Reputation & Regulations: Evidence from eBay*

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Abstract

To mitigate inefficiencies arising from asymmetric information, some markets rely on government interventions, while others rely on reputation systems, warranties, or guarantees. This paper explores the impact of two mechanisms, namely reputation badges and buyer protection programs, and their interaction on eBay's marketplace. Adding buyer protection reduces the premium for the reputation badge and increases efficiency in the marketplace. These efficiency gains are achieved by reducing moral hazard through an increase in sellers' quality and by reducing adverse selection through a higher exit rate for low-quality sellers. Our estimates suggest buyer protection increases the total welfare by 2.9%.

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

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1 Introduction

Asymmetric information can lead to adverse selection, moral hazard, market inefficiency, or even market failure (Akerlof [1970]). To mitigate these problems, some markets rely on government interventions, while others rely on reputation systems, warranties, or guarantees.[1] This paper explores the impact of two asymmetric information mitigation mechanisms, namely reputation badges and buyer protection programs, and their interaction on eBay's marketplace. Reputation badges take the form of the eBay Top Rated Seller (eTRS) program, in which eBay identifies its most reliable sellers based on their past performance and volume of sales. By contrast, the recently introduced eBay Buyer Protection (eBP) program guarantees purchases from all sellers.

These two programs, eTRS and eBP, correspond to information regulation and more active policing, respectively. Under the former, eBay as the market designer simply discloses information about seller reliability. Under the latter, it takes complaints from unhappy buyers and then extracts payment from errant sellers.

Advocates of "information regulation" argue that only light intervention is needed to make markets operate well. If consumers are armed with good information about seller performance, then sellers will behave well. Skeptics of the magic of the marketplace, on the other hand, argue that overcoming asymmetric information requires not just information, but also a police force that holds sellers to their promises.

Does adding eBP undermine the effect of eTRS? In the absence of third-party enforced guarantees, there is private value in developing reputation. When eBP is in place, however, sellers might draw fewer benefits from investing in reputation, especially because eBP's guarantee that

[1] Many papers have considered the effect of asymmetric information on financial markets and insurance markets, e.g., Myers and Majluf [1984], Glosten and Milgrom [1985], Pauly [1974], and Rothschild and Stiglitz [1992], among others. 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.

every seller can be trusted threatens to destroy the private value they have created through their reputations.

In this paper, we start by establishing a signaling value for the eTRS badge. We show that the badge has a positive signaling value, even after the introduction of the eBP program. To demonstrate this, we compare the performance of sellers who are badged and of those who are not badged, as well as the effect of a change in reputation status. We show that the reputation signal raises the average sales price for badged sellers by 3%.

Having established the signaling value of the eTRS badge, we then study the effect of adding eBP. We determine that this policy has increased efficiency in the market through two main channels. First, by reducing moral hazard, the incidence of negative feedback ratings decreases by an average of 23%.[2] Second, by reducing adverse selection, eBP leads to an increase in the exit rate of low-quality sellers and also to an increase in the share of eTRS. Both, the reduction in moral hazard and adverse selection, contributes to a lower probability of undesirable outcomes for buyers. Additionally, buyers who experience undesirable outcomes receive higher payoffs through refunds. Consequently, we observe an increase in prices for both high-reputation and low-reputation sellers. However, the increase in prices is higher for low-reputation sellers, which leads to a decrease in the price premium for high reputation. We additionally estimate the change in total welfare due to the eBP. We estimate that these changes contribute to a welfare increase of 2.9%. To do the estimation, we use highest bids as a proxy for willingness to pay.

Two more effects of buyer protection are worth mentioning. First, the drop in the premium for reputation is the largest (50%) for the most expensive items but negligible for the least expensive ones. Even though buyers do not incur monetary costs if they decide to return an item through eBP, they still incur intangible costs. However, these costs do not vary greatly with items'

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

values. Therefore, returning low-cost items is relatively more costly for buyers. Second, before the introduction of the eBP, experienced buyers on eBay used to value the reputation badge more than novice buyers. However, following the introduction of the eBP, experienced buyers value the reputation badge less than novice buyers. This difference can be explained by reduced costs related to filing disputes, as experienced buyers are more familiar with eBay's rules and regulations.

Our work contributes to the reputation and e-commerce literature in two respects. First, to the best of our knowledge, this paper is the first empirical work that identifies an increase in welfare as a result of added guarantee mechanisms to the overall trust system. 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 if sellers are not responsible for the return fees. 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 that the added buyer protection does not change the value of reputation, either in terms of final prices or sales probability, except for sellers with very high feedback ratings. However, having accessed data of a broader set of products on eBay, we find a robust pattern that buyer protection affects the value of reputation badges across different item characteristics.

Second, our paper empirically identifies reputation-based badge effects in terms of price premium or sales probability. A few other authors have taken similar approaches to estimating the values of reputation in online markets. Saeedi [2014] studies the effect of eBay Powerseller status and store status in the eBay marketplace.[3] She finds the reputation system significantly increases seller profit and consumer surplus. Fan et al. [2013] analyze the effect of badges on Taobao.com, the

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

leading e-commerce platform in China. They find sellers offer price discounts to move up to the next reputation level. Elfenbein et al. [2013] studies the signaling effects of eTRS in the eBay UK marketplace. They find that 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. Another paper related to ours is Nosko and Tadelis [2015]. They illustrate that buyers who encounter better sellers through a better screening mechanism return to eBay with higher probability, emphasizing another important benefit of a working reputation mechanism for the marketplace.

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 the eBP; Section 5 analyzes the effects of adding eBP on the reputation badge; Section 6 provides welfare analysis; Section 7 reports various robustness checks; and Section 8 concludes the paper.

