

Certification, Reputation and Entry: An Empirical Analysis

Xiang Hui¹ Maryam Saeedi² Giancarlo Spagnolo³ Steve Tadelis⁴

¹MIT-Sloan

²CMU-Tepper

³SITE

⁴UC-Berkeley

October 30, 2017

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

- 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).
- 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

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



eTRS



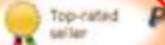
Airbnb Superhost



Upwork Top Rated

- Buyers can identify who “passes the bar”

Badges in Search Results: eBay

	<p>Apple iPod 8gb Touch 2nd gen - Sealed / Apple warranty</p> <p>In stock and ready for dispatch by next day delivery!</p> <p>Item: 250521403533 Seller User ID: windsorsal</p>			<i>Buy It Now</i>
<hr/>				
	<p>Apple iPod nano 2nd Generation (PRODUCT) RED™ Special Edition</p> <p>FAULTY APPLE IPOD 8gb Bargain!!!!!!</p> <p>Item: 130339299510 Seller User ID: anis1471</p>		4 Bids	
<hr/>				
	<p>APPLE iPod 1GB SHUFFLE BLUE 3RD GEN. GRADE A</p> <p>Fast shipping and Minimum 60 day warranty!</p> <p>Item: 260498178029 Seller User ID: windsorsal</p>			<i>Buy It Now</i>

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 $\sim G(f)$

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 $\sim G(f)$
- Market has observable certification badge
 - Signals if the quality is weakly above a threshold z^*

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 $\sim G(f)$
- 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} : $P(Q) + \bar{z}$.

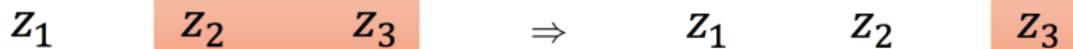
Stylized Model

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



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

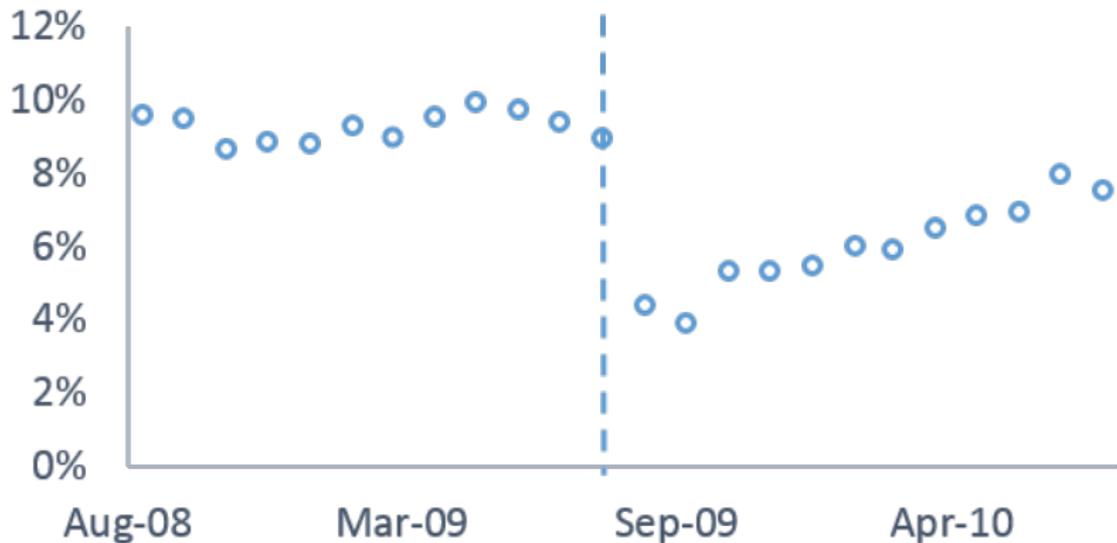
- Proprietary data from eBay
- Information on product attributes, listing features, buyer history, and seller feedback and reputation.
- eBay product catalog:
 - 400+ sub-categories that are exhaustive, e.g., Fiction & Literature, and Fresh Cut Flowers.
 - Product IDs for homogeneous goods, e.g., iPhone 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



Empirical Strategy

Empirical Strategy

- We use a two-stage approach
- First stage:

