Posting Frequency and Pricing in an Online Resale Market

Yeonju Baik

Korea Institute of Finance

April 20, 2023

Motivation

Motivation

- Product visibility in online markets can increase traffic and consumer purchases

Motivation

- Product visibility in online markets can increase traffic and consumer purchases
  - Wall Street Journal (2019):
    When people are searching for products on Amazon, nearly
    two-thirds of all product clicks come from the first page of results

Motivation

- Product visibility in online markets can increase traffic and consumer purchases
  - Wall Street Journal (2019):
    When people are searching for products on Amazon, nearly
    two-thirds of all product clicks come from the first page of results
- In many used markets, sellers use posting as a tool to promote their products:

Motivation

- Product visibility in online markets can increase traffic and consumer purchases
  - Wall Street Journal (2019):
    When people are searching for products on Amazon, nearly two-thirds of all product clicks come from the first page of results
- In many used markets, sellers use posting as a tool to promote their products:
  - Re-posting (도배: 중고나라, Facebook marketplace, Craigslist)

Example

Motivation

- Product visibility in online markets can increase traffic and consumer purchases
  - Wall Street Journal (2019):
    When people are searching for products on Amazon, nearly two-thirds of all product clicks come from the first page of results
- In many used markets, sellers use posting as a tool to promote their products:
  - Re-posting (도배: 중고나라, Facebook marketplace, Craigslist)

Example

- Question:
  - How does product visibility affect prices in equilibrium?
  - Why is reposting commonly observed across many secondhand trading platforms?

Overview of Research

Research Question

1. How does posting frequency relate to a seller's pricing?
   - Using theoretical predictions, I infer how sellers compete in price
2. To what extent is posting frequency responsible for a seller's market power(pricing power)?
3. How does posting frequency relate to platform's profit?

Overview of Research

Research Question

1. How does posting frequency relate to a seller's pricing?
   - Using theoretical predictions, I infer how sellers compete in price
2. To what extent is posting frequency responsible for a seller's market power(pricing power)?
3. How does posting frequency relate to platform's profit?

Overview of Research

Research Question

1. How does posting frequency relate to a seller's pricing?
   - Using theoretical predictions, I infer how sellers compete in price
2. To what extent is posting frequency responsible for a seller's market power(pricing power)?
3. How does posting frequency relate to platform's profit?

- Data: Collect high-frequency data on listings in a unique online cellphone resale platform, "Cetizen"

Overview of Research

Research Question

1. How does posting frequency relate to a seller's pricing?
   - Using theoretical predictions, I infer how sellers compete in price
2. To what extent is posting frequency responsible for a seller's market power(pricing power)?
3. How does posting frequency relate to platform's profit?

- Data: Collect high-frequency data on listings in a unique online cellphone resale platform, "Cetizen"
- Match price competition model: Using the observed price distribution, I infer how sellers compete in price
  - Match the data with model prediction

Overview of Research

Research Question

1. How does posting frequency relate to a seller's pricing?
   - Using theoretical predictions, I infer how sellers compete in price
2. To what extent is posting frequency responsible for a seller's market power(pricing power)?
3. How does posting frequency relate to platform's profit?

- Data: Collect high-frequency data on listings in a unique online cellphone resale platform, "Cetizen"
- Match price competition model: Using the observed price distribution, I infer how sellers compete in price
  - Match the data with model prediction
- Quantify market power: Recover the cost parameter for advertising and calculate markups

Preview of Results

- Sellers whose post share is higher by 10%, sell at a 6.6% higher price
  - e.g., Galaxy S9 has 10 posts/hr, seller A posts 1/hr (10%), B posts 2/hr (20%), then seller B has 6.6% higher price than seller A
- In the inferred pricing competition structure, sellers who post less face more elastic consumer demand
- Frequent posters have higher market power in the inferred price competition structure than infrequent posters

Literature

- Online market
  - Seller behavior in the online market: Huang(2021), Jolivet et al.(2016)
  - Rankings: Ursu(2018), Santos et al.(2017), Moshary(2021)
- Models of advertising
  - Butters(1977), Stahl II(1994), McAfee(1994), Haan and Moraga-Gonzalez(2011), Robert and Stahl(1993), Armstrong et al.(2009)
  - The role of prominence: Rhodes(2011), Armstrong et al(2009), Chen and He(2011), Armstrong, Zhou(2011), Armstrong, Vickers(2022)
- Testing between search models
  - De Los Santos(2012), Hong and Shum(2006), Honka and Chintagupta(2017)

Literature

- Online market
  - Seller behavior in the online market: Huang(2021), Jolivet et al.(2016)
  - Rankings: Ursu(2018), Santos et al.(2017), Moshary(2021)
- Models of advertising
  - Butters(1977), Stahl II(1994), McAfee(1994), Haan and Moraga-Gonzalez(2011), Robert and Stahl(1993), Armstrong et al.(2009)
  - The role of prominence: Rhodes(2011), Armstrong et al(2009), Chen and He(2011), Armstrong, Zhou(2011), Armstrong, Vickers(2022)
- Testing between search models
  - De Los Santos(2012), Hong and Shum(2006), Honka and Chintagupta(2017)

→ **Contributions**

- First paper to test interaction framework(Armstrong, Vickers(2022)) prediction
- First paper to provide empirical evidence regarding how posting frequency is related to market price

Outline

Data: Used Cellphone

- Used cellphone trading platform called Cetizen
- Accounts for 20% of used cell phone market trades
  - Listings from Feb. 5th-Aug. 29th (2020) Samsung and Apple
  - No extra fee, no algorithm Data cleaning
  - Postings are listed in the order of the arrival
  - A number of sellers provide wide range of products Seller heterogeneity
  - Repeated posting (도배): Advertising effort
    - Re-posting: Renewing an old posting
    - Duplicate posting: Posting the same thing repeatedly

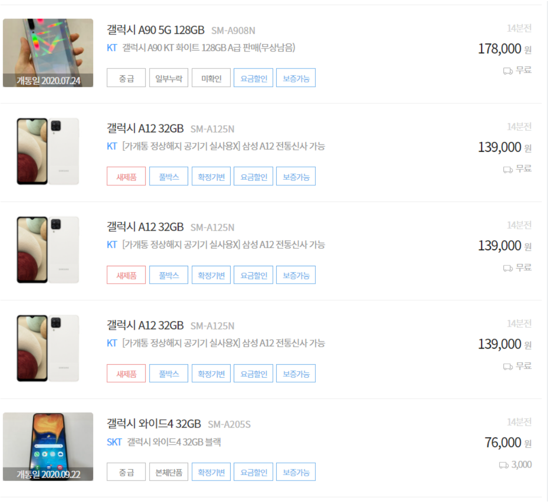
Platform rules

Repeated Posting: Re-Posting

- After sellers post the product, they have a choice to renew
- Sellers do not change the price frequently when they repost

Price dynamics

Repeated Posting: Duplicated Posting



Back to data

Empirical Fact 1

- Repeated posting increases the probability of a sale (i post, j seller k product)

$$\text{Sold}_{ijk} = \beta_1 \underbrace{F_{ijk}}_{\text{posting freq}} + \beta_2 \underbrace{F_k}_{\text{model freq}} + \beta_3 \underbrace{F_j}_{\text{seller freq}} + \beta_4 Z_{ijt} + e_{ijt}$$

Table 1: Product Sales

	Sold	Sold
# Repeated/Day(avg.)	0.0936***	0.0901***
	(0.00890)	(0.00878)
Model share(avg.)	-0.356	-0.168
	(0.495)	(0.557)
# Seller Freq/Day(avg.)	0.000133***	0.000149***
	(0.0000233)	(0.0000284)
Daygap(avg.)		0.000484*
		(0.000226)
N	84849	52225
R-sq	0.011	0.015

Distribution | On sales

- Unit of analysis: posting with a unique description
- Z_{ijt} (controls): Price Ratio ($), memory size, conditions, warranty

Empirical Fact 2

- Listings that are posted more have higher prices

$$Pr_{ijkt} = \beta_1 \underbrace{F_{ijk}}_{\text{Posting Freq}} + \beta_2 \underbrace{F_{kt}}_{\text{Model Freq}} + \beta_3 \underbrace{F_{jt}}_{\text{Seller Freq}} + \beta_4 \underbrace{F_{jkt}}_{\text{Seller,Model Freq}} + \beta_4 Z_{ijkt} + \eta_k + \gamma_j + \gamma_t + e_{ijt}$$

Table 2: Price and the Number of Postings

Variable	Price($)	Price($)	Price($)
# Repeated	0.168***	0.155***	0.144***
	(0.0276)	(0.0267)	(0.0272)
# Model×date×hour	-0.285**	-0.304**	-0.425***
	(0.102)	(0.102)	(0.102)
# Seller×date×hour		0.0438***	-0.00114
		(0.0126)	(0.0215)
# Seller×date×hour×model			1.743**
			(0.615)
Const	YES	YES	YES
Controls[1]	YES	YES	YES
Model FE	YES	YES	YES
Month FE	YES	YES	YES
Seller FE	YES	YES	YES
N	38965	38965	38965
R-sq	0.941	0.941	0.941

* Unit of analysis is a posting with a unique description, Only include listings from the sellers who post more than 20 postings per 1 hour ($> 20/hr$)

[1] Controls: machine condition, warranty, Unit of analysis is each listing

Empirical Observations

- Why are the sellers who post more able to charge higher prices?

