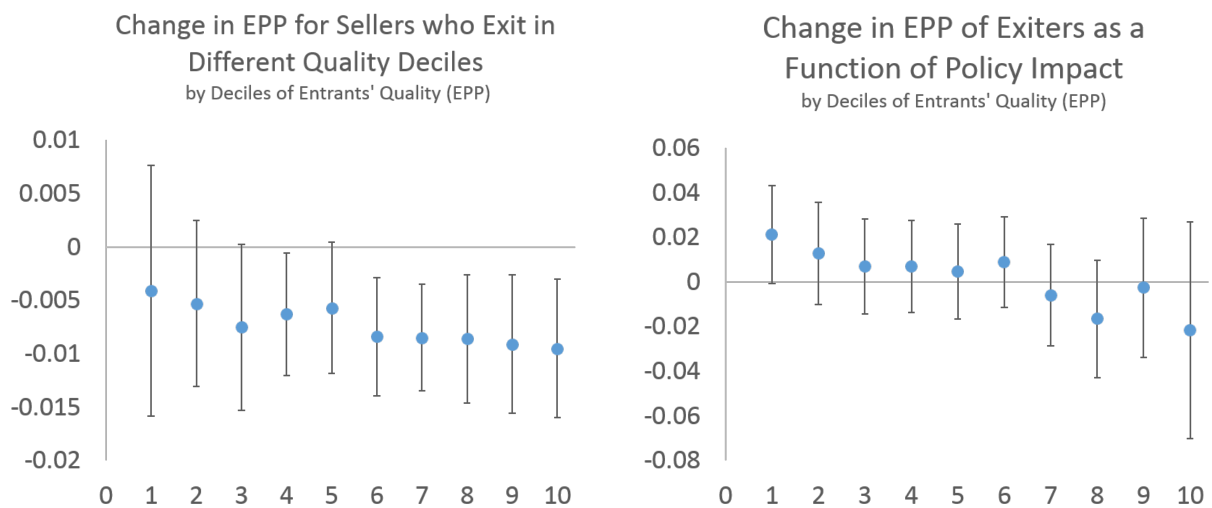
Online Appendix for: "Raising the Bar: Certification Thresholds and Market Outcomes"

Xiang Hui Maryam Saeedi Giancarlo Spagnolo Steve Tadelis

September 20, 2021

Contents

Figure 1: Change in EPP for Sellers Who Exit in Different Quality Deciles



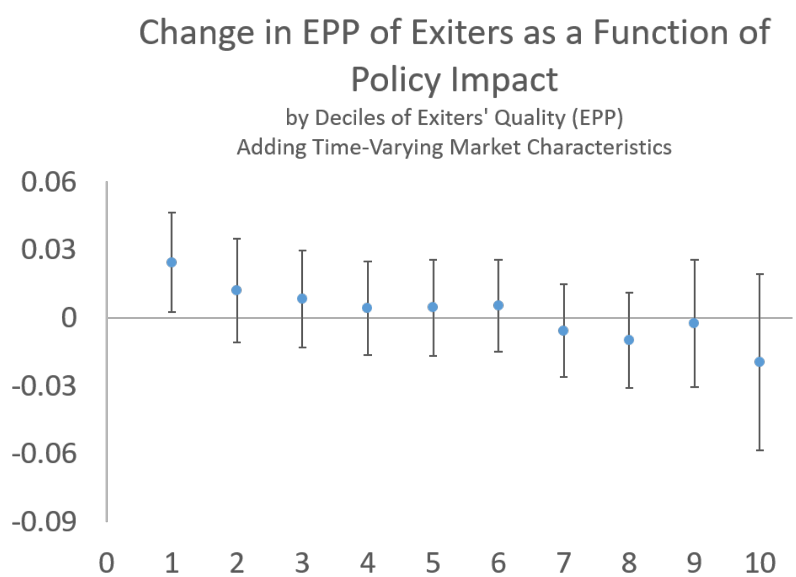
Notes: The left figure shows the average within-subcategory change in EPP. The right figure shows the across-subcategory change in EPP as a function of policy exposure. Bars indicate 95% confidence intervals.

1 Quality Distribution of Exiters: Thinner Tails

In this section, we study the natural complement to entry, which is changes in the quality distribution of sellers who exit. Figure 1 shows the regression results for each decile of sellers who exit, with the left panel plotting within-subcategory changes and the right panel plotting across-subcategory changes. We define a seller as exited if she does not list any item on the market in a year. A positive coefficient for decile 1 in the left figure means that the average quality of the lowest decile increases, and in the right figure it means that the average quality of the lowest decile increases more in more exposed markets, both implying a thinner tail on the left of the distribution in absolute and relative senses. In this figure, we see that the estimates generally decrease as the quality decile increases, which is the opposite trend of what we see in the figure for entrants in the paper. In the right figure, we rely on the DiD specification to control for a common time trend across categories. Positive coefficients for bottom deciles and negative coefficients for top deciles imply thinner tails on the left and right of the distribution, respectively, for the quality of sellers who exit. This result is the mirror image of the result that the policy change improves incumbents' outcomes at the tails, thereby reducing their incentive to exit and offering further evidence consistent with the predictions of our model.

Next, we rerun our second-stage regressions, controlling for time-varying market characteristics to test whether the estimates are robust to the inclusion of these time-varying market characteristics. The results are plotted in Figure 2 and are qualitatively the same.

Figure 2: Changes in EPP for Entrants in Different Quality Deciles, Controlling for Time-Varying Market Characteristics



Notes: The figure shows the across-subcategory change in EPP as a function of policy exposure using the DiD specification. Bars indicate 95% confidence intervals.

