Raising the Bar: Certification Thresholds and Market Outcomes

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Asymmetric Info, Reputation and Certification

- Sellers often have better info about product quality than buyers.
  - Lemons problem: market frictions and inefficiencies (Akerlof, 1970)
- Reputation and feedback is one way consumers can gain trust.
- Another standard solution: Certification
  - Eco-labels; Fair trade; Iso-9000; Restaurant hygiene grades; Credit scores/BBB-Investment grade; etc.
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- Another standard solution: Certification
  - Eco-labels; Fair trade; Iso-9000; Restaurant hygiene grades; Credit scores/BBB-Investment grade; etc.
- Marketplaces: Label sellers who meet minimum quality thresholds

![eBay Top-rated seller](image1)
![eTRS](image2)
![Airbnb Superhost](image3)
![Upwork Top Rated](image4)
Badges in Search Results: eBay

- Buyers can identify who “passes the bar” when they search
This Paper

- Badges pro: Mitigates asymmetric information.
- Badges con: Can be a barrier for entry.
- Badges may affect incentives of all market participants.
This Paper

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- What will be the effects of a higher certification bar:
  - On number and quality of entrants?
  - On reaction by incumbents and exiters?
  - On quality and prices in the market?
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- What will be the effects of a higher certification bar:
  - On number and quality of entrants?
  - On reaction by incumbents and exiters?
  - On quality and prices in the market?

- Approach:
  - Develop a simple model of “raising the bar”
  - Study a policy change on eBay to answer these questions
Overview of Results

- **Model:** How does raising the bar affect markets?
  - Raises average quality/price both above and below the bar
  - Encourages (discourages) entry at “tails” (middle) of quality range
  - Increases effort for some but not all marginal sellers
  - Raises prices for those who benefit
  - **Results amplified in more affected markets**

- **Data:** Diff-in-Diff across markets (categories)
  - Confirm fatter tails, and more so in more impacted markets
  - Confirm price effects
  - Tease out selection from change in incumbent quality

- **What model can’t pin down w/o distributional assumptions**
  - More entrants (temporary)
  - Higher quality (long-lasting)
Guiding Theoretical Framework
Supply

- Continuum of sellers each can produce 1 unit at 0 marginal cost
- Entry cost $k \in [0, \infty)$, $k \sim G(\cdot)$, $G(0) = 0$ and $G(\infty) = 1$
Supply

• Continuum of sellers each can produce 1 unit at 0 marginal cost

• Entry cost $k \in [0, \infty)$, $k \sim G(\cdot)$, $G(0) = 0$ and $G(\infty) = 1$

• Hidden type & action: 3 types of sellers (Diamond (1989))
  - $\mu_\ell$ measure of sellers who can only produce low quality, $L$
  - $\mu_h$ measure of sellers who can only produce high quality, $H$
Supply

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- Hidden type & action: 3 types of sellers (Diamond (1989))
  - $\mu_\ell$ measure of sellers who can only produce low quality, $L$
  - $\mu_h$ measure of sellers who can only produce high quality, $H$
  - $\mu_s$ measure of strategic sellers
    - shirk at zero cost and produce medium quality, $M$ ($H > M > L \geq 0$)
    - exert effort produce high quality at cost $e \in [0, \infty)$, $e \sim F(\cdot)$, $F(0) = 0$ and $F(\infty) = 1$
    - Note: $s$-types have two dimensions of heterogeneity: $(e, k)$
Demand

- Buyers value the quality of the good
- Willing to pay up to expected quality of the good
- On the long side of the market

⇒ Price = expected quality
Information

• Buyers do not observe sellers’ quality directly.
• Market regulator observes the sellers’ quality
• It can produce a credible and observable badge: $B \in \{M, H\}$
• The badge certifies that the quality is above a threshold $B$. 
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• Buyers do not observe sellers’ quality directly.

• Market regulator observes the sellers’ quality

• It can produce a credible and observable badge: $B \in \{M, H\}$

• The badge certifies that the quality is above a threshold $B$.

