Certification, Reputation and Entry: An Empirical Analysis *

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Abstract

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More precise information about past performance of incumbent firms has implications for entry decisions and affects the quality distribution of firms in the market. However, this relationship has not been well studied empirically, because of limited data. We exploit a policy change on eBay as a quasi-experiment, in which the "eBay Top Rated Seller" badge substituted the previous "Powerseller" badge, by making the requirements more stringent and adding new performance measures for qualification. This change results in some incumbent sellers losing their badge, implying that the quality of both certified and uncertified sellers increases. This change can generate countervailing incentives for entrants of different quality levels. On one hand, it may induce more entry by high-quality firms by increasing their future payoff conditional on receiving the badge. On the other hand, it may induce more entry by low-quality firms, because the average quality of uncertified sellers with whom they may pool increases. We exploit the differential impact of the policy change on different subcategories of the eBay marketplace for identification. First, we document a negative correlation between the number of entrants and the share of badged sellers across categories. We find that after the policy change, categories that experience a higher reduction in the share of badged sellers experience a larger increase in the number of entrants. However, this difference tends to disappear once the market adjusts to the new equilibrium after about six months. Second, we find that the distribution of quality provided by entrants changes and has fatter tails. In other words, a larger share of

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entrants provides qualities from the first and last two deciles of the quality distribution after the policy change. This finding is consistent with the prediction that entrants from the extremes of the quality distribution have stronger incentives to enter, although it could be due to similar entrants changing their behavior. Third, we find almost no change in the quality provided by incumbents. This last finding suggests that the increase in the quality provided by entrants at the tails of the distribution is more likely to come from improved selection rather than from a change in entrants' behavior. The results have relevant implications for the design of reputation and certification mechanisms in electronic and other markets, and shed some light on the concerns expressed by the U.S. senate and the EU that allowing public buyers to use past performance information when selecting contractors may hinder entry by novel or foreign firms in public procurement markets.

Keyword: Certification, Reputation, Entry, Adverse Selection, Moral Hazard

1 Introduction

Certification and reputation mechanisms help market participants to overcome information asymmetries, and are therefore crucial for markets where these asymmetries are pronounced, such as digital markets. More precise information about incumbent firms, however, may also have implications for entry decisions, and it may therefore affect the quality distribution of firms in the market through this channel.

While early studies on reputation for quality were concerned about its potential to affect entry (e.g., Klein and Leffler [1981]), the relationship between increased market transparency through certification and reputation and the entry of new firms remained relatively understudied, despite the issue being of primary importance for understanding the effects of different information policies on the evolution of markets.

Improved information on the past performance of incumbent firms is likely to increase the value of reputation and certification for them, but may change the discounted lifetime profit of new entrants, hence their ability and incentives to enter and survive, depending on entrants' characteristics. It may affect market structure for sellers with an established track record, and may change the perceived quality of sellers without such a record. Theoretically, the net effect of improved market transparency on the number, quality, and success of entry is therefore ambiguous, so empirical evidence on these effects is essential.

In this paper, we shed light on these issues through an empirical study of the effects of a policy change that took place on eBay, one of the largest and best-known electronic markets. We exploit a quasi-experiment that occurred in 2009 when eBay changed its information policy by replacing the previous "Powerseller" badge awarded to particularly virtuous sellers with the eBay Top Rated Seller (eTRS) badge.[1] We use a simple model to show that in the short run, given the population of incumbent sellers, the policy change should increase buyers' perceived quality of both badged and non-badged sellers. These more stringent requirements imply that the average quality of the badged sellers should increase following the policy change. However, since some incumbents lose their badge and are pooled with the other sellers, the average perceived quality of non-badged sellers should also increase following the policy change. This parallel sudden change may generate different incentives for entrants, depending on their type (quality). It may induce more entry of top-end-quality firms by increasing their future payoff conditional on obtaining a more informative and selective badge; but it may also induce more entry of low-quality entrants, because the higher average quality of non-badged sellers may increase the propensity of buyers to trade with them. More average-quality sellers may instead find entry less attractive after this policy change. With time, the structure and behavior of the market population is affected, and different new equilibria may be reached depending on market characteristics.

To identify these potential effects empirically, we exploit the differential impact the policy change had on different subcategories of the eBay marketplace. We begin by documenting a negative correlation between the number of entrants and the share of badged sellers across categories. We find that after the policy change, this correlation becomes stronger, However, this change is temporary, as it tends to disappear once the sub-market adjusts to the new equilibrium after about six months. We also measure a significant drop in the share of badged sellers at the policy change date, as predicted by our reasoning above, with substantial heterogeneity of this effect between categories.

Turning to our main research questions, the dynamic effects of the policy change on entry and market composition and structure, we find that in the first three to six months after the policy change, entry of badged sellers increases by 30% in sectors affected more by the policy, i.e. 10% higher drop in fraction of badged sellers result in a 3% increase in entry. This change become statistically insignificant if we consider 7 to 12 month after the policy change when trying to study more long term effects of the policy. We then show that the average quality provided by entrants,

[1] The reputation mechanism on eBay has changed multiple times in the past six–seven years, and there have been many improvements to manage sellers' quality; however, the study of those changes is beyond the scope of this paper.

as measured by the effective percent positive (EPP) increases significantly after the policy change. In contrast to the long term effect of the policy on the number of entrants, this effect persists when we consider a longer time period. We find that entrants in the more affected subcategories tend to be smaller on average, however, their total market share increases after the policy change. Importantly, we find that the distribution of quality provided by entrants also changes with the policy and gains fatter tails: a larger share of entrants provide quality at the first and last two deciles of the quality distribution. This finding is consistent with the prediction that sellers from the extremes of the quality distribution have stronger incentives to enter immediately after the policy change is implemented, although the effect could also be due to similar entrants changing their behavior.

Subsequently, we study the behavior of different types of incumbent sellers (with and without badge before and after the policy change) and find almost no change in the quality provided after the new badge is introduced. This last finding leads us to conclude that the increase in the quality provided by entrants at the tails of the quality distribution is more likely to come from improved selection rather than from a change in entrants' behavior.

Finally, we study how price and market share changed for the four groups of sellers: BB, BN, NB, NN, where B indicates that the seller is badged and N indicates that the seller is not badged. We find that all groups of sellers experience an increase in the relative price except for group BN. The magnitude in descending order is NB, BB, NN, and BN. In terms of seller-level market share, we find that sellers in the BN and NN experience in higher increase in market share in categories that are more affected.

Our results have relevant implications for the design of reputation and certification mechanisms in electronic and other markets, and shed some light on the concerns expressed by several prominent U.S. senators and the EU that the extensive use of past performance information for selecting federal contractors could hinder the ability of new or small businesses to enter public procurement markets. The debate led the General Accountability Office to study dozens of procurement decisions across multiple government agencies, but the resulting report, published in 2011, was rather inconclusive.

The remainder of the paper is organized as follow: In Section 2, we discuss the related literature; in Section 3, we provide details about the policy change; and in Section 4, we provide a simple framework and an example to theoretically illustrate how the policy could affect entry. Section 5 describes our data, and Section 6 discusses our empirical strategy. In Section 7, we provide our results, while in Section 8, we provide robustness checks. Section 9 concludes the paper.

2 Related Literature

The closest papers to our study are Elfenbein et al. [2015], Klein et al. [2016], and Saeedi et al. [2013]. The authors of these papers also used data from eBay to study the effects of different information policies on market structure. In particular, Elfenbein et al. [2015] studied the value of the certified badge across different markets among different types of sellers. They found that certification provides more value when the number of certified sellers is low and when markets are more competitive. They did not explicitly study the impact of certification on the dynamic entry process. In the setting of procurement auctions, Spagnolo [2012] and Butler et al. [2013] studied the relationship between entry and the use of performance information to select contractors. They found through lab experiments that that appropriately designed reputation system may stimulate new entry besides improving quality.

Klein et al. [2016] and Saeedi et al. [2013] studied a different policy, which prevents sellers to rate buyers. Klein et al. [2016] shows that transaction quality increased after the policy change. Furthermore, the change comes almost entirely from changes in seller behaviors because they do not observe change in sellers' exit rates after the policy change. Using administrative data from eBay, Saeedi et al. [2013] show that there is a large shift in market share of sellers of different quality levels, which is also a source of change in adverse selection. They estimate that 68% of the increase in seller quality comes from reduced adverse selection. Similarly, our paper also suggests that the change in moral hazard is minimal among incumbents and almost all the quality lift comes from selection of better pools of entrants.

