2001] where with fully persistent types, reputation has no value in equilibrium.

about seller's previous sales. In particular, one explanatory factor that affects price dispersion is the number of past disputes for sellers which is not observable directly to the consumers but they can infer this information from the Top Rated Sellers status given it is part of requirements.

There is a unit measure of sellers, who produce a single item each time period, which can be of high quality or low quality, $a_{jt} \in \{H, L\}$. The cost of producing a low-quality item is $c(L, \epsilon_{jt}) = c_l$ for all sellers at any time period. The cost of producing a high-quality item for seller j at time period t is $c(H, \epsilon_{jt}) = c_l + c_j + \epsilon_{jt}$, where $c_j, \epsilon_{jt} > 0$, ϵ_{jt} has a cumulative distribution function $G(\epsilon)$ and is iid over time and across sellers. The cost, c_j, is distributed according to the cumulative distribution function $F(c)$. We assume that the cost of producing a high-quality item has two components: a fixed and persistent component, c_j; a variable component, ϵ_{jt}, that is i.i.d over time. Sellers are privately informed about their cost and type of items they produce. The buyer realizes the type of item after consumption. Sellers choose the type of item they produce each period to maximize their expected profit given the price. The higher cost of providing a good with high quality in context of eBay can be interpreted as the increase in cost for sellers from providing detail description of the item, communicating effectively with the buyers, shipping the item promptly, and good packaging. These actions will increase the cost of selling an item on eBay while they increase the utility of buyers. Note that in the data sections we control for the item type and item condition and the differences in quality.

3.1 Benchmark Model without Reputation and Warranty

When buyers receive no information about sellers' quality and past behavior (this can be thought of as absence of a reputation mechanism and warranties), 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 to exert higher efforts and produce high-quality items. As a result, the buyers' belief is that the items are always of low quality and hence the equilibrium price of items is zero.

3.2 Reputation and Warranty

We capture a reputation mechanism by simply allowing the buyers to observe the outcome of a sale in the previous time period. We assume that buyers have limited recall in that they can only observe last period's outcome. 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 past year is taken into account with special emphasis on observations in the past three months. There are two possible states for the level of reputation, $\phi \in \{H, L\}$. H sellers offered high-quality items in the previous period, whereas L sellers offered low-quality items. This is the only sellers' history that buyers observe. Buyers have a belief about the distribution of sellers' persistent levels of cost conditional on sellers reputation status, $\mu(\phi)$. The difference in the belief can potentially lead to different prices for sellers with different reputation statuses: $p(\phi)$.

We make a rather strong assumption that the price in the market will be equal to buyers' expected utility from purchasing a good from each type of sellers. If we consider a more general Nash bargaining scenario, the 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 weight. Here we make the assumption that the sellers' Nash bargaining weight is much bigger to simply the model further, when we consider the change in welfare we only examine at the change in total welfare. Note that our assumption do not change the directional changes for prices or share or reputatble sellers.[10]

We assume when warranty exists in the market, sellers pay a one-time penalty of τ if they offer low-quality items. τ can be interpreted as the probability that buyers report the incident, times the probability they become successful in proving the item is of low quality, times the static and dynamic fine that sellers must pay.[11] Additionally, buyers will get γ units of utility when the quality of the good is low; this can be interpreted as the percentage of times they can prove the quality of good they purchased is low, times the return they get in those states, minus any costs they should pay to dispute the transaction. We assume buyers are honest and will not misreport the items' quality.

In equilibrium, buyers' belief about sellers' type is consistent with sellers' actions, and the equilibrium price clears the market given the buyers' belief. We additionally assume the equilibrium is stationary; hence, sales price is only a function of the sellers' reputation level and not a function

[10] In a more realistic set-up, especially in auctions, or a Nash bargaining problem, buyers and sellers each get a share of the surplus. However, the simplifying assumption in our paper suffices for our interest in estimating the change in total welfare, which is captured by higher average sales price. In the absence of a structural model, separate welfare changes for buyers and sellers are not identified.

[11] Strictly speaking, even sellers who produce high-quality items could incur higher cost from the buyer protection 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 and it seems that the share of these buyers is very small.

of the time period. The maximization problem of sellers in this case is:

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

where $\phi' = a_j \in \{H.L\}$, the action of seller j. Note that $\tau = 0, \gamma = 0$ represent the special case with 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. However, adding warranty will increase sellers' static cost of producing a low-quality item by adding the fine τ.

Lemma 1 *Controlling for c_j and ϵ_{jt}, the optimal action of the seller is not a function of its reputation status: $a_{jt}(\phi, c_j, \epsilon_{jt}) = a_{jt}(c_j, \epsilon_{jt})$. Furthermore,*

$$V(c_j, H) - V(c_j, L) = p(H) - p(L)$$

Proof. For a given ϵ_{jt}, seller j's optimal choice at time t is to choose H iff:

$$-c_j - \epsilon_{jt} + \beta V(c_j, H) \geq -\tau + \beta V(c_j, L)$$

which is not a function of ϕ, hence $a_{jt}(\phi, c_j, \epsilon_{jt}) = a_{jt}(c_j, \epsilon_{jt})$. Moreover, the difference, $V(c_j, H) - V(c_j, L)$, equals to the difference in prices, $p(H) - p(L)$, since ϕ does not affect sellers' decision at the current period or in future periods, and only affects the prices sellers get at the current period. ■

Given Lemma 1, sellers' strategy can be reformulated as choosing H iff:

$$\epsilon_{jt} \leq \beta(p(H) - p(L)) + \tau - c_j \Rightarrow Pr(a_{jt} = H | c_j) = G(b - c_j)$$

where b is defined as $\beta(p(H) - p(L)) + \tau$. b can be interpreted as expected benefit for sellers from producing a high-quality item; the first term is the dynamic benefit, higher prices in the next period; and the second term, τ, is the static benefit of not paying the penalty at the current period due to warranty. Furthermore, in the equilibrium buyers' belief on sellers cost distribution as a function of their reputation status is consistent with sellers action:

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

The above and our assumption on the price in the equilibrium, will characterize the equilibrium as a function of b as it comes in the following theorem.

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

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

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

$$\begin{aligned}
p(H) &= u * Pr(a_{jt} = H|a_{jt-1} = H) + \gamma * Pr(a_{jt} = L|a_{jt-1} = H) \\
&= (u-\gamma)Pr(a_{jt} = H|\phi = H) + \gamma \\
&= (u-\gamma)\int Pr(a_{jt} = H|c_j)\mu(c_j|H)dF(c_j) + \gamma \\
&= (u-\gamma)\frac{\int G(b-c_j)^2 dF}{\int G(b-c_j)dF(c_j)} + \gamma
\end{aligned}$$

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

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 theorem in terms of b will give us the equilibrium, after finding the equilibrium level of $b*$, we can find the value for $p(H)$ We can solve the above equation for various functional assumptions on G and F. Assuming that G and F are uniform distribution between 0 and 1, Figure 1 shows $K(b)$. 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 u-shaped function similar to the case of Figure 1. 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 will produce