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

$$Share_Badged_{ct} = \beta_c Policy + \eta_c + \alpha_c t + \epsilon_{ct},$$

Empirical Strategy

- We use a two-stage approach
- First stage:

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

$$Share_Badged_{ct} = \beta_c Policy + \eta_c + \alpha_c t + \epsilon_{ct},$$

- 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)

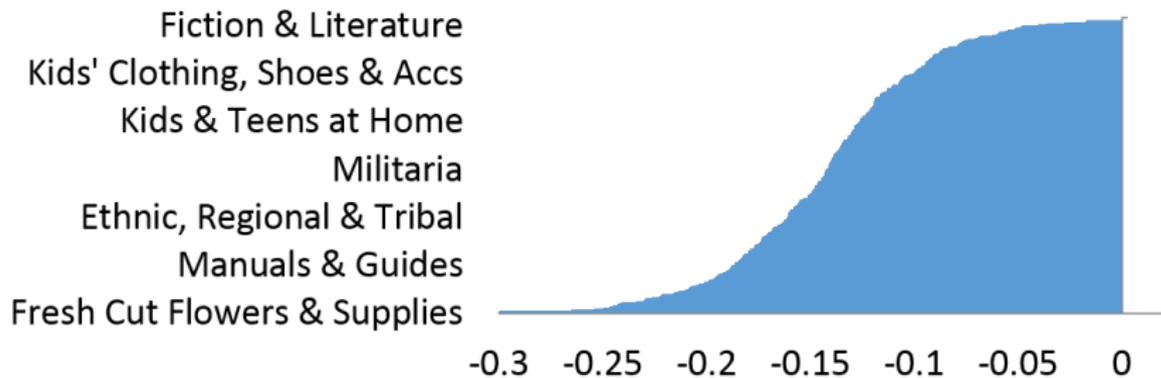
▶ Robustness

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

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

First Stage Estimates

Distribution of β_c



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

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

<i>Dependent Variable: Entrant Ratio</i>			
	(1)	(2)	(3)
	+/- 3 Months	+/- 6 Months	Month 7 to 12
γ	-0.299***	-0.204***	-0.047
	(0.041)	(0.027)	(0.051)
R^2	0.913	0.889	0.691

Effect on Quality of Entrants

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

Dependent Variable: EPP Conditional on Survival in the Second Year

	6-Month Window	12-Month Window	Month 7 to 12
γ	-0.102*** (0.034)	-0.066*** (0.023)	-0.062** (0.026)
R^2	0.758	0.717	0.690

- On average higher quality entrants enter in more affected categories

Distribution of Entrants' Quality

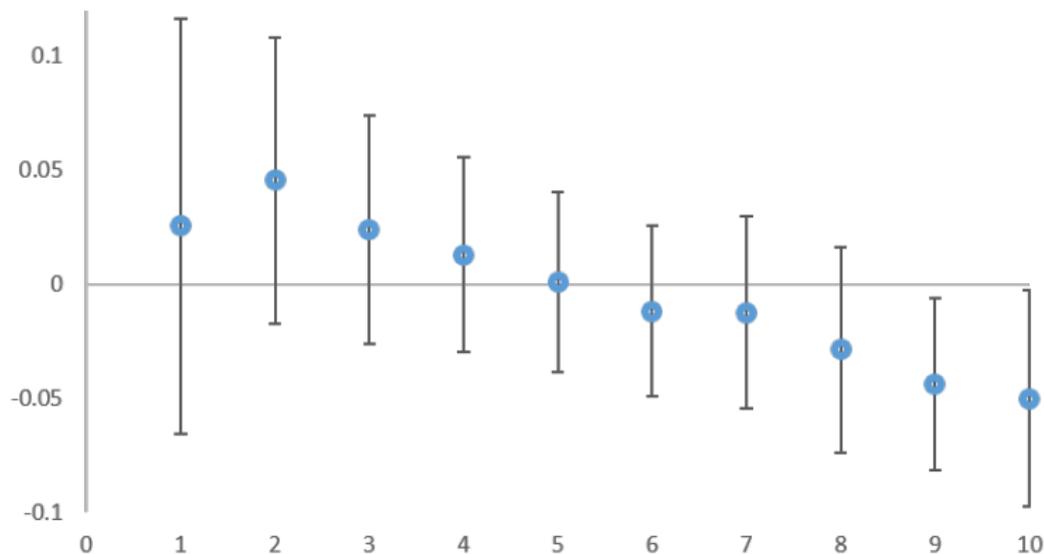
- Last exercise shows
 - More affected categories: higher average quality of entrants

