Certification, Reputation and Entry: An Empirical Analysis

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Asymmetric Information in Markets

● Sellers often have better info about product quality than buyers.
  ○ eBay sellers: product condition
  ○ Airbnb hosts: noise level of the neighborhood
  ○ Upwork freelancers: knowledge and experience
  ○ procurement contractors: quality of their work

● This may result in inefficiently low-quality sellers in markets (Akerlof, 1970).
Asymmetric Information in Markets

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  ◦ eBay sellers: product condition
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• A common solution in markets: Reputation Mechanisms
  ◦ e.g., eBay’s Feedback System, followed by most marketplaces
  ◦ Better Business Bureau records
  ◦ Yelp reviews

• How else can asymmetric information be mitigated?
Badges and Certification

- One standard solution: Certification
  - e.g., licensing for service providers (also barrier...)
  - Marketplace can use data/process to certify quality
Badges and Certification

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• Badges identify sellers who meet minimum quality thresholds
  
  ![eBay Top-rated seller](image1)
  ![Airbnb Superhost](image2)
  ![Upwork Top Rated](image3)

• Buyers can identify who “passes the bar”
Badges in Search Results: eBay
This Paper

- Badges pro: mitigates asymmetric information
- Badges con: can be a barrier for entry

What will be the effects of a higher certification Bar?
  - Incentives of new sellers to enter the market?
  - Quality distribution of sellers in the market?

- We study a policy change on eBay to answer these questions
Related Literature

• Elfenbein, Fisman and McManus (2015)
  ○ Study value of a certification badge across different markets among different types of sellers
  ○ Certification provides more value when the number of certified sellers is low and when markets are more competitive
  ○ We focus on change in standard and market outcomes

• Klein, Lambert & Stahl (2016); Hui, Saeedi & Sundaresan (2017)
  ○ Exploited a different policy change on eBay: One sided feedback
  ○ Klein et al.: clever DiD with scraped data - looks like moral hazard
  ○ Hui et al.: use internal data to show about 70% adverse selection
  ○ Our results more consistent with AS than MH
Guiding Framework
Stylized Model

- Competitive market for goods (eBay...)
- Firms differ in two dimensions
  - Quality $z \in \{z_1, z_2, z_3\}$, $z_1 < z_2 < z_3$, with mass $m_1, m_2, m_3$
  - Entry costs $f$, independently distributed $\sim G(f)$
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- Market has observable certification badge
  - Signals if the quality is weakly above a threshold \( z^* \)
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- Market has observable certification badge
  - Signals if the quality is weakly above a threshold $z^*$
- Baseline demand function (lowest quality): $P(Q)$.
- Demand for a good with expected quality $\bar{z}$: $P(Q) + \bar{z}$. 
Stylized Model

- Policy Change: \( z^* = z_2 \quad \Rightarrow \quad z^* = z_3 \)
Stylized Model

- Policy Change: $z^* = z_2 \Rightarrow z^* = z_3$

- Effect on entry depends on changes in prices

- For $z_2$ types:
  - Lower price
    - Unable to get badged any more
  - $\Rightarrow$ Less entry

- For $z_3$ and $z_1$ types:
  - Price for at least one of $z_3$ and $z_1$ increases, possibly both
    - $z_3$ type: Able to get more informative badge
    - $z_1$ type: Pooled with better sellers
  - $\Rightarrow$ More entry of $z_3$ ($z_1$) if the price for $z_3$ ($z_1$) increases
Data
Data

• Proprietary data from eBay

• Information on product attributes, listing features, buyer history, and seller feedback and reputation.

• eBay product catalog:
  
  o 400+ sub-categories that are exhaustive, e.g., Fiction & Literature, and Fresh Cut Flowers.

  o Product IDs for homogeneous goods, e.g., iPhone 6, Black, 32GB, Unlocked.

• Data on sellers’ first listing date
Policy Change

- eBay switched from Powerseller to the eTRS badge in Sept 2009
- Certification requirements more stringent
  - eTRS = Powerseller + other more stringent requirements
  - Powerseller badge became obsolete
Change in Share of Badged Sellers

![Graph showing change in share of badged sellers from Aug-08 to Apr-10. The graph indicates a decrease in share from Aug-08 to Sep-09, followed by an increase from Sep-09 to Apr-10.](image-url)
Empirical Strategy
Empirical Strategy

- We use a two-stage approach

- First stage:

  Estimate impact on share of badged sellers in each category $c$:

\[
\text{Share}_{Badged_{ct}} = \beta_c Policy + \eta_c + \alpha_{ct} + \epsilon_{ct},
\]
Empirical Strategy

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• First stage:
  Estimate impact on share of badged sellers in each category $c$:

\[ \text{Share}_{Badged_{ct}} = \beta_c Policy + \eta_c + \alpha_{ct} + \epsilon_{ct}, \]