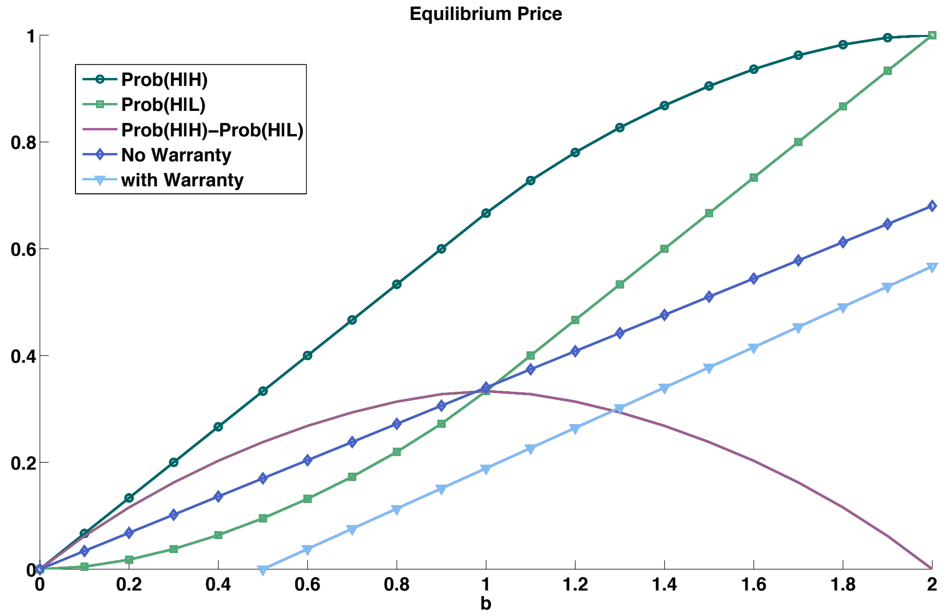

Figure 1: Equilibrium Price

Notes: The x-axis shows benefit that sellers get from producing H in a period. The 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 $\tau = 0.5$.

high quality items at all the times. Therefore the difference in price at the two extreme is always zero. The equilibrium value for b can be found in the intersection of $K(b)$ and $(b - \tau)/(\beta(u - \gamma))$. When there is no warranty, τ and γ are zero. Let $0 \leq \gamma, \tau \leq u$, buyers' utility is still lower when the item is of low quality. Therefore, when we have positive γ and τ the line will be flatter with a non-positive intercept, which result in a higher value for b in equilibrium. b is the expected benefit of producing high-quality item, therefore both type of sellers, those with high-level of reputation or low-level of reputation, produce high-quality items more often. This yields to higher $p(H)$ and also $p(L)$, and also higher fraction of sellers will become of high-level of reputation from the next period, as benefit of producing high-quality items gone up.

However, the difference in price for the types of sellers, with high or low reputation, can go up or down; this comes from the fact that $K(b)$ is u-shaped. 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.

For the parameter values used in Figure 1, adding warranty increases the equilibrium value of b and decreases the equilibrium of $K(b)$. Higher value for b corresponds to higher values for $p(H|H)$ and $p(H|L)$, and lower value for $K(b)$ corresponds to lower difference between $p(H)$ and $p(L)$. Additionally, higher values for $p(H|H)$ and $p(H|L)$ results in higher percentage of high reputation sellers in the economy and also higher levels of price.

4 Data and Empirical Approaches

Our data consists of posted price and auction listings whose product IDs are defined, which accounts for about 10% of total listings on the eBay U.S. marketplace between 2009 and 2012. We observe several listing attributes, such as the name of items listed with their conditions, the dates that they are listed, the number of page views on listings, and sellers' eTRS status. We also know whether listings result in sales and what their sale prices are, as well as who purchases the item. Our analyses are mainly based on single-item listings data.[12] We choose 2011 as the benchmark year to estimate the badge effect of eTRS, as no eTRS-related policy change took place, and it is the earliest year from which item conditions data are available to us.

Sales prices in our data vary from less than ten cents to more than \$10,000. Among different sales formats, Buy It Now (BIN) and auction formats accounted for more than 80% of the total sales, which justifies the focus on these two formats in the literature.[13] In our dataset, auction listings enjoy higher conversion rates, but they yield lower sales prices on average, which is consistent with previous literature. In our sample, 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 eTRS status on seller performance, both in terms of increases in average sales price and conversion rate. Our key regression specification is given as

$$P_{ij} = \beta ETRS_{ij} + \eta_i + \epsilon_{ij}, \tag{1}$$

[12]Our early analyses were done with single-item listings. We later incorporated multi-item listings in Section 5, but found no qualitative differences in the estimates. Therefore, we keep samples of single-item listings in Section 6.

[13]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 the smallest 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 essence, eBay auctions are second-price auctions with sealed bids.

where P_{ij} is the final price of item i from seller j; $ETRS_{ij}$ is a dummy variable that equals to 1 if the seller j is badged when item i is sold; η_i is a product-specific unobservable effect; lastly, ϵ_{ij} is a conventional error term that captures any additional variations in P_{ij}.

It is important to point out 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 the robustness check part in Section 5 that the positive effects of eTRS are persistent even after we include additional observable characteristics and seller fixed effects. Specifically, regression 1 yields qualitatively the same results as those from the following regression:

$$P_{ij} = \alpha X_{ij} + \beta ETRS_{ij} + \gamma X_{ij} * ETRS_{ij} + \eta_{ij} + \epsilon_{ij},$$

where X_{ij} are the observable characteristics of item i listed by seller j, such as item conditions and page views of this item; η_{ij} represents product-seller pair fixed effects. The other variables are defined in the same way as in regression 1. We use the key regression 1 for Section 6 since we are more interested in directional effects 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 different policies in general, and the key regression specification allows for a comprehensive comparison of seller performance before and after each policy change.

Our analysis exploits the variations of sellers' eTRS status and their performance variables in different groups. In particular, we group items by their product IDs.[14] In recent years, eBay has improved its catalog and much more items are assigned with Product IDs on the website. product ID is very finely defined and two items with the same product ID are usually the same. 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 are their ISBN codes.[15] This method of control is adopted in Sections 5 and 6.

[14]There is a small chance that items with the same product ID are different as reported in a recent working paper by Dinerstein et al. [2013]. They study consumer's price search behavior on eBay and find there are some miss-specifications within a product ID. This is not a big problem for our study because these errors seem to be independent of the sellers' Top Rated status and therefore do not systematically bias our results.

[15]The drawback of using product ID 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.

eBay merchants sell a wide variety of products with different item conditions and values. Items listed on eBay could be new, refurbished, or used. Refurbished items are further divided into manufacturer refurbished and seller refurbished conditions, while used items include conditions ranging from "like new" to "for parts/not working". Similar to Einav et al. [2011], we defined the value of a product to be the average successful Buy It Now price of this product within different sample periods, and will use this particular definition of product value throughout the paper. We also used alternative definitions of value, such as the average successful price across both formats as the value, or monthly fitted values to adjust for monthly depreciation in product values. Our results are robust to changes in the definition of values; some of the robustness checks will be discussed in Section 5.

A couple of methods have been adopted to control for item condition and values. First, full samples are divided into subsamples with different conditions and value ranges, and the key regression is performed on these subsamples. Additionally, different combinations of condition dummies, value dummies, and their interactions with sellers' eTRS status are included in the regression analyses for robustness checks. We find that controlling for item condition and values by either method yields the same results.

5 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 with various robustness checks. This year is chosen due to the absence of any eTRS-related policy changes and the availability of item condition data. In addition, more items were categorized into eBay's catalog compared to prior years, which helps us measure product values more accurately through our method mentioned previously. 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 in our subsamples. Next, we incorporate more regressors and extra controls to show that our key regression 1 was able to capture most of the badge value. Finally, we perform robustness checks to confirm the validity of our findings.