Empirical Observations

- Why are the sellers who post more able to charge higher prices?
  - We want to understand how sellers are competing

Empirical Observations

- Why are the sellers who post more able to charge higher prices?
  - We want to understand how sellers are competing
  - This depends on how consumers are searching: Competitors are the one who are included in the same consideration set

Empirical Observations

- Why are the sellers who post more able to charge higher prices?
  - We want to understand how sellers are competing
  - This depends on how consumers are searching: Competitors are the one who are included in the same consideration set
  - Posting changes how consumer form its consideration set

Empirical Observations

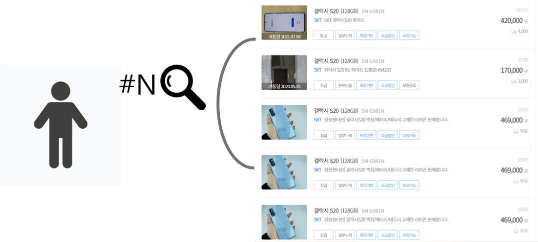
- Why are the sellers who post more able to charge higher prices?
  - We want to understand how sellers are competing
  - This depends on how consumers are searching: Competitors are the one who are included in the same consideration set
  - Posting changes how consumer form its consideration set
  - Two competing models: Independence, nested

Empirical Observations

- Why are the sellers who post more able to charge higher prices?
  - We want to understand how sellers are competing
  - This depends on how consumers are searching: Competitors are the one who are included in the same consideration set
  - Posting changes how consumer form its consideration set
  - Two competing models: Independence, nested
- Model (Armstrong, Vickers(2022))
  - Assumption: Homogeneous good, competing in price (mixed pricing strategy)
  - (Consumer's) Consideration probability: Reach $(\sigma; \sigma_1, \sigma_2, \sigma_3)$

Model: idea

- Each posting by seller i enters the market with the rate σ_i ($\sigma_1 \leq \cdots \leq \sigma_n$ (poisson))
- Frequency of meeting any seller: λ
- Consumer considers N options on the first page

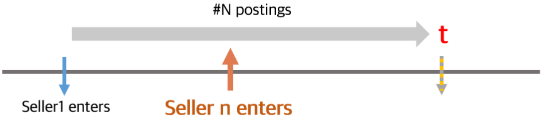


Model: idea

$$P(\sigma_n \text{ enters within N elements} | \sigma_1)$$

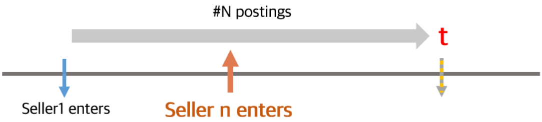
Model: idea

$$P(\sigma_n \text{ enters within N elements}|\sigma_1)$$



Model: idea

$$P(\sigma_n \text{ enters within N elements} | \sigma_1)$$



- S_N : the time t until N postings enter the market (Gamma(N, λ))
- $X_n(t)$: time t elapsed until seller n enter (Exp(σ_n))

$$P(\sigma_n \text{ enters within N elements} | \sigma_1) =$$

$$\int_0^\infty P(S_N = t)P(X_n \leq t)dt = \int_0^\infty \frac{\lambda^N z^{N-1} e^{-\lambda z}}{(N-1)!}(1 - e^{-\sigma_n z})dz$$

$$= 1 - \frac{\lambda^N}{(\lambda + \sigma_n)^N}$$

Model: Starting from the list

- If $N = 1$, meeting seller n : $\frac{\sigma_n}{\lambda+\sigma_n}$

Model: Starting from the list

- If $N = 1$, meeting seller n : $\frac{\sigma_n}{\lambda+\sigma_n}$
- If N gets larger$\cdots$

Model: Starting from the list

- If $N = 1$, meeting seller n : $\frac{\sigma_n}{\lambda+\sigma_n}$
- If N gets larger$\cdots$

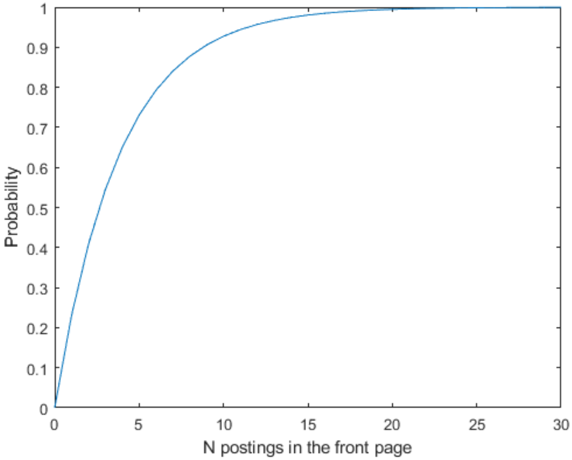


Figure 1: Meeting probability

Potential Models of Seller Pricing Competition

- Simple case: 3 seller competition
  - Sellers: Reach $(\sigma_1, \sigma_2, \sigma_3)$
  - Consumers: $\alpha_1, \alpha_{12}, \cdots$

1. Independent (Random match)

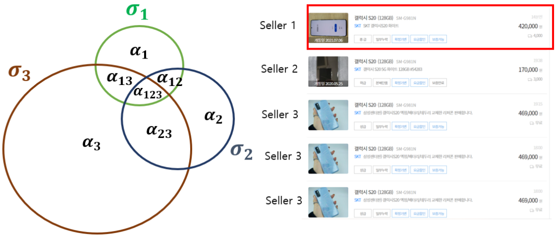


Figure 2: Independent Structure

- Consumers choose the product at the top of the list
- $P(\text{Large}\,\sigma | \text{Small}\,\sigma) = P(\text{Large}\,\sigma)$

❷ Nested Structure (Extensive search)

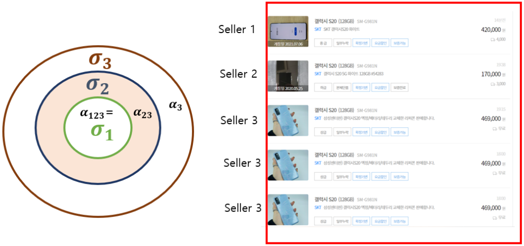


Figure 3: Nested Structure

Nested structure

- Compare the options in the list
- The probability is Not independent across the sellers
- $P(\text{Large}\,\sigma | \text{Small}\,\sigma) = 1$

Potential Models of Seller Pricing Competition

❷ Nested Structure (Extensive search)

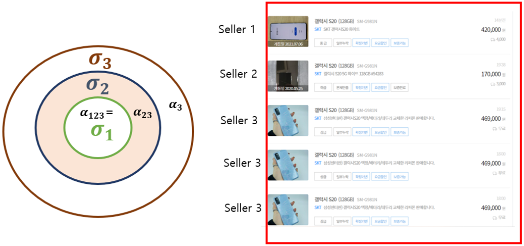


Figure 3: Nested Structure

Nested structure

- Compare the options in the list
- The probability is Not independent across the sellers
- $P(\text{Large}\,\sigma|\text{Small}\,\sigma) = 1$
- **Key intuition**: In nested model, consumers who see small-reach sellers already saw the big-reach sellers
  $\rightarrow$ Small sellers face elastic demand