• Notation, when threshold at $B$:
  
  ○ $\overline{p}_B$ : Price for badged sellers
  ○ $\underline{p}_B$ : Price for unbadged sellers
  ○ $\overline{v}_B$ : Average quality of badged sellers
  ○ $\underline{v}_B$ : Average quality of unbadged sellers
Lax Badge:  $B = M$

Lemma 1: All $s$-types shirk in any equilibrium with $B = M$.

- Obvious: no benefit from working and producing $H$, cost $e > 0$

Unique equilibrium:

- **behavior**: All $s$-types who enter choose to shirk.
- **prices**: $\bar{p}_M = \bar{v}_M = \frac{\mu_s M + \mu_h H}{\mu_s + \mu_h}$, and $p_M = v_M = L$,
- **entry**: $\mu_{\ell M} = G(L)\mu_{\ell}$, $\mu_{s M} = G(\bar{p}_M)\mu_s$ and $\mu_{h M} = G(\bar{p}_M)\mu_h$, 


Stringent Badge:  $B = H$

Lemma 2: Some $s$-types exert effort in any equilibrium with $B = H$.

- Intuition: there is always a badge premium

Proposition 1: When $B = H$ there exists an equilibrium with

$$\bar{p}_H = H \text{ and } M > p_H > L.$$ 

Equilibrium:

- $s$-type sellers will be badged IFF they choose to exert effort
- $\bar{p}_H = H$
- $L < p_H < M$
Stringent Badge: \( B = H \), Strategic Types

\[ e \]

Shirk

Exit

Work

\[ H - p_H \]

\[ p_H \]

\[ H \]

\[ k \]
Comparative Statics: Lax to Stringent Badge

Corollary 1: $\bar{p}_H < \bar{p}_M$.

- $\Rightarrow$ Some $s$-types lose badge and entry by $s$-types decreases

Corollary 2: $\bar{p}_H > \bar{p}_M$ and $\bar{p}_H > \bar{p}_M$.

- $\Rightarrow$ Prices higher for both $l$- and $h$-types, so more entry at tails compared to middle ($s$-types)

Corollary 3: $s$-types who keep badge produce higher quality.

- Obvious – by design of the policy
Comparative Statics: Lax to Stringent Badge

Corollary 4: Let market A have a higher measure of s-types than market B, fixing the measures of \( l \)- and \( h \)-types across both markets. A change from lax to stringent implies more entry of \( l \)- and \( h \)-types in market A so it has even “fatter” entry tails.

- Follows from the fact that the increase in both \( p_H \) and \( \bar{p}_H \) is larger in market A than in market B.

- **This is central to our identification strategy.**

- Idea: if a market lost more badges, other things equal, then it had a larger measure of s-types and the distributional impacts of the policy should be more severe in that market.
Comparative Statics and Model Predictions

• Quality and prices increase for both badged and unbadged sellers

• The distribution of entrant sellers’ quality will have thicker tails
  ○ Conversely, the distribution of exiting sellers will have thinner tails.

• Some incumbents that retain their badge increase their quality

• Across markets: In more impacted markets (lost more badges ⇔ more s-types other things equal), there will be a larger impact on the tails of the quality distribution of entrants (and exits).
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- The distribution of entrant sellers’ quality will have thicker tails
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What our model cannot predict:

- Changes in the total entry rate
- Changes in average quality of entrants
Data
Data

- Proprietary data from eBay
- **For all transactions:** Information on product attributes, listing features, buyer history, and seller feedback and reputation.
- eBay product catalog:
  - 400+ sub-categories that are exhaustive, e.g., Fiction & Literature, and Fresh Cut Flowers.
    - **We treat each subcategory as a market.**
  - Product IDs for some homogeneous goods, e.g., iPhone 6, Black, 32GB, Unlocked. (Used for more refined “apples-to-apples” analyses.)
- Data on sellers’ first listing date (Entry)
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
Powerseller and eBay Top Rated Seller

- Old Powerseller badge requirements:
  - Sell 100+ items \textbf{OR} $1,000+ value monthly over past 3 months
  - 98\% positive feedback
  - 4.6 / 5.0 detailed seller ratings (DSRs)
Powerseller and eBay Top Rated Seller

- Old Powerseller badge requirements:
  - Sell 100+ items **OR** $1,000+ value monthly over past 3 months
  - 98% positive feedback
  - 4.6 / 5.0 detailed seller ratings (DSRs)