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
Conversion Rate	0.38	0.14	0.36	0.08

Notes: This table uses BIN and auction listings with Product IDs in the eBay U.S. marketplace in 2011. Products that are sold by only Top Rated Sellers or only non-Top Rated Sellers are not included. Relative price is defined to be price over product value, where this value is the average successful BIN prices. Conversion rate is defined as the ratio of the successful listing to total listings.

5.1 Summary Statistics in 2011

We begin by taking the average of prices and conversion rates for different seller groups and sales formats.[16] 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' valuations more closely as the price cannot be directly controlled by sellers.

Table 1 shows the overall performances of badged sellers and non-badged sellers using listings with Product IDs. Somewhat counter-intuitive, the average sales prices received by badged sellers is lower compared to that of non-badged sellers. However, we should be cautious about interpreting this result since item values are not controlled. The next step is to define the value of a product to be the average successful BIN price of that product; it will be shown shortly that our results are robust to changes in the definition of value. Subsequently, we define the value-normalized sales price, or relative price, to be price over product value previously defined. In our dataset, we find consumers are willing to pay 9% more over the product value to badged sellers in auctions; additionally, badged sellers are able to receive on average 4% larger markups in BIN listings.

Our dataset shows badged sellers also have an advantage on conversion rates in both sales formats. They convert 38% of their auction listings, compared to 36% from non-badged sellers. The

[16] 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 (Einav et al. [2013] studies possible reasons behind this change).

gap in conversion rate is as big as 6% for BIN listings, even though badged sellers charge 4% larger markups on average. These results suggest that the badge have some signaling values. The results are consistent with two patterns on eBay: auctions convert listings faster but result in lower average sales price.

The above analysis indicates that Top Rated Sellers received price and conversion rate premiums compared to non-Top Rated Sellers. However, these differentials might stem from discrepancies in seller quality between badged sellers and non-badged sellers, instead of the signaling values of the badge. In other words, badged sellers would have received these premiums anyway from their superior products and services even without the badge. To deal with this concern, we study the changes in average (relative) sales prices in the vicinity of sellers' badge certification date. In particular, we identify sellers who became Top Rated during 2011 and analyze the daily average (relative) sales price trends of 60-day intervals centered at their badged date.

Figure 2a plots daily average sales price of new items with Product IDs by sellers who become Top Rated in 2011 in our dataset. Negative/positive numbers on the x-axis represent numbers of days before/after sellers become badged sellers. Sellers receive higher average sales price after they become Top Rated, but this could be due to listing more expensive items after their badge certification. To control for the values, we construct Figure 2b which plots the average relative sales price of new items with Product IDs as a function of number of days after sellers become badged in 2011. Consistent with Figure 2a, average relative sales price received by these sellers also increases after they become badged. Another interesting pattern in these two graphs is that average (relative) sales price declines slightly as time approached the end of monthly badge evaluation cycles. In our dataset, it appears that many sellers lower their (relative) sales prices to boost sales to meet the eTRS minimum sales requirement. In the appendix, Figure A.1a and A.1b are analogously produced but with only auction listings. We also plot similar graphs for sellers who lost their badges in 2011 and find that average (relative) sales price decreases after the loss.

The above two figures essentially represent buyers' responses to the badge. Another interesting aspect is to study sellers' listing behaviors after receiving the badge. Similar to the previous approaches, Figure 2c plots the average listing values as a function of days after sellers become badged. Since we are interested in changes in sellers' behavior, we utilize both successful and unsuccessful

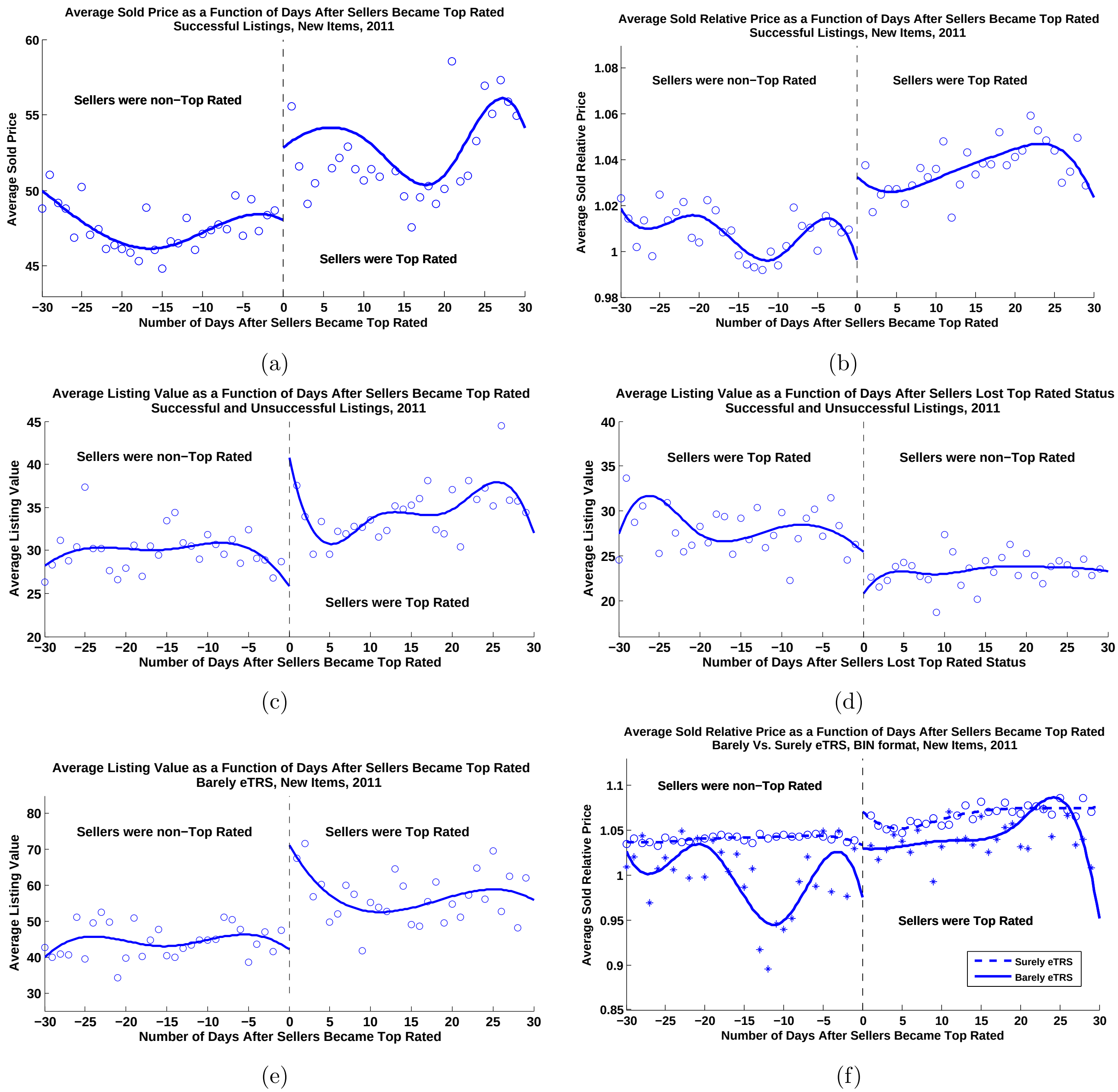

Figure 2: Average Sales/Listings Variable as a Function of Days After Sellers Became/Lost eTRS

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 become (or lost) Top Rated. Integers on the y-axis represent the variables of interest, which are averaged across all sellers who become (or lost) eTRS for any number of days after/before they become (or lost) eTRS. In Figure (a), (b), and (f), only successful listing are used to compute the average (relative) prices. In Figure (c), (d), and (e), both successful and unsuccessful listings are used to compute the average listing values. The value of a product is defined to be the average successful BIN price. In Figure (e) and (f), we define barely 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. Surely eTRS are those who are at least 20% away from the minimum eTRS requirements in GMV and sales quantity.

listings for the computation of average listing values. One subtle but crucial difference between Figure 2c and Figure 2a is that the dates in Figure 2a indicate when the items are sold, whereas the dates in Figure 2c represent when the items are listed. In our dataset, we observe that sellers list more expensive items after becoming badged. Figure 2d is similarly constructed with sellers who have lost their eTRS and the average listing value drops after the loss.