2 Lateral versus New Entrants

The model has further implications about heterogeneity in entry costs. There are two kinds of entrants into an eBay market-segment: new sellers who never sold before on eBay, and existing sellers who are laterally entering a new market segment after gaining experience in another market. One would expect experienced sellers who enter a new market segment laterally to be more familiar with eBay, and hence, on average, have lower entry costs than sellers who are new to the platform.[1] Our theoretical framework implies that these two kinds of entrants should behave differently. Namely, if the entry costs of new sellers are on average higher than those of existing sellers, then new sellers need to have higher quality to compensate for the entry cost relative to the increase in quality among existing sellers. By the same logic, there should be more entry of existing sellers relative to the increase in entry of new sellers. We find that among the entrants into new markets, about 13% are new sellers to eBay and 87% are existing sellers entering a new market.

Table 1 shows some summary statistics for these two groups. The first two columns show the entrant

[1]Note that laterally entering sellers can carry with them their reputation badges earned in other markets, consistent with that novel entering sellers have larger entry barrier.

Table 1: New versus Lateral Entry - Entrant Ratio and Share Badged

	Entrant Ratio		Share Badged	
	1 Mo. Before	1 Mo. After	1 Mo. Before	1 Mo. After
New Entrants	0.045	0.044	0%	0%
Lateral Entrants	0.295	0.303	11%	4%

Table 2: New versus Lateral Entry - Policy Change Impact

	New Sellers		Lateral Entrant	
Panel A. Entrant Ratio				
	(1)	(2)	(3)	(4)
	+/- 3 Months	+/- 6 Months	+/- 3 Months	+/- 6 Months
Estimate	0.033***	0.019***	0.124***	0.066***
	(0.006)	(0.004)	(0.021)	(0.016)
R^2	0.898	0.886	0.911	0.889
Panel B. EPP				
	(1)	(2)	(3)	(4)
	+/- 3 Months	+/- 6 Months	+/- 3 Months	+/- 6 Months
Estimate	0.077*	0.188***	0.043***	0.068***
	(0.043)	(0.059)	(0.014)	(0.019)
R^2	0.298	0.401	0.717	0.746

Notes: The regressions are performed at the subcategory-month level.
*** indicates significance at p $\leq$ 0.01; ** p $\leq$ 0.05; * p $\leq$ 0.10.

ratio (number of entrants divided by the number of incumbents), which does not change after the policy change. The entrant ratio is around 0.04 for new sellers and 0.3 for the existing sellers. The next two columns show the share of entrants of each group that had a badge prior to entering new categories. Obviously, no new entrant to the system can be badged upon entry; this is indicated by the 0% in the first row. When we look at existing sellers, prior to the policy change 11% of them had a badge and after the policy change only 4% of them did. This drop echoes the same drop in the share of badged sellers for the average seller.

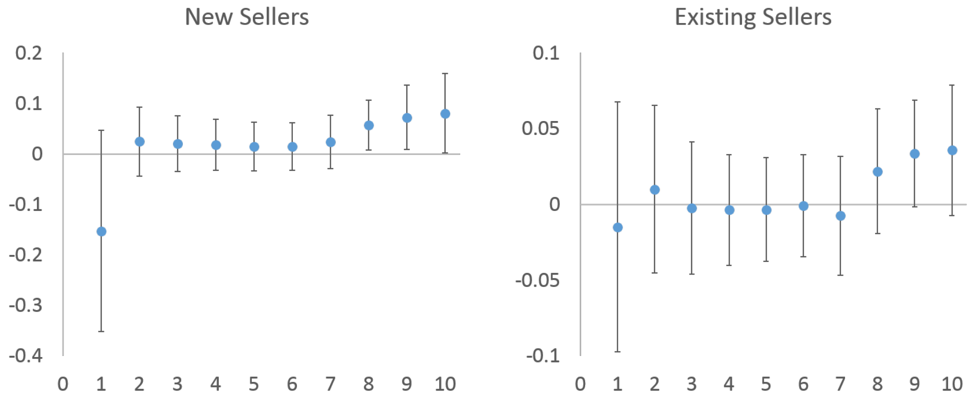
Through the lens of our theoretical model, these two kinds of entrants likely differ in their entry cost: the cost of entering eBay is higher than the cost of entering a new market for existing eBay sellers. On the one hand, the former requires sellers to understand the marketplace, its rules and regulations, and to decide which items to sell. On the other hand, the latter only requires that sellers decide to expand laterally into a new subcategory. Differences in the fixed cost of entry will result in differences in the entry decision of sellers as a result of the policy change.

We perform our previous DiD analyses for the two kinds separately (see Table 2). The relative magnitudes of these estimates are consistent with our theory. Namely, if the entry costs of starting to sell on eBay are higher than those of entering a new market for an existing seller, then new sellers need to have higher quality to compensate for the entry cost relative to the increase in quality among existing sellers. By the same logic, there should be more entry of existing sellers relative to the increase in entry of new sellers.

Finally, we regress the simulated policy exposure on the share of already badged sellers entering each market. The estimated coefficient is 0.65, and is highly significant. Hence, markets that were more affected by the change attract more previously badged entrants. Because certification is based on past performance, this can be regarded as a selection effect, suggesting that for this policy change, selection is indeed an important determinant of increased quality (EPP).