- New eTRS badge requirements:
  - **Powerseller** status
  - Sell 100+ items **AND** $3,000+ value over past 12 months
  - <0.5% low DSRs (1 or 2 stars)
  - <0.5% buyer complaints
Change in Share of Badged Sellers

![Graph showing the change in share of badged sellers over time from August 2008 to April 2010. The share decreases significantly after September 2009.](image-url)
Empirical Strategy:
Two Stage Approach
Empirical Strategy: First Stage

- Simulate policy exposure in each category $c$ in terms of reduction in share of badged sellers.
  - Apply the new certification requirements on badged sellers in the month before the policy change and compute the drop in number of badged sellers divided by the total number of badged sellers.
- Markets with more reduction in share of badged sellers have more affected sellers ($s$-types) and hence will be differentially impacted.
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- Markets with more reduction in share of badged sellers have more affected sellers ($s$-types) and hence will be differentially impacted

![Distribution of $\beta_c$]
Empirical Strategy: Second Stage

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

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

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

• **Identification:** all markets were hit by *the same* policy change while *more impacted* markets are due to an exogenously different distribution of seller types
Results
## Effect on Entrants

Table 1: Policy Impact on Rate and Quality of Entrants

<table>
<thead>
<tr>
<th></th>
<th>Panel A. Entrant Ratio</th>
<th>Panel B. EPP Conditional on Survival in the Second Year</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>(1) +/- 3 Months</td>
<td>(2) +/- 6 Months</td>
</tr>
<tr>
<td>Estimate</td>
<td>0.124***</td>
<td>0.066***</td>
</tr>
<tr>
<td></td>
<td>(0.021)</td>
<td>(0.016)</td>
</tr>
<tr>
<td>$R^2$</td>
<td>0.911</td>
<td>0.888</td>
</tr>
</tbody>
</table>

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

Notes: The regressions are at the subcategory-month levels.
Distribution of Entrants’ Quality

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

- **Empirical prediction:** more affected markets have fatter tails
Distribution of Entrants’ Quality: Fatter Tails

Change in EPP for Entrants in Different Quality Deciles by Deciles of Entrants’ Quality (EPP)

Change in EPP of Entrants as a Function of Policy Impact by Deciles of Entrants’ Quality (EPP)

Notes: The left figure shows average within-subcategory changes in EPP. The right figure shows across-subcategory changes in EPP as a function of policy exposure. Bars indicate 95% confidence intervals.
Distribution of Exiters’ Quality: Thinner Tails

Figure 8: Change in EPP for Sellers who Exit in Different Quality Deciles

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

Table 2: Policy Impact on Quality of Incumbents

<table>
<thead>
<tr>
<th></th>
<th>(1)</th>
<th>(2)</th>
<th>(3)</th>
</tr>
</thead>
<tbody>
<tr>
<td><strong>Panel A. EPP from Incumbents</strong></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>+/- 3 Months</td>
<td>0.023</td>
<td>0.019</td>
<td>-0.012</td>
</tr>
<tr>
<td></td>
<td>(0.015)</td>
<td>(0.012)</td>
<td>(0.013)</td>
</tr>
<tr>
<td><strong>R^2</strong></td>
<td>0.899</td>
<td>0.869</td>
<td>0.860</td>
</tr>
</tbody>
</table>

<table>
<thead>
<tr>
<th></th>
<th>(1)</th>
<th>(2)</th>
</tr>
</thead>
<tbody>
<tr>
<td><strong>Panel B. Sellers who Entered n Months before the Policy</strong></td>
<td></td>
<td></td>
</tr>
<tr>
<td>n = 3</td>
<td>-0.042</td>
<td>-0.058</td>
</tr>
<tr>
<td></td>
<td>(0.027)</td>
<td>(0.050)</td>
</tr>
<tr>
<td><strong>R^2</strong></td>
<td>0.463</td>
<td>0.409</td>
</tr>
</tbody>
</table>

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.
## Incumbents by Badge Status