We interpret these results as sellers switching to listing more expensive/cheaper items in possibly different categories once they gain/lose the badge. For re-certifications in the following months, sellers who have lost the badge list cheaper items at lower prices, hoping to sell sufficient amounts to meet the minimum requirements and to gain good ratings from buyers. In our dataset, badged sellers who have lost their certification list cheaper products on average, which is consistent with the findings in Fan et al. [2013]. On the other hand, once sellers become Top Rated, they worry less about sales requirements for badge certification and switch back to items they used to sell, which are typically more expensive. This is exactly what we observe in Figure 2c. Towards the end of certification cycles each month, sellers who have not met the sales requirements start to sell cheaper items again, and thus a drop in the graph.

If the reputation badge is valuable, we should expect to see some extreme behavior from marginal sellers who were "barely" Top Rated on the certification date. We define barely eTRS to be the badged sellers whose annual GMV and sales quantities were no more than 10% of the enforced minimum eTRS annual GMV and sales quantities on the date of certification. Surely eTRS are defined to be the Top Rated sellers who were at least 20% away from the minimum eTRS requirements. Figure 2f plots the average relative prices of all BIN sales for the two groups of sellers as a function of number of days after they become badged in our dataset. Interestingly, barely eTRS set significantly lower relative price in about two weeks before the certification date. In addition, it seems that the decreases in average relative prices are not from switching to selling cheaper items, as suggested by Figure 2e. These two results combined illustrate that barely eTRS lower the price of their listings as the evaluation date approached, rather than changing categories and selling items with cheaper values. We also produced an analogous graph to Figure 2f with only auction listings; there is no trend in average relative sales price received by barely eTRS before the certification date.

5.2 Regression Results in 2011

In this section, we apply the key regression specification 1 to successful BIN and auction sales with Product IDs in the eBay U.S. marketplace in 2011. The aim is to identify the badge effect of eTRS badge for sellers in terms of receiving higher sales prices and relative sales prices. Panel A in Table 2 shows the estimates of badge effect. In the key specification case, the badge effect is positive and significant in terms of receiving higher (relative) prices across both sales formats. In our dataset, badged sellers receive 15% higher average markup in both formats and 10% from auction listings. In the variation case, Sellers ID fixed effects are in lieu of Product ID fixed effects. By using relative price, we indirectly control for product characteristics by normalizing its sales price by its value. The estimates suggest the signaling badge effect is 0.03 for BIN and auction listings and 0.02 for auction sub-samples in terms of relative price.

Buyer valuations of the Top Rated badge may vary with item conditions. Purchasing used items involves more risk because being "used" is vaguely defined and its meaning varies among market participants. Therefore, for used items, buyers should care more about the badge due to the inherent higher uncertainty. The eBay Top Rated Seller program provides a mechanism to signal sellers who have been trustworthy and have described their items accurately in the past; this augmented certainty should increase buyers' willingness to pay. On the other hand, new items are in principle homogeneous and badge effect here should be lower. For items with high values, as buyers could potentially suffer from large losses from buying a lemon, badge effect should be higher than that for cheaper items.

To test the above hypotheses, the key regression has been performed on subsamples of items with different conditions and value ranges. Refurbished items could be both manufacturer-refurbished and seller-refurbished; used items include conditions ranging from "like new" to "for parts/not working". The estimates for different conditions are reported in Table 2 Panel B, and they indeed show that the badge effect in terms of relative prices is the highest for used items; this number is the smallest for refurbished items. The reason for the latter result is that most refurbished items are expensive in our dataset and expensive items are generally sold at a relative price close to 1 due to the large value base. Panel C displays the results for different product value ranges. Low, medium, and high value ranges go from \$0.01 to \$10, from \$10 to \$100, and from \$100 to \$500,

Table 2: Regression Results, 2011

Panel A. BIN and Auction Sales with Product ID				
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
	(0.00)	(0.00)		Characteristics
R^2	0.62	0.81		
Observations	28,279,096	16,783,646		
Rel. Price	0.03***	0.02***		Seller
	(0.00)	(0.00)		Fixed Effect
R^2	0.50	0.54		
Observations	28,279,096	16,783,646		

Panel B. 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
	(0.00)	(0.00)	(0.00)	Characteristics
R^2	0.84	0.90	0.60	
Observations	10,223,129	620,057	13,068,809	

Panel C. 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
	(0.00)	(0.00)	(0.00)	Characteristics
R^2	0.70	0.22	0.21	
Observations	10,853,792	12,294,778	4,174,947	

Notes: Coefficients are estimated from regression 1 on different sub-samples. The regressions are based on of successful BIN and auction listings with Product IDs on the eBay U.S. site in 2011. The reported coefficients are estimated from regressing the dependent variables on the eTRS dummy with different controls. Standard errors are the numbers in parentheses. Refurbished items include both manufacturer-refurbished and seller-refurbished items. Used items include conditions ranging from "like new" condition to "for parts/not working" condition. Low, medium, and high value ranges go from $0.01 to $10, from $10 to $100, and from $100 to $500, respectively. Results for $500 to $1000 value is as expected and therefore omitted.

***Significant at the 1 percent level.
**Significant at the 5 percent level.
*Significant at the 10 percent level.

respectively.[17] For items with higher values, the badge value is higher in terms of price but lower in terms of relative price. 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 become very low.

6 eBay Buyer Protection

In September 2010, eBay introduced a new website-wide buyer protection for most of items listed on the website. From documentation on the website:

> 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 the transactions on the marketplace, regardless of the sellers' status and experience on the website. This program affects buyers' welfare through two main channels. The first is the risk reduction effect in that eBay Buyer Protection decreases buyers' losses for unsatisfactory transactions. The second is the unravelling effect, since the quality of sellers has increased after the introduction of this program. However, it should be noted that buyers' cost are not zero under the buyer protection, since the process of filing eBP claims is time consuming and buyers prefer not to encounter any problem in the first place.

6.1 Overall Effects of the eBay Buyer Protection

We start with analyzing summary statistics of our dataset for the period consisting of 10 months before and 10 months after the introduction of the eBay Buyer Protection program.[18] Table 3 uti-

[17] The estimates for value range from \$500 to \$1000 are omitted as they follow the observed pattern perfectly.

[18] The eBay Buyer Protection program was introduced in September 2010; 10 months before the eBP are from November 2009 to August 2010 and 10 months after the buyer protection are from October 2010 to July 2011. The

lizes 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 buyer protection but probability of sales has declined by 9%. The percentages of eTRS and and percentage of items sold by badged sellers both have gone up by about 30% after introducing buyer protection. The share of negative feedback has decreased by about 10% and the percentages of low level of seller performance indicated by their Detailed Seller Rating scores have declined. On the other hand, INR and SNAD dispute rates for both seller groups have increased after the policy change. This result is as expected as buyers take advantage of buyer protection. Another observation is that changes in INR claims are smaller than changes in SNAD claims, suggesting that some dishonest sellers have been weeded out of the platform. Before moving on, it is important to note that the composition of new badged sellers in terms of their time spent on eBay do not vary much across the entire 20-month period. Therefore our results are not driven by change in the composition of new top-rated sellers.