Our paper also relates to the literature that analyzes the effects of changes in eBay's feedback mechanisms on price and quality (Klein et al. [2016], Hui et al. [2016], and Nosko and Tadelis [2015]). Consistent with the findings reported in these papers, we found that the reputation badge yields price and conversion rate premiums. Furthermore, changes of these premiums for sellers in different groups, which are based on their badge status before and after the policy change, are consistent with our theoretical model. In particular, we find a decrease in badge premiums for sellers that lost their badge after the policy change, and the increase in badge premiums is the largest for sellers that were not badged before but badged after.

Our paper also fits broadly into the theme of understanding the effect of certification and reputation in e-commerce. These papers are surveyed in Dellarocas et al. [2006], Bajari and Hortacsu [2004], and Tadelis [2016].

A few papers in the finance literature found mixed results on how increased competition from entry interacts with reputational incentives and affects quality (e.g., Becker and Milbourn [2011] and Doherty et al. [2012].

3 Background and Policy Change

eBay's reputation mechanism includes various measures and signals. It started by the very well-studied feedback rating in which sellers and buyers can give one another a positive, negative, or neutral feedback rating. Given the concerns regarding the retaliation from sellers to buyers, eBay first introduced the detailed seller ratings in which buyers give the seller a rating between 1 and 5 in four categories (i.e., item as described, communication, shipping rate, and shipping speed). Then eBay made the feedback rating one-sided so sellers can only leave a positive rating for buyers. Later, eBay started certifying the highest-quality sellers by awarding them the "Powerseller" badge.[2]

To qualify for the Powerseller program, a seller needed to sell at least 100 items or at least $1000 worth of items every month for three consecutive months. The seller also needed to maintain at least 98% of positive feedback and 4.6 out of 5.0 detailed seller ratings. The main benefit of being a Powerseller was receiving discounts on shipping fees of up to 35.6%. There were different levels of Powersellers depending on the number and value of annual sales, but all Powersellers enjoyed the same benefits from eBay.

An important update of eBay's reputation system was the introduction of the "Top Rated Seller" status, which was announced in July 2009 and became effective in September 2009. To qualify as a Top Rated Seller, a seller must have at least 100 transactions and sell $3000 worth of items over the previous 12 months. Finally, the seller must have less than 0.5% or 2 transactions with low DSRs (1 or 2 stars), and low dispute rates from buyers (less than 0.5% or 2 complaints from buyers). The information on dispute rates, only available to eBay, was not used before.

Top Rated Sellers must meet stricter requirements, but also enjoy greater benefits, than other sellers. Top Rated Sellers receive a 20% discount on their final value fee and have their listings positioned higher on the page showing a buyer's "Best Match" search results, which is eBay's default sorting order. The resulting higher visibility of these listings should increase sales. Finally, the Top Rated Seller badge appears on all listings from a Top Rated Seller, signaling the seller's superior quality to all potential buyers.

[2]The highest-quality sellers are the most successful in terms of their sales and consumer feedback.

4 Simple Example

To illustrate the intuition of the results, we go over a simple three-type example based on Hopenhayn and Saeedi [2016]. Assume that a market is perfectly competitive. Firms differ along two dimensions, quality $z \in \{z_1, z_2, z_3\}, z_1 < z_2 < z_3$, with mass m_1, m_2, m_3, respectively; and fixed costs f independently distributed with cumulative distribution function $G(f)$. To simplify notation, we normalize the total mass of firms to 1. Production technology is the same for all firms, and is given by a strictly increasing supply function $q(p)$, the corresponding variable cost $c(q)$, and the variable profit function $\pi(p)$.

All consumers observe a coarse signal related to quality, which we call the reputation badge. We assume that this badge signals if the quality is above a certain threshold. We compare when the badge is assigned to the top two quality levels versus just to the highest-quality sellers. Letting p_H and p_L denote the competitive price for firms above and below the threshold, respectively, the number of sellers entering from each type will be $n(p) = G(\pi(p)), p = p_L, p_H$; therefore, the number of entrants increases in price.

The demand side is given as follows. There is a baseline demand function $P(Q)$ and an additive quality offset $\Delta \bar{z}$ for a good of expected quality $\bar{z}$ so that if the total quantity in the market of all goods is Q, the demand price for this good is $P(Q) + \Delta \bar{z}$.

An *equilibrium* for threshold $z^* \in \{z_2, z_3\}$ is a pair of prices, p_H and p_L, and quantities, Q_H and Q_L, such that

1. $p_H = P(Q) + \Delta_H(z^*)$,
2. $p_L = P(Q) + \Delta_L(z^*)$,
3. $Q_H = q(p_H)\, n(p_H)\, m_H(z^*)$, and
4. $Q_L = q(p_L)\, n(p_L)\, m_L(z^*)$,

where $Q = Q_L + Q_H; and \Delta_H(z^*), \Delta_L(z^*)$ represent the average quality of sellers above and below the threshold, respectively; and $m_H(z^*), m_L(z^*)$ represent of share of the entrant cohort above and below the threshold, respectively.

We are interested in the effect of increasing z^* from z_2 to z_3, in other words, on the effect of making the badge more restrictive by only giving the badge to the highest-quality sellers. For ease of notation, let p_H^1, p_L^1 to be the prices under $z^* = z_2$, and p_H^2, p_L^2 to be the prices under $z^* = z_3$.

Lemma 1 $p_2^L < p_1^H$.

Proof. Suppose towards a contradiction that $p_2^L \geq p_1^H$. Since $p_2^H > p_2^L$, it follows that both prices have increased. Hence the total output must increase too (i.e., $Q_2 > Q_1$). Then $p_2^L = P(Q_2) + \Delta_L(z_3) < P(Q_1) + \Delta_H(z_2) = p_1^H$, which is a contradiction. ∎

The above Lemma shows that the transition will hurt the middle-quality sellers, the ones who could get a badge before and no longer can under the stricter badge requirements. This will result in a smaller entry threshold for these sellers and therefore their number will go down. The effect on the other two groups depends on the parameters of the model such as cost, entry cost, and quality levels. However, we can show that at least one of the two prices should go up.

Proposition 1 *It cannot happen that both prices are smaller under z_3.*

Proof. If both prices were lower, then

$$\begin{aligned}
Q_2 &= q\left(p_H^2\right) n\left(p_H^2\right) m_H(z_3) + q\left(p_L^2\right) n\left(p_L^2\right) m_L(z_3) \\
&= q\left(p_H^2\right) n\left(p_H^2\right) m_3 + q\left(p_L^2\right) n\left(p_L^2\right)(m_1 + m_2) \\
&< q\left(p_H^1\right) n\left(p_H^1\right) m_3 + q\left(p_L^1\right) n\left(p_L^1\right)(m_1 + m_2) \\
&= q\left(p_H^1\right) n\left(p_H^1\right)(m_3 + m_2) + q\left(p_L^1\right) n\left(p_L^1\right)(m_1) \\
&\quad - m_2(q\left(p_H^1\right) n\left(p_H^1\right) - q\left(p_L^1\right) n\left(p_L^1\right)) \\
&< Q_1.
\end{aligned}$$

But if the total output decreases, both prices must increase (since both quality premiums increase) and this is a contradiction. ∎

If p_H goes up, then more sellers of the highest quality will enter the market; the higher premium makes it profitable for more sellers to enter the market. Additionally, if p_L also goes up, sellers of the lowest quality will have higher incentives to enter the market, as they are pooled with higher-quality sellers and are receiving higher prices.

With time, entrants will change the composition of sellers in different classes, leading prices and entry rates to adjust to a new equilibrium.

Of course, this simple model with perfect competition within informational classes misses the effects of changes in within-class market structure, which are not the focus of our paper (see Elfenbein et al. [2015] on these).

5 Data

We use proprietary data from eBay. The data includes detailed characteristics on product attributes, listing features, buyer history, and seller feedback and reputation. In our difference-in-difference estimation, we use data from October 2008 to September 2010, which includes all listing and transaction data in the year before and the year after the policy change.

One important feature of the data that we exploit is information on products' subcategories cataloged by eBay. There are about 400 subcategories such as Office, Lamps and Lighting, Beads and Jewelry Making, Video Game Memorabilia, Digital Cameras, and Makeup. A subcategory is the finest level of eBay's catalog that includes all items.[3]

Another important feature of these data is that we know when sellers publish their first listings on eBay. We treat this date as sellers' entry date. This information is difficult to obtain using scraped data. Additionally, we observe the number of incumbents in any month, which allows us to compute a normalized number of entrants across the subcategories–entrant ratio.