Model Predictions

- Model predictions Why

Model Predictions

- Model predictions Why
  1. In the independent structure, the minimum price is the same across the sellers, maximum price increases
  2. In the nested structure, the price supports of each seller increase by the size of σ

Model Predictions

- Model predictions Why
  1. In the independent structure, the minimum price is the same across the sellers, maximum price increases
  2. In the nested structure, the price supports of each seller increase by the size of σ
- **Two tests:**
  - **Sanity check**: First order stochastic dominance price distributions
  - **Test between two pricing models**: Minimum price

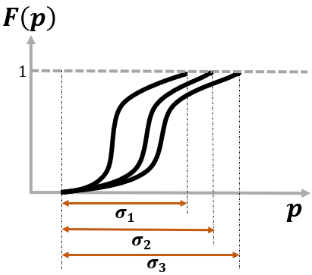


Figure 4: Independent Structure

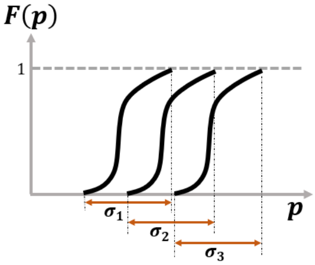


Figure 5: Nested Structure

Applying Model Predictions to Data

1. Identify which of the two models better fits the data

Applying Model Predictions to Data

1. Identify which of the two models better fits the data
2. Using the model, quantify seller's market power (pricing power)

Applying Model Predictions to Data

1. Identify which of the two models better fits the data
2. Using the model, quantify seller's market power (pricing power)
   - Why two models? Difference in demand price elasticity lead to difference in markups: The ability to charge price premium
   - It can show how much each seller can enjoy by posting more than competitors.

Applying Model Predictions to Data

1. Identify which of the two models better fits the data
2. Using the model, quantify seller's market power (pricing power)
   - Why two models? Difference in demand price elasticity lead to difference in markups: The ability to charge price premium
   - It can show how much each seller can enjoy by posting more than competitors.

$\rightarrow$ **To do so**

Applying Model Predictions to Data

1. Identify which of the two models better fits the data
2. Using the model, quantify seller's market power (pricing power)
   - Why two models? Difference in demand price elasticity lead to difference in markups: The ability to charge price premium
   - It can show how much each seller can enjoy by posting more than competitors.

$\rightarrow$ **To do so**

- Check model assumptions

Applying Model Predictions to Data

1. Identify which of the two models better fits the data
2. Using the model, quantify seller's market power (pricing power)
   - Why two models? Difference in demand price elasticity lead to difference in markups: The ability to charge price premium
   - It can show how much each seller can enjoy by posting more than competitors.

$\rightarrow$ **To do so**

- Check model assumptions
- Calculate Key components

Applying Model Predictions to Data

1. Identify which of the two models better fits the data
2. Using the model, quantify seller's market power (pricing power)
   - Why two models? Difference in demand price elasticity lead to difference in markups: The ability to charge price premium
   - It can show how much each seller can enjoy by posting more than competitors.

$\rightarrow$ **To do so**

- Check model assumptions
- Calculate Key components
- Compare model predictions

Applying Model Predictions to Data

1. Identify which of the two models better fits the data
2. Using the model, quantify seller's market power (pricing power)
   - Why two models? Difference in demand price elasticity lead to difference in markups: The ability to charge price premium
   - It can show how much each seller can enjoy by posting more than competitors.

$\rightarrow$ **To do so**

- Check model assumptions
- Calculate Key components
- Compare model predictions
  - Compare the two competing price competition models
    - Statistical tests are conducted on each cellphone model (Galaxy S9, iPhone 10, etc.)

Applying Model Predictions to Data

- Check model assumptions

Applying Model Predictions to Data

- Check model assumptions

1. Product homogeneity assumption
   $\rightarrow$ Several assumptions are needed
   - Consumers are homogeneous in utility (Wildenbeest (2011))
   - Observable characteristics are additively separable (Wildenbeest (2011), Haile,Hong,Shum (2003))
     - Sellers are competing with residual price: (i: listing, k: model, t: market)

$$
\begin{aligned}
p_{ikt} &= \delta_{ikt} + \epsilon_{ikt} \\
&= QT_{ikt}\beta_1 + GR_{ikt}\beta_2 + \text{Size}_{ikt}\beta_3 + \gamma_k + \text{Month FE} + \epsilon_{ikt} \\
\hat{p}_{ikt} &= \hat{\gamma}_k + \hat{\epsilon}_{ikt}
\end{aligned}
$$

Price variation decomposition | Price regression | Price regression Comparison

Applying Model Predictions to Data

- Check model assumptions

1. Product homogeneity assumption
   → Several assumptions are needed
   - Consumers are homogeneous in utility (Wildenbeest (2011))
   - Observable characteristics are additively separable (Wildenbeest (2011), Haile,Hong,Shum (2003))
     - Sellers are competing with residual price: (i: listing, k: model, t: market)

$$
\begin{aligned}
p_{ikt} &= \delta_{ikt} + \epsilon_{ikt} \\
&= QT_{ikt}\beta_1 + GR_{ikt}\beta_2 + \text{Size}_{ikt}\beta_3 + \gamma_k + \text{Month FE} + \epsilon_{ikt} \\
\hat{p}_{ikt} &= \hat{\gamma}_k + \hat{\epsilon}_{ikt}
\end{aligned}
$$

Price variation decomposition | Price regression | Price regression Comparison

2. Mixed pricing strategy assumption
   - Rank reversal statistics (Chandra, Tappata(2011))
   - Similar to the literature

Statistics | Autocorrelation

Construction of Reach (σ)

- Reach (σ): Matching chance for each seller
  - Hour: Frequency of listings
    - e.g., Galaxy S9 posted 10/hr, seller A posts 2/hr = 20%
  - Robustness check: Alternative definition of σ
    - Posting share of a seller measured in one month window
    - Posting of each title measured in 1 week window
- Classify sellers into three groups based on the size of σ

Construction of Reach (σ)

- Reach (σ): Matching chance for each seller
  - Hour: Frequency of listings
    - e.g., Galaxy S9 posted 10/hr, seller A posts 2/hr = 20%
  - Robustness check: Alternative definition of σ
    - Posting share of a seller measured in one month window
    - Posting of each title measured in 1 week window
- Classify sellers into three groups based on the size of σ

Table 3: Construction of σ Group

Seller tercile	σ (mean)	σ (median)	σ (std.)
Group 1	0.134	0.128	0.048
Group 2	0.224	0.209	0.074
Group 3	0.350	0.320	0.155

Time variation Step 2

Step 1: Stochastic Monotonicity Test

- **Step 1: Stochastic Monotone (FOSD)** (Chetverikov et al.(2020))
- H_0: Price distributions increase wrt. σ
- Cannot reject H_0: Sanity check test $\vee$

Table 4: Step 1 Result: Galaxy S9

Samples	Galaxy S9
April, prof.	1.23
	(0.17)
July, prof.	0.99
	(0.5)
April, prof., brand>0.8	1.45
	(0.06)
April, prof., brand<0.6	0.78
	(0.70)
Whole data	0.53
	(1.00)
p-value mean	0.354
Criterion p-value	0.025

- Numbers are T stats of the non-parametric test, p-value in the parentheses.
- Prof.: The sellers who sell more than 5 models within 1 month
- Unit of analysis: Unique listing Step 1 test

Step 2: Quantile Testing

- Step 2: Quantile test (Wilcox et al.(2014))
  - Group sellers into 3 by σ Reach
  - Compare the quantiles

$$H_0 : \hat{p}_{iq} - \hat{p}_{jq} = 0 \qquad (1)$$

- Overall: **Nested Structure**[2]
  - Some heterogeneity across cellphone models, which depends on market thickness

Other grouping | Other cellphone models | Market thickness

Table 5: Step 2 Result: Galaxy S9, July

	Group1	Group3	Diff.	p-value
$p_{0.01}$	0.103	0.154	-0.051	0.0000
			(-0.057,-0.044)	
$p_{0.05}$	0.145	0.168	-0.023	0.0000
			(-0.032,-0.017)	
$p_{0.1}$	0.158	0.183	-0.025	0.0000
			(-0.034,-0.019)	
n	976	976		

[2] Joint testing across various sub samples (DiCiccio et al.(2020))