Distribution of Entrants' Quality

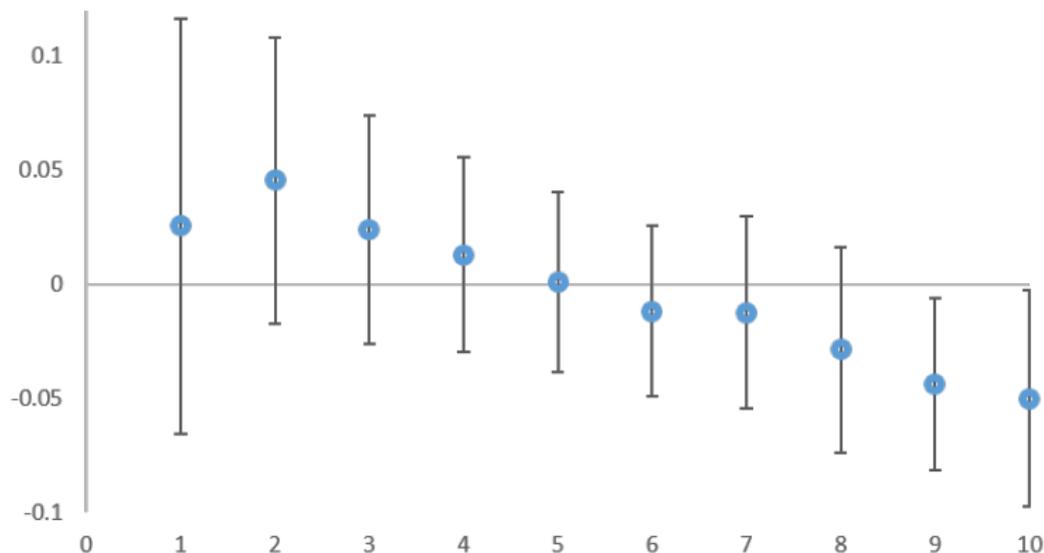
- Last exercise shows
 - More affected categories: higher average quality of entrants
- What is the effect on the distribution of entrants?
- Divide entrants in each subcategory into deciles based on EPP in the first year after entry
- For each decile, perform the DiD.

$$Y_{ct}^{decile} = \gamma \hat{\beta}_c Policy + \mu_c + \xi_t + \epsilon_{ct},$$