Finally, the use of internal data allows us to observe how many items are sold by sellers in different time periods. This is the denominator of calculating our preferred quality measure–effective percentage positive (EPP), which is the number of positive feedback transactions divided by the number of total transactions over a given period. Nosko and Tadelis [2015] show that EPP contains much more information on transaction quality than conventional feedback and reputation scores.

6 Empirical Strategy

We use the policy change described in section 3 as a quasi-experiment. This policy change causes a significant decrease in the share and number of badged sellers, as shown in Figure 1.

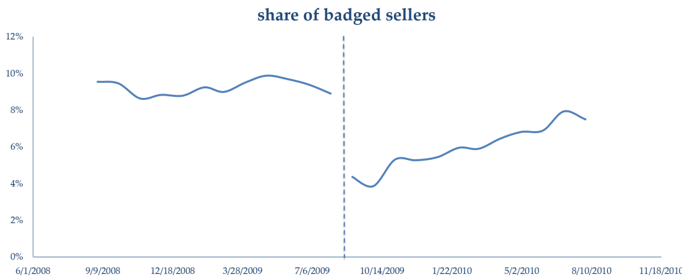
Furthermore, Figure 2 shows that the policy impact differs by subcategories, ranging from roughly 0% to -30%. The plotted policy impacts are the estimated changes in the share of badged sellers before and after the policy change using the following event study approach:

$$Share\_Badged_{ct} = \beta_c Policy + \eta_c + \alpha t + \epsilon_{ct},$$

where $Share\_Badged_{ct}$ is the share of badged sellers in subcategory c in month t; $Policy$ is a dummy variable which equals 1 after the policy change; η_c are subcategory fixed effects; α is a linear time

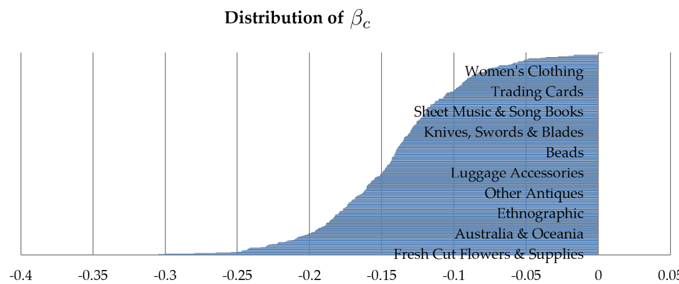
[3] Prior work has used product ID for finer cataloging (Hui et al. [2016] and Hui [2017]), but these product IDs are only defined for homogeneous products such as electronics and books.

Figure 1: Share of Badged Sellers



Notes: "Badge" refers to the PowerSeller badge before the policy change and to the eTRS badge after the policy change.

Figure 2: Heterogeneous Impact of Policy Change on Different Sub-Categories



trend; and ϵ_{ct} are standard error terms. In addition to use the absolute value of estimated changes in share of badged sellers across categories, we also rank these categories by these estimated changes use the percentiles across categories as the estimated policy impacts, namely $\widehat{\beta_c^{pct}}$ in place of $\widehat{\beta_c}$, as robustness checks.

Our identification strategy exploits the variability in changes in share of badged sellers ($\widehat{\beta_c}$) in different subcategories to identify the impact of this policy on the number and quality of entrants using a continuous difference-in-difference (DiD) approach. In particular, we estimate the policy impact by comparing the changes in number and quality of entrants in the subcategories that experience larger estimated policy impacts before and after the policy change against "baseline" changes of these two measures in subcategories that experience smaller estimated policy impacts over the same time periods. This DiD approach is continuous in the sense that the "treatments" (i.e., policy impacts on share of badged sellers across subcategories) take continuous values between 0 and 1. Specifically, the DiD specification is given as

$$Y_{ct} = \gamma \widehat{\beta_c} Policy + \mu_c + \xi_t + \epsilon_{ct}, \tag{1}$$

where Y_{ct} are variables of interest in subcategory c in month t, such as entrant ratios; $\widehat{\beta_c}$ is the estimated policy impact on the share of badged sellers shown in Figure 2; μ_c are subcategory fixed effects; ξ_t are month fixed effects; and ϵ_{ct} are standard error terms.

Our coefficient of interest is γ, which indicates the percentage change in entrant ratio as a result of variations in the share of badged sellers due to the policy change. Specifically, a statistically significant negative $\widehat{\gamma}$ means that a larger decrease in the share of badged sellers increases the entrant ratio, because the signs of $\widehat{\beta_c}$ are negative.

The DiD approach controls for time-invariant differences in the variables of interest across subcategories; for example, the entrant ratio in the clothing market is higher than that in the antiques market. The approach also controls for differences in the entrant ratio over time, for example, changes in the overall popularity of selling on eBay over time. As in most DiD approaches, our key identification assumption to ensure a causal interpretation of $\widehat{\gamma}$ is that serially correlated unobserved errors do not systematically correlate with $\widehat{\beta_c}$ and Y_{ct} simultaneously. We believe that this is a reasonable assumption because 1) the policy change applies to all subcategories without any selection issues, and 2) it is difficult for sellers and buyers to anticipate eBay's forthcoming policies.

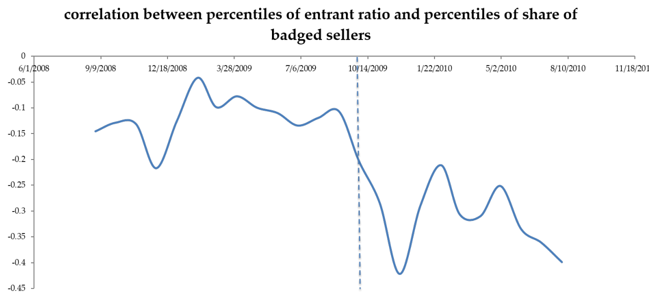
7 Results

In this section, we estimate the effects of the policy change on the number and quality of entrants, as well as those of incumbents with different badge statuses.

7.1 Effect on Number of Entrants

As shown in Figure 2, after the policy change, the share of badged sellers differentially changes across different subcategories. We now provide evidence that this distribution of changes has meaningful implications for the entrant cohorts. Figure 3 reports the correlation between the size of the entrant cohort and the share of badged sellers in each subcategory. Given the change in both size of entrant cohort and share of badged sellers, to be able to compare the results before and after the policy change, we need to normalize the two. To do so, we rank subcategories in both metrics each month and assign the percentile they are at to the subcategory. Figure 3 shows that there is indeed a negative correlation between the number of entrants and the share of badged sellers across subcategories (e.g., the higher the share of badged sellers in a subcategory, the smaller the size of

Figure 3: Market Structure and Entry



the entrant cohort in that subcategory). This negative correlation is present even before the policy change, but it becomes stronger after the policy change (following the dashed line), suggesting a variation in the entry pattern.

First, we would like to quantify the impact of the policy change on the number of entrants.

To further study the impact of the policy change on the number of entrants, we look at regression 1. Table 1 reports $\widehat{\gamma}$ from regression 1 for four outcome variables. To normalize across categories, we use the entrants' ratio $Entrant\_Ratio_{ct}$, which is defined as "flow over stock": the number of entrants divided by the number of incumbents (sellers who listed in $t-1$) in subcategory c in month t. We see in Panel A of Table 1 that the impact of the policy change is about -30% in the six-month window (data from three months before and three months after the policy change). We interpret this result as follows: a 10% larger decrease in the share of badged sellers leads to 3% more entrants. The impact of the policy change decreases to -20% if we expand our window length to 12 months. This lower estimate shows that the marginal impact from month 4 to month 6 is smaller than that from month 1 to month 3. In column 3, we compare categories 7 to 12 months after the policy change to capture long term effect of the policy.[4] The result show that the marginal impact of policy becomes -4.7% and is not statistically significant. These results suggest that the impact shrinks dramatically in a year and stabilizes towards a new steady state after six months.

To observe the differential impact of the policy change on the number of entrants, we illustrate its impact on the top and bottom 20 percentiles of the affected subcategories as determined by regression 1, $\widehat{\beta_c}$. Figure 4a shows that in the top 20 percentile of categories, the share of badged sellers decreases from about 35% to less than 15% after the policy change, whereas in the bottom 20 percentile, the share of badged sellers decreases from about 18% to 10%. There is no obvious variation in the number of entrants for the bottom 20 percentiles of subcategories, whereas the

[4] We do not include longer time periods, as eBay has made significant changes to their trust mechanism.

average number of entrants to the top 20 percentiles has increased by 25%. Additionally, entry rates seem to stabilize after three months.

7.2 Average Performance of the Entrant Cohort

Now, we study how the performance, or quality, of the entrant cohort is affected by this policy change. We look at three measures of performance: effective percentage positive (EPP), the average sales' quantity, and the survival rate.