Finally, we plot the decile graphs for the two kinds of entrants separately, as in Figure 5 in the paper. Recall that "10" is the highest decile of EPP and "1" is the lowest decile. For each quality decile of a market,

Figure 3: Change in EPP for New versus Lateral Entrants in Different Quality Deciles: Simulation Based First Stage



Notes: Bars indicate 95% confidence intervals.

we perform the DiD estimation across markets. Figure 3 shows qualitatively similar findings for both kinds of entrants. In particular, the top-two decile point estimates are positive and statistically significant, as predicted. Though the other estimates are not statistically different from zero, we do observe an overall increasing relationship that is consistent with our model's fatter-tail predictions.

3 Robustness of First Stage Estimation

3.1 Event-Study Approach as a First Stage

In this section, we repeat the difference-in-difference analyses using a different first-stage estimation method. Instead of simulating the change in the share of badged sellers across different subcategories, we estimate the change in the share of badged sellers in different subcategories using the following event-study approach:

$$Share\_Badged_{ct} = \beta_c Policy + \eta_c + \alpha_c t + \epsilon_{ct}, \tag{1}$$

where $Share\_Badged_{ct}$ is the share of badged sellers in subcategory c in month t; $Policy$ is a dummy variable that equals 1 after the policy change; η_c are subcategory fixed effects; α_c is a subcategory-specific linear time trend; and ϵ_{ct} are error terms.

Event study: +/- 6 Months The first stage estimates of changes in the share of badged sellers are reported in Figure 4. The correlation between these estimates and those in Figure 3 in the paper (using the simulation approach) is 0.863, hence leading to very similar results on average entry rate and EPP, which are show in Table 3.

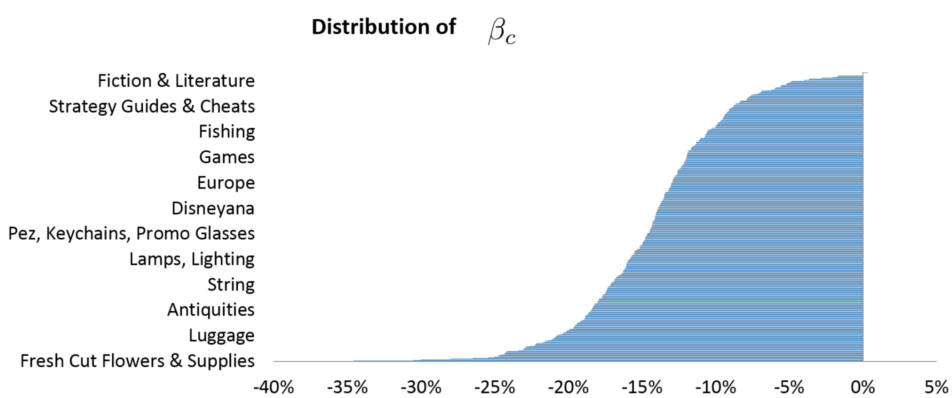
In Table 5, we repeat the placebo test to provide evidence for the exclusion assumption our two-stage

Table 3: Event-Study Approach as First Stage

Panel A. Entrant Ratio			
	(1)	(2)	(3)
	+/- 3 Months	+/- 6 Months	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			
	+/- 3 Months	+/- 6 Months	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

Notes: The regressions are performed at the subcategory-month level.
*** indicates significance at p = 0.01; ** p = 0.05; * p = 0.10.

Figure 4: Heterogeneous Impact of Policy Change Based on Event-Study Approach



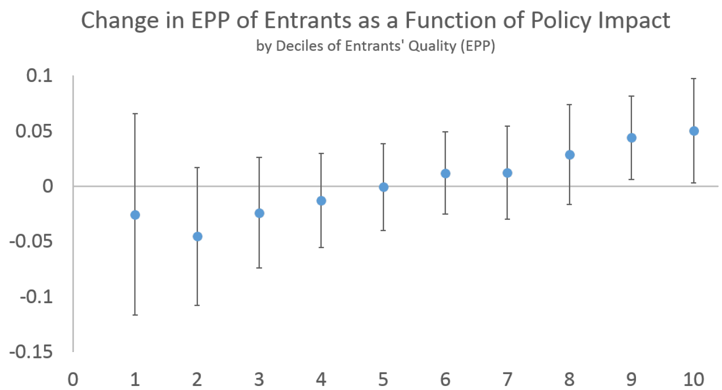
Notes: The estimates are based on data from six months before and six months after the policy change using an event-study approach. The labels on the left are just some examples of about 400 subcategories.

empirical strategy. Similar to the results in panel A1 of Table 6 in the paper, the estimates here show that policy exposures estimated from the policy year cannot explain changes in entry patterns across markets in the previous year.

To study whether our results hold for the two types of entrants, namely new entrants on the platform and exisiting sellers starting to sell in new markets, we separately perform the DiD analyses for the two types of entrants in Table 6. The results are similar to those in Table 6 in the paper. In Figure 6, we repeat the DiD analyses for different quality deciles for the two types of entrants. The results are similar to those in Figure 3, where we use simulated policy exposure as the first stage β's. These two exercises suggest that our results are not driven by a particular type of entrants.

Event study: +/- 3 Months We repeat the difference-in-difference analyses using an event study approach for our first-stage estimation. In particular, we use data from three months before and three months after the policy change for the estimation of the first stage. Estimates reported in Table 7 are consistent

Figure 5: Change in EPP for Entrants in Different Quality Deciles: Event Study as First Stage



Notes: Bars indicate 95% confidence intervals.