• Identification:
  ○ Policy change was “one size fits all”
  ○ Different markets will be affected differentially
  ○ Assume differential impact is exogenous (Run placebo test)
Empirical Strategy

• Second stage:
  Difference-in-difference approach (%-interaction for treatment)

\[ Y_{ct} = \gamma \beta_c Policy + \mu_c + \xi_t + \epsilon_{ct}, \]

• \( Y_{ct} \): Various variables of interest:
  - Number of entrants
  - Quality and performance of entrants
  - Quality of incumbents
First Stage Estimates

- Lots of variation across markets (subcategories)
- Second stage uses this variation to identify differential impact

Distribution of $\beta_c$

- Fiction & Literature
- Kids' Clothing, Shoes & Accs
- Kids & Teens at Home
- Militaria
- Ethnic, Regional & Tribal
- Manuals & Guides
- Fresh Cut Flowers & Supplies

[Graph showing the distribution of $\beta_c$ with categories listed on the left and the x-axis ranging from -0.3 to 0]
Results: Entrants
Effect on Number of Entrants

\[ Y_{ct} = \gamma \hat{\beta}_c Policy + \mu_c + \xi_t + \epsilon_{ct}, \]

- Entrant ratio = \# entrants at \( t \) / \# sellers at \( t - 1 \)
- \( \gamma < 0 \): more entrants in more affected categories. (\( \hat{\beta}_c < 0 \))
- Over time entry seems to converge to new equilibrium

<table>
<thead>
<tr>
<th>Dependent Variable: Entrant Ratio</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
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<tr>
<td></td>
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<tr>
<td>( \gamma )</td>
</tr>
<tr>
<td></td>
</tr>
<tr>
<td>( R^2 )</td>
</tr>
</tbody>
</table>
**Effect on Quality of Entrants**

- **EPP** = No. of positive feedback / No. of *transactions*
  - Effective Positive Percentage
  - Nosko, Tadels (2015)

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**Dependent Variable: EPP Conditional on Survival in the Second Year**

<table>
<thead>
<tr>
<th></th>
<th>6-Month Window</th>
<th>12-Month Window</th>
<th>Month 7 to 12</th>
</tr>
</thead>
<tbody>
<tr>
<td>$\gamma$</td>
<td>-0.102***</td>
<td>-0.066***</td>
<td>-0.062**</td>
</tr>
<tr>
<td></td>
<td>(0.034)</td>
<td>(0.023)</td>
<td>(0.026)</td>
</tr>
<tr>
<td>$R^2$</td>
<td>0.758</td>
<td>0.717</td>
<td>0.690</td>
</tr>
</tbody>
</table>

- On average higher quality entrants enter in more affected categories
Distribution of Entrants’ Quality

• Last exercise shows
  ○ More affected categories: higher average quality of entrants
Distribution of Entrants’ Quality

• Last exercise shows
  ◦ More affected categories: higher average quality of entrants

• What is the effect on the distribution of entrants?

• Divide entrants in each subcategory into deciles based on EPP in the first year after entry

• For each decile, perform the DiD.

\[ Y_{ct}^{decile} = \gamma \hat{\beta}_c Policy + \mu_c + \xi_t + \epsilon_{ct}, \]
Distribution of Entrants’ Quality, Fatter Tails

Decile 10: highest quality entrants
- Negative coefficient: Higher EPP in more affected markets

Decile 1: lowest quality entrants
- Positive coefficient: Lower EPP in more affected markets
Distribution of Entrants’ Quality, Fatter Tails

- Decile 1: lowest quality entrants
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- Decile 10: highest quality entrants
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Distribution of Entrants’ Quality, Fatter Tails

- Decile 10: highest quality entrants
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- Decile 1: lowest quality entrants
  - Positive coefficient: Lower EPP in more affected markets
Results: Incumbents
Response of Incumbents?

EPP, Entrants Vs. Incumbents

-5 -4 -3 -2 -1 0 1 2 3 4 5 6

Average EPP Incumbent  Average EPP Entrants
Incumbents by Quality Quartile

Incumbents in Top EPP Quartile
Fixed Set of Incumbents

Incumbents in Bottom EPP Quartile
Fixed Set of Incumbents

- Average EPP Previous Year
- Average EPP Policy Year
- Average EPP Following Year
Effect on Price and Market Share by Group

• For each group BB, BN, NB, and NN
  ○ Relative Price:= listing price/product value
    - Product value = average price of the product in posted price format
  ○ Sales probability
  ○ Sales quantity
  ○ Market Share

• Changes in magnitude: NB(+) > BB(+) > NN(+) > BN(-)
Effect on Price and Market Share by Group