First, we study the effective percentage positive (EPP), the number of positive feedback transactions divided by the number of total transactions over a given period. Nosko and Tadelis [2015] show that EPP contains more information on transaction quality than conventional feedback ratings. Specifically, we define a seller's EPP using the number of transactions and positive feedbacks in the first year of entry, conditional on the entrant's survival (i.e., selling at least one item) in the second year. We condition both measures on survival in the second year to eliminate the survival effect. We have also tried alternative definition of EPPs and also without conditioning on survival of sellers, and the results are reported in section 8 and show similar patterns.

Panel B in Table 1 shows that there is an increase in entrants' average quality in the more affected subcategories, as measured by the EPP, after the policy change. This effect stabilizes from -10% to -6.6% as we expand the window length from six to twelve months. Column 3 shows that the increase in EPP persists from the seventh to the twelfth month after the policy change, suggesting that its quality effect is persistent over longer time period.

Figure 4b shows the average EPP for entrants in the top and bottom 20 percentiles of the affected subcategories. Note that EPPs are decreasing on eBay over time, but the average EPP is higher for the top 20 percentile of the affected subcategories compared to the bottom 20 percentile of subcategories.

Second, we look at the sales quantity during a seller's first year of entry, conditional on entrant's survival in the second year. Positive and significant coefficient in column 1 of Panel C shows that over the short term, sales quantity from the entrants is smaller in subcategories affected more by the policy change; however, this drop becomes insignificant when considering longer time period. Additionally, from the seventh to the twelfth month after the policy change, the change in the entrants' sales quantity remains statistically insignificant. This result indicates that the average entrant is smaller in the subcategories most affected by the policy change. Recall that these categories have more entrants on average as well. As a result, this regression does not necessary

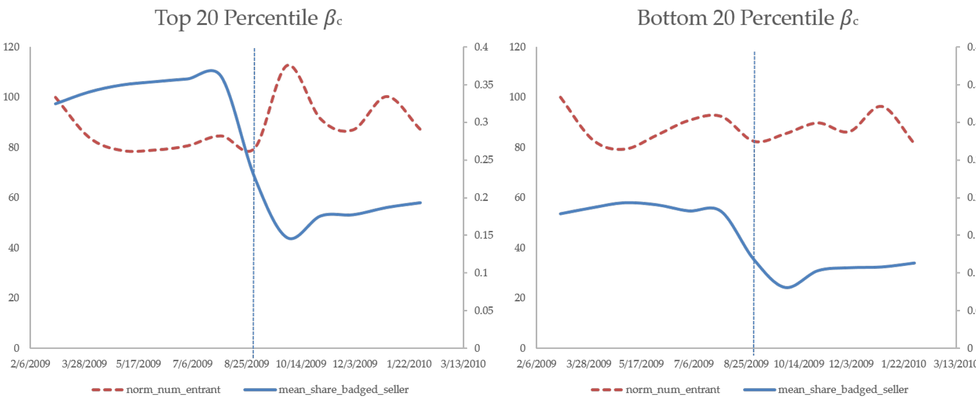
Table 1: Policy Impact on Number and Quality of Entrants

Panel A. Entrant Ratio			
	(1)	(2)	(3)
	6-Month Window	12-Month Window	Month 7 to 12
Estimate	-0.299***	-0.204***	-0.047
	(0.041)	(0.027)	(0.051)
R^2	0.913	0.889	0.691
Panel B. EPP Conditional on Survival in the Second Year			
	6-Month Window	12-Month Window	Month 7 to 12
Estimate	-0.102***	-0.066***	-0.062**
	(0.034)	(0.023)	(0.026)
R^2	0.758	0.717	0.690
Panel C. Sales Quantity Conditional on Survival in the Second Year			
	6-Month Window	12-Month Window	Month 7 to 12
Estimate	15.082***	2.867	2.560
	(4.455)	(2.877)	(3.533)
R^2	0.605	0.549	0.505
Panel D. Total Sales			
	6-Month Window	12-Month Window	Month 7 to 12
Estimate	-6883	-9895***	-4737
	(6611)	(4025)	(3678)
R^2	0.930	0.930	0.942
Panel E. 2nd-yr Sales Quantity/ # Entrants			
	6-Month Window	12-Month Window	Month 7 to 12
Estimate	5.573**	2.002	3.046
	(0.039)	(2.042)	(2.121)
R^2	0.496	0.404	0.381
Panel F. 2nd-yr Sales Quantity			
	6-Month Window	12-Month Window	Month 7 to 12
Estimate	1098	-3015	11644
	(10375)	(6801)	(7477)
R^2	0.745	0.736	0.723
Observations	2,501	4,996	10,012

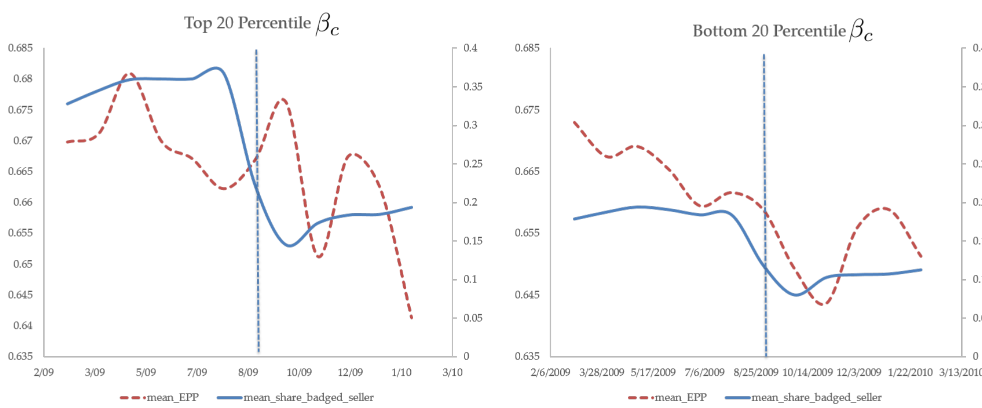
Notes: The regressions are at the category-month levels. Entrant ratio is defined as the number of entrants divided by the number of incumbents. EPP is defined as the number of positive feedback divided by the total number of feedback. An entrants survives the second year if she sells at least one item in the second year after entry.

*** indicates significance at p = 0.01; ** indicates p = 0.05.

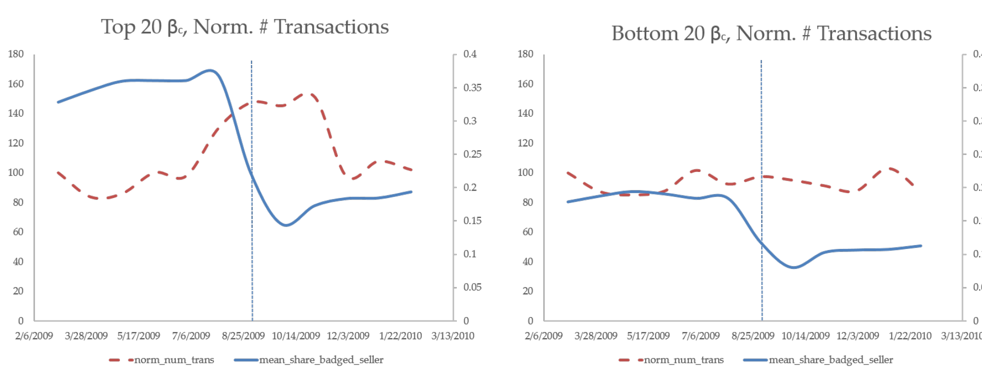
Figure 4: Policy Impact on Entrants



(a) Policy Impact on Number of Entrants



(b) Policy Impact on EPP



(c) Policy Impact on Sales

Notes: The vertical axis on the right shows the share of badged sellers, and the one on the left shows the normalized number of entrants. The numbers of entrants in the six-month period before the policy change are normalized to 100. The figure on the left is for the top 20 percentile of the affected subcategories and the one on the right is for the bottom 20 percentile of the affected subcategories.

imply a decrease in the total number of sales by entrants. In fact, when we run a regression of sales by entrants, as indicated by Panel D in Table 1, we observe that the subcategories more affected by the policy change have a higher total number of sales by entrants. Additionally, we plot analogous graphs to analyze sales by the top and bottom 20 percentiles of the affected subcategories in Figure 4c, which shows a short-run surge in the number of total sales in the top 20 percentile of the affected subcategories with very little impact on the bottom 20 percentile of the affected subcategories.