2 Background

An important update for the eBay reputation system is the introduction of the eBay Top Rated Seller (eTRS) certification, which was announced in July 2009 and became effective in October 2009. This certification is awarded on the 20th of each month to sellers who have met the following requirements:

- 98% or higher positive feedback
- 4.6/5.0 Detailed Seller Ratings[4]
- No more than 1% low Detailed Seller Ratings

[4] The Detailed Seller Ratings (DSR) system is a rating mechanism including ratings from buyers to sellers in four categories: item as described, communication, shipping time, and shipping and handling charges. Buyers can rate sellers from 1 to 5 stars in each category.

- Selling 100 items and $3,000 in the past 12 months
- Selling 100 items or $1,000 monthly for the past three consecutive months
- Low dispute rates

This mechanism combines various reputation signals for sellers: feedback ratings, Detailed Seller Ratings, and the number of disputes. Buyers can only see the first two.

The eTRS status has three potential benefits for sellers. First, the eTRS badge appears on all listings from these sellers to signal their quality. Second, eTRS listings are better exposed in search results under eBay's default *Best Match* sorting order, which enhances buyers' visibility of eTRS listings. We control for this higher visibility in the robustness analysis in Section 7. Lastly, sellers with an eTRS badge receive a 20% discount on the *final value fee* charged by eBay. The average final value fee is approximately 10% of the sales price. Therefore, these sellers benefit an average of 2% of the final price through this discount. In this paper, we are mainly interested in the signaling value of the badge and, therefore, we attempt to identify the first benefit mentioned above.

On September 21, 2010, eBay announced that a new buyer protection program would be implemented in October 2010 to protect buyers' rights when they encounter problems with their purchases. In particular, the policy mandates that sellers refund buyers if items received are not as described or if the items are not received. This policy was widely advertised on eBay's website.

To receive a refund through eBP, buyers are instructed to first contact sellers. Afterwards, if they cannot resolve the issue, they should escalate the case to eBay and open a dispute. At this stage, an eBay employee reviews the case and makes a decision. If eBay finds in favor of the buyer, the seller should refund the buyer in full, including the original and return shipping fees.

3 Data and Empirical Approach

Our dataset consists of posted price and auction listings with Product IDs within eBay's internal catalog between 2009 and 2012. Product IDs are very finely defined and two items with the same Product ID are usually the same type. For example, a 4GB Silver 3rd-generation iPod Nano has unique Product ID, different from the Product ID of an iPod from a different generation, with a different color or internal memory; for books or CDs, these Product IDs represent their ISBN codes. The drawback of using Product IDs is that hard to categorize products, such as collectibles or apparel, do not have Product IDs, and they are therefore excluded from our dataset. Items with a Product ID account for approximately 10% of all listings. Additionally, we observe many listing attributes, such as post/sale date, item condition, number of page views, Seller ID, eTRS status of the seller, buyer ID, and buyer's experience level. Most of our analyses are based on single-unit listings. We have considered multi-unit listings as well but found no qualitative differences.

Considering the wide range of items sold on eBay, we must control for their composition. We can achieve this by controlling for Product IDs or by using Product ID categories to define a reference price for products. Following Einav et al. [2011], we define the reference price for each Product ID to be the average sales price of items with the same Product ID that were sold using the Buy-It-Now (BIN) format. For an item sold with price p, we define relative price to be p divided by its corresponding reference price. Both methods yield roughly the same results. Our results are robust to changes in the definition of reference price, as discussed in Section 7.[5]

We perform various regression discontinuity design (RDD) and difference in difference (DiD) estimations to study the effect of the two policies, reputation certification and guarantee, and their interaction. We first show that the reputation badge has a signaling value for sellers. Then, we explore the effect of adding the guarantee on the market and on the signaling value.

[5] We cannot get reference price for products through another website, e.g. Amazon, because we have 3,257,454 distinct products in our dataset.

Table 1: Summary Statistics (2011)

	Top Rated Seller		Non-Top Rated Seller	
	Auction	BIN	Auction	BIN
Price	100.00	84.75	133.58	100.99
Relative Price	0.87	1.02	0.78	0.98
Probability of Sale	0.38	0.14	0.36	0.08

Notes: This table uses Buy It Now (BIN) and auction listings with Product IDs in 2011. We normalize the prices by setting the price of auctions from Top Rated Sellers to 100 and report the rest relative to this value. Relative price is defined to be the sales price over the product reference price–the average successful BIN price within a given Product ID. Probability of sale is defined as the share of the successful listing among total listings.

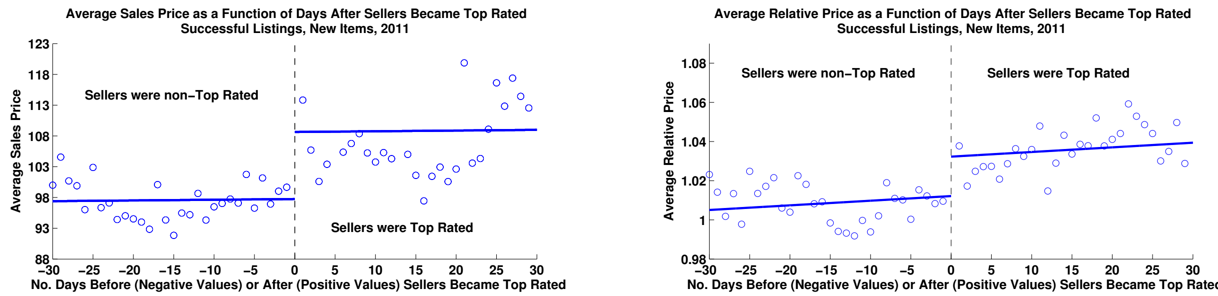
4 Signaling Value of the Reputation Badge

We first evaluate the signaling value of the certification badge. To do so, we focus on transactions in 2011 for three main reasons. First, no policy changes related to eBay's reputation mechanism took place during that year. Second, the availability of item condition allows us to further control for items' value. Third, establishing a positive value of the badge in 2011 shows that its signaling effect remains positive even after the introduction of the eBay Buyer Protection (eBP) in 2010.

