Foreclosure Complementarities: Exclusionary Bundling and Predatory Pricing

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Motivation

The rise of **BIG** tech



20/01/18



22/02/20



23/03/19

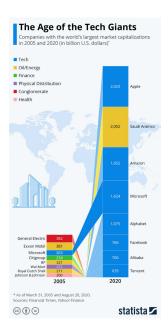


27/02/21

Motivation

The rise of BIG tech

• BIG in size

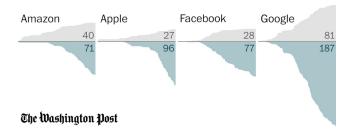


Number of acquisitions

In original business sectors
In new sectors

The rise of BIG tech

- BIG in size
- ...and in **scope**



Policy Response

• Policimakers reports



Policy Response

• Policimakers reports



- ... turning into policy **actions**
 - AU: Digital Platform Branch (12/19) \rightarrow Media Bargaining Code (04/20)
 - UK: Digital Markets Unit (4/21)
 - EU: Digital Markets Act and Digital Services Act (12/20)
 - US: Klobuchar Bill (02/21), Cicilline Bill (06/21), Blumenthal+ Bill (08/21)

Common denominators (potentially because of data)

- Economies of **scale**
- Integration across markets

Foreclosure concerns

- The growth of today's leading digital platforms can be explained by a number of distinct contributing factors, including:
 - the transition of communications to the online world, and the rapid increase in the number of internet users in the past two decades
 - the innovative, user-friendly services the platforms provide
 - the role of network effects in building scale in platform user bases
 - the ability of digital platforms to collect and harness user data for advertising purposes
 - the vertical and horizontal integration of platform businesses.

Figure 2: From ACCC Digital Platform Report (2019)

This Paper

- We build a **computational model** of dynamic competition capturing several essential features of large DP markets:
 - Complementary products/markets
 - Increasing returns to scale (IRS) in at least some markets
 - Mergers
 - Foreclosure practices (predatory pricing and exclusionary bundling)
- We analyze how these economic fundamentals interact to determine industry **structure**
- ...distinguishing between pro- and anti-competitive incentives
- ...and show how **policy** interventions can mitigate consumer harms

Contributions

- Extend existing bundling-to-foreclose literature by **endogenizing market structure**
 - Existing literature "always" starts with a dominant firm in market A and potential competition in a complementary market B
 - Where does that market power come from?
 - Was it obtained competitively?
- Assess interplay between two foreclosure practices
 - Predatory pricing
 - Exclusionary bundling
- Address issues from real-world cases and **policies**

Results

- Predatory pricing and bundling are **complementary strategies**
 - Without one, lower incentives for/effectiveness of the other
 - Potential for domino effect
- Anti-competitive incentives are key
 - Significant drivers for both pricing and bundling, leads to tipping
 - Exit-inducing more important than entry-preventing
- Effective **policies** are possible
 - Ban mergers between market leaders
 - \cdot Ban bundling when only one firm can offer the integrated product
 - Soften the benefits of IRS through data/knowledge sharing

Literature

• Dynamic Stochastic Games

Ericson & Pakes (1995); Doraszelski & Pakes (2007); Doraszelski & Satterthwaite (2010)

- with Learning-by-doing Cabral & Riordan (1994, 1997); Besanko et al. (2010, 2014, 2019)
- Exclusion and Predation Rey & Tirole (2007); Fumagalli et al. (2018)
 - Exclusion with learning-by-doing: predatory pricing Ordover & Willig (1981); Farrell & Katz (2005); Besanko et al. (2020)
 - Exclusion in complementary markets: bundling to foreclose Whinston (1990); Choi & Stefanadis (2001); Carlton & Waldman (2002); Choi (2008)
- Data as a source of scale economies Prufer & Schottmüller (2017); Hagiu & Wright (2020); De Corniere & Taylor (2020)
- Data as a source of complementarities Chen et al. (2020); Condorelli & Padilla (2020a,b); Motta & Peitz (2020)

Model

Setting

- 1. Learning by doing in market A (+ entry/exit)
 - As in Besanko et al. (2010)
 - State variable: *e_n*, firm *n* stock of know-how
 - Winning a sale increases know-how by 1, with probability q_n (demand)
 - Concave learning curve for marginal cost:

 $c(e_n)=c_0e_n^\alpha$

• Entry and exit as in Doraszelski & Satterthwaite (2010)

more details

3.