From the second part of Table 3, we see that non-badged sellers on average receive higher average sales price than the badged sellers, similar to the pattern we have seen earlier. However, once we control for the value of the products, badged sellers receives on average higher average relative sales price. Average conversion rate decreases for both types of sellers, but the decline is larger for non-badged sellers. Finally, average relative sales price decreases slightly for badged sellers but goes up for non-badged sellers after the introduction of buyer protection. This information suggests that buyer protection has moved buyers away from heavily relying on the reputation badge. This is consistent with the negative coefficient in front of the interaction term of ETRS and EBP in the regression, where the sales relative prices are regressed on a few dummy variables, controlling for week, product, and seller fixed effects. ETRS and EBP are dummies for sellers' badge status and whether buyer protection has been 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. One important observation is that buyers willingness to pay goes up on average for all sellers and for all products across different value ranges. This suggests that the implementation of buyer protection benefits sellers overall by raising their average revenue.

In the last part of Table 3, we regress sellers' sizes in the following month on their sizes this month,

reason we look at a 10-month period is that eTRS was not introduced until October 2010.

Table 3: Adding Buyer Protection

Single-Item BIN and Auction Listings on eBay U.S. Marketplace with Product IDs	
	% Change: 10M Before to 10M After
Number of Listings	18.71%
Number of Successful Listings	8.33%
Conversion Rate	-8.75%
Number of Active Buyers	3.14%
Percentage of eTRS	30.49%
Percentage of Quantity Sold by eTRS	30.94%
Amount of Feedback Left	1.68%
Percentage of Neutral Feedback	-2.86%
Percentage of Negative Feedback	-10.61%
Amount of Item as Described Score Left	5.06%
Percentage of Low Item as Described Score	-4.31%
Amount of Communication Score Left	5.07%
Percentage of Low Communication Score	-3.44%
Amount of Prompt Shipping Score Left	5.88%
Percentage of Low Prompt Shipping Score	-14.42%
Amount of Reasonable Shipping Charge Score Left	7.28%
Percentage of Low Reasonable Shipping Charge Score	-8.08%

Top Rated Sellers						
		Buy It Now			Auction	
	Price	Conv. Rate	Rel. Price	Price	Conv. Rate	Rel. Price
10M Before	37.22	0.2051	1.30	45.58	0.4473	1.04
10M After	37.75	0.1892	1.28	50.56	0.4206	1.03
Pct. Change	1.42%	-7.75%	-1.54%	10.92%	-5.97%	-0.96%
Non-Top Rated Sellers						
		Buy It Now			Auction	
	Price	Conv. Rated	Rel. Price	Price	Conv. Rated	Rel. Price
10M Before	41.73	0.1730	1.12	54.95	0.4742	0.91
10M After	64.16	0.1438	1.13	66.85	0.4025	0.92
Pct. Change	53.76%	-16.88%	0.89%	21.65%	-12%	1.10%
Seller's Future Size						
FUT_SIZE	SIZE	#CMPLNT	#CMPLNT*EBP	R^2	Observations	
	0.78***	-2.12***	-0.03***	0.93	24,043,776	
	(0.00)	(0.00)	(0.00)			

Notes: This table uses single-item BIN and auction listings with Product ID on 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. In September 2010, eBay Buyer Protection was introduced which covers items purchased on eBay with eligible payment methods that are not received (INR) or not as described (SNAD). Relative prices are the final prices divided by item values. Conversion rate is defined to be the share of successful listings on eBay. eTRS and eBP are dummies for sellers' eTRS status 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 last regression, sellers' sizes 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.

the number of complaints they have received in this period, and the interaction of this number with the dummy variable indicating whether buyer protection is implemented. A complaint from buyers is constructed by us to be either a non-positive feedback, a low detailed seller rating, or a dispute. Our result shows that, prior to the introduction of eBay Buyer Protection, having a complaint this month reduces seller sizes in the following month by about 2; after the eBP introduction, there is an additional reduction in size of 0.03. This result suggest that eBP adds a cost for sellers in the cases of unsatisfactory transactions and reduces future sales from lower-quality sellers.

6.2 Regression Analysis on Effects of Buyer Protection

To further investigate the effect of buyer protection, we perform our key regression, namely regressing relative sales prices of items on their seller's eTRS status, controlling for product-specific fixed effects. Panel A in Table 4 reports the results with all single-listing listings with Product IDs on the eBay U.S. marketplace. Consistent with the discussions before, being a badged seller raises both prices and relative prices that sellers received. In addition, the estimated badge effect in terms of relative price has decreased by 19% after adding buyer protection. Essentially, the buyer protection reduces buyers' costs of encountering bad experience, and from their perspective decreases the badge effect. In auctions, the estimated coefficient from the price regression has decreased much larger than that from the relative price regression. This indicates that non-badged sellers start to sell more high-priced items compared to badged sellers. In both samples, the decline in badge effect suggests a reasonable complementarity between buyer protection and seller reputation, indicating eBay is managing its marketplace more effectively with the addition of buyer protection.

As indicated by results in Section 5, both item condition and values are important in determining final sales prices. Unfortunately we do not have condition data prior to 2011. Nevertheless we think that analyzing the effect of buyer protection for different value ranges is more illuminating since price should be more relevant to buyers' return decisions compared to conditions. 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 was smaller for cheaper items in terms of price but larger in terms of relative price. This makes sense because marking up on $2 USB cables by 50 cents is significant, but it is negligible for MP3 players. Most of the estimated values decreases after the introduction of buyer protection; the drop for inexpensive item is small,

Table 4: Regression Results, Adding Buyer Protection

Price Regressions With Product Fixed Effects

Panel A. Single-Item BIN and Auction Listings on 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%
	(0.00)	(0.00)		(0.00)	(0.00)	
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%
	(0.00)	(0.00)		(0.00)	(0.00)	
R^2	0.35	0.33		0.56	0.58	
Relative Price	0.28***	0.28***	-1.34%	0.11***	0.11***	-4.61%
	(0.00)	(0.00)		(0.00)	(0.00)	
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%
	(0.00)	(0.00)		(0.12)	(0.00)	
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%
	(0.00)	(0.00)		(0.00)	(0.00)	
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 from October 2010 to July 2011. Relative price is defined to be price over value, where the value of an item is the average successful BIN prices. The coefficients are estimated from regressing (relative) prices on the eTRS dummy after controlling for product characteristics. Standard errors are the numbers in parentheses. Low value range is from $0.01 to $10; Medium price range is from $10 to $100; High price range if from $100 to $500. The result for 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.