Distribution of Entrants' Quality, Fatter Tails

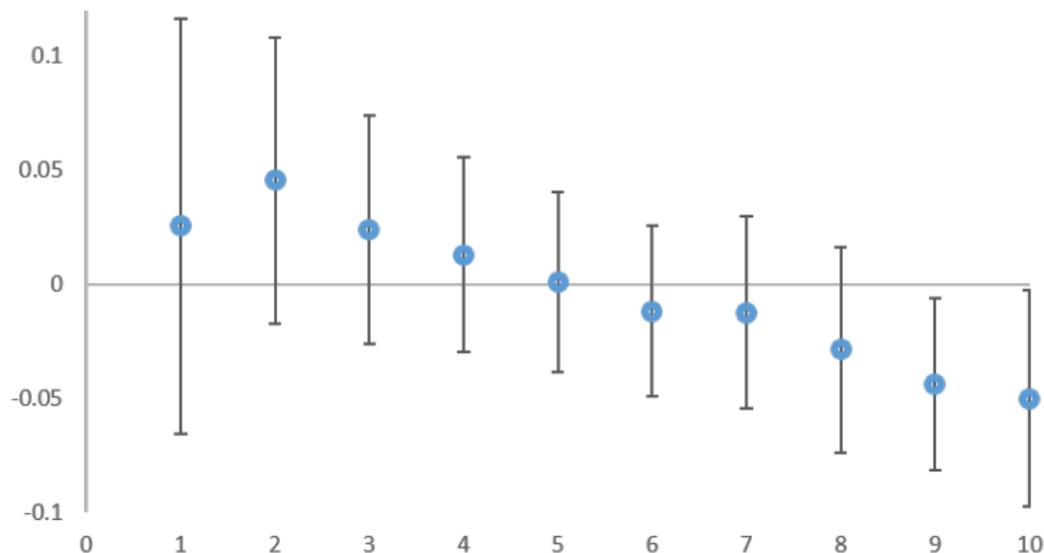


Distribution of Entrants' Quality, Fatter Tails



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

Distribution of Entrants' Quality, Fatter Tails

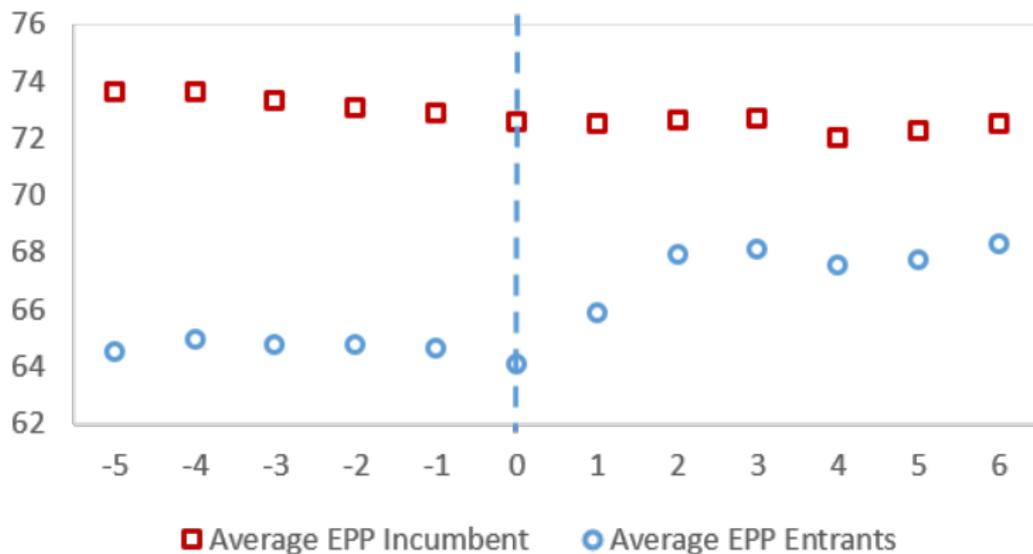


- Decile 10: highest quality entrants
 - Negative coefficient: Higher EPP in more affected markets
- Decile 1: lowest quality entrants
 - Positive coefficient: Lower EPP in more affected markets

Results: Incumbents

Response of Incumbents?

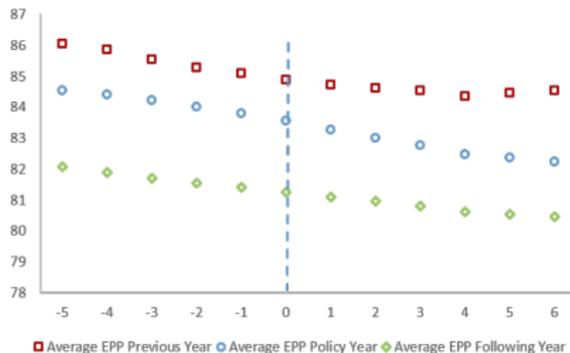
EPP, Entrants Vs. Incumbents



Incumbents by Quality Quartile

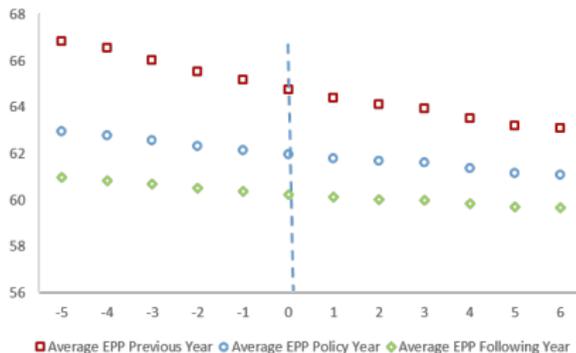
Incumbents in Top EPP Quartile

Fixed Set of Incumbents



Incumbents in Bottom EPP Quartile

Fixed Set of Incumbents



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

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

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 [▶ Go back](#)

Two Types of Market Entrants

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

Table 5: Two Types of Entry

	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

Econometric Specification

- Check robustness of the first stage β_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 β_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!