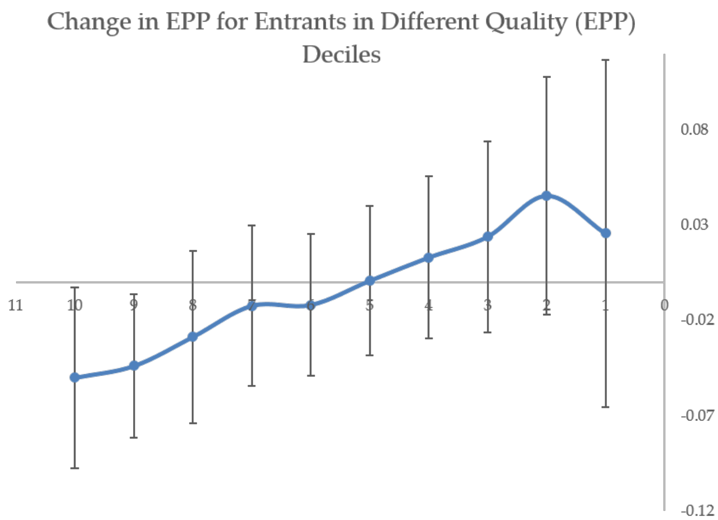
Finally, we study entrants' survival by looking at the average size of entrants a year after entry, with giving 0 to sellers who do not sell any items in their second year. The advantage of this measure over a simple survival dummy is that it is able to capture a seller's change in size as well as seller's exit.[5] Panel E shows that the average sales quantity in the second year per entrant decreases more for entrants in categories that are more affected by the policy change. This observation is consistent with the fact that the entrants tend to be smaller in the affected area as shown in Panel C. However, this effect does not stay significant when we consider longer time period or if we consider 7 to 12 months after the policy change. Additionally, the total number of items sold by entrants in the second year does not change significantly, as shown in Panel F.

7.3 Quality Distribution of Entrant Cohort

An important test for our simple theory is how the distribution of entrants' quality varies after the policy change. The theory predicted that under mild assumptions, there should be more entrants of high quality, as being high-quality becomes more rewarding. Additionally, the theory predicted that sellers of low quality may enter more often if pooling with a better set of sellers would imply lower-quality sellers can receive higher average prices in equilibrium. To test this prediction, within each subcategories, we look at different deciles of sellers. For example, we look at entrants within the top 10 percentile as determined by their EPP score. Then we check if these EPPs have increased more for the subcategories more affected by the policy change. A positive number will indicate a fatter tail of the distribution on the right. Respectively, if we look at the bottom 10 percentile of entrants in terms of their EPP and compare the subcategories, a negative number means a fatter tail on the left. Another prediction was that the sellers who had a chance of becoming badged before and no longer have this opportunity after the policy change will enter less often. A distribution of entrants' quality with a fatter tail from both left and right will indicate a fewer

[5] Another method to study the survival rate is to have a dummy variable equal to zero if the seller does not sell any item in the second year. However, we believe that is not a very good measure, as many sellers, even if they quit selling professionally on eBay, may still sell occasionally on the platform.

Figure 5: Change in EPP for Entrants in Different Quality Deciles



Notes: Bars indicate 95% confidence intervals.

share of average-quality entrants.

We plot the change in EPP for entrants of different quality deciles in Figure 5. EPPs are computed based on the number of transactions in the first three years after entry. For consistency, we condition the EPP calculation on an entrant's survival in the second year. Entrants are counted every two months. To be able to take the average of cohorts, we restrict our attention to subcategories with at least 100 entrants. As a result, for each subcategory, we have three observations (six-month equivalent) before the policy change and three observations after it. Additionally, we only consider subcategories that have entry in all of the six two-month periods and remove subcategories with a small number of entrants. This leaves us with 228 out of the 400 subcategories.

The x-axis in Figure 5 indicates different quality deciles, with "10" being the lowest decile of EPP and "1" being the highest decile of EPP. The dots are point estimates of the changes in EPP for the entrant cohorts, and the bars are 95% confidence intervals. Although only a couple of the point estimates are statistically different from 0, we observe a monotonically increasing relationship that is consistent with our prediction that the quality distribution of entrants after the policy change varies and has fatter tails because sellers from the extremes of the quality distribution now have stronger incentives to enter.

7.4 Impact on Incumbents

The results in the previous subsections show that the policy change had an impact on the entry decision of sellers into different subcategories, and that this impact differed among entrants selling different quality levels, suggesting a selection-of-entrants interpretation. However, the impact on the quality sold by entrants could in principle be solely driven by a moral-hazard story, where similar entrants changed their behavior after the policy change depending on the subcategory they entered. Figure 6 plots the average EPP of all entrants and incumbents within six months of the policy change. As indicated in the figure, the average EPP of entrants has increased, while no apparent change in the average EPP of incumbents is observed. However, we might not observe any significant change in the average EPP of the incumbents, but there would be a change in the distribution of incumbents' quality.

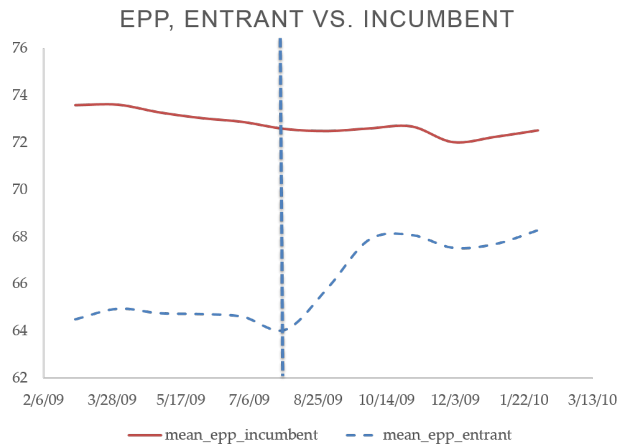
To address this concern, we study the behavior of different types of incumbent sellers. In Figure 7a, we plot the average monthly EPP for incumbents with different badging status. There are four groups of incumbents, with all possible combinations of their badging status before and after the policy change. We only show the incumbents that were never badged and those who were always badged; for the other two groups, we observe similar results. In particular, there is no obvious difference between the incumbents' EPP in 2009 (the year of the policy change) and their EPP in 2008 and 2010. This suggests that the change in the average monthly EPP observed in these two figures is due to seasonality.

We created a similar plot for sellers of different quality quartiles. We again note that there is no observable change in incumbents' EPP after the policy change after removing seasonality. Thus, the incumbents do not seem to change their behavior in response to the policy change. This observation suggests that the increase in quality provided by entrants at the tails of the quality distribution is more likely due to improved selection rather than to behavioral changes.

7.5 Impact on Badge Premium

We study how badge premiums change for the four groups of sellers: BB, BN, NB, NN, where B indicates that the seller is badged and N indicates that the seller is not badged. We use the BB group as an example to illustrate how these groups are defined: 1) We find if a seller is badged for a given month. 2) A seller belongs to the BB group if she is a Powerseller for at least 91.6% of her active months on eBay before the policy change (eleven out of twelve months) and is eTRS

Figure 6: Change in EPP of Incumbents and Entrants



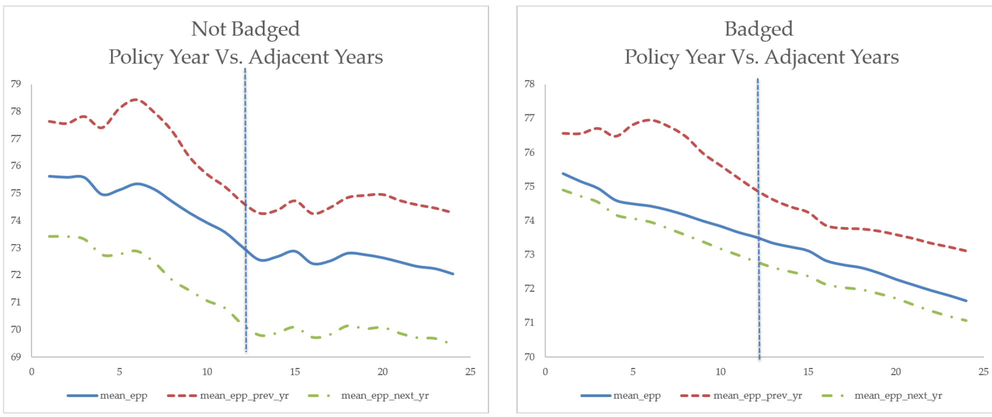
for at least 91.6% of her active months after the policy change. Note that sellers in all these four groups must be active before and after the policy change. For robustness, we also change the sample period from twelve-month period to six-month period and three-month period. The results are qualitatively similar.