Step 2: Quantile Testing

- Step 2: Quantile test (Wilcox et al.(2014))
  - Group sellers into 3 by σ Reach
  - Compare the quantiles

$$H_0 : \hat{p}_{iq} - \hat{p}_{jq} = 0 \quad (1)$$

- Overall: **Nested Structure**[2]
  - Some heterogeneity across cellphone models, which depends on market thickness

Other grouping | Other cellphone models | Market thickness

Table 5: Step 2 Result: Galaxy S9, July

	Group1	Group3	Diff.	p-value
$p_{0.01}$	0.103	0.154	-0.051	0.0000
			(-0.057,-0.044)	
$p_{0.05}$	0.145	0.168	-0.023	0.0000
			(-0.032,-0.017)	
$p_{0.1}$	0.158	0.183	-0.025	0.0000
			(-0.034,-0.019)	
n	976	976		

- Takeaway: Min. price for group 3 is larger

[2] Joint testing across various sub samples (DiCiccio et al.(2020))

Robustness Check: Quantile Regression

- Quantile regression: (in general) **Nested structure** Nested prediction

$$p_{imt} = \delta_q \sigma_{im} + \gamma_t + \mu_m + u_{q,imt} \tag{2}$$

Table 6: Quantile Regression

τ	Estimate of δ
0.05	56.28***
	(3.203)
0.1	53.04***
	(4.624)
0.5	59.84***
	(3.592)
0.9	41.15***
	(4.254)
0.95	29.90***
	(5.557)
No. Models	14
Month FE	O
No. Observations	23098

- seller i, market t, model m
- p_{imt} : price, γ_t: month FE, μ_m: model FE
- Unit of analysis: Average weekly price of a seller

Robustness check

Market Power: Price Competition Structure

- To what extent is advertising responsible for a seller's market power?
- Assume the following
  1. Sellers form beliefs about price distributions and σ distributions
  2. Based on beliefs and the advertising cost, a seller decides σ
  3. Compete in price, $F(p|\sigma)$
- Assumption: Input market is competitive (same input cost), difference in implicit cost for posting

Market Power: Price Competition Structure and Intuition

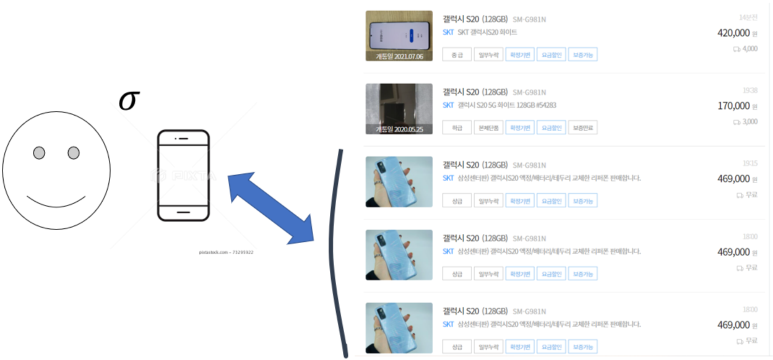
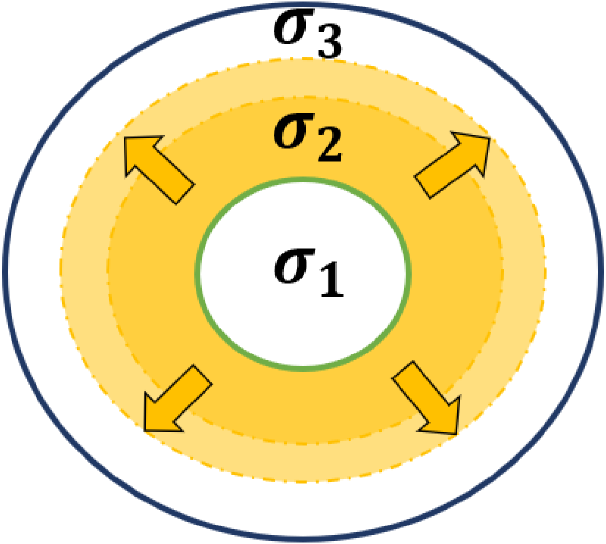


Figure 6: Posting Decision

Market Power: Price Competition in Nested Structure

- Compete with the firms that are posting more frequently



Market Power: Price Competition in Nested Structure

- Focusing on the choice of an arbitrary seller 2
- Seller 1 and seller 3 are also conducting mixed pricing strategy $(F_1(p), F_3(p))$

Market Power: Price Competition in Nested Structure

- Focusing on the choice of an arbitrary seller 2
- Seller 1 and seller 3 are also conducting mixed pricing strategy $(F_1(p), F_3(p))$
- Nested structure

$$\pi_2(p, \sigma_2) = \underbrace{\underbrace{p(1 - F_3(p))}_{\sigma > \sigma_2}}_{\text{Marginal revenue}} ((\sigma_2 - \sigma_1) + \sigma_1 \underbrace{(1 - F_1(p))}_{\sigma < \sigma_2}) - c(\sigma_2)$$

Market Power: Price Competition in Nested Structure

- Focusing on the choice of an arbitrary seller 2
- Seller 1 and seller 3 are also conducting mixed pricing strategy $(F_1(p), F_3(p))$
- Nested structure

$$\pi_2(p, \sigma_2) = \underbrace{\underbrace{p(1 - F_3(p))}_{\sigma > \sigma_2}}_{\text{Marginal revenue}} ((\sigma_2 - \sigma_1) + \sigma_1 \underbrace{(1 - F_1(p))}_{\sigma < \sigma_2}) - c(\sigma_2)$$

- The cost of advertising: $c(\sigma_2) = \frac{1}{2}\sigma_2^2 w_2$
  - σ_2: size of reach, w_2: cost parameter

Market Power: Price Competition in Nested Structure

- Focusing on the choice of an arbitrary seller 2
- Seller 1 and seller 3 are also conducting mixed pricing strategy $(F_1(p), F_3(p))$
- Nested structure

$$\pi_2(p, \sigma_2) = \underbrace{\underbrace{p(1 - F_3(p))}_{\sigma > \sigma_2}}_{\text{Marginal revenue}} \left((\sigma_2 - \sigma_1) + \sigma_1 \underbrace{(1 - F_1(p))}_{\sigma < \sigma_2}\right) - c(\sigma_2)$$

- The cost of advertising: $c(\sigma_2) = \frac{1}{2}\sigma_2^2 w_2$
  - σ_2: size of reach, w_2: cost parameter

$$(\text{Nested}) : \text{MR} = p(1 - F_3(p)) = c'(\sigma_2) = w_2\sigma_2 = \text{MC}$$

Market Power: Price Competition in Nested Structure

- Focusing on the choice of an arbitrary seller 2
- Seller 1 and seller 3 are also conducting mixed pricing strategy $(F_1(p), F_3(p))$
- Nested structure

$$\pi_2(p, \sigma_2) = \underbrace{\underbrace{p(1 - F_3(p))}_{\sigma > \sigma_2}}_{\text{Marginal revenue}} ((\sigma_2 - \sigma_1) + \sigma_1 \underbrace{(1 - F_1(p))}_{\sigma < \sigma_2}) - c(\sigma_2)$$

- The cost of advertising: $c(\sigma_2) = \frac{1}{2}\sigma_2^2 w_2$
  - σ_2: size of reach, w_2: cost parameter

$$(\text{Nested}) : \text{MR} = p(1 - F_3(p)) = c'(\sigma_2) = w_2\sigma_2 = \text{MC}$$

- Mixed price strategy: Seller's minimum price (L_2, 5% price)

$$w_2 = \frac{L_2}{\sigma_2}$$

Market Power: Price Competition in Nested Structure

- Focusing on the choice of an arbitrary seller 2
- Seller 1 and seller 3 are also conducting mixed pricing strategy $(F_1(p), F_3(p))$
- Nested structure

$$\pi_2(p, \sigma_2) = \underbrace{\underbrace{p(1 - F_3(p))}_{\sigma > \sigma_2}}_{\text{Marginal revenue}} ((\sigma_2 - \sigma_1) + \sigma_1 \underbrace{(1 - F_1(p))}_{\sigma < \sigma_2}) - c(\sigma_2)$$

- The cost of advertising: $c(\sigma_2) = \frac{1}{2}\sigma_2^2 w_2$
  - σ_2: size of reach, w_2: cost parameter

$$(\text{Nested}) : \text{MR} = p(1 - F_3(p)) = c'(\sigma_2) = w_2\sigma_2 = \text{MC}$$