4.1 Summary Statistics

Table 1 shows the overall performance of badged and non-badged sellers. The average sales prices of items sold by badged sellers in auction and BIN transactions are both lower (by 25% and 16%, respectively) than those of non-badged sellers.[6] However, after controlling for the composition of items sold using Product ID, as explained in Section 3, we find consumers are willing to pay 9% and 4% more to badged sellers for auctions and BIN listings, respectively. Additionally, badged sellers have an advantage on sales probabilities in both listing formats. They sell 2% more of their auction listings than non-badged sellers, and 6% more in BIN listings. In the next section, we establish this finding using a more in-depth data analysis.

[6] We normalize the prices by setting the price of auctions from Top Rated Sellers to 100 and report the rest relative to 100.



(a) (b)

Figure 1: eTRS Certification Leads to Higher Prices

Notes: These figures use listings of new items with Product IDs in 2011. Integers on the y-axis represent the variables of interest, averaged across all sales in that day by sellers who obtain the eTRS certification. In Figure 1a, we normalize the prices by setting the average sales price in the 30th day before sellers became Top Rated to 100 and report the rest relative to this price.

4.2 eTRS Certification and Price Premium

To further establish that the price premium we observe in Table 1 is not caused by unobservable changes in seller quality, we study changes in average relative sales prices in the vicinity of sellers' badge certification date. To further control for product quality, we focus on new items only. Figure 1a plots the daily average sales prices of new items sold by sellers who become top rated.[7] This figure shows that sellers receive higher average sales prices after they become eTRS, suggesting a signaling value of the badge. However, higher prices could be due to changes in the composition of items sold after the sellers received their badge certification. To control for value, we study the change in relative prices and consider only *new* goods. Figure 1b, consistent with Figure 1a, shows an increase in the relative price of items sold by sellers after they become badged.

Next, we apply an RDD analysis to evaluate the effect the eTRS has on price. We perform two main analyses, with and without controlling for Seller ID. The first approach gives the value of the badge for marginal sellers, those that experience a change in badge status in the time period considered. Since we control for Seller ID, sellers who have been eTRS or non-eTRS throughout

[7]We normalize the prices by setting the average sales price in the 30 days before sellers became Top Rated to 100 and report the rest relative to 100.

Table 2: eTRS Certification Leads to Higher Price

	Relative Sales Price			
	All Listings		Auctions	
	(1)	(2)	(3)	(4)
ETRS	0.15***	0.03***	0.10***	0.02***
	(4.70E-04)	(9.60E-04)	(1.90E-03)	(1.90E-03)
Product Fixed Effects	✓		✓	
Seller Fixed Effects		✓		✓
R^2	0.62	0.50	0.81	0.54
No. Observations	28,279,096	28,279,096	16,783,646	16,783,646

Notes: Our sample contains successful Buy It Now and auction listings with Product IDs in 2011. Relative price is defined to be sales price over the product reference price–the average successful BIN price for a given Product ID.

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

our sample will not affect the coefficient of ETRS. The second approach includes all sellers in the sample and estimates the price premium for an average seller with the badge. For measuring the signaling value of the reputation badge, we use the following regression:

$$Y_{ijpt} = \beta_1 ETRS_{ijpt} + \eta_p + \nu_j + \epsilon_{ijpt},$$

where Y_{ijpt} is relative price of item i from seller j with Product ID p at time t. $ETRS_{ijpt}$ is a dummy variable that equals to 1 if the seller is badged at the time of sale. η_p and ν_j represent product and seller fixed effects, respectively, and ϵ_{ijpt} is a conventional error term that captures any additional variations in Y_{ijpt}.

Table 2 reports the estimated value β_1, the coefficient for the effect of eTRS. Columns (1) and (2) show the effect of eTRS for both BIN and auction listings, and columns (3) and (4) show the effect for auction format. In columns (1) and (3), we only control for Product ID, and in columns (2) and (4) we control for Seller ID. We find badged sellers receive a 15% premium in both formats and 10% in auction listings. Controlling for Seller ID in order to control for endogeneity results in 3% premium for both formats and 2% for auctions. By controlling for Seller ID, we find the price premium for marginal sellers as sellers lose or gain their badge. In Section 7, we perform

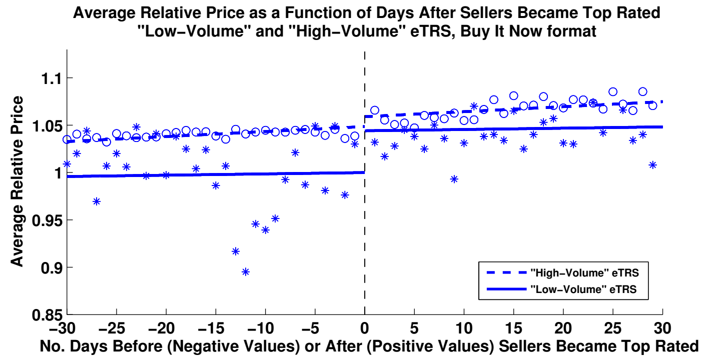


Figure 2: Differential Effect of eTRS Certification on Sellers with Different Size

Notes: This figure uses listings of new items with Product IDs in 2011. "High-volume" eTRS sellers ($\geq$ 20% of volume threshold). "Low-volume" eTRS sellers ($\leq$ 10% of volume threshold)

various robustness checks to ensure that the effect we find is not the result of omitted variables or endogeneity issues.