Table 4: Policy Impact on Quality of Incumbents

Panel A. EPP from Incumbents			
	(1)	(2)	(3)
	+/- 3 Months	+/- 6 Months	Month 7 to 12
Estimate	-0.044*	0.020	-0.021
	(0.025)	(0.018)	(0.021)
R^2	0.887	0.853	0.823
Panel B. Sellers who Entered n Months before the Policy			
	n=3	n=6	
Estimate	-0.068	0.027	
	(0.054)	(0.053)	
R^2	0.459	0.415	

Notes: The regressions are at the subcategory-month levels. An incumbent is defined as a seller who has listed at least one item before and one item after the policy change in the specified time windows.

*** indicates significance at p = 0.01; ** p = 0.05; * p = 0.10.

Table 5: Placebo Test on the Exclusion Restriction: Event Study as First Stage

	Entrant Ratio		EPP		Total Sales	
	(1)	(2)	(3)	(4)	(5)	(6)
	+/- 3 Mths	+/- 6 Mths	+/- 3 Mths	+/- 6 Mths	+/- 3 Mths	+/- 6 Mths
Estimate	-0.606	-0.365	0.021	-0.008	-1.619	-4.072
	(2.802)	(1.585)	(0.024)	(0.018)	(4.725)	(3.180)
R^2	0.117	0.068	0.832	0.793	0.618	0.536

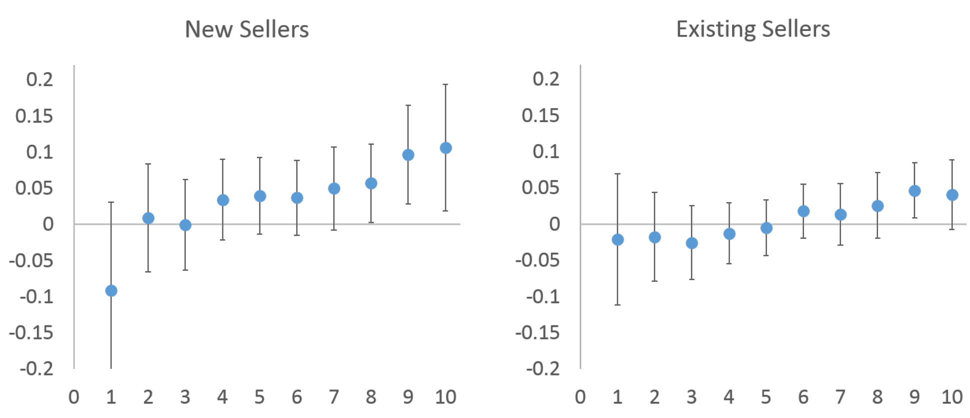
Notes: We use the $\widehat{\beta}$ estimated from the year of the policy change, and re-perform the second-stage regression using data from both three months and six months before and after September in the previous year.

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

Table 6: Two Types of Entry: Event Study as First Stage

	New Sellers		Existing Sellers	
Panel A. Entrant Ratio				
	(1)	(2)	(3)	(4)
	+/- 3 Months	+/- 6 Months	+/- 3 Months	+/- 6 Months
Estimate	0.057***	0.041***	0.295***	0.215***
	(0.012)	(0.007)	(0.042)	(0.028)
R^2	0.887	0.898	0.890	0.912
Panel B. EPP				
	(1)	(2)	(3)	(4)
	+/- 3 Months	+/- 6 Months	+/- 3 Months	+/- 6 Months
Estimate	0.559***	0.123*	0.144***	0.093***
	(0.123)	(0.074)	(0.037)	(0.024)
R^2	0.309	0.418	0.706	0.733

Figure 6: Change in EPP for Two Types of Entrants in Different Quality Deciles: Event Study as First Stage



Notes: Bars indicate 95% confidence intervals.

with the estimates in Table 1 in the paper.

Table 7: Policy Impact on Rate and Quality of Entrants: +/- 3 Mo.'s (Event Study as 1st Stage)

Panel A. Entrant Ratio			
	+/- 3 Months	+/- 6 Months	Month 7 to 12
Estimate	0.299***	0.154***	-0.003
	(0.041)	(0.032)	(0.057)
R^2	0.914	0.888	0.691
Panel B. EPP Conditional on Survival in the Second Year			
	+/- 3 Months	+/- 6 Months	Month 7 to 12
Estimate	0.102***	0.093***	0.005
	(0.034)	(0.025)	(0.028)
R^2	0.758	0.717	0.670

*** indicates significance at p = 0.01; ** p = 0.05; * p = 0.10.

Event study: +/- 4 Weeks We repeat the difference-in-difference analyses using an event study approach for our first-stage estimation. In particular, we use data from four weeks before and four weeks after the policy change for the estimation of the first stage. Estimates reported in Table 8 are consistent with the estimates in Table 1 in the paper.

Table 8: Policy Impact on Number and Quality of Entrants: +/- 4 Wks (Event Study as 1st Stage)

Panel A. Entrant Ratio			
	+/- 3 Months	+/- 6 Months	Month 7 to 12
Estimate	0.310***	0.176***	0.173**
	(0.033)	(0.026)	(0.074)
R^2	0.915	0.889	0.547
Panel B. EPP Conditional on Survival in the Second Year			
	+/- 3 Months	+/- 6 Months	Month 7 to 12
Estimate	0.075**	0.050***	0.049*
	(0.031)	(0.023)	(0.026)
R^2	0.759	0.716	0.691

*** indicates significance at p = 0.01; ** p = 0.05; * p = 0.10.

Event study: +/- 1 Week We repeat the difference-in-difference analyses using an event study approach for our first-stage estimation. In particular, we use data from one week before and one week after the policy change for the estimation of the first stage. Estimates reported in Table 9 are consistent with the estimates in Table 1 in the paper.