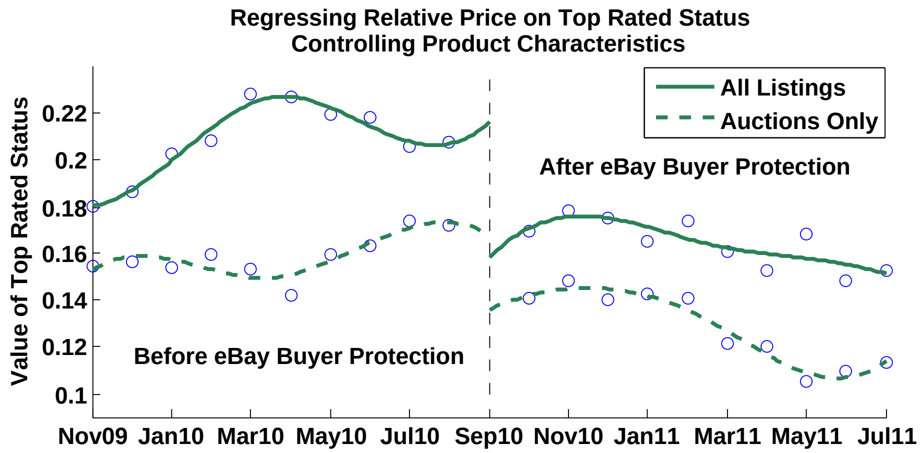

Figure 3: Monthly Badge Effect of Being Top Rated

Notes: This figure uses single-item BIN and auction sales with Product IDs from sellers who earned the badge at some point during 10 months before and 10 months after the introduction of buyer protection. Each circle in the graph represents the badge value in a given month. These monthly values are the estimated coefficients from regressing relative price on its seller's eTRS dummy after controlling for product fixed effects.

whereas it is large for items with high values. The reason is that, even though buyers do not incur monetary cost if they decide to return items through buyer protection, they still have to pay other costs, such as communicating with sellers, troubles of filing complaints, or bringing the item to a post office. However, these costs are fixed and do not depend on item values. Therefore, returning cheap items is relatively more costly for buyers, and they might merely put up with unsatisfactory transactions even if they are guaranteed refunds through buyer protection. The story is reversed for returning items with high values.

The regression results in Table 4 demonstrate a decline in the average badge effect after adding buyer protection in our dataset. However, this measure does not necessarily imply that buyer protection is the trigger for the decrease. It might be that the average badge effect dropped linearly over time and the policy had no impact whatsoever. To remove this possibility, we perform the key regression 1 on monthly levels. In each month, we identify sellers who gains the badge and sample all their transactions 30 days before and after their certification dates. Then for each month, we regress relative prices for these sellers on their Top Rated status, controlling for product IDs. From Figure 3, we see a sudden decline in badge effect after buyer protection was introduced, and this value stays at lower levels for the entire 10 months after this introduction. This implies the drop in badge effect is indeed due to eBP.

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	0.028***	0.033***	0.024***	0.026***
	(0.000)	(0.000)	(0.000)	(0.000)
PRICE	-2.88E-6	-3.40E-6**	-2.96E-6**	-3.51E-6**
	(0.000)	(0.000)	(0.000)	(0.000)
ETRS*PRICE	-2.03E-5***	-2.53E-5***	-3.14E-5**	-2.98E-5**
	(0.000)	(0.000)	(0.000)	(0.000)
QTY_AVAIL_IN_2_10	0.078***	0.041***	0.105***	0.057***
	(0.000)	(0.000)	(0.000)	(0.000)
QTY_AVAIL_IN_11_100	0.154***	0.079***	0.154***	0.054***
	(0.000)	(0.000)	(0.000)	(0.000)
QTY_AVAIL_IN_101_UP	0.179***	0.076***	0.148***	0.043***
	(0.001)	(0.001)	(0.001)	(0.001)
PROD-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. Different robustness checks from Section 5 show consistent results and are not reported here.

***Significant at the 1 percent level.

**Significant at the 5 percent level.

*Significant at the 10 percent level.

The benefits of being an badge seller are multi-dimensional. We have found that buyer protection provides a reasonable complement for the badge system in terms of price premiums received by badged sellers. The next natural question is whether the badge effect also declined in terms of sales and conversion rates. Following the approach in Elfenbein et al. [2013], we regress the log of one plus quantity sold and the sales indicator on sellers' badge status with proper controls. Only BIN sales are utilized in this exercise, since quantities sold in any successful auction listing necessarily equals to 1. In Table 5, QTY_SOLD is the total quantity sold in a listing; SUCCESS is a dummy variable equaling 1 if there was at least 1 sale in a listing; QTY_AVAIL_IN_i_j is an indicator that is turned on if the total available items in a listing are between i and j units. Prior to introducing buyer protection, the badge raised the percentage of quantity sold in listings by 2.8%, but this number drops slightly to 2.4% afterwards; the badge increased the conversion rate by 3.3% but

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)	(0.00)	(0.08)	(0.00)
ETRS*LOW	0.80***	0.25***	1.35***	0.25***
	(0.06)	(0.00)	(0.07)	(0.00)
ETRS*MED	4.10***	0.15*	3.81***	0.14***
	(0.06)	(0.00)	(0.06)	(0.00)
ETRS*HIGH	23.75***	0.12***	10.26***	0.06***
	(0.12)	(0.00)	(0.12)	(0.00)
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 on 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 Top Rated Status. FREQUENT equals to 1 if a seller has spent more than $2500 in the year prior to this 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.

decreases to 2.6% afterwards. Indeed, the decline in the badge effect of eTRS is also found in quantities sold and conversion rates after the introducing buyer protection, further suggesting the complementarity between buyer protection and seller reputation.

6.3 Different Buyer Experience

Buyers on eBay marketplace differ in their experience and the amount of spending on eBay. It is interesting to see how much badge effect changes for different segments after the introduction of eBay Buyer Protection. For the sake of this analysis, we partition buyers based on their amount spent in the past year prior to the observed purchases. In particular, we define FREQUENT as the dummy variable for sellers who have spent at least $2500 in the past year. We then perform regression analysis on our dataset, which contains BIN and auctions sales with Product ID from November 2009 to July 2011, excluding September 2010 when eBP was introduced.

Table 6 reports estimation results for buyers with different experience on eBay and for different value ranges. 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. Consistent with our previous findings, the badge effect has weakly decreased for all segment-value range combinations in terms of relative price, suggesting that eBay Buyer Protection has positive values for buyers in general. One interesting observation is that before the introduction of buyer protection, frequent buyers have larger value on the reputation badge, which is 0.03 in terms of relative price,compared to the value of less frequently buyers. After the eBP introduction, however, frequent buyers value the eTRS badge 0.02 less compared to novice buyers. Typically, frequently buyers often spend more time on eBay to hunt for good deals, which are often offered by non-badged sellers. Frequent buyers are better at identifying good-quality sellers that are non-badged, either through their experience or by spending more time on reading sellers' previous feedback. Less experienced buyers, however, rely more on eBay's help of identifying good sellers through the badge, thereby having a larger value for this badge. This observation indicates that top 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 their costs in case of a lemon would be large; after introducing eBP, the valuation decreases since frequent buyers know that poor transactions would be covered by buyer protection. Novice buyers are, in comparison, not as responsive to changes in market rules.

7 Welfare Analysis

For the estimation of welfare impacts, we need to make some further assumptions on the cost structure of items sold on eBay. To prevent making strong assumptions on sellers' mark-ups and on the mode of competition in the marketplace, we estimate the benefit of adding eBay Buyer Protection on the total market efficiency by analyzing the change in total welfare. Adding eBay Buyer Protection increases the cost for sellers in cases where buyers dispute a transaction, thereby increasing buyers' welfare in those instances. We assume the sum of this cost and benefit is small. Without having a structural model, we cannot estimate this cost and benefit per-se.