4.3 Investment in Reputation

Theoretical literature on reputation has long predicted that agents may forgo short-term benefits in order to gain reputation and receive long-term benefits, e.g., Shapiro [1983] and Holmström [1999]. The setup for assessing the requirements for the eTRS badge enables us to find evidence for investment in reputation from sellers. On eBay, sellers are evaluated, or re-evaluated, for the eTRS badge on the 20th of each month. In addition, sellers are notified two weeks prior to this status check if they are close to becoming top rated. Figure 1b shows a small drop in the average relative price of items sold during the last two weeks before sellers become badged.

We partition sellers into two groups based on their proximity to the volume threshold. Specifically, "high-volume" eTRS sellers are those who are at least 20% above the volume threshold and "low-volume" eTRS sellers are those within 10% of the volume threshold on the date they were granted the badge. Figure 2 shows the change in relative price for these two sets of sellers. In the the two weeks before the 20th on each month, "low-volume" sellers tend to drop their prices in order to meet the volume requirements for earning an eTRS badge. Therefore, they sacrifice short-term gains in favour of long-term ones.[8] This result is consistent with Fan et al. [2013]'s finding.

5 eBay Buyer Protection

In October 2010, eBay started a new website-wide buyer protection. 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.

Therefore, this policy influences both buyers' and sellers' welfare. It can affect buyers' welfare through three possible channels: first, a reduction in moral hazard by giving incentives to sellers to exert more effort; second, a decrease in adverse selection by increasing the exit rate of low-quality sellers and by increasing the market share of high-quality sellers; and third, a reduction in buyers' losses in case of unsatisfactory transactions. As a result of this protection, buyers are more willing to purchase from sellers without the reputation badge. Therefore, the policy might reduce the value of the reputation badge. In this section, we first evaluate the impact of the policy change on measures of quality of transactions and the composition of sellers. Next, we evaluate the impact of the policy on the value of reputation.

[8] We also studied the value of items listed and there is no drop in the value during these two weeks.

5.1 Moral Hazard and Adverse Selection

To explore the effects of buyer protection on seller behavior, we consider changes in the number and share of eTRS sellers, as well as changes in different performance measures. Table 3 utilizes BIN and auction listings within 10 months of adding the guarantee. The number of listings increased by about 19% after the introduction of buyer protection, while the probability of sales declined by 9%. The percentage of eTRS sellers and their market share increased each by about 30%. This increase is partly explained by the upward trend on the number of eTRS sellers on eBay. After detrending the number of eTRS sellers, we find a 10% increase in this measure due to the policy change. This increase is consistent with a rise in the cost of dishonest behavior, suggesting an alleviation of both moral hazard and adverse selection.

To examine the alleviation of moral hazard more closely, we study changes in conventional seller performance measure: feedback rating and Detailed Sellers Ratings (DSR). Considering sellers who are active both before and after implementing the eBP, Table 3 shows that the share of negative feedback decreased for both eTRS and non-eTRS sellers by about 15% and 26%, respectively. The share of transactions from non-eTRS with low DSRs (1 or 2) on the criteria "item as described" and "communication" dropped by about 12% and 11%, respectively.[9] For eTRS sellers, the changes in low DSRs are about -3% and 3%, respectively. These results indicate better performance for both eTRS and non-eTRS sellers.

As argued above, another potential effect of adding buyer protection is the mitigation of adverse selection through a reduction in the size of low-quality sellers. As shown in Cabral and Hortacsu [2010], a seller's growth is affected by past performance. One might conjecture that this selection effect becomes stronger in the presence of eBP. To test this hypothesis, we define a new variable

[9] In August 2010, eBay implemented a policy that if sellers offer free shipping, they get 5 stars for the DSR on "shipping charges" automatically. In October 2010, a similar policy was implemented so 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. Therefore, we do not report the changes on these two categories.

Table 3: eBay Buyer Protection Increases Seller Quality

Reduction in Moral Hazard	
	Pct. Change
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%

Reduction in Adverse Selection			
	(1)	(2)	(3)
	Future Size	Future Size	Future Size
Intercept	-0.102***	-0.413***	-0.103***
	(0.023)	(0.023)	(0.023)
Size	0.993***	0.964***	0.983***
	(9.2E-05)	(6.3E-05)	(1.2E-04)
EBP	0.350***	0.668***	0.271***
	(0.033)	(0.033)	(0.033)
Complaint	-2.076***		-1.587***
	(0.004)		(0.007)
Complaint*EBP	0.344***		0.814***
	(0.004)		(0.007)
Dispute		-2.587***	-0.583***
		(0.005)	(0.010)
Dispute*EBP		-0.938***	-2.041***
		(0.011)	(0.017)
R^2	0.914	0.914	0.915
Observations	24,043,776	24,043,776	24,043,776

Notes: The time intervals for these two samples are from November 2009 to July 2011, excluding September 2010, when eBP was announced. In the regressions, sellers' future size in terms of sales volume in the following month are regressed upon their size at current month, the number of complaints/disputes, and the interaction of these two measures with whether buyer protection is implemented.

called complaint. This variable is equal to 1 if a buyer has expressed dissatisfaction by any channel to eBay, including non-positive feedback, a low DSR, or a dispute. Disputing a transaction is escalating a case to eBay, which is a necessary step to receive a refund through the eBP. The number of complaints or disputes is the total that sellers receive within a month. The size of a seller is equal to the total number of items they have transacted within a month. Data consist of transactions in the 10 months before and the 10 months after the policy change.

To evaluate the impact of the policy change on these measures of performance, we perform various regressions with the size of a seller at current month as the dependent variable. The independent variables are the size of the seller, number of complaints and/or disputes, and their interactions with the dummy variable for eBP at the previous month as shown in Table 3. It shows sellers' future sizes decrease as they get more complaints or disputes. In addition, the negative effect of disputes increases after the guarantee policy was added, alleviating adverse selection. This might be due to the higher costs of disputes for sellers since they need to fully reimburse the buyers in case of disputes. As the first regression in Table 3 illustrates, the negative effect of complaints has not surged after the introduction of eBP. This can be due to a lack of an increase in costs associated with negative feedback or low DSR.