- Mixed price strategy: Seller's minimum price (L_2, 5% price)

$$w_2 = \frac{L_2}{\sigma_2}$$

- Use empirical objects: L_2, σ_2 are observed

Market Power: Price Competition in Independent Structure

- Independent structure
- For any arbitrary seller i, shares the same minimum price p_0

$$\pi_i(p, \sigma_i) = \sigma_i \underbrace{p_0}_{\text{Marginal revenue}} - c(\sigma_i)$$

$$\text{(Independent)} : MR = p_0 = c'(\sigma_i) = w_i \sigma_i = MC$$

$$w_i = \frac{p_0}{\sigma_i}$$

- Mixed price strategy: Same minimum price (5% price)
- Use empirical objects: p_0, σ_i are observed

Estimated Results: Markups

- Markups: $\frac{p - \sigma_i w_i}{p}$
- Frequent sellers have higher markup in the nested structure

Table 7: Markups in Interaction Structure

Galaxy S9 (Nested)	Median
Group 1 seller	0.061
Group 2 seller	0.128
Group 3 seller	0.135
iPhone XR (Independent)	**Median**
Group 1 seller	0.124
Group 2 seller	0.141
Group 3 seller	0.084

- Takeaway: The sellers who post more have more market power if the interaction structure is nested

Platform's Return

- Platform's revenue: Commission
- Re-posting increases the probability of sale
- The sellers who repost more have higher prices
  - Increases platform's return
  - Consumer's welfare would decrease

$$E(p\hat{q}_{\text{sell}}|\sigma, X) = \int p\hat{q}_{\text{sell}}(p, \sigma) f(p|\sigma, X) dp \tag{3}$$

Table 8: One listing expected return, Galaxy S9

Seller Group	Mean ($)
Group 1	5.718
	(1.549)
Group 2	6.082
	(2.128)
Group 3	7.32
	(2.572)

- Takeaway: Repeated posting can be good for platform

Conclusion

- **Online market sellers' behavior**
  - I find that sellers who post more charge higher prices
  - The mechanism: Nested interaction structure gives more market power to the frequent posters
  - Thinner markets are likely to show nested structure
  - Platform gets higher profit from the sellers who post more

Thank You!

Re-posting

	제목	작성자	작성일	조회
536855817	[스팀] 다크사이더스3 22000원 판매	직[redacted]Man	2018.12.04.	11
536806672	스팀 카스 글옵 ㄱㅈ팜 판매	[redacted]아신비주의	2018.12.04.	6
536725976	스팀 게임키 팝니다 (험블번들 10월자// 히든포크스, 그렘린즈, 아메리칸트럭, 위워히어투, 올드맨스저니) 판매	1[redacted]	2018.12.04.	29
536610442	스팀선물로 배그/gta팔아요 21000원 판매	찌[redacted]잉	2018.12.04.	13
536596863	▶▶ 스팀게임 PC 몬스터 헌터 월드&디럭스 기프트판매합니다 ◀◀ 판매	TO[redacted]STEAM	2018.12.04.	11
536596188	▶▶ 스팀게임 PC 어쎄신크리드(어쌔신크리드) 오디세이 기프트판매합니다 ◀◀ 판매	TO[redacted]STEAM	2018.12.04.	11
536595398	●스팀게임선물판매● 어쎄신크리드 오디세이 몬스터헌터 FM2019 림월드 등 모든스팀게임, VR판매 ● 후기2300개++ ● 지인추천, 후기이벤트 중 ● 사업자 등록 판매업체 ● 판매	TO[redacted]STEAM	2018.12.04.	18
536487932	스팀 GTA5 + 카스글옵 판매합니다. 판매	지[redacted]	2018.12.03.	24
536476829	스팀 GTA5 판매합니다 판매	유[redacted]	2018.12.03.	26
536328063	▶▶ 스팀게임 FM2019 (Football Manager 2019) 기프트판매합니다 ◀◀ 판매	TO[redacted]STEAM	2018.12.03.	5
536294964	▶▶ 스팀게임 PC 몬스터 헌터 월드&디럭스 기프트판매합니다 ◀◀ 판매	TO[redacted]STEAM	2018.12.03.	9
536288535	▶▶ 스팀게임 PC 어쎄신크리드(어쌔신크리드) 오디세이 기프트판매합니다 ◀◀ 판매	TO[redacted]STEAM	2018.12.03.	5
536259315	●스팀게임선물판매● 어쎄신크리드 오디세이 몬스터헌터 FM2019 림월드 등 모든스팀게임, VR판매 ● 후기2300개++ ● 지인추천, 후기이벤트 중 ● 사업자 등록 판매업체 ● 판매	TO[redacted]STEAM	2018.12.03.	24
536113987	GTA5 + 카스글옵 스팀아이디 싸게 급처합니다. 판매	지[redacted]	2018.12.02.	13
536092750	아크서바이벌 스팀 선물로 삽니다.. 판매	su[redacted]	2018.12.02.	29

Figure 7: Re-Posting: 중고나라

Back

Re-Posting

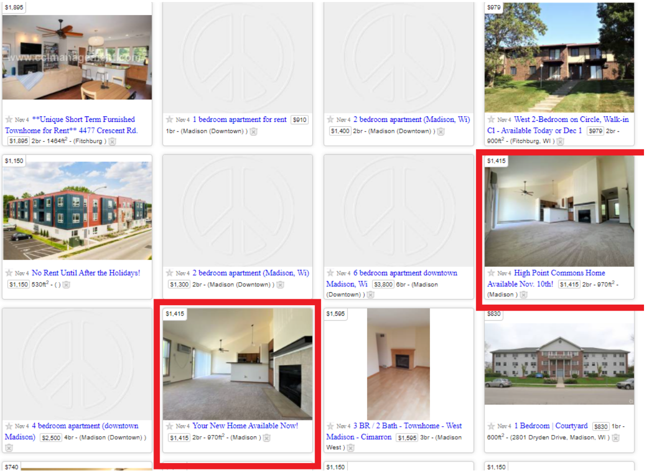


Figure 8: Re-Posting: Craigslist

Back

Data Cleaning Procedure

Table 9: Number of Observations

Data Cleaning	Number of Observation
Total number of postings	810,585
Postings with memory size	500,482
Unique postings	104,173
Sold items	116,018
With original price	248,497
Number of models	15

Back to data

Testing Serial Correlation

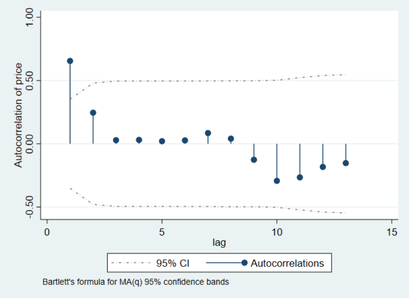


Figure 9: Auto Correlation: Seller ID "tam**" with A1905 Product

Table 10: Statistical Test Results

Model	Yule-Walker Average Pvalue	Bartel's Rank test Average Pvalue
SM-N950	0.376	0.291
A1901	0.301	0.242
A1905	0.298	0.213
A2097	0.365	0.267
A2105	0.350	0.245
A2215	0.403	0.316
A2221	0.367	0.308
SM-A530	0.265	0.175
SM-G960	0.288	0.182
SM-G973	0.377	0.284
SM-G975	0.354	0.274
SM-G977	0.351	0.266
SM-J330	0.243	0.144
SM-N960	0.369	0.293
SM-N976	0.395	0.300

Assumptions

Testing Serial Correlation

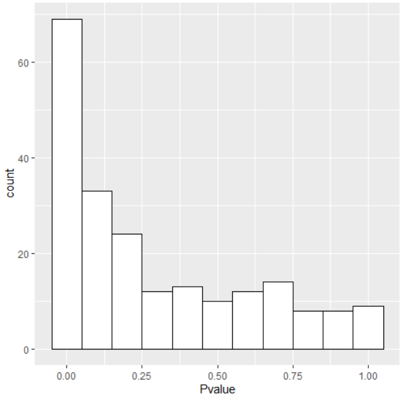


Figure 10: Pvalue from Bartels' Test(week)