We use the change in price as a proxy for change in total welfare. This method is supported by a few different theoretical models. In our model, the increase in price is equal to the change in buyers expected benefit from consuming an item, if we assume that costs are proportional sales

Table 7: Welfare Changes: Adding Buyer Protection

Auction Listings								
	ETRS	EBP	ETRS*EBP	EBP*LOW	EBP*MED	EBP*HIGH	R^2	Obs.
Rel. Price	0.009	0.121	-0.018	-0.006	0.163	0.029	0.99	309,475
	(0.018)	(0.115)	(0.027)	(0.116)	(0.117)	(0.125)		
BIN + Auction Listings								
	ETRS	EBP	ETRS*EBP	EBP*LOW	EBP*MED	EBP*HIGH	R^2	Obs.
Rel. Price	0.012	0.020	-0.006	0.032	0.178	0.043	0.99	624,663
	(0.009)	(0.047)	(0.011)	(0.048)	(0.048)	(0.050)		

Notes: This table uses single-item listings with Product ID on eBay U.S. marketplace. Transactions in the month before the introduction of eBay Buyer Protection and the month after are included in the sample. Relative prices are the final transaction prices divided by product values. ETRS and EBP are dummies for sellers' eTRS status 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 in addition control for the week of sales, Product ID, and Seller ID in the regression.

prices. Another supportive model can be a Nash Bargaining problem, where we have an increase in prices that is a result of a rise in total welfare when the cost is a constant share of the sales price. We note that the change in the amount of sales and the number of buyers are 0.33% and 3.14%, respectively, so our welfare estimations are not driven by change in the level of competition in the marketplace.

Given our assumption on the cost structure of acquiring items for sellers, we look at one month before and after implementing eBay Buyer Protection. Most of items tend to have a decreasing price trend; therefore, to control for this dynamic pricing we control for weekly time trends. We further control for sellers with the Top Rated status and also different product value ranges. Finally, we control for Product ID of items which makes our assumption on the constant cost more realistic. Table 7 shows the result for Auction only versus Auction and Buy it Now items. The change in average sales price in the auction subsample after implementing eBay Buyer Protection ranges between 9.7% and 28.4%, given different sellers type and different product value ranges. The change in average sales price for Buy it Now and Auction listing is in between 4.6% and 19.8%. Taking weighted averages of these numbers based on the population of each category results in 19.6% change in welfare for Auction only and 12.4% for all items.

8 Robustness Analysis

In this section, various robustness checks are performed to verify the validity of our key regression design. In particular, we have tried alternative definitions for product value and added more regressors: listing page views, listing start prices, and interactions between eTRS and condition/value dummies. We also have tried to control for Product-Seller pair fixed effects, instead of Product ID. Additionally, we have studied the effects of eTRS for the group of sellers who have lost but re-gain the badge in 2011. Finally, we pick out sellers who are "almost" eTRS and "barely" eTRS in terms of meeting the minimum sales requirements for badge certification, and estimate the badge effect for this group of sellers.

Recall we define the value of a product to be the average successful BIN price of this product within 2011. We have also tried an alternative definition that calculates average price from both sales formats, and found no qualitatively different estimates. A somewhat bigger concern is that if product prices have changed 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.[19] All but two categories have depreciation rates that are less than 1% of their estimated intercepts: the Computer & Network category have a monthly depreciation rate of \$5.06 with an estimated intercept of \$296.89, and the Cell Phones & PDA category suffer a \$3.00 monthly depreciation with an intercept of \$198.28. For these two exceptions, we define the adjusted relative price to be prices over the depreciation-adjusted monthly fitted value of this product, and perform our key regression. The results are shown in column (1) and (2) in Table 8. The badge effects in terms of relative prices are 0.04 and 0.06, respectively, and are larger compared to the estimates without incorporating monthly value depreciation.

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

[19]We have more than 3 million distinct products in our dataset and it's close to impossible to compute product-level depreciation rates; in contrast, we only have 30 categories. The top 5 most popular categories in our data are: DVDs & Movies, Books, Video Games, Cell Phones & PDA, Consumer electronics.

badge, but also its "informational effects". Another concern is that lower starting prices in auction listings might attract more bidders, and increased competitions could lead to higher final price. Therefore, we include the number of page views of a listing and the start prices in our key regression. Column (3) utilizes sales with both formats and column (4) looks at auction listings only. We find, somewhat surprisingly, that neither of the variables have significant effect on the final relative prices and the badge effect is still positive.

The next thing we try is to add interactions of eTRS and condition/value dummies in our key regression and control for Product-Seller pair fixed effects. Overall, the statistical powers here are not as big and magnitudes of the estimates are smaller. Results under this specification are displayed in column (7) and (8); the positive effects of eTRS still exist for the following condition-value combos: new-low, new-med, refurbished-low, and refurbished-med. The badge effect turns negative for items in the high value range ($100-$500) for all conditions, but it is again positive for the highest value range ($500-$1000) with all conditions. In column (9) and (10), we study the sub-sample with only new and refurbished items. The reason we get rid of used items is because of their quality heterogeneity. The results are qualitatively the same as when we included listings of used items.

Another scenario could invalidate our argument: that sellers gains eTRS and that they receive higher prices could be caused by a third common factor such as an increase in seller quality. In this case, our estimates are inconsistent and meaningless. To remove this possibility, we employ the regression discontinuity design that investigates sellers who are "almost" eTRS and those who are "barely" eTRS in our dataset, in terms of the annual Gross Merchandise Value requirement ($3000) and the annual quantity requirement (100 items). In particular, all these sellers qualify for the quality requirements for badge certification and they differ only in meeting the minimum GMV or quantity requirements. In other words, were these "almost" eTRS sellers lucky enough to sell a few more items, they would have achieved the Top Rated badge, just like the "barely" eTRS sellers. Conversely, for the "barely" eTRS sellers, they would have been non-badged sellers if they lost a few sales. Essentially, we assume that seller qualities are the same around the GMV and quantity threshold for badge certification, after controlling for sellers' quality measures. In column (5) and (6) of Table 8, the 10% band includes "almost" eTRS sellers whose annual GMV is between $2700 and $2999.99 or whose annual sales quantities are between 90 and 99; "barely" eTRS were sellers

Table 8: Robustness Check, 2011

	Cellphone	Computer	BIN+Auction	Auctions Only	10% Band	20% Band	All Conditions		New and Refurb	
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)
	Adj_Rel_Price	Adj_Rel_Price	Rel_Price	Rel_Price	Rel_Price	Rel_Price	Price	Rel_Price	Price	Rel_Price
ETRS	0.06***	0.04***	0.14***	0.12***	0.04***	0.05***	0.15	-0.01		
	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.17)	(0.01)		
VIEW_COUNT			0.0004***	0.0052***						
			(0.0000)	(0.0003)						
START_PRICE			0.0013***	0.0020***						
			(0.0000)	(0.0000)						
NEW							14.19***	0.24***	38.92***	0.25***
							(0.05)	(0.00)	(0.14)	(0.00)
REFURB							4.33***	0.07***		
							(0.10)	(0.00)		
ETRS*NEW							0.89***	0.02***	-1.32***	0.00*
							(0.05)	(0.00)	(0.08)	(0.00)
ETRS*REFURB							3.38***	0.02***	-0.65***	0.00
							(0.11)	(0.00)	(0.11)	(0.00)
ETRS*LOW							-0.49	0.02***	1.52***	0.02***
							(0.32)	(0.01)	(0.10)	(0.00)
ETRS*MED							-0.78**	0.01	1.67***	0.02***
							(0.32)	(0.01)	(0.09)	(0.00)
ETRS*HIGH							-4.97***	-0.02***		
							(0.32)	(0.01)		
ETRS*HIGHEST									7.17***	0.01***
									(0.29)	(0.00)
PRODUCT FE	✓	✓	✓	✓	✓	✓				
PROD-SELLER FE							✓	✓	✓	✓
Observations	2,327,469	979,775	28,261,701	16,783,646	415,240	839,995	27,705,329	27,705,329	10,843,186	10,843,186
R^2	0.88	0.89	0.63	0.81	0.92	0.88	0.99	0.98	0.99	0.99