5.2 Value of eTRS

The guarantee policy covers all items sold by both types of sellers; therefore, it can potentially act as a substitute for the reputation badge. In particular, this policy could have changed price premium, sales probability, and sales volume by badged sellers. The summary statistics in Table 4 show that after implementing the guarantee, the average relative price for badged sellers decreased (around -1.5% for BIN and -1% for auctions) while the relative price for non-eTRS sellers increased (around 0.9% for BIN and 1.1% for auctions). These changes suggest buyers rely on eBP to make

Table 4: Summary Statistics, Adding Buyer Protection

Top Rated Sellers						
	Buy It Now			Auction		
	Price	Rel. Price	Sales Pr.	Price	Rel. Price	Sales Pr.
10M Before	100.00	1.30	0.21	122.46	1.04	0.45
10M After	101.42	1.28	0.19	135.84	1.03	0.42
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	Sales Pr.	Price	Rel. Price	Sales Pr.
10M Before	112.12	1.12	0.1730	147.64	0.91	0.4742
10M After	172.38	1.13	0.1438	179.61	0.92	0.4025
Pct. Change	53.76%	0.89%	-16.88%	21.65%	1.10%	-12%

Notes: This table uses a sample of listings from November 2009 to July 2011, excluding September 2010, when buyer protection was announced. We normalize the prices by setting the price of Buy It Now sales from Top Rated Sellers in the 10 months before to 100 and report the rest relative to this value. Relative price is the sales price over the product reference price– the average successful BIN price within a given Product ID.

purchases and pay less price premium to badged sellers.

To estimate the value of guarantee, we use a regression similar to the one used for estimating the value of eTRS by adding a fixed effect for eBP and its interaction with eTRS. We expand our sample to include transactions in the 10 months before and after adding the buyer protection. Column (1) in Table 5 shows that, consistent with the estimates in Table 2, badged sellers receive higher average relative price than non-badged sellers. In addition, this price premium decreases by 0.025 (or 13%) after adding the buyer protection. Column (2) shows shows a reduction in the signaling value of the badge by 0.004 (or 15%) when controlling for Seller ID. By controlling for Seller ID, we only consider marginal sellers with status change. In comparison, column (1) shows the effect on average sellers, including sellers without status changes.

Next we study the change in badge value in terms of sales volume and sales probabilities. Similar to Elfenbein et al. [2013], we use the logarithm of 1 plus quantities sold in a listing and sales indicator as our dependent variable and expand our sample to include multi-unit listings. In columns (3) and (4), Success is a dummy variable for whether there is at least one sale in a listing. Quantity $\in (x, y)$ is an indicator for whether the total available items in a listing are between x

Table 5: Regression Results, Adding Buyer Protection

	All Items		All Buy it Now Items	
	(1)	(2)	(3)	(4)
	Relative Price	Relative Price	log(1+Quantity Sold)	Success
ETRS	0.187***	0.026***	0.280***	0.395***
	(1.0E-03)	(8.3E-04)	(4.1E-04)	(4.4E-04)
EBP	0.005***	0.002***	-0.076***	-0.063***
	(2.0E-03)	(5.3E-04)	(2.3E-04)	(2.5E-04)
ETRS*EBP	-0.025***	-0.004***	-0.186***	-0.276***
	(1.0E-03)	(9.0E-04)	(3.7E-04)	(3.9E-04)
log(price)			-0.084***	-0.090***
			(5.4E-05)	(5.7E-05)
ETRS*log(price)			-0.011***	-0.022***
			(8.1E-05)	(8.6E-05)
Quantity $\in (2, 10)$			0.078***	0.019***
			(8.5E-05)	(9.0E-05)
Quantity $\in (11, 100)$			0.124***	0.020***
			(1.4E-04)	(1.4E-04)
Quantity > 100			0.089***	0.007***
			(2.3E-04)	(2.4E-04)
Product Fixed Effects	✓		✓	✓
Seller Fixed Effects		✓		
R^2	0.407	0.322	0.343	0.350
No. Observations	48,780,055	48,780,055	105,524,913	105,524,913

Notes: EBP is a dummy variable, defined to be 1 after the implementation of eBP policy. ETRS is a dummy variable, defined to be 1 for sellers with eTRS badge. Quantity $\in (x, y)$, is a dummy variable, defined to be one if quantity available is within x and y.

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

and y units. We also include dummy variables for the number of quantities available in different listings because the total number sold cannot exceed the available units in each listing. Prior to implementing buyer protection, the badge raises the percentage of quantity sold in listings by 28%, but this number drops to around 9% afterwards. The badge increases sales probabilities by about 40% before the policy change and 12% afterwards.

Lastly, we show that the decrease in value of the eTRS is not the result of a decreasing trend. In Figure 3, we identify sellers who become badged in each month. Then, we estimate the badge effect β_1 using the discontinuity regression mentioned before and their transactions in the 30 days before and after becoming badged. Figure 3 shows a sudden decline in badge effect after the buyer protection has been introduced.