3.2 Event study: Number of Badged Sellers as Dependent Variable

In this section, we repeat the difference-in-difference analyses using an event study approach for our first-stage estimation. The difference in this exercise is that we use *number* of bagded sellers as the dependent variable for the estimation of the first stage. Estimates reported in Table 10 are consistent with the estimates in Table 1 in the paper.

Table 9: Policy Impact on Number and Quality of Entrants: +/- 1 Wk (Event Study as 1st Stage)

Panel A. Entrant Ratio			
	+/- 3 Months	+/- 6 Months	Month 7 to 12
Estimate	0.088***	0.072***	0.081**
	(0.021)	(0.016)	(0.032)
R^2	0.910	0.889	0.691
Panel B. EPP Conditional on Survival in the Second Year			
	+/- 3 Months	+/- 6 Months	Month 7 to 12
Estimate	0.048**	0.012***	0.086***
	(0.020)	(0.014)	(0.026)
R^2	0.760	0.719	0.694

*** indicates significance at p = 0.01; ** p = 0.05; * p = 0.10.

Table 10: Policy Impact on Number and Quality of Entrants: Alternative Dependent Variable in First Stage

Panel A. Entrant Ratio			
	+/- 3 Months	+/- 6 Months	Month 7 to 12
Estimate	6E-7	2E-6**	2E-6***
	(1E-6)	(1E-6)	(8E-7)
R^2	0.911	0.888	0.872
Panel B. EPP Conditional on Survival in the Second Year			
	+/- 3 Months	+/- 6 Months	Month 7 to 12
Estimate	1E-6	9E-9	1E-6
	(1E-6)	(1E-6)	(1E-6)
R^2	0.757	0.717	0.690

*** indicates significance at p = 0.01; ** p = 0.05; * p = 0.10.

3.3 Use Percentiles of Policy Exposure

We replicate the DiD estimation using percentiles of $\widehat{\beta}_c$, rather than their actual values as in Table 8 in the paper. The percentiles represent the relative position of each subcategory, which is ranked by the drop in the share of badged sellers. This normalization enables scale-free comparisons across subcategories. We see that the qualitative results are the same as before, as shown in Table 11.

Table 11: Policy Impact on Rate and Quality of Entrants: Using Percentiles of $\widehat{\beta_c}$ in the First Stage

Panel A. Entrant Ratio			
	+/- 3 Months	+/- 6 Months	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			
	+/- 3 Months	+/- 6 Months	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

Notes: We use percentiles of $\widehat{\beta_c}$ for the DiD analyses, rather than their absolute values.
*** indicates significance at p = 0.01; ** p = 0.05; * p = 0.10.

4 Robustness of Second Stage Estimation

4.1 Number of Entrants as Dependent Variable

As a robustness check for using the entrant ratio as the dependent variable to study change in entry rate, we use number of entrants as the dependent variable in the second stage. In Table 12, we see that average entry rate in terms of increase in number of entrants is higher in markets that are more affected by the policy. This result is consistent with our findings in Table 1 in the paper.

Table 12: Policy Effect on Number of Entrants

Dependent Variable: Number of Entrants			
	+/- 3 Months	+/- 6 Months	Month 7 to 12
Estimate	5203.22***	2842.83***	3701.00***
	(906.56)	(582.08)	(455.84)
R^2	0.97	0.97	0.96

*** indicates significance at p = 0.01; ** p = 0.05; * p = 0.10.

4.2 Different Window for Defining EPP

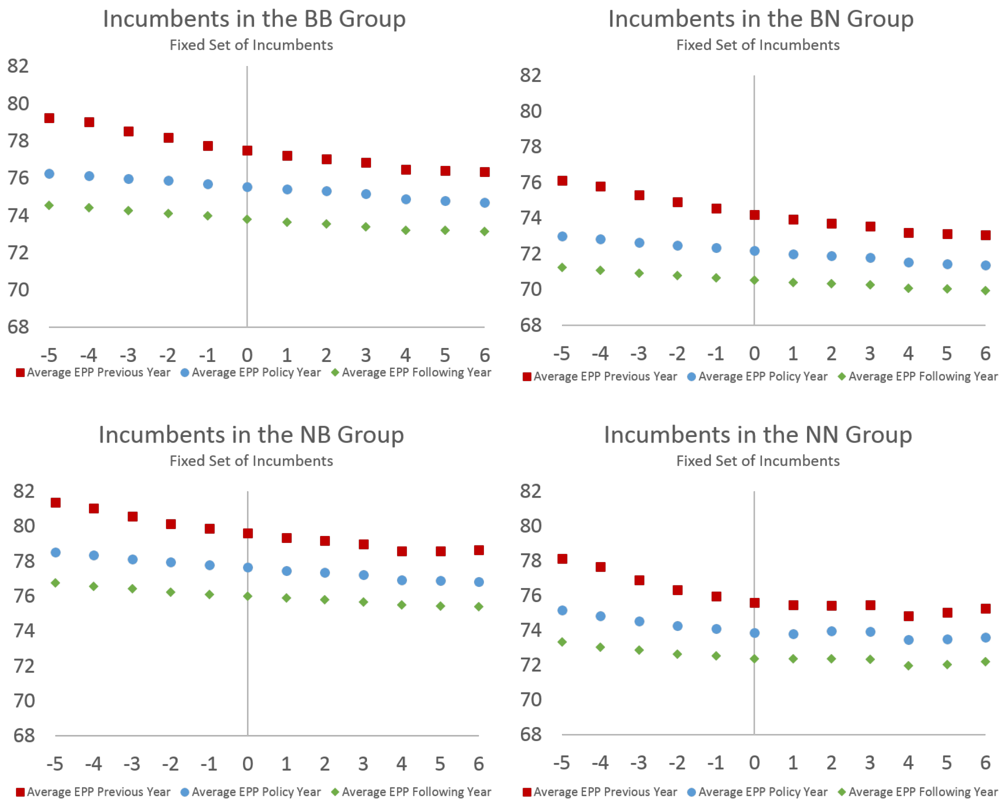
In Figure 4, we plot the monthly EPPs for different groups of incumbents in the policy year, the year before, and the year after. EPPs in this graph are computed based on sellers' transactions from six months before the focal month.