Notes: Regressions are based on successful BIN and auction listings with Product IDs on the eBay U.S. site in 2011. ETRS is a dummy variable indicating seller's Top Rated Status. In regression 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 depreciation in dollar values for these two categories are the largest ($3 and $5 decrease per month) among all the categories. In regression 3 and 4, VIEW_COUNT is the number of page views for a product; START_PRICE is either the BIN posted price or the auction reservation price. In regression 9 and 10, we remove used items from our sample due to the quality heterogeneity. Low, medium, high, and highest value ranges go 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 prices. In regression 5 and 6, the sample being used contains transactions from sellers who are "almost" Top Rated and those who are "barely" Top Rated, in terms of the annual Gross Merchandise Value requirement ($3000) and the annual quantity requirement (100 items) for eTRS. In particular, all these sellers qualify for the eTRS quality requirements and they differ only in meeting the minimum GMV or quantity requirements. The 10% band includes "almost" eTRS sellers whose annual GMV was between $2700 and $2999 or whose annual sales quantities were between 90 and 99, and "barely" eTRS sellers were those whose annual GMV was between $3000 and $3299 with annual sales quantity between 100 and 109.

***Significant at the 1 percent level.

**Significant at the 5 percent level.

*Significant at the 10 percent level.

Table 9: 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
Rel Price	1.02	1.07	0.87	1.03	1.02	1.03
Conv. Rate	0.41	0.15	0.38	0.11	0.32	0.18

Notes: The statistics are based on successful BIN and auction sales with Product IDs on eBay U.S. marketplace from sellers who have lost their badge for some time but later re-gain it within the 2011. We have about 5,000 such sellers. Relative price is defined to be price over product value, where this value is the average successful BIN prices. Conversion rate is the share of successful listings of a product.

whose annual GMV is between \$3000 and \$3299.99 with annual sales quantities between 100 and 109. The 20% band is similarly defined. The coefficients are estimated by applying regression 1 to this sub-sample. The results from our dataset indicate that the badge effect is around 0.04 in terms of relative price with this approach.

Our regression designs could be biased if sellers endogenously respond, for example by pricing more aggressively, after they become badged. Was this the case, the estimated coefficients will capture the effects of sellers' endogenous responses on top of the signaling badge effect. To investigate this possibility, we study the behavior of sellers who have lost and later re-gain the badge in our dataset. In Table 9, we report important statistics for this group of sellers during the period when they were eTRS, when lost their eTRS, and when they eventually re-gain eTRS. It appears that sellers at large do not charge higher relative prices in posted price format after getting re-badged, as this value stays at 1.03. Instead, the benefit comes from an increase in conversion rate from 0.11 to 0.18. On the other hand, changes in relative price are seen from the auction listings, in that the average relative price sellers received decreases from 1.02 to 0.86 after they have lost their Top Rated status, and jumps back to 1.02 once they are re-certified. Similar patterns are observed for prices. These numbers suggest that the price premiums that badged sellers enjoyed is demand-driven and is unlikely due to sellers' aggressive pricing behavior after becoming badged.

9 Conclusion

In online marketplaces, asymmetric information of product qualities can lead to adverse selections and market inefficiencies. Market designers commonly develop seller reputation systems and buyer warranties to solve this problem. Significant theoretical work has focused on both mechanisms, and some empirical work has identified the badge effect of seller reputation systems. However, only a couple of empirical papers have analyzed the interactions between the two mechanisms.

Our dataset incorporates both mechanisms, the eBay Top Rated Seller (eTRS) program and eBay Buyer Protection (eBP) from the eBay U.S. marketplace. This unique dataset enables us to estimate the badge effect and also to analyze its change after the introduction of buyer protection. Our study indicates that the reputation system raises the average sales price and the sell-through rate for badged sellers by 4% and 3%, respectively. The signaling value of the badge is positive and is larger for used items, as well as for high-priced items, even after we control for item conditions, items values, listing page views, listing starting prices, and product and seller fixed effects. Various robustness checks are performed to ensure the validity of our results.

Subsequently, we have studied how the reputation system is affected by the eBay Buyer Protection. The buyer protection mandates that sellers must refund sales prices plus shipping costs to buyers if the items received are not as described in the listings, or if they are not received at all. This program ensures the buyers of item qualities and should decrease their dependence on the reputation badge. Our findings indicate that the badge effect of eTRS decreased by 19% in terms of value-normalized sales prices and by 21% in terms of conversion rates. Another interesting result is the decrease in badge effect is larger for more expensive items; in other words, buyers rely more on buyer protection for higher-valued items. The reason is that, even though buyers do not incur monetary costs if they decide to return the item through buyer protection, they still incur costs from communicating with sellers, from the trouble of filing complaints to eBay, or from having to bring the item to the post office. However, these costs are fixed and do not depend on the value of the item. Therefore, returning cheap items is relatively more costly for buyers, and they might not file disputes even if they are guaranteed refunds through eBP.

This buyer protection also increases the number and share of reputable sellers by increasing the cost for dishonest behavior. Finally, it raises high-quality sellers' welfare by increasing the average sales price, and buyers' welfare by decreasing the frequency of their bad experiences and losses in those cases.

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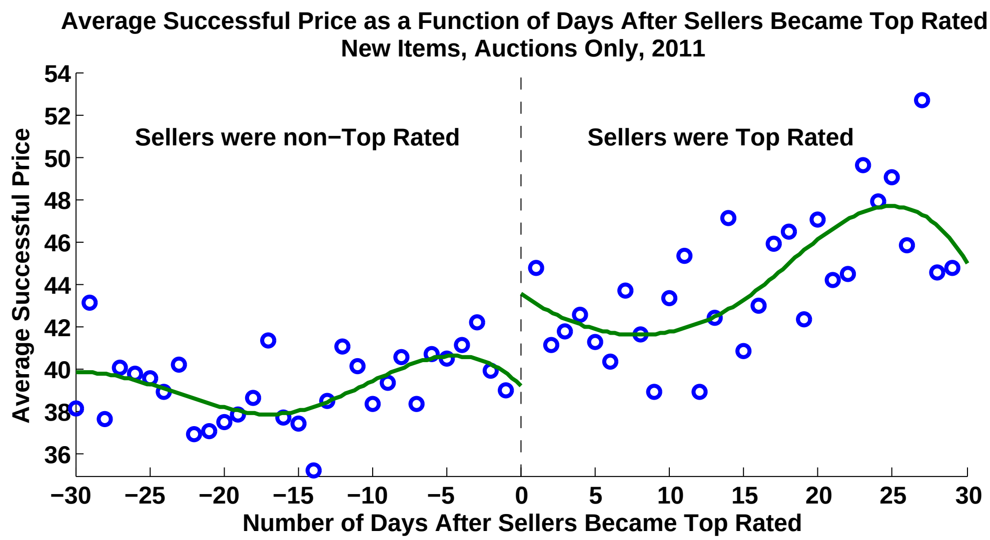
A Additional Figures



(a)

(b)

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

Notes: These figure 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 became eTRS for any number of days before and after they became Top Rated.