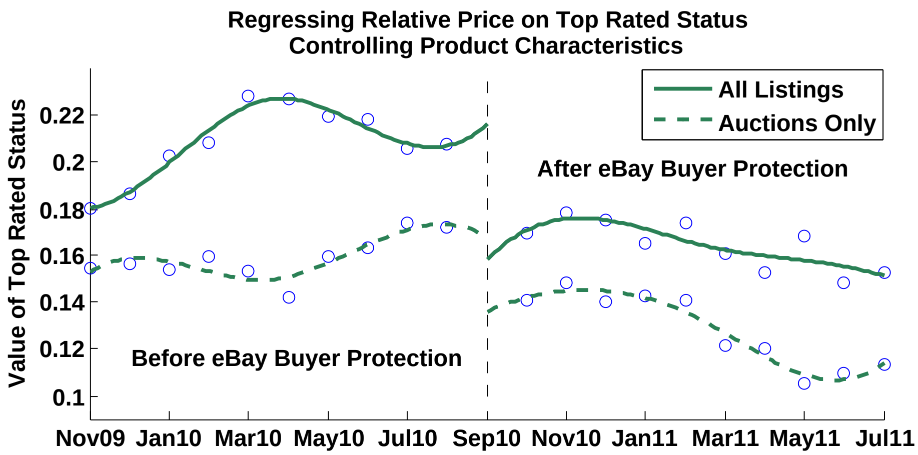


Figure 3: Trend on Average Badge Effect

Notes: We identify sellers who become badged in each month. Then we estimate the badge effect β_1 in regression 1 using their transactions in the 30 days before and after becoming badged. Each circle in the graph represents $\widehat{\beta_1}$ in a given month.

5.3 Different Buyer Experience

eBay buyers differ in their levels of experience and familiarity with eBay's rules and regulations. Consequently, they may conceive the value of reputation differently and may be affected by the buyer protection differently. We partition buyers based on their spendings and define experienced buyers to be those who spent at least $2,500 during the 365 days prior to the purchase. We then perform the regression discontinuity estimation to capture consumer heterogeneity in responses to buyer protection.

Table 6 presents the estimation results for buyers with different levels of experience. Column (1) shows that experienced buyers value eTRS by 0.04 (or 22%) less. This suggests that experienced buyers may have their own ways of identifying good sellers and therefore rely less on eBay's certification. This estimate is the average value across the entire 20-month period. Column (2) shows the average value of eTRS across buyers has decreased by 0.025 (or 13%) after the introduction of the eBP. To account for buyer heterogeneity in this change, we further include the Experienced dummy and interactions of these three dummy variables in column (3). After the introduction of

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

	(1) Relative Price	(2) Relative Price	(3) Relative Price
ETRS	0.180***	0.187***	0.188***
	(0.001)	(1.0E-03)	(0.001)
Experienced	0.019***		0.013***
	(0.001)		(0.001)
EBP		0.005***	0.003
		(2.0E-03)	(0.003)
ETRS*Experienced	-0.040***		0.002
	(0.001)		(0.002)
ETRS*EBP		-0.025***	-0.015***
		(1.0E-03)	(0.001)
Experienced*EBP			0.011***
			(0.002)
ETRS*EBP*Experienced			-0.069***
			(0.003)
Product Fixed Effects	✓	✓	✓
R^2	0.522	0.407	0.522
Observations	48,185,361	48,780,055	48,185,361

Notes: This table uses transactions from November 2009 to July 2011, excluding September 2010, when eBay Buyer Protection was announced. ETRS is the dummy variable for seller's eTRS status. Experienced is a dummy variable defined to be 1 if a buyer has spent more than $2,500 in the year prior to her purchase. EBP is a dummy variable defined to be 1 after eBP was implemented.

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

the eBP, experienced buyers' valuation for the eTRS badge decreases more (0.069 or 37%) than that of novice buyers (0.015 or 8%). This is possibly because of experienced buyers' better familiarity with the guarantee policy. Novice buyers, by contrast, are not as responsive to changes in market rules because they may be skeptical about the new rules or unaware of the details.

5.4 Different Items' Prices

To study the heterogeneous impacts of adding the eBP to products with different reference prices, we partition products based on their reference prices. We define low price range to be from $0.01 to $10, medium price range from $10.01 to $100, and high price range from $100.01 to $500. As shown in Table 7, adding eBP has the smallest effect on price premium for low-price items, and this effect is the highest for high-price items, where the premium drops by 0.077 (or 57%). Even though buyers do not pay monetary costs for returns through the eBP policy, they still incur intangible

Table 7: Regression Results, Adding Buyer Protection

	Low Price Relative Price	Med Price Relative Price	High Price Relative Price
ETRS	0.239***	0.153***	0.135***
	(1.3E-03)	(4.4E-04)	(6.7E-04)
ETRS*EBP	-0.001	-0.021***	-0.077***
	(1.9E-03)	(5.9E-04)	(8.6E-04)
Product Fixed Effects	✓	✓	✓
R^2	0.435	0.186	0.193
No. Observations	20,331,826	20,998,483	6,828,075

Notes: This table uses successful single-item listings with Product IDs from November 2009 to July 2011. We define the low price range to be from \$0.01 to \$10, medium price range from \$10.01 to \$100, and high price range from \$100.01 to \$500.

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

costs, such as the time they spend on comprehending regulations, communicating with sellers, and filing disputes. These costs are fairly fixed and do not depend on items' prices. Therefore, returning low-price items is relatively more costly for buyers, which leads to a lower impact of the eBP on price premium for low-cost items.

6 Welfare Analysis: Adding Buyer Protection

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

Total welfare equals total buyers' willingness to pay minus total sellers' cost. We do not directly observe buyers' willingness to pay, but we observe the 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 or his own bid, whichever is smaller. The increment can potentially lead buyers to bid values that are different from their willingness to pay.[10] 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 this parameter has not changed as a result of the policy change.[11] Therefore, any percentage change in the highest bids will translate to the same percentage change in the buyers' willingness to pay. The buyer protection was introduced in the first week of October, but was announced two weeks earlier. Therefore, Table 8 uses transactions in the last two weeks of August and first two weeks of September and transactions in the last three weeks of October and first week of November. The reference price of a product is the average BIN sales prices of items in each Product ID category in September. In the regressions in Table 8, we control for a weekly time trend to capture exogenous changes in the value of products. We remove auction listings in which the highest bids are five times larger than the final sales prices ($< 1\%$ of all auctions) from our dataset, as they may be mistakenly recorded.[12]

Regression 1 in Table 8 shows a 3.7% increase in the average relative highest bid for non-eTRS sellers and a 1.3% increase for eTRS sellers, which equals to a 2.9% increase in weighted (by the

[10] 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.