We plot a similar graph in Table 8. The difference is that, we calculate EPP in each based on sellers' transactions in that particular month. A comparison between the two graphs suggest very similar patterns.

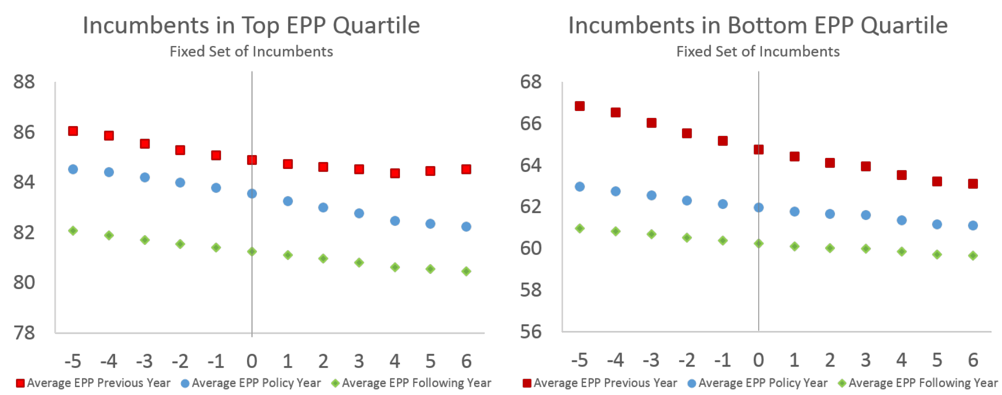
4.3 Alternative Quality Measures

Our main quality measure for seller is EPP. In this section, we use alternative quality measures to replicate the analyses in Table 1. In panel A of Table 13, we repeat our DiD analysis using percentage positive as