<table>
<thead>
<tr>
<th></th>
<th>BB Incumbents</th>
<th></th>
<th>BN Incumbents</th>
<th></th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>+/- 3 Months</td>
<td>+/- 6 Months</td>
<td>+/- 3 Months</td>
<td>+/- 6 Months</td>
</tr>
<tr>
<td>$\gamma$</td>
<td>0.067</td>
<td>0.048</td>
<td>-0.018</td>
<td>0.043**</td>
</tr>
<tr>
<td></td>
<td>(0.047)</td>
<td>(0.039)</td>
<td>(0.028)</td>
<td>(0.020)</td>
</tr>
<tr>
<td>$R^2$</td>
<td>0.661</td>
<td>0.534</td>
<td>0.820</td>
<td>0.779</td>
</tr>
</tbody>
</table>

<table>
<thead>
<tr>
<th></th>
<th>NB Incumbents</th>
<th></th>
<th>NN Incumbents</th>
<th></th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>+/- 3 Months</td>
<td>+/- 6 Months</td>
<td>+/- 3 Months</td>
<td>+/- 6 Months</td>
</tr>
<tr>
<td>$\gamma$</td>
<td>-0.064</td>
<td>0.014</td>
<td>-0.012</td>
<td>0.007</td>
</tr>
<tr>
<td></td>
<td>(0.059)</td>
<td>(0.041)</td>
<td>(0.038)</td>
<td>(0.028)</td>
</tr>
<tr>
<td>$R^2$</td>
<td>0.494</td>
<td>0.473</td>
<td>0.692</td>
<td>0.648</td>
</tr>
</tbody>
</table>
Incumbents by Badge Status Continued

• Divide BN into two groups:
  ○ if they *regain/to regain* their badge in 3 months: BN-B & BN-N

• Quality improvement should come from BN-B Incumbents
Incumbents by Badge Status Continued

- Divide BN into two groups:
  - if they \textbf{regain/not-regain} their badge in 3 months: BN-B & BN-N
- Quality improvement should come from BN-B Incumbents

<table>
<thead>
<tr>
<th></th>
<th>BN-B Incumbents</th>
<th></th>
<th>BN-N Incumbents</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>+/- 3 Months</td>
<td>+/- 6 Months</td>
<td>+/- 3 Months</td>
</tr>
<tr>
<td>$\gamma$</td>
<td>0.084**</td>
<td>0.121***</td>
<td>-0.044</td>
</tr>
<tr>
<td></td>
<td>(0.041)</td>
<td>(0.032)</td>
<td>(0.029)</td>
</tr>
<tr>
<td>$R^2$</td>
<td>0.705</td>
<td>0.610</td>
<td>0.783</td>
</tr>
</tbody>
</table>
Effect on Prices: Event Study

- Relative Price: listing price/product value (IDs only)
- Theory predicts that BN gets hurt; BB and NN better off

Table 4: Changes in Relative Prices: Event Study

<table>
<thead>
<tr>
<th></th>
<th>(1)</th>
<th>(2)</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>+/−1 Month</td>
<td>+/−3 Months</td>
</tr>
<tr>
<td>Policy</td>
<td>0.005</td>
<td>0.027***</td>
</tr>
<tr>
<td></td>
<td>(0.004)</td>
<td>(0.008)</td>
</tr>
<tr>
<td>BB*Policy</td>
<td>0.017***</td>
<td>0.027***</td>
</tr>
<tr>
<td></td>
<td>(0.003)</td>
<td>(0.002)</td>
</tr>
<tr>
<td>BN*Policy</td>
<td>-0.009***</td>
<td>-0.033***</td>
</tr>
<tr>
<td></td>
<td>(0.002)</td>
<td>(0.002)</td>
</tr>
<tr>
<td>NB*Policy</td>
<td>-0.005</td>
<td>0.059***</td>
</tr>
<tr>
<td></td>
<td>(0.011)</td>
<td>(0.008)</td>
</tr>
<tr>
<td>Week FE</td>
<td>√</td>
<td>√</td>
</tr>
<tr>
<td>( R^2 )</td>
<td>0.006</td>
<td>0.004</td>
</tr>
</tbody>
</table>

Notes: 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.