Table 3: Change in Badge Premium

<table>
<thead>
<tr>
<th></th>
<th>(1) Relative Price</th>
<th>(2) Sales Probability</th>
<th>(3) Sales Quantity</th>
<th>(4) Market Share</th>
</tr>
</thead>
<tbody>
<tr>
<td>Policy</td>
<td>-0.003</td>
<td>0.015***</td>
<td>0.009</td>
<td>-1.5E-07(-2%)</td>
</tr>
<tr>
<td></td>
<td>(0.003)</td>
<td>(0.001)</td>
<td>(0.006)</td>
<td>(1.4E-06)</td>
</tr>
<tr>
<td>BB*Policy</td>
<td>-0.003</td>
<td>0.024***</td>
<td>0.032***</td>
<td>6.2E-06**(15%)</td>
</tr>
<tr>
<td></td>
<td>(0.003)</td>
<td>(0.001)</td>
<td>(0.005)</td>
<td>(2.2E-06 )</td>
</tr>
<tr>
<td>BN*Policy</td>
<td>-0.007***</td>
<td>-0.001***</td>
<td>-0.010***</td>
<td>-3.3E-06*(-6%)</td>
</tr>
<tr>
<td></td>
<td>(0.002)</td>
<td>(4.E-04)</td>
<td>(0.004)</td>
<td>(1.8E-06)</td>
</tr>
<tr>
<td>NB*Policy</td>
<td>0.001</td>
<td>0.097***</td>
<td>0.221***</td>
<td>1.8E-06(13%)</td>
</tr>
<tr>
<td></td>
<td>(0.012)</td>
<td>(0.003)</td>
<td>(0.026)</td>
<td>(4.1E-06)</td>
</tr>
<tr>
<td>Seller FE</td>
<td>✓</td>
<td>✓</td>
<td>✓</td>
<td>✓</td>
</tr>
<tr>
<td>Week FE</td>
<td>✓</td>
<td>✓</td>
<td>✓</td>
<td>✓</td>
</tr>
<tr>
<td>$R^2$</td>
<td>0.288</td>
<td>0.808</td>
<td>0.862</td>
<td>0.813</td>
</tr>
</tbody>
</table>

Notes: Standard errors in parentheses, *** p < 0.01, ** p < 0.05, * p < 0.1.
Robustness Analyses
Subcategory Heterogeneity

- Concern: Results driven by serially-correlated subcategory heterogeneity that simultaneously correlates with $\hat{\beta}_c$ and $Y_{ct}$.
- Assuming this confounding correlation persists over time, we should see that $\hat{\beta}_c$ can explain variations in entry in the past.
- Placebo test:
  - Use $\hat{\beta}_c$ estimated from the policy year
  - DiD re-estimated using data around September in the previous year.
  - No statistically significant coefficient for entrant ratio, quality, or their size.
  - Not a proof but reassuring
Two Types of Market Entrants

- New sellers Vs. existing sellers entering new subcategories
- Consistent with differential entry costs

Table 5: Two Types of Entry

<table>
<thead>
<tr>
<th></th>
<th>New Sellers</th>
<th>Existing Sellers</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>Panel A. Entrant Ratio</td>
<td></td>
</tr>
<tr>
<td></td>
<td>(1)</td>
<td>(2)</td>
</tr>
<tr>
<td></td>
<td>+/- 3 Months</td>
<td>+/- 6 Months</td>
</tr>
<tr>
<td>Estimate</td>
<td>-0.057*** (0.012)</td>
<td>-0.041*** (0.007)</td>
</tr>
<tr>
<td>$R^2$</td>
<td>0.887</td>
<td>0.898</td>
</tr>
<tr>
<td></td>
<td>Panel B. EPP</td>
<td></td>
</tr>
<tr>
<td></td>
<td>(1)</td>
<td>(2)</td>
</tr>
<tr>
<td></td>
<td>+/- 3 Months</td>
<td>+/- 6 Months</td>
</tr>
<tr>
<td>Estimate</td>
<td>-0.559*** (0.123)</td>
<td>-0.123* (0.074)</td>
</tr>
<tr>
<td>$R^2$</td>
<td>0.309</td>
<td>0.418</td>
</tr>
</tbody>
</table>
Econometric Specification

- Check robustness of the first stage $\beta_c$
  - Use number of badged sellers instead of share
  - Use immediate drop in share of badged sellers in the week before and the week after the policy change
  - Use different time windows for estimation.

- Check robustness of the second stage $\beta_c$
  - Use number of entrants instead of entrant ratio
  - Use percentiles of $\hat{\beta}_c$ across subcategories for DiD analyses
  - Different quality measures and time windows for defining EPP
Other Robustness Analyses

- Price and market share regressions with different types of listings
- Exit behavior of incumbents
  - The distribution of the quality of exits have thinner tails
  - Sellers in the $BN$ group shrink in their market share
Conclusion

• How does more demanding certification affect entry?

• In more affected markets,
  ◦ More entrants
  ◦ Higher quality with fatter tails
  ◦ Quality change from improved selection

• Managerial implications for digital platforms
  ◦ Certification policies can affect rate and quality of entry
    - Innovation, e.g., Kickstarter
  ◦ Certification policies seem more effective in affecting selection.
Thank You!