We take the average price of successful fixed price items in each product ID as the value of that product in that category. We then define the relative price for each item as the price over the value of the item, following the previous literature studying price changes on eBay (e.g Einav et al. [2011] and Hui et al. [2016]). In table 2, we find that all groups of sellers experience an increase in the relative price except for group BN. The magnitude in descending order is NB (8.6%), BB (5.4%), NN (2.7%) and BN (-0.6%). We perform the analyses with and without controlling for seller fixed effects. When we do not control for fixed effecdts, we capture buyers perception on the badge value for all sellers in the market. On the other hand, controlling seller fixed effects allows us to study within-seller change in outcome variables after the policy change.

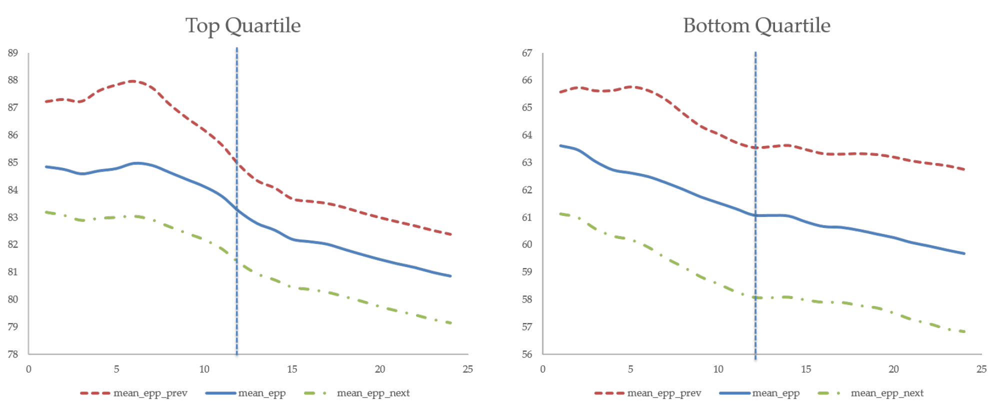
Out interpretation is that, the sellers in the NB group experience an increase in the sales outcome because they gained the reputation badge. The sellers in the BB group experience an increase because the new badge conveys more information and therefore is more valuable than the old one. The sellers in the NN group are better off because they are being pooled with higher-quality sellers than before. Finally, the sellers in the BN group are worse off because they lose their badge.

We then studied badge premium in terms of sales probability and quantity. The results in table 3 are qualitatively similar to those in table 2. In particular, quantity, the results are qualitatively

Figure 7: Change in EPP of Incumbents



(a) Badged Vs. Non-Badged



(b) Top Vs. Bottom 20 Percentile

Notes: The solid lines correspond to EPPs in the year when the policy change took place (2009). The dashed lines and the dashed-dotted lines are for EPPs in the year before and year after the policy year, respectively. The x-axis indicates months, and its interaction with the vertical dotted line is 12.

Table 2: Change in Badge Premium: Relative Price

	6M Win	4M Win	2M Win	6M Win	4M Win	2M Win
BB*Pol	0.027***	0.018***	0.017***	0.001	0.014***	0.014***
	(0.002)	(0.003)	(0.003)	(0.002)	(0.002)	(0.003)
BN*Pol	-0.033***	-0.018***	-0.009***	-0.015***	0.014***	0.014***
	(0.002)	(0.002)	(0.002)	(0.002)	(0.002)	(0.002)
NB*Pol	0.059***	0.051***	-0.005	0.014*	0.009	0.017*
	(0.008)	(0.010)	(0.011)	(0.009)	(0.008)	(0.010)
Seller FE				✓	✓	✓
R^2	0.004	0.004	0.006	0.944	0.971	0.955
Benchmark Change in NN Group						
Pol	0.027***	0.032***	0.005	0.026***	-0.016***	-0.028***
	(0.008)	(0.004)	(0.004)	(0.008)	(0.004)	(0.004)
Seller FE				✓	✓	✓

Notes: We also control for BB, BN, and NB, and week dummies. The benchmark changes for the NN group are displayed in the second panel. The estimation on benchmark cases also controls for $log(Price)$, week dummies, and the constant term. B indicates that the seller is badged and N indicates that the seller is not badged. The first letter refers to the the seller's status before the policy change, and the second letter refers to the seller's status after the policy change.

*** indicates significance at p = 0.01; ** indicates p = 0.05 ; * indicates p = 0.1.

similar, and the magnitude of changes in descending order is NB, BB, NN, and BN.

7.6 Impact on Market Shares

In this section, we analyze the policy impact on market share for different groups of sellers. We define market share based on sellers' transactions in one-month or three-month intervals. We use three months so that the market share of entrants is not too small.

Panel A in Table 4 shows that the market share of entrants as a whole is larger in categories that are more affected by the policy change: a 10% larger decrease in share of badged seller leads to an increase in market share for entrants by 0.49% and 2.25%, respectively, depending on whether we calculate market share based on one-month or three-month intervals. Relatedly, Panel B shows that the average size of entrants is smaller in categories that are more affected by the policy change: a 10% larger decrease in share of badged seller leads to an decrease in market share for entrants by 0.08% and 0.03%, respectively, depending on the window length for defining market share. These two results together show that entrants as a whole are grabbing a larger market share as their quality has increased after the policy change, but each individual entrant is smaller due to

Table 3: Change in Badge Premium: Sales Probability and Sales Quantity

Panel A. Sales Probability						
	6M Win	4M Win	2M Win	6M Win	4M Win	2M Win
BB*Pol	0.015***	0.023***	0.016***	0.033***	0.031***	0.024***
	(4.E-04)	(4.E-04)	(0.001)	(4.E-04)	(4.E-04)	(0.001)
BN*Pol	0.006***	0.016***	0.002***	0.007***	0.010***	-0.001***
	(2.E-04)	(3.E-04)	(4.E-04)	(3.E-04)	(3.E-04)	(4.E-04)
NB*Pol	2.E-04	0.018***	0.057***	0.074***	0.084***	0.097***
	(0.002)	(0.002)	(0.003)	(0.002)	(0.003)	(0.003)
Seller FE				✓	✓	✓
R^2	0.329	0.318	0.354	0.729	0.741	0.808
Benchmark Change in NN Group						
Pol	0.008 ***	-0.018***	-0.009***	0.045***	0.001	0.017***
	(0.001)	(0.001)	(0.004)	(0.001)	(0.001)	(0.001)
Seller FE				✓	✓	✓
Panel B. Sales Quantity						
	6M Win	4M Win	2M Win	6M Win	4M Win	2M Win
BB*Pol	0.003	0.012***	0.036***	0.027***	0.037***	0.032***
	0.003	0.003	0.004	0.005	0.003	(0.005)
BN*Pol	-0.003	0.006***	-0.008***	0.005***	0.006***	-0.010***
	(0.002)	(0.002)	(0.003)	(0.003)	(0.002)	(0.004)
NB*Pol	-0.077***	-0.086***	0.086***	-0.021	0.017*	0.221***
	(0.015)	(0.013)	(0.019)	(0.026)	(0.019)	(0.026)
Seller FE				✓	✓	✓
R^2	0.531	0.638	0.686	0.533	0.840	0.862
Benchmark Change in NN Group						
Pol	-0.046***	-0.026***	-0.044***	0.37***	-4E-4	0.019**
	(0.005)	(0.004)	(0.006)	(0.005)	(0.004)	(0.008)
Seller FE				✓	✓	✓

Notes: We also control for $log(Price)$, BB, BN, and NB, and week dummies. The benchmark changes for the NN group are displayed in the second panel. The estimation on benchmark cases also controls for $log(Price)$, week dummies, and the constant term. B indicates that the seller is badged and N indicates that the seller is not badged. The first letter refers to seller's status before the policy change, and the second letter refers to the seller's status after the policy change.

*** indicates significance at p = 0.01; ** indicates p = 0.05 ; * indicates p = 0.1.

larger competition induced by a larger number of entrants. This suggests higher consumer welfare resulting from higher competition.

Table 4 also shows that the average size of the seller in the NN group increases more in categories that are more affected by the policy change. This finding is consistent with our model that non-badged sellers are being pooled with higher-quality sellers after the policy change, and therefore are valued more. We also observe a similar-magnitude change for sellers in the BN group when we look at their market share in the three months after their status change. On the other hand, we do not find any significant change for sellers in the BB and NB groups. In a robustness check, we find similar results when we use normalized change in the share of badged sellers in Table 6.