[11] 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.

[12] We have also tried changing this threshold to 10, 20, 50, and 100. The results are robust since outliers are rare.

proportion of transactions from eTRS and non-eTRS) average relative highest bid. This increase in willingness can be dampened by even a higher increase in costs. We do not observe nor can we identify the cost parameters. However, the BIN prices are set by sellers and are a function of sellers' costs, as well as buyers' willingness to pay. The average price of BIN items is mainly unchanged, with a 2.8% decrease for non-eTRS sellers and a 0.5% increase for eTRS sellers, or a 1.2% decrease in the weighted average. This small change in prices, lower than the change in the willingness to pay, suggests the change in the cost parameters cannot be very large. The percentages of the items with a dispute and returns remain small and do not vary much after adding the eBP program, which can explain the small change in the prices of BIN items. We also report the change in prices of only auction items and both auction and BIN formats. In both of these cases, the change in average price is less than the change in willingness to pay or the change in highest bid. Hence, the change in willingness to pay provides a lower bound on the change in welfare. This 2.9% increase in welfare confirms the increase in efficiency gains as a result of the added guarantee mechanism. The reader should note that the welfare calculation is an approximation. Because, it is defined in the short-run as we abstract away from possible change in the equilibrium of the market structure and also we use evidence from change in highest bids to infer the change in consumers' willingness to pay.

7 Robustness Analysis

In this section, we perform various robustness checks to verify the validity of our results. We focus on competing theories that may lead to a price premium for eTRS status and show that these cannot explain the premium fully. Next, we consider alternative definitions of reputation to show that the effect of eBP on reputation and total welfare gain is not specifically limited to eTRS.

Table 8: Welfare Changes: Adding Buyer Protection

	Auctions		Buy it Now	Auctions+Buy it Now
	(1)	(2)	(3)	(4)
	Relative Highest Bid	Relative Price	Relative Price	Relative Price
eTRS	0.081***	0.096***	0.108***	0.137***
	(0.007)	(0.006)	(0.004)	(0.004)
eBP	0.037**	0.028**	-0.028**	0.047***
	(0.016)	(0.013)	(0.011)	(0.009)
eTRS*eBP	-0.024**	-0.025***	0.033***	0.002
	(0.011)	(0.009)	(0.006)	(0.006)
Week	-0.007***	-0.006***	-0.001	-0.008***
	(0.002)	(0.002)	(0.001)	(0.001)
Product Fixed Effects	✓	✓	✓	✓
Observations	332,057	332,057	394,623	729,967
R^2	0.745	0.749	0.900	0.757

Notes: Transactions in the last two weeks of August and first two weeks of September and the last three weeks of October and first week of November are used. Relative price is defined to be the sales price over the product reference price; relative highest bid is the highest bid divided by product reference price, which is the average BIN sales prices of items in each Product ID in September.

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

7.1 Robustness Check on Signaling Value of eTRS Badge

We start by showing that the results are not sensitive to the definition of the reference price and our normalization method for prices. We defined the reference price of an item to be the average successful BIN price of items listed under a given Product ID. Changing this definition to include all listing formats has little to no effect on the results. Another concern might be that the reference price of items may vary over the time period considered. To account for this time trend, we define monthly fitted reference prices with linear depreciation for each category level.[13] 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 reference price and perform our key regression. The results are shown in columns (1) and (2) in Table 9. The price

[13] We have more than three million distinct products in our dataset with few observations for many of them, which leads to very noisy estimates for the time trend. In contrast, there are 30 categories for these products.

premium values are 0.04 and 0.06, respectively, for the above-mentioned categories, compared to 0.03 and 0.04, respectively, if we do not incorporate monthly price depreciation. This shows that we may underestimate the badge effect of the eTRS if we do not account for depreciation in product values because most items show a decreasing trend in their valuations.

We next show that the change in visibility is not the main cause for premium. eBay's default search ranking is *Best Match*, and being a badged seller increases the probability that one's listings appear in buyers' query search results. 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 does not change much: the premium is 14% for BIN, compared to 15% without controlling for the number of visits. An even better measurement for visibility would be the number of impressions, or the number of times a listing was shown on a search query to a user, because such a figure could indicate whether buyers were more likely to click on listings from badged sellers. However, we do not have access to these data and the number of page views is the closest proxy for this variable. For auctions, we control for the number of visits as well as the starting bid. Column (4) shows that the effect of the reputation badge remains positive and significant after controlling for the two new parameters.

Our earlier analyses show that sellers may list items with a discount in the two weeks before they become badged to satisfy the eTRS requirement. To deal with this potential endogeneity problem, we consider the subsample of transactions from sellers whose statuses have changed and remove transactions within two weeks of sellers' status change. Doing so results in a 7.3% price premium compared to 7.1%. Therefore, the price premium for badged sellers is not driven by the inclusion of these extreme behaviors.