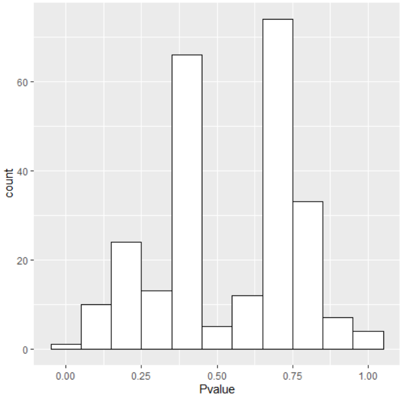


Figure 11: Pvalue from Bartels' Test(month)

Rank Reversal Statistic

- For 2 seller pair i and k

$$r_{ik} = \frac{1}{T_{ik}} \sum_{t=1}^{T_{ik}} I(\hat{p}_{kt} > \hat{p}_{it}) \quad \text{when} \quad \frac{1}{T_{ik}} \sum_{t=1}^{T_{ik}} I(\hat{p}_{it} > \hat{p}_{kt}) > 0.5$$

Table 11: Rank Reversal Statistics

Model	Rank Reversal
SM-A530	0.148
SM-G960	0.124
SM-G973	0.120
SM-G975	0.122
SM-G977	0.141
SM-J330	0.139
SM-N950	0.135
SM-N960	0.127
SM-N976	0.120
A1901	0.119
A1905	0.145
A2097	0.140
A2105	0.138
A2215	0.140
A2221	0.140

Assumptions

Step 1: Stochastic Monotonicity Test (Chetverikov(2020))

- The null hypothesis

$$H_0 : \text{For each p} \in P, F_{p|\sigma}(p|\sigma) \leq F_{p|\sigma'}(p|\sigma') \text{ if } \sigma \geq \sigma' \quad \text{for } \sigma, \sigma' \in \Sigma$$

- It can be written as following equation

$$E\left(1(p_i \leq p) - 1(p_j \leq p)\right) sign(\sigma_i - \sigma_j) K_h(\sigma_i - \sigma) K_h(\sigma_j - \sigma)) \leq 0 \tag{4}$$

- Simplifying the notation by using
$K_{ij,h}(\sigma) = sign(\sigma_i - \sigma_j) K_h(\sigma_i - \sigma) K_h(\sigma_j - \sigma)$,
$k_{i,h}(\sigma) = \sum_{j=1}^{n} (K_{ij,h}(\sigma) - K_{ji,h}(\sigma)) = 2 \sum_{j=1}^{n} K_{ij,h}(\sigma)$

$$T = \max_{(\sigma,p,h) \in \Sigma_n \times p_n \times B_n} \frac{\sum_{i=1}^{n} k_{i,h}(\sigma) 1(p_i \leq p)}{\left(\sum_{i=1}^{n} k_{i,h}(\sigma)^2\right)^{1/2}} \tag{5}$$

- Critical values are calculated using bootstrap Testing

Robustness Check: With Only Professional Sellers

- Unit of analysis: Seller monthly average, only professional sellers (who sell more than 5 different models within a month)

Table 12: Quantile Regression: Professional Sellers

τ	Estimate of δ	
	(1)	(2)
0.05	56.57***	50.89**
	(10.21)	(18.05)
0.1	51.87**	49.47**
	(17.69)	(18.89)
0.5	261.8***	246.9***
	(22.69)	(27.66)
0.9	245.2***	215.1***
	(32.44)	(32.52)
0.95	193.5***	181.1***
	(29.29)	(38.39)
No. Models	14	14
Month FE	X	O
No. Observations	23098	23098

Summary of Tests

Robustness Check: Time Gaps

- Unit of analysis: Seller monthly average price

Table 13: Quantile Regression: Time Gaps (hours) between Postings

τ	Estimate of δ	
	(1)	(2)
0.05	-0.00574***	-0.00618***
	(0.00102)	(0.00103)
0.1	-0.00600***	-0.00580***
	(0.000665)	(0.000947)
0.5	-0.00402***	-0.00472***
	(0.000413)	(0.000404)
0.9	-0.00180*	-0.00212*
	(0.000710)	(0.000933)
0.95	0.000159	-0.00129
	(0.00222)	(0.00216)
No. Models	14	14
Month FE	X	O
No. Observations	18335	18335

Summary of Tests

Minimum Price and Independent Case

- If both seller 1 and 2 charge the same minimum p_0, the profit of the two sellers are $\pi_1 = \sigma_1 p_0, \pi_2 = \sigma_2 p_0$
- What if seller 1 has higher minimum price? $(p_L^1 \geq p_0 = p_L^2)$
- Then $p_L^1 \in [p_0, p_2^H]$, the profit of seller 2 would be written as

$$p_L(1 - F_1(p_L))\alpha_{12} + \alpha_2 p_L = \sigma_2 p_L \geq \sigma_2 p_0 \,(\text{contradiction})$$

- Therefore, in the independent case, the minimum price is the same

Model Predictions

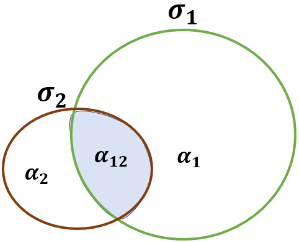


Figure 12: Independent

Minimum Price and the Nested Case

- Assume seller 3 has the same minimum price as seller 2
- Since consumers of seller 2 compare seller 3 at the same time, seller 2 can achieve higher profit by lowering the minimum price
- Intuition: In the nested structure, the seller inside faces more elastic demand $\rightarrow$ Lower minimum price

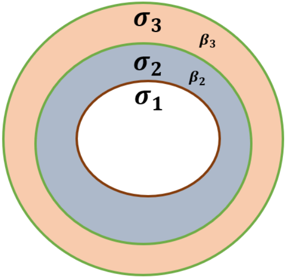


Figure 13: Nested

Model Predictions

Data Cleaning Procedure

Table 14: Number of Observations

Data cleaning	Number of observation
Total number of postings	810,585
Postings with memory size	500,482
Unique postings	104,173
Sold items	116,018
With original price	248,497
Number of Models	15

Back to data

Sensitivity to Choice of Groups

- If group the sellers to 5, compare group 5 and 1 (finer grouping) gives more frequent rejection: Different minimum price

Table 15: Nestedness with Grouping

Model	3 group	5 group
iPhone X	1	1
iPhone 8	1	1
iPhone XS	1	0
iPhone XR	0	0
iPhone 11	0	1
Galaxy A8	1	0
Galaxy S9	1	1
Galaxy S10	0	0
Galaxy J3	0	1
Galaxy Note8	1	1
Galaxy Note9	0	0
Galaxy Note10	0	0

Quantile testing

Platform

- In principle, one item for one posting
  - But in practice, sellers are making duplicate posts
  - The postings with the same description and characteristics are likely to have the same picture: Same product
  - Characteristics: memory, condition, warranty period, seller
- Platform does not allow the use of macro or automatic re-posting
- Platform manages the trade
  - Item disappears from the list with flag of "sold" when the item is sold

Back to platform

Distribution of the Number of Re-Posting

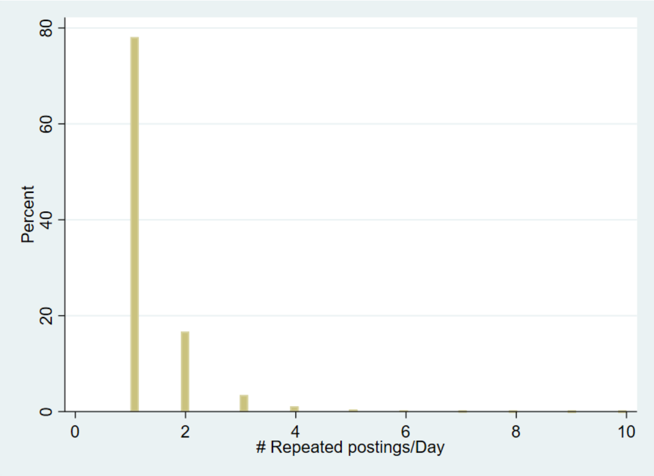


Figure 14: Number of Re-Posting Per Day

Back to sales

Table 16: Changes in Group

		Seller group(in each month)		
		1	2	3
(Time invariant) Seller group	1	83,676	11,298	541
		87.61	11.83	0.57
	2	14,288	46,775	13,961
		19.04	62.35	18.61
	3	3,826	20,203	53,929
		4.91	25.92	69.18

Reach

Homogeneity Assumption

Table 17: Price Regression

Price regression	Price ($)	Log (Price)
Controls	Yes	Yes
Model FE	Yes	Yes
Month FE	Yes	Yes
N	810578	810578
R-sq.	0.939	0.948