8 Robustness Check

In this section, we check the robustness of our regression results. In particular, we use percentiles of $\widehat{\beta}_c$ across subcategories in Regression 1. This normalization enables scale-free comparisons across subcategories. The results in Table 5 are consistent with the results in Table 1. Note that all the estimates switched signs because a larger percentile of change in the share of badged sellers corresponds to a larger decrease in this share. Additionally, the results in this table are easier to interpret as $\widehat{\beta}_c$ takes values between 0 and 1.

In another robustness check, we consider alternative definitions for EPP. EPP is the average number of positive feedback over the total number of transactions. Considering different intervals for the transactions will result in slightly different numbers. In Figure 8a, EPP is defined over transactions of a seller within the past six months of any given month. As shown, there is no change in the average quality of incumbents, but there is an increase in the average quality of entrants immediately after the policy change. In Figure 8b, EPP is estimated over the transactions of the sellers in the following six months. The result does not change with this alternative definition.

In Figure 9 we plot a parallel to the Figure 4 with the difference that we show the top and bottom 10 percentiles. The result does not change as we change the percentiles of the subcategories. We have considered other subsections as well as removing the top and bottom one–five percentiles and the result remains the same.

Table 4: Change in Market Share for Different Groups

Panel A. Change in Market Share for Different Groups					
Market Share Based on One-Month Intervals					
	Entrants	BB	BN	NB	NN
Estimate	-0.049***	0.727***	-0.170***	-0.059***	-0.559***
	(0.019)	(0.035)	(0.023)	(0.017)	(0.035)
R^2	0.825	0.882	0.843	0.439	0.801
Observations	5129	5129	4776	4902	5151
Market Share Based on Three-Month Intervals					
	Entrants	BB	BN	NB	NN
Estimate	-0.225***	1.854***	-0.509***	-0.258***	-1.803***
	(0.075)	(0.644)	(0.069)	(0.082)	(0.158)
R^2	0.525	0.435	0.797	0.728	0.778
Observations	4710	5113	4979	5072	5157
Panel B. Change in Average Seller Size for Different Groups					
Market Share Based on One-Month Intervals					
	Entrants	BB	BN	NB	NN
Estimate	0.008**	0.004	-0.007	-0.002	-0.009**
	(0.003)	(0.004)	(0.008)	(0.006)	(0.004)
R^2	0.572	0.958	0.323	0.412	0.738
Market Share Based on Three-Month Intervals					
	Entrants	BB	BN	NB	NN
Estimate	0.003**	0.004	-0.009**	-0.005	-0.008***
	(0.001)	(0.002)	(0.004)	(0.004)	(0.003)
R^2	0.582	0.989	0.411	0.596	0.668

Notes: We use data from six months before and six months after the policy change. Definition of the four groups are defined in the text. Market shares are defined based on sellers' sales in one month or three months .

*** indicates significance at p = 0.01; ** indicates p = 0.05.

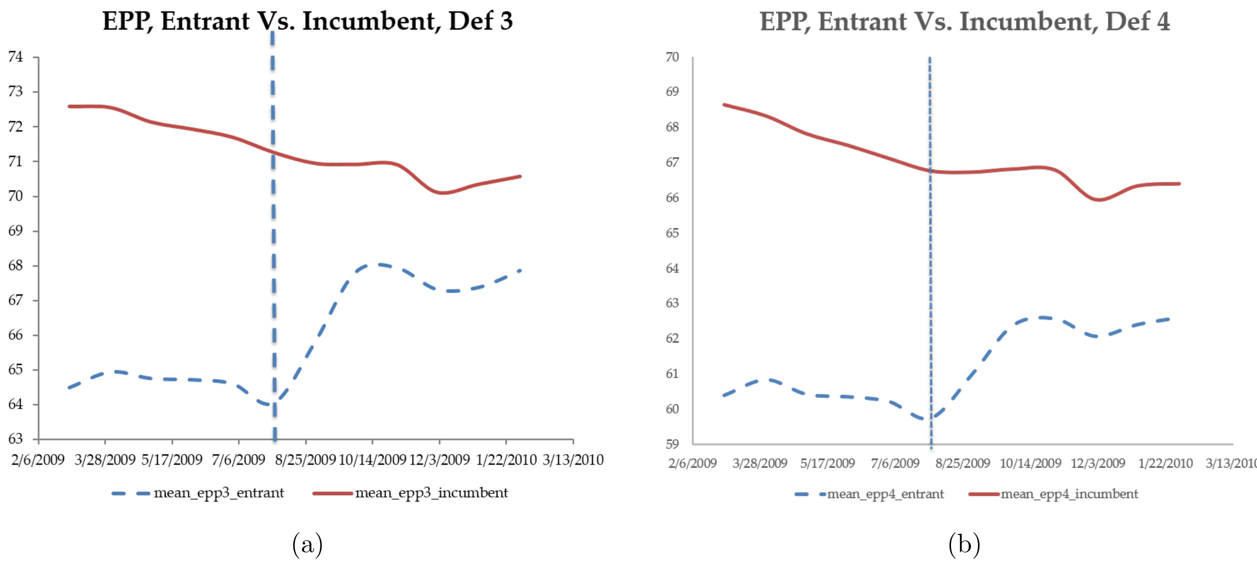
Table 5: Robustness Check: Policy Impact on Number and Quality of Entrants

Panel A. Entrant Ratio			
	6-Month Window	12-Month Window	Month 7 to 12
Estimate	0.046***	0.030***	0.015
	(0.006)	(0.004)	(0.009)
R^2	0.914	0.889	0.687
Panel B. EPP Conditional on Survival in the Second Year			
	6-Month Window	12-Month Window	Month 7 to 12
Estimate	0.010*	0.008**	0.007
	(0.006)	(0.004)	(0.005)
R^2	0.757	0.717	0.691
Panel C. Sales Quantity Conditional on Survival in the Second Year			
	6-Month Window	12-Month Window	Month 7 to 12
Estimate	-2.159***	-0.527	-0.411
	(0.735)	(0.512)	(0.632)
R^2	0.605	0.549	0.505
Panel D. Total Sales			
	6-Month Window	12-Month Window	Month 7 to 12
Estimate	2101*	1791***	739
	(1096)	(726)	(659)
R^2	0.927	0.928	0.942
Panel E. 2nd-yr Sales Quantity/ # Entrants			
	6-Month Window	12-Month Window	Month 7 to 12
Estimate	-0.974**	-0.511	-0.729*
	(0.499)	(0.378)	(0.390)
R^2	2.518	2.508	0.381
Panel F. 2nd-yr Sales Quantity			
	6-Month Window	12-Month Window	Month 7 to 12
Estimate	-371	422	-2973**
	(1921)	(1258)	(1374)
R^2	0.745	0.736	0.722
Observations	2,501	4,996	10,012

Notes: The regressions are at the category-month levels. Entrant ratio is defined as the number of entrants divided by the number of incumbents. EPP is defined as the number of positive feedback divided by the total number of feedback. An entrant survives the second year if she sells at least one item in the second year after entry.

*** indicates significance at p = 0.01; ** indicates p = 0.05 ; * indicates p = 0.1.

Figure 8: Robustness: Change in EPP of Incumbents and Entrants



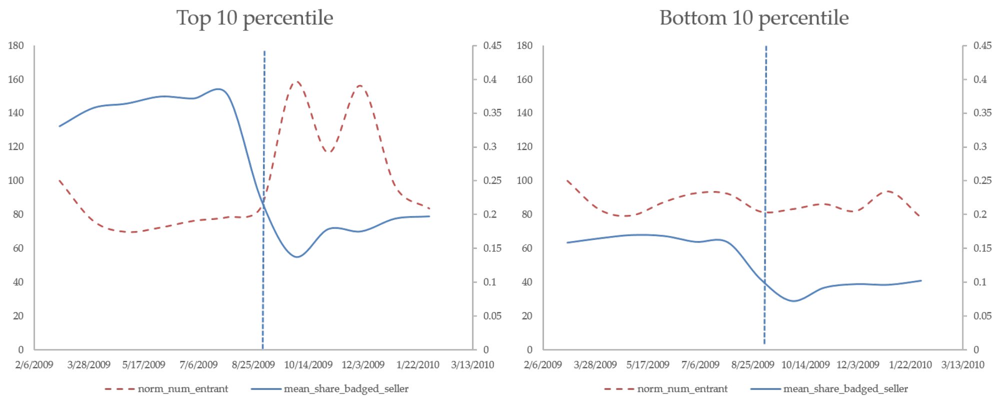
Notes: In definition 3, EPP is calculated with transactions from six months before the policy change. In definition 4, EPP is calculated with transactions from six months after the policy change.