Figure 7: Change in EPP of Incumbents: EPP Based on Past 6 Months



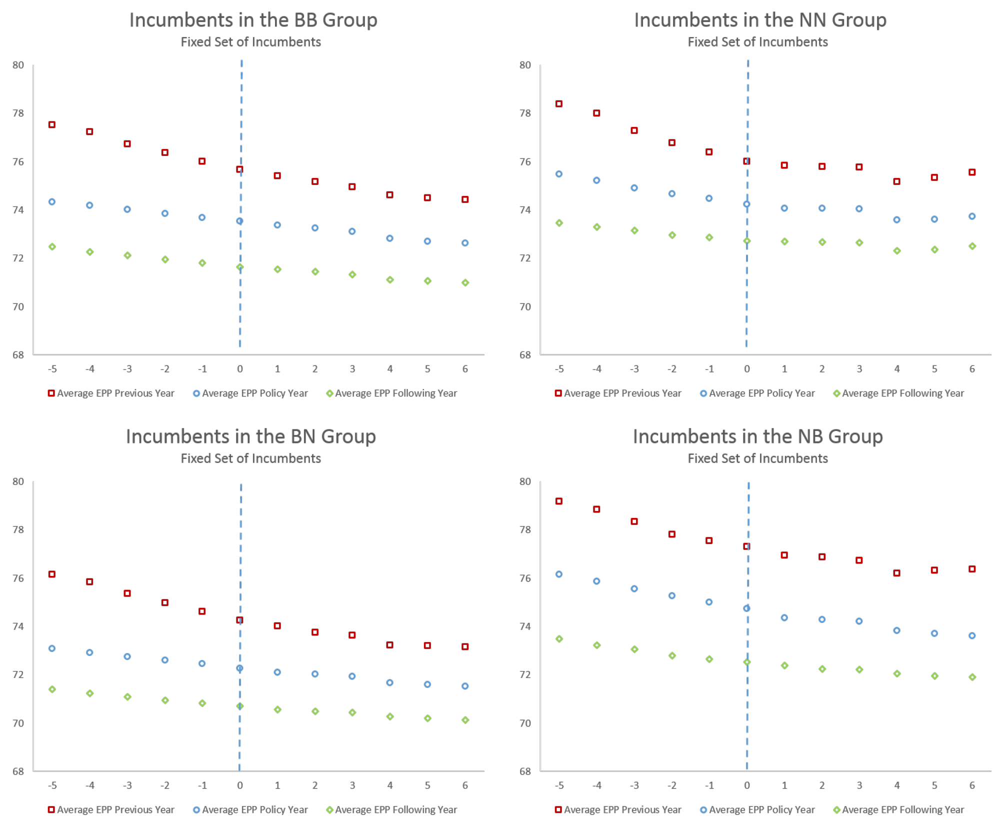
(a) Four Groups of Incumbents



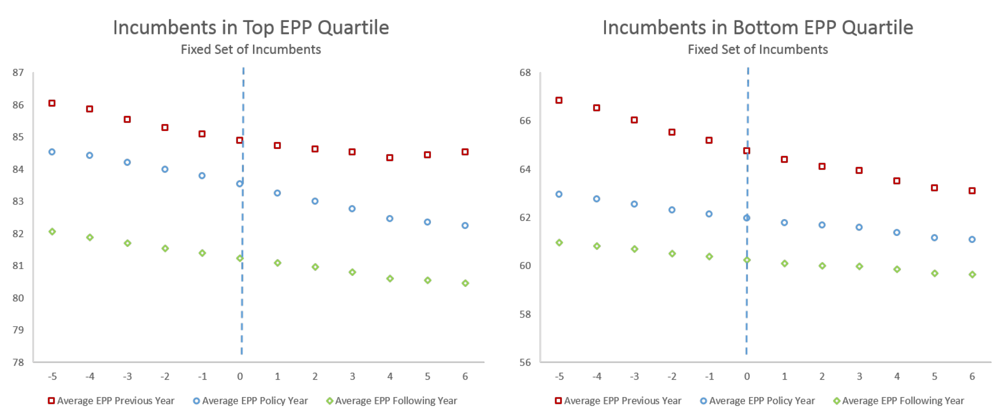
(b) Top Vs. Bottom Quartiles

Notes: The circles are the average monthly EPP provided by incumbents of a particular group in the year of the policy change. The squares and diamonds are the average EPP provided by the same set of incumbents in the previous year and the following year, respectively. The x-axis shows normalized months, with 0 being the month where the policy change took place.

Figure 8: Change in EPP of Incumbents: EPP Based on Focal Months



(a) Four Groups of Incumbents



(b) Top Vs. Bottom 20 Percentile

Notes: The circles are the average monthly EPP provided by incumbents of a particular group in the year of the policy change. The squares and diamonds are the average EPP provided by the same set of incumbents in the previous year and the following year, respectively. The x-axis shows normalized months, with 0 being the month where the policy change took place.

the outcome variable. Note that the percentage positive measure is computed as the number of positive feedback divided by total number of feedback left. Therefore, the distinction between percentage positive and EPP is the denominator. In column 1, we see that a market with 10% larger drop in share of badged sellers experienced a 0.07 percentage point increase in percentage positive. Note that the magnitude is much smaller than changes in EPP, which is expected given that this measure is highly inflated on eBay: According to Nosko and Tadelis (2015), the mean of this measure is 99.3% and the median is 100%). In columns (2) and (3), we see that sellers' performance measured by percentage positive is higher in more affected markets on average, although the estimates are not statistically significant at the 10% level.

In Panel B, we use another performance measure as the outcome variable, namely the share of low DSRs. A low DSR is defined as a "1" or "2' rating on any of the four dimensions in the DSR on a 5-point scale. We see that in more affected markets, entrants receive less low DSRs, consistent with them being of higher quality. Lastly, in Panel C, we use claim rate as the quality measure. When the items are not as described according to the listing or that buyers did not receive them, buyers can file claims to eBay to get full refund of the item. Again, we see that claim rates are smaller in more affected markets,

Although some estimates are not statistically significant at the 5% level in this section, the sign of these estimate are consistent with the regressions when we use EPP as the outcome measure, which is reassuring.

In Table 14, we study changes in incumbents' quality using the same set of alternative quality measures. The results are qualitative the same and indicate that an average incumbent's quality does not change.

Table 13: Alternative Quality Measures: Entrants

Panel A. Percentage Positive			
	+/- 3 Months	+/- 6 Months	Month 7 to 12
Estimate	0.007**	0.005	0.006
	(0.004)	(0.002)	(0.004)
R^2	0.405	0.336	0.361
Panel B. Share of Low DSRs			
	+/- 3 Months	+/- 6 Months	Month 7 to 12
Estimate	-0.014***	-0.006	-0.004
	(0.005)	(0.006)	(0.004)
R^2	0.304	0.361	0.321
Panel C. Claim Rates			
	+/- 3 Months	+/- 6 Months	Month 7 to 12
Estimate	-0.008*	-0.006***	-0.004
	(0.004)	(0.002)	(0.003)
R^2	0.423	0.501	0.428

Notes: The regressions are at the subcategory-month levels.
*** indicates significance at p $\leq$ 0.01; ** p $\leq$ 0.05; * p $\leq$ 0.10.

4.4 Entrants with At Least Ten Sales

In this section, we replicate Table 1 using entrants with at least 10 sales in the first year of entry. The goal here is to study whether the results hold for more serious sellers.

Table 14: Alternative Quality Measures: Incumbents

Panel A. Percentage Positive			
	+/- 3 Months	+/- 6 Months	Month 7 to 12
Estimate	0.004	0.004	0.001
	(0.005)	(0.006)	(0.001)
R^2	0.476	0.431	0.444
Panel B. Share of Low DSRs			
	+/- 3 Months	+/- 6 Months	Month 7 to 12
Estimate	-0.002	-0.002	0.001
	(0.004)	(0.003)	(0.004)
R^2	0.317	0.367	0.352
Panel C. Claim Rates			
	+/- 3 Months	+/- 6 Months	Month 7 to 12
Estimate	-0.005	-0.006	-0.002
	(0.005)	(0.006)	(0.004)
R^2	0.389	0.41	0.437

Notes: The regressions are at the subcategory-month levels.
*** indicates significance at p $\leq$ 0.01; ** p $\leq$ 0.05; * p $\leq$ 0.10.

In Panel A of Table 15, we see that the entry rate is higher in more affected markets. The magnitudes are larger than those in Table 1 in the paper. Despite the larger magnitude, the estimate for the seventh to the twelfth month after the policy change is not statistically significant, suggesting that market has reached a new equilibrium in the six months after the policy change. In Panel B, we see that results on the EPP of entrants are similar to the ones in the paper. In particular, the average quality of entrants is higher in more affected markets, and the quality effect seems to be persistent because the estimate in column (3) is statistically significant.