Table 18: Difference between Regression Model and the Data

Stats	Linear	Log Linear
Mean	34.62	34.28
p25	11.08	8.42
p50	24.24	20.08
p75	45.02	42.49

Homogeneity Assumptions

Price Regression

Table 19: Price Regression

Regression	$\log p(1)$	$\log p(2)$	$\log p(3)$
Controls	O	O	O
Model FE	O	O	O
Month FE	O	O	O
Model # post/hr	X	O	X
# seller/mth		X	O
R-sq	0.948	0.948	0.948
N	810578	810578	810578

Assumptions

Price Estimation Difference

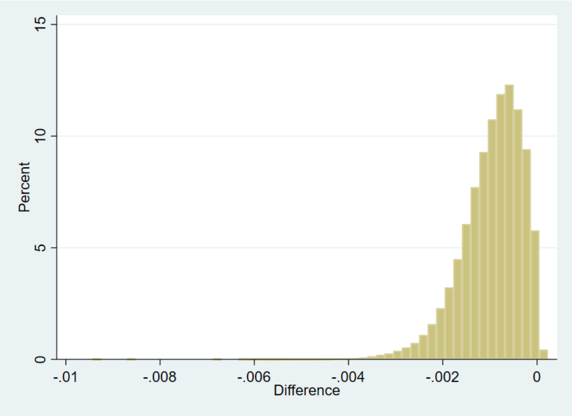


Figure 15: Price Difference (1) and (2)

Homogeneity Assumptions

Price Variation Decomposition

Table 20: Price Variation Decomposition

Dep: Residuals	Whole		Galaxy S9	
Regressor	Coef.	Group %R2	Coef.	Group %R2
Seller,Model # Post/Hr	0.0020	24.86	0.0019	26.80
Seller # Post/Hr	0.0019	73.53	0.0058	72.75
Model # Post/Hr	-0.0004	1.61	-0.0004	0.46
Observations	248497		32084	
Overall R2	0.0210		0.0938	

Homogeneity Assumption

Posting is the Key Component of Sales

Table 21: Sales Outcome Decomposition

Dep: Sales (0,1)	Whole	
Regressor	Coef.	Group %R2
# repeated posting daily	0.095	56.56
Price ratio($)	-0.064	10.84
Controls		25.45
Model share	0.572	1.89
Avg Seller Freq/Day	0.000	5.27
Observation	104169	
Overall R2	0.010	

To sales

Robustness Check: Inventory

- Inventory?: A seller with more postings may have a larger inventory
- The granular level of σ construction
- Unit of analysis: Seller unique description monthly average price, listing share

Table 22: Quantile Regression : posting level

τ	Estimate of δ (1)	Estimate of δ (2)
0.05	0.110*	0.175*
	(2.20)	(2.02)
0.1	0.197*	0.309**
	(2.53)	(2.65)
0.5	0.291**	0.667***
	(2.98)	(9.40)
0.9	-0.344***	-0.113*
	(-3.65)	(-2.13)
0.95	-0.144	-0.258**
	(-1.23)	(-3.15)
No. Models	14	14
Month FE	O	O
Seller Freq	O	X
No. Observations	221577	221577

Robustness check

Robustness Check: Price Endogeneity

- Price endogeneity?: Unobserved demand factors
- Used instruments:
  - Price of other products that are posted within the same hour
  - Used normalized price (btw 0 and 1)

Table 23: Quantile Regression: Price of Other Products

τ	Estimate of δ	
	(1)	(2)
0.05	0.119***	0.131***
	(16.96)	(12.36)
0.1	0.102***	0.128***
	(12.78)	(13.42)
0.5	0.0492***	0.0507***
	(13.32)	(7.71)
No. Models	14	14
Month FE	X	O
No. Observations	12422	12422

Robustness check

Robustness Check: Price Endogeneity

- Price endogeneity?: Unobserved demand factors
- Used instruments:
  - The initial price of repeated listing (with the same description)

Table 24: Quantile Regression: Initial Price

τ	Estimate of δ (1)	(2)
0.05	458.7***	459.7***
	(42.68)	(48.61)
0.1	411.3***	404.4***
	(36.58)	(53.78)
0.5	1187.5***	1184.2***
	(76.24)	(73.46)
No. Models	14	14
Month FE	X	O
No. Observations	51028	51028

Robustness check

Price Adjustment

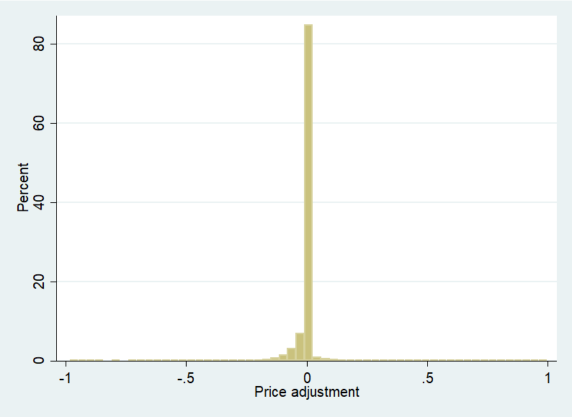


Figure 16: Price Adjustment (Listing Level)

Back to Data

Model Testing

Table 25: Summary of Tests: Other Models

Summary	Step 1	Step 1 test	Step 2	Step 2 test	Result
Model	Mean p-value	Reject	Mean p-value(0.05)	Reject	Nested
iPhone X	0.233	0	0	1	1
iPhone 8	0.867	0	0	1	1
iPhone XS	0.090	0	0	1	1
iPhone XR	0.000	1	0.093	0	0
iPhone 11	0.003	0	0.133	0	0
Galaxy A8	0.047	0	0	1	1
Galaxy S9	0.347	0	0	1	1
Galaxy S10	0.723	0	0.147	0	0
Galaxy J3	0.000	1	0.8	0	0
Galaxy Note8	0.143	0	0	1	1
Galaxy Note9	0.583	0	0.24	0	0
Galaxy Note10	0.000	1	0.013	0	0

2nd step testing

Market Thickness and Nestedness

- The difference between the nested/ non-nested models
  - More sellers in the non-nested models
  - In the nested models, more listings are posted within one hour on average

Table 26: Nested and Non-Nested Model

Variable	Nest		Non nest		Diff (Non nest-Nest)	
	Mean	SD	Mean	SD	β	t
G1 frequency	0.154	0.047	0.127	0.026	-0.027***	(-92.164)
G3 frequency	0.391	0.144	0.366	0.134	-0.025***	(-22.298)
Difference (G3-G1)	0.237	0.115	0.246	0.140	0.008***	(16.248)
Sold probability	0.228	0.161	0.119	0.121	-0.109***	(-189.675)
# G1 sellers	80.730	31.803	96.006	33.471	15.275***	(116.654)
# G2 sellers	20.482	6.134	27.581	9.794	7.099***	(217.299)
# G3 sellers	12.687	6.290	16.339	6.836	3.652***	(138.633)
ave. # postings / hour	8.572	2.751	11.738	2.901	3.166***	(279.205)
Observations	122171		126326		248497	

2nd step testing

Robustness Check

- Potential endogeneity concerns

1. Seller with larger inventory
   - σ constructed based on listing level (e.g., "SKT Galaxy Folder G150 White")
   - Still show statistically significant positive coefficient in 5%, 10% price. Inventory story
2. Price endogeneity
   - Unobserved demand shock
     - Price of other models that are posted within the same hour by the seller Price Inst1
     - The initial price of repeated listing (with the same description) Price Inst2
   - All show similar statistical significance and positive coefficients for 5%, 10% price

- Other test results also show similar results - Time lapse, with only professional sellers (who sell more than 5 different models within a month)