Table 6: Change in Market Share for Different Groups

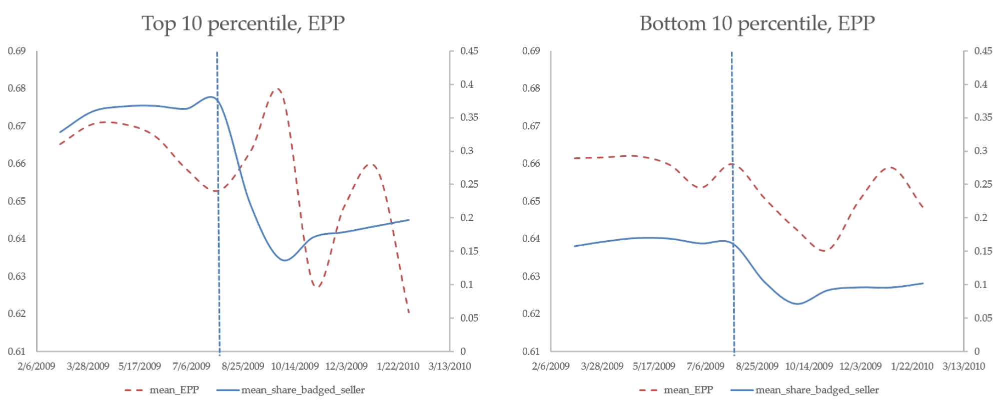
Change in Seller Size for Different Groups					
Market Share Based on One-Month Intervals					
	Entrants	BB	BN	NB	NN
Estimate	0.000	-0.001*	0.000	0.000	0.003***
	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)
R^2	0.581	0.950	0.384	0.420	0.741
Observations	5129	5129	4776	4902	5151
Market Share Based on Three-Month Intervals					
	Entrants	BB	BN	NB	NN
Estimate	0.000	-0.001***	-0.001	0.001	0.003***
	(0.000)	(0.000)	(0.001)	(0.001)	(0.001)
R^2	0.547	0.985	0.512	0.670	0.743
Observations	5138	5113	4979	5072	5157

Notes: Definition of the four groups are given in the text.
*** indicates significance at p = 0.01.

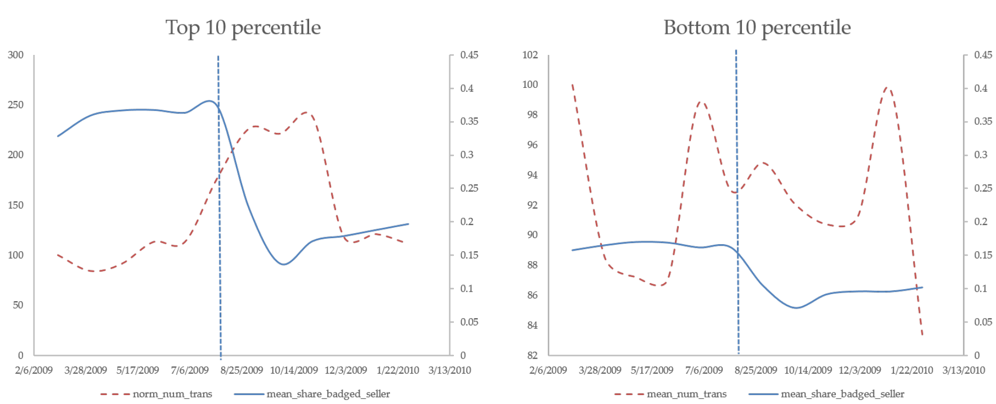
Figure 9: Robust: Policy Impact on Entrants, Top and Bottom 10 Percentile



(a) Policy Impact on Number of Entrants



(b) Policy Impact on EPP



(c) Policy Impact on Sales

Notes:The axis for share of badged sellers areis on the right, and the axis for normalized number of entrants, EPP, and normalized number of transactions areis on the left. The numbers of entrants in the six month-months before the policy change are normalized to 100. The numbers of transactions in the six monthmonths before the policy change are normalized to 100.

Table 7: Change in Badge Premium in Price, Single-Item Listings

	6M Win	4M Win	2M Win	6M Win	4M Win	2M Win
BB*Pol	0.018***	0.007***	0.008***	0.001	4.20E-06	-0.001
	(0.002)	(0.002)	(0.003)	(0.002)	(0.002)	(0.003)
BN*Pol	0.012***	0.008***	0.002	-0.01***	-0.007***	-0.005**
	(0.001)	(0.002)	(0.002)	(0.001)	(0.002)	(0.002)
NB*Pol	0.055***	0.035***	-0.001	0.009	0.012	0.007
	(0.007)	(0.01)	(0.014)	(0.007)	(0.010)	(0.013)
Seller FE				✓	✓	✓
R^2	0.007	0.006	0.006	0.271	0.261	0.289

Notes: We also control for $log(Price)$, BB, BN, and NB, and week dummies. The estimation on benchmark cases also controls for $log(Price)$, week dummies, and the constant term. B indicates that the seller is badged and N indicates that the seller is not badged.The first letter refers to the status of the seller before the policy change, whileand the second letter refers to itsthe status of the seller after the policy change.

*** indicates significance at p = 0.01; ** for p = 0.05 ; * for p = 0.1.

9 Conclusion

Following a policy change on eBay, more demanding criteria and more precise information are used to award a quality-signalling badge to sellers. We use this change to gauge insight into the effects of more stringent certification and reputation measures on entry, which is a hard-to-study relationship. We exploit the differential impact of the policy change on different subcategories of sellers for identification, and document a negative correlation between the share of badged sellers and the rate of entry across categories affected by the change. Categories that experience a higher reduction in the share of badged sellers because of the policy change have larger entry rates after the policy change. However, this effect is temporary, and tends to disappear once the market adjusts to the new equilibrium after about six months.

We also find that the distribution of quality provided by entrants has fatter tails after the policy change. This finding is consistent with the prediction of a simple model where a high bar for certification implies that entrants from both extremes of the quality distribution have stronger incentives to enter.We also find a significant increase in the overall quality provided by entrants in the more affected subcategories, as measured by the EPP, an increase that, contrary to that of entry rates, persists even from the seventh to the twelfth month after the policy. We find nochange in the quality provided by incumbents, instead, which suggests that the observed change in the distribution of quality provided by entrants is indeed likely to be linked to selection rather than to

Table 8: Change in Badge Premium in Sales Probability and Quantity, Single-Item Listings

Panel A. Sales Probability						
	6M Win	4M Win	2M Win	6M Win	4M Win	2M Win
BB*Pol	0.023***	0.025***	0.016***	0.038***	0.032***	0.021***
	(5.E-04)	(5.E-04)	(0.001)	(0.001)	(0.001)	(0.001)
BN*Pol	0.006***	0.012***	0.002***	0.006***	0.012***	0.004***
	(3.E-04)	(4.E-04)	(0.001)	(4.E-04)	(4.E-04)	(0.001)
NB*Pol	0.006***	0.031***	0.064***	0.108***	0.129***	0.125***
	(0.002)	(0.003)	(0.004)	(0.003)	(0.004)	(0.005)
Seller FE				✓	✓	✓
R^2	0.379	0.364	0.408	0.788	0.797	0.849
Panel B. Sales Quantity						
	6M Win	4M Win	2M Win	6M Win	4M Win	2M Win
BB*Pol	0.016***	0.021***	0.014***	0.032***	0.031***	0.020***
	(5.E-04)	(5.E-04)	(0.001)	(0.001)	(0.001)	(0.001)
BN*Pol	0.007***	0.012***	0.003***	0.005***	0.011***	0.004***
	(3.E-04)	(4.E-04)	(0.001)	(4.E-04)	(4.E-04)	(0.001)
NB*Pol	0.019***	0.043***	0.069***	0.105***	0.126***	0.125***
	(0.002)	(0.003)	(0.004)	(0.003)	(0.004)	(0.005)
Seller FE				✓	✓	✓
R^2	0.367	0.352	0.398	0.776	0.786	0.841

Notes: We also control for $log(Price)$, BB, BN, and NB, and week dummies. The estimation on benchmark cases also controls for $log(Price)$, week dummies, and the constant term. B indicates that the seller is badged and N indicates that the seller is not badged.The first letter refers to the status of the seller before the policy change, whileand the second letter refers to itsthe status of the seller after the policy change.

*** indicates significance at p = 0.01; ** for p = 0.05 ; * for p = 0.1.

a change in entrants' behavior. These results indicate that the availability and precision of past performance information are important not only for the rate of entry in a market, but also for the quality of who is actually entering hence for how markets evolve in the long run. This finding has direct implications for the design of reputation and certification mechanisms in electronic and other markets plagued by information asymmetries, including public procurement markets.

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APPENDIX