***significance at \( p \leq 0.01 \); ** \( p \leq 0.05 \); * \( p \leq 0.1 \).
Effect on Prices: Diff-in-Diff

- More impacted markets should exhibit larger price increases

Table 5: Policy Impact on Price in Different Categories

<table>
<thead>
<tr>
<th></th>
<th>(1)</th>
<th>(2)</th>
<th>(3)</th>
</tr>
</thead>
<tbody>
<tr>
<td>Dependent Variable: Relative Price</td>
<td>+/- 3 Months</td>
<td>+/- 6 Months</td>
<td>Month 7 to 12</td>
</tr>
<tr>
<td>Estimate</td>
<td>0.063***</td>
<td>0.094***</td>
<td>0.295***</td>
</tr>
<tr>
<td></td>
<td>(0.006)</td>
<td>(0.005)</td>
<td>(0.009)</td>
</tr>
<tr>
<td>$R^2$</td>
<td>0.445</td>
<td>0.394</td>
<td>0.514</td>
</tr>
</tbody>
</table>

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

- **Assumption:** no time-varying heterogeneities across subcategories affecting both share of badged sellers and entry variables.
  - **Placebo test 1:** Use simulated $\hat{\beta}_c$ and run 2nd-stage regression on data around September in the previous year: no significant effects.
  - **Placebo test 2:** Simulate change at a different date and repeat regressions around that date: no significant effects.
  - Rerun our second stage regressions controlling for many time-varying variables (non-serially-correlated time-varying factors).
- Event study; IV (simulated IV for actual)
- Lateral vs. new entrants (common sense: different entry costs)
Two Types of Entrants

- New sellers vs. existing sellers (lower \( k \)) entering new subcategories

<table>
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<th>Panel A. Entrant Ratio</th>
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<td>Estimate</td>
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</tbody>
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<tr>
<th>Panel B. EPP</th>
</tr>
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<tbody>
<tr>
<td>(1) +/- 3 Months</td>
</tr>
<tr>
<td>Estimate</td>
</tr>
<tr>
<td></td>
</tr>
</tbody>
</table>
Two Types of Entrants

![Graph showing two types of sellers: New Sellers and Existing Sellers.](image)
Econometric Specification

- Check robustness of the first stage $\beta_c$
  - Use number of badged sellers instead of share
  - Use an event study approach to estimate the drop in share of badged sellers in different time windows: +/-3 months, +/- 1 month, and +/- 1 week.
Econometric Specification

- Check robustness of the first stage $\beta_c$
  - Use number of badged sellers instead of share
  - Use an event study approach to estimate the drop in share of badged sellers in different time windows: +/-3 months, +/- 1 month, and +/- 1 week.

- 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
Conclusion

• How does more demanding certification affect entry and quality?

• In more affected markets,
  ○ (Higher quality) with fatter tails
  ○ Improved selection and higher “effort” at the margin (BN-B)

• Implications for digital platforms and other markets
  ○ Certification policies affects quality distribution
    - Broaden (or contract) the quality range
  ○ Quality control policies seem more about affecting selection.
Thank You!
Stringent Badge: $B = H$, Equilibrium

$v_H(p_H) = \text{unbadged quality given } p_H \text{ and all sellers acting optimally:}$

$$v_H(p_H) = \frac{\mu_l G(p_H) L + \mu_s G(p_H)(1 - F(H - p_H)) M}{\mu_l G(p_H) + \mu_s G(p_H)(1 - F(H - p_H))}$$
Quality? Distribution of Reputation on eBay

- median = 100%, mean = 99.3%, 10\textsuperscript{th} percentile = 97.8%

- Feedback is heavily biased and uninformative
Quality: Effective Percent Positive (EPP)

“Silence” conveys information (Nosko & Tadelis, 2015)

\[
EPP = \frac{\text{# of positive feedback}}{\text{# of transactions}}
\]

• **A:** \(P = 99, \ N = 1, \ \text{Silence} = 20 \rightarrow PP = 99\%, \ EPP = 82.5\%

• **B:** \(P = 99, \ N = 1, \ \text{Silence} = 50 \rightarrow PP = 99\%, \ EPP = 66\%

• Seller A is **higher quality** than seller B
EPP Distribution

- A lot more “spread” and information in EPP
- EPP does measure seller quality (revealed preferences)