Other test results

Back

Re-Posting

	제목	작성자	작성일	조회
536855817	[스팀] 다크사이더스3 22000원 판매	직[redacted]Man	2018.12.04.	11
536806672	스팀 카스 글옵 ㄱㅈ팜 판매	[redacted]아신비주의	2018.12.04.	6
536725976	스팀 게임키 팝니다 (험블번들 10월자// 히든포크스, 그렘린즈, 아메리칸트럭, 위워히어투, 올드맨스저니) 판매	1[redacted]	2018.12.04.	29
536610442	스팀선물로 배그/gta팔아요 21000원 판매	찌[redacted]잉	2018.12.04.	13
536596863	▶▶ 스팀게임 PC 몬스터 헌터 월드&디럭스 기프트판매합니다 ◀◀ 판매	TO[redacted]STEAM	2018.12.04.	11
536596188	▶▶ 스팀게임 PC 어쌔신크리드(어쌔신크리드) 오디세이 기프트판매합니다 ◀◀ 판매	TO[redacted]STEAM	2018.12.04.	11
536595398	●스팀게임선물판매● 어쎄신크리드 오디세이 몬스터헌터 FM2019 림월드 등 모든스팀게임, VR판매 ● 후기2300개++ ● 지인추천, 후기이벤트 중 ● 사업자 등록 판매업체 ● 판매	TO[redacted]STEAM	2018.12.04.	18
536487932	스팀 GTA5 + 카스글옵 판매합니다. 판매	지[redacted]	2018.12.03.	24
536476829	스팀 GTA5 판매합니다 판매	유[redacted]	2018.12.03.	26
536328063	▶▶ 스팀게임 FM2019 (Football Manager 2019) 기프트판매합니다 ◀◀ 판매	TO[redacted]STEAM	2018.12.03.	5
536294964	▶▶ 스팀게임 PC 몬스터 헌터 월드&디럭스 기프트판매합니다 ◀◀ 판매	TO[redacted]STEAM	2018.12.03.	9
536288535	▶▶ 스팀게임 PC 어쌔신크리드(어쌔신크리드) 오디세이 기프트판매합니다 ◀◀ 판매	TO[redacted]STEAM	2018.12.03.	5
536259315	●스팀게임선물판매● 어쎄신크리드 오디세이 몬스터헌터 FM2019 림월드 등 모든스팀게임, VR판매 ● 후기2300개++ ● 지인추천, 후기이벤트 중 ● 사업자 등록 판매업체 ● 판매	TO[redacted]STEAM	2018.12.03.	24
536113987	GTA5 + 카스글옵 스팀아이디 싸게 급처합니다. 판매	지[redacted]	2018.12.02.	13
536092750	아크서바이벌 스팀 선물로 삽니다.. 판매	su[redacted]	2018.12.02.	29

Figure 17: Re-Posting: 중고나라

Back

Re-Posting

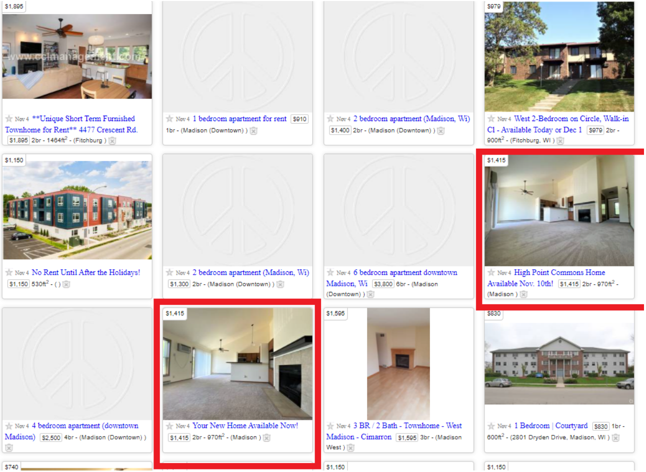
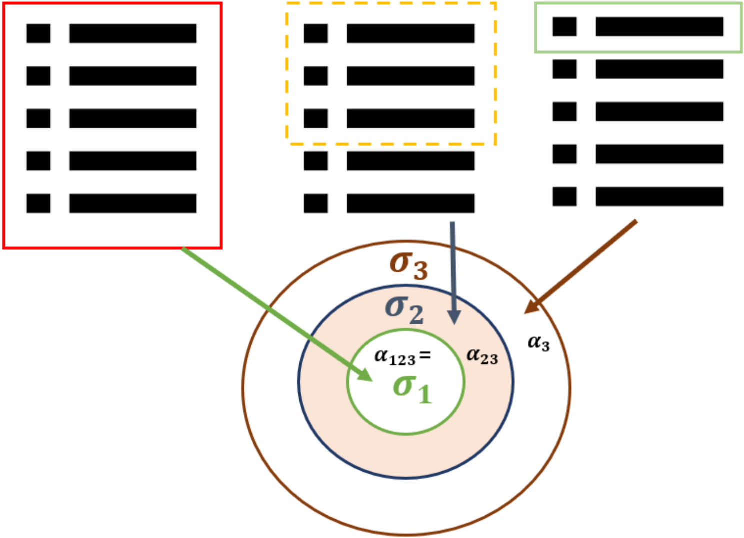


Figure 18: Re-Posting: Craigslist

Back

Nested Structure with Consumer Search



Back to model

Seller Heterogeneity

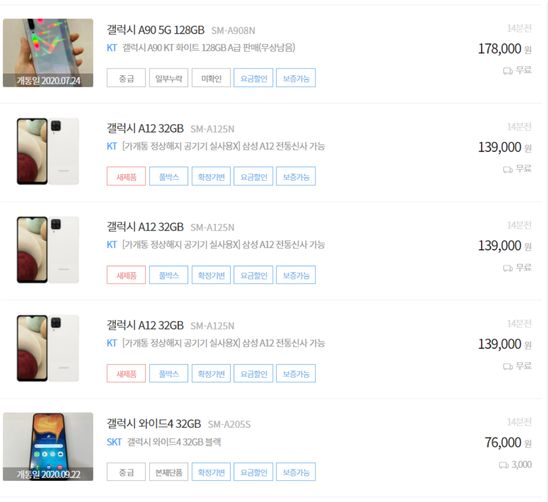
Table 27: Seller Shares

Stats	Mean	SD	P25	P50	P75
Prof Seller/Day,Model	0.934	0.069	0.909	0.950	0.979
Non prof Seller/Day,Model	0.123	0.182	0.036	0.066	0.125
Prof Seller/Hr	0.927	0.039	0.911	0.933	0.951
Non prof Seller/Hr	0.053	0.078	0.026	0.036	0.051

* Prof seller: The sellers who sell more than 5 cellphone models/month

Back to Data

Repeated Posting: Duplicated Posting



Back to data

Why it is important?

- Contribution to the literature
  - Giving empirical evidence on the theoretical predictions that were conflicted in the literature
- Practical aspect
  - Used product trading platforms in Korea suffer from the over-posting problem: Some sellers put too many postings.
  - Platform needs to understand why the sellers are over-posting
  - My analysis could be used as evidence to understand seller behavior.

Back

Model Predictions: Nested

- Predictions from nested structure

1. The entry of new sellers will not cause changes for a nested case.

Table 28: Pricing after Group 1 Entrants

	Δ Group 1 price(wk)	Δ Group 2 price(wk)	Δ Group 3 price(wk)
Δ # seller(wk)	0.0383	0.143	0.206
	(0.101)	(0.0787)	(0.153)
Δ # sold item(wk)	-0.00952	-0.0105	-0.00183
	(0.00621)	(0.00682)	(0.00868)
Δ # Group1 seller(wk)	-0.0544	-0.149	-0.254
	(0.121)	(0.0816)	(0.178)
Const	0.0405	-0.386***	1.127***
	(0.0656)	(0.0548)	(0.101)
Model FE	O	O	O
N	450	450	450
R-sq	0.014	0.015	0.013

Back

Model Predictions: Nested

2. $F_1(p) - F_3(p)$ is positively associated with σ_3/σ_1 if $\sigma_1 < \sigma_2 < \sigma_3$
   - Instruments: Release of new model(Galaxy S21, etc.), Brand, Number of sellers in the previous week

Table 29: Concentration and Price Distribution Difference

	OLS		IV	
	p10(G3)-p10(G1)	p10(G3)-p10(G1)	p10(G3)-p10(G1)	p10(G3)-p10(G1)
$\sigma_{G_3}/\sigma_{G_1}$	2.733*	2.516*	8.241*	9.397**
	(1.184)	(1.174)	(3.508)	(3.492)
# sold		0.0271		0.0238
		(0.0146)		(0.0150)
Const	-0.418	-0.423	-16.66	-21.39*
	(4.830)	(4.825)	(9.183)	(9.210)
Model FE	Yes	Yes	Yes	Yes
N	465	465	450	450
R-sq	0.462	0.467	0.457	0.441
1stage F stat			19.37	20.11

Back