Discussion of “Certification, Reputation and Entry: An Empirical Analysis” by Hui, Saeedi, Spagnolo and Tadelis

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Motivation

Lemons problem (Akerlof):
  • Consumers cannot identify low and high quality sellers/goods.
  • Only the lowest quality sellers/goods are traded.
  • Example: used cars.
  • Information asymmetries (presumably) worse in online markets.

Institutions can help with lemons problem:
  • Warranties/Guarantees, dynamic reputation, certification.

BUT, these can be barriers to entry.
This paper

What are the ‘long-run’ effects of introducing (changing) the certification program on eBay?

- **Entry:** do incentives from higher prices outweigh the barriers to entry?
- **Quality:** how does overall quality change (entrants v. incumbents)?
- **Prices and market shares of incumbents.**

**Strategy:**

- Utilize a policy change that occurred on eBay in 2009 that made certification more difficult.
- Evidence suggests that policy had heterogeneous impact across product categories.

**Results:**

- Stricter certification qualifications $\rightarrow$ increase in entry.
- This entry from top and bottom of quality distribution.
- Incumbents quality does not change.
What I like

Motivation:

- Reputation mechanisms important as these markets continue to grow.
- Clear policy implications.
- Think about LR effects of introducing institution.

Data:

- Proprietary data from eBay.
- Utilize a policy change.
Limitations

Model:
- Are there situations where entry would decrease? Quality decrease?
- What is the role of market power?
- Exit an issue?

Results:
- Can we say something about concentration?
- Effect on consumers?
- eBay revenue? What are eBay’s incentives?

Empirical Strategy:
- I wonder about the exogeneity of the instrument.
Identification

The primary analysis utilizes the following DiD specification:

\[ Y_{ct} = \gamma E_{c} Policy + \mu_c + \xi_t + \epsilon_{ct} \]

- \( Y \) is some outcome of interest.
- \( E_c \) measures the ‘exposure’ of product category \( c \) to the policy.
- Intuition: more exposed categories are ‘treated’ and less exposed categories are ‘control’.
- \( E_{c} Policy \) a ‘Bartik instrument’
  - Goal: IV for labor demand in a local market.
  - Interaction between growth of industry across US (\( Policy \)) and a measure of importance of that industry in the local market (\( E_c \)).
  - Example: Mian and Sufi (2012), \( E_c \) is ex ante number of ‘clunkers’.
- Key assumption: \( E_{c} Policy \) independent of \( \epsilon_{ct} \).
- How to measure \( E_c \)?
Exposure

In order to calculate the exposure of a given category, run the following regression:

\[ \text{ShareBadged}_{ct} = \beta_c \text{Policy} + \eta_c + \alpha_c t + \epsilon_{ct} \]

- Use \( \hat{\beta}_c = E_c \)
- Problem: this is an ex post measure of exposure.
  - ShareBadged\(_{ct}\) is an equilibrium outcome that is a function of \( Y_{ct} \).
- Example: if the policy leads to entry in category \( c \), then that is going to affect the share of sellers who are badged.

\[ \Delta \text{ShareBadged}_c = \frac{\text{Badged}_{ct}}{\text{Incumbent}_{ct-1} + \text{Entry}} - \frac{\text{Badged}_{ct-1}}{\text{Incumbent}_{ct-1}} \]

- Result: there is a mechanical relationship between treatment and outcome (more entry \( \rightarrow \) lower % badged).
Suggestions:

Fortunately, I think this can be solved without too much trouble. Suggestions:

1. Use a measure of ex ante exposure to a given category.
   - On the day the policy was enacted, how many sellers would have received the new badge.

2. Determine categories/goods that would be affected ex ante and use this as control group
   - Categories that have more high volume sellers (?).
   - Categories where quality is more or less salient (e.g., new versus used goods).

3. Take an event study approach for each category.
   - Problem: was the policy change due to falling demand/quality?
Other Suggestions

Estimate other effects of policy:

- Other signals of quality (e.g., photographs).
- Types of products within a category (e.g., name brand v. knock off, new v. used).
- Overall price levels.
- Concentration: do powerful sellers become more powerful?

Is Figure 5 (quality result) showing a mechanical relationship?

- If EPP decreased (increased) after the policy, then those sellers are likely to have a low (high) EPP.
- Suggestion: estimate DiD model for some measure of quality dispersion.
Other Random Comments/Questions

• What about dynamic reputation building (through lower prices, e.g.)?
• Do you consider the first stage estimates when you calculate standard errors?
• “...a more stringent badging requirement causes the average quality of both badged and unbadged sellers to increase...” is this always true? It seems like the marginal benefit from being a badged seller may decrease under some circumstances.
• What about exit?
• Why don’t incumbents change their quality? Is their a theoretical justification for this?
• Does eBay use this mechanism as a way to align incentives (revenue generation)?
• Why not juse absolute value of \( \hat{\beta} \)?
• Can we think of you exercise as a test of asymmetric information?