Another concern is unobservable variables and learning over time as sellers become more experienced. We use two separate methods to address this issue. First, we only include sellers who are within a narrow band of meeting the requirements. We then compare two groups of sellers who

Table 9: Robustness Check, 2011

Panel A: Multiple Robustness Regressions

	Cell Phone	Computer	BIN	Auctions	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*REFURBISHED							-0.01**
							(3.9E-3)
ETRS*LOW							-0.07***
							(5.6E-3)
ETRS*MEDIUM							-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 Lose and Later Regain the Badge

	Sellers Are eTRS		Sellers Lost eTRS		Sellers Regain eTRS	
	Auction	BIN	Auction	BIN	Auction	BIN
Price	100.00	73.11	94.44	51.20	128.88	80.03
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: ETRS is a dummy variable for sellers' eTRS status. In regressions (1) and (2), Adj_Rel_Price is the adjusted relative price defined as price with monthly depreciation-adjusted reference price for a product. In regressions (3) and (4), VIEW_COUNT is the number of page views for a product; START_PRICE is the starting (public reserve price) price of the auction. In regressions 5 and 6, we only consider sellers who meet all quality requirements for eTRS and within 10% and 20% of quantity thresholds. Low, medium, high, and highest price ranges are from \$0.01 to \$10, from \$10.01 to \$100, from \$100.01 to \$500, and from \$500.01 to \$1000, respectively. In regression (7), we also control for conditions and price-range dummy variables. The statistics in Panel B are for sellers who have lost their badge but later regain it. We normalize the prices by setting the price of auctions from "Sellers Are eTRS" to 100 and report the rest relative to 100.

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

both meet quality thresholds, but only one group that does not meet the quantity thresholds. The results are presented in columns (5) and (6) in Table 9, for the 10% and 20% band around the quantity thresholds; the badge effect is 4% in terms of the relative price for the 10% band and 5% for the 20% band.

Another test for endogeneity and learning is to consider sellers who have lost and regained the badge repeatedly. If sellers receive higher prices just as they become more experienced, the subsequent status changes should have much lower impact on the price premium. However, the results in Panel B of Table 9 suggest sellers who lost and later regained their status have received a price premium 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 regain this status. In another exercise, we study sellers who have lost and regained the eTRS status for one time, two to three times, or more than four times, and find that they receive an 8%, a 6%, and an 8% price premium from the badge, respectively.

Lastly, 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 the eTRS status, item conditions, and items' price 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-price combinations.

7.2 Robustness Check on the Effect of eBP

To check the sensitivity of the eBP effects on the definition of eTRS, we use alternative definitions of reputation based on feedback ratings and feedback numbers. A seller's feedback number is a cumulative score, which changes by 1, 0, or -1 if the seller receives a positive, neutral, or negative feedback, respectively. We define reputable sellers as those who meet eBay's minimum selling stan-

Table 10: Robustness Analysis, Effect of eBP on Alternative Reputation

Panel A: Alternative Reputation Signals						
Dept 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						
Dept Var: Rel. Highest Bid		100Fdbk	500Fdbk	1000Fdbk	2000Fdbk	5000Fdbk
FDBK		-0.019	0.023	0.061***	0.073***	0.076***
		0.019	0.018	0.018	0.018	0.020
EBP		0.083*	0.067	0.072*	0.060	0.055
		0.048	0.044	0.043	0.042	0.042
FDBK*EBP		-0.007	0.014	0.004	0.026	0.046
		0.032	0.028	0.028	0.028	0.030
Product FE		✓	✓	✓	✓	✓
Panel C: Welfare Analysis with Alternative Reputation Signals: BIN Listings						
Dept Var: Relative Price		100Fdbk	500Fdbk	1000Fdbk	2000Fdbk	5000Fdbk
FDBK		0.061	0.061***	0.074***	0.082***	0.051***
		(0.012)	(0.010)	(0.010)	(0.010)	(0.010)
EBP		0.031	0.037	0.046**	0.053***	0.048***
		(0.026)	(0.010)	(0.020)	(0.019)	(0.019)
FDBK*EBP		0.038**	0.037***	0.027**	0.015	0.027*
		(0.020)	(0.014)	(0.014)	(0.014)	(0.014)
Product FE		✓	✓	✓	✓	✓

Notes: In Panel A, coefficients are estimated from regressing relative sales prices on eTRS or other reputation signals based on feedback number, controlling for product fixed effects. Dummy variable #Fdbk equals to 1 if the total number of seller feedback is larger than this number and the seller is not below eBay's selling standard at the time of the transaction. 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 Panels B and C, we replicate our welfare analyses in Table 8 by using an alternative definition of reputation based on feedback number.

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

dard and have feedback of at least x, where $x \in \{100, 500, 1000, 2000, 5000\}$.[14] Given that feedback numbers change gradually over time, we cannot disentangle signaling value and unobservable heterogeneity among sellers. Therefore, we do not take a stand on the share of the signaling effect. Panel A of Table 10 shows the price premium of being in each group. The price premium for most sellers drops after the change in policy, which is consistent with our earlier results: eBP lowers the value of reputation. Panels B and C of Table 10 report the welfare results based on these alternative reputation signals, using the method in Table 8. The buyer protection has increased welfare for all reputation signals.

8 Conclusion

Market designers frequently develop seller reputation policies and guarantee policies to overcome problems caused by asymmetric information, including adverse selection, market inefficiency, and market failure. 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.

We first show that the value of reputation is positive: certified sellers receive a price premium and also sell their items with a higher probability. We then focus on the introduction of eBay buyer protection. This policy provides an efficiency gain through two mechanisms that lead to fewer undesirable transactions: a reduction in moral hazard and a reduction in adverse selection. The added cost of a buyer protection policy on sellers when they provide a low-quality service induces sellers to provide a better service, alleviating moral hazard. It also forces low-quality sellers to exit the market more often, alleviating adverse selection. Furthermore, buyers receive compensation

[14] 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%.

when they encounter a bad outcome, which leads to higher willingness to pay for items sold by both types of sellers. By assuming that the policy has not affected competition in the market, we estimate that the total welfare rises by 2.9% after the introduction of the buyer protection program. This increased welfare demonstrates an efficiency gain by having the two mechanisms, the eBay Buyer Protection and eBay Top-Rated Sellers, in place.

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