Table 15: Entrants with At Least 10 Sales

Panel A. Percentage Positive			
	+/- 3 Months	+/- 6 Months	Month 7 to 12
Estimate	0.185***	0.265***	0.037
	(0.038)	(0.035)	(0.025)
R^2	0.971	0.943	0.964
Panel B. Share of Low DSRs			
	+/- 3 Months	+/- 6 Months	Month 7 to 12
Estimate	0.019	0.020**	0.036***
	(0.012)	(0.008)	(0.009)
R^2	0.941	0.935	0.939

Notes: The regressions are at the subcategory-month levels.
*** indicates significance at p $\leq$ 0.01; ** p $\leq$ 0.05; * p $\leq$ 0.10.

4.5 Other Performance Measures

We have shown that the quality of entrants increases more in markets with higher policy exposure in Table 1 in the paper. In this section, we study how other performance measures have changed across markets, and in particular, the average and total sales quantity during a seller's first year of entry, conditional on her survival in the second year. A negative coefficient in column 1 of Panel A in Table 16 shows that over the short term, the sales quantity from each entrant is smaller in markets affected more by the policy change; however, this drop becomes much smaller and insignificant when considering a longer time period after the policy change. This result indicates that the average entrant is smaller in the markets most affected by the policy change. Recall that these markets have more entrants on average as well. As a result, this regression does not necessarily imply a decrease in the total number of sales by entrants as a whole. In fact, when we run a regression of total sales from all entrants in Panel B, we observe that markets more affected by the policy change have a higher total number of sales by entrants.

Finally, we study entrants' survival by looking at the average size of entrants in the year after entry, assigning zero to sellers who do not sell any items in their second year.[2] Panel C shows that the average sales quantity in the second year per entrant decreases more for entrants in subcategories that are more affected by the policy change. This observation is consistent with entrants being smaller in the affected area, as shown in Panel A, although none of the estimates are statistically significant. In Panel D, we see that the total number of items sold in the second year by entrants as a whole increased in the short term.

Table 16: Policy Impact on Rate and Quality of Entrants

Panel A. Average Entrant Size Conditional on Survival in the Second Year			
	+/- 3 Months	+/- 6 Months	Month 7 to 12
Estimate	-4.702*	-0.688	-0.628
	(2.563)	(1.792)	(2.084)
R^2	0.612	0.553	0.528
Panel B. Total Sales			
	+/- 3 Months	+/- 6 Months	Month 7 to 12
Estimate	1326.530	1090.567	4028.375*
	(3908.002)	(2551.776)	(2261.147)
R^2	0.927	0.928	0.943
Panel C. Average Entrant Size in the Second Year			
	+/- 3 Months	+/- 6 Months	Month 7 to 12
Estimate	-1.380	0.341	-1.588
	(2.162)	(1.577)	(1.339)
R^2	0.422	0.354	0.398
Panel D. Total Sales in the Second Year			
	+/- 3 Months	+/- 6 Months	Month 7 to 12
Estimate	2898.81	2814.841	-7991.153*
	(7018.056)	(4459.005)	(4676.972)
R^2	0.720	0.720	0.723

Notes: The regressions are at the subcategory-month levels. An entrant survives the second year if she sells at least one item in both the first and second years after entry.

*** indicates significance at p $\leq$ 0.01; ** p $\leq$ 0.05; * p $\leq$ 0.10.

[2] Alternatively we could set a dummy variable equal to zero if the seller does not sell any item in the second year. This is not appealing because even if they quit selling professionally, many sellers still sell occasionally on eBay.

5 Changes in Sales Probability and Quantity

In Table 17, we repeat the event-study analyses in Table 3 in the paper to study changes in sales probability and sales quantity for incumbents of different groups based on their badge status before and after the policy change. Note that our model does not directly speak to changes in sales probability and quantity for sellers of different types.

The positive coefficients on $BB * Policy$ and $NB * Policy$ in column (1) show that sales probability increase after the policy change, which suggests that these two groups of sellers do better after the policy change. These two groups are also better off in terms of sales quantity, as indicated in column 3. The change in sales probability for the baseline NN group (holdout group) is negative, although the sign of this estimate flips when we consider a longer time window. Finally, BN group also appears to have higher sales probability after the policy change; however, their sales quantity are actually lower, as shown in column (3) of the table. These results are largely consistent with our findings on price changes in Table 4 in the paper.

Table 17: Changes in Sales Probability and Quantity: Event Study

	(1)	(2)	(3)	(4)
	Sales Probability		Sales Quantity	
	+/- 1 Month	+/- 3 Months	+/- 1 Month	+/- 3 Months
Policy	-0.009***	0.008***	-0.044***	-0.046***
	(0.004)	(0.001)	(0.006)	(0.005)
BB*Policy	0.016***	0.015***	0.036***	0.003
	(0.001)	(4.E-04)	(0.004)	(0.003)
BN*Policy	0.002***	0.006***	-0.008***	-0.003
	(4.E-04)	(2.E-04)	(0.003)	(0.002)
NB*Policy	0.057***	2.E-04	0.086***	-0.077***
	(0.003)	(0.002)	(0.019)	(0.015)
Week FE	✓	✓	✓	✓
R^2	0.354	0.329	0.686	0.531

Notes: We also control for relative price. B (or N) indicates that the seller is badged (or not badged). The first (second) letter refers to the seller's status before (after) the policy change.

*** indicates significance at p = 0.01.