2.

(A1) (A2)

Setting

- 1. Learning by doing in market A (+ entry/exit)
- 2. Complementary market B (no dynamics)
 - 4 products: $\{A_1, A_2, B_1, B_2\}$
 - + 4 systems: $\{A_1B_1, A_1B_2, A_2B_1, A_2B_2\}$ + outside option
 - Consumers demand one unit of each product
 - Consumer *i* utility from system A_1B_1

$$u_{i,A_1B_1}(\boldsymbol{p}) = v_i - \sigma(p_{A_1} + p_{B_1}) + \varepsilon_{i,A_1B_1}$$



3.



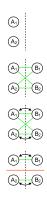
- 1. Learning by doing in market A (+ entry/exit)
- 2. Complementary market B (no dynamics)
- 3. Firms can merge across markets
 - Same mechanism as entry/exit
 - random merger costs
 - Surplus splitting rule: Nash bargaining







- 1. Learning by doing in market A (+ entry/exit)
- 2. Complementary market B (no dynamics)
- 3. Firms can merge across markets
- 4. And bundle their products
 - One firm, one system
 - E.g. consumers cannot combine A_1 and B_2



more details

Equilibrium concept: symmetric Markow Perfect Equilibrium. Prices p^* , value V and policy functions Φ such that

- p^* solves the price maximization problem, $\forall n, \omega$, given V, Φ
- Φ solves the entry, exit, and merger problems $\forall n, \omega$, given p^* , V

Multiple equilibria? Yes.

Solution concept: value function iteration with $V_n^0(\omega) = 0 \ \forall n, \omega$

• We can interpret the computed equilibrium as the MPE of a finite game for $t \to \infty$

- 1. Learning by doing (in one market, A)
 - Basically Besanko et al. (2010)
 - Dynamic pricing incentives
 - Efficient: price as an investment to climb the learning scale
 - Predatory: exclude competitor and recoup after its exit

 (A_1)

 (A_2)

2.

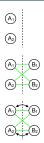
3.

4.

- 1. Learning by doing (in one market, A)
- 2. Add complementary market (no mergers/bundling)
 - · Internalization of price effects is only partial
 - Mixed effects
 - Complementary products (B) do not internalize dynamic incentives
 - Increase prices in (B) in response to below-cost pricing in (A)
 - Response in market (A): further decrease prices
 - Predatory or not?

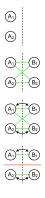


- 1. Learning by doing (in one market, A)
- 2. Add complementary market (no mergers/bundling)
- 3. Add mergers (no bundling)
 - Firms merge to internalize cross-market externalities
 - Higher prices, less predation
 - But externalities still not fully internalized
 - Remains externality w.r.t. competitors
 - Consumers can combine (A_1) and (B_2)



more details

- 1. Learning by doing (in one market, A)
- 2. Add complementary market (no mergers/bundling)
- 3. Add mergers (no bundling)
- 4. Add bundling
 - Pricing externalities fully internalized
 - Back to (1)?
 - No, worse, now firms compete for 2 markets instead of 1
 - Same efficient incentives
 - Higher predatory incentives



Results

Start from the big picture and gradually zoom into the details

- 1. Where do we go?
 - To which state does the model converge?
- 2. How?
 - What do the dynamics look like?
- 3. Why?
 - What incentives drive the dynamics?

Explore the dynamics across two main parameters

- Product differentiation σ
 - Determines the intensity of competition
 - Higher σ : lower competition
- Learning rate α
 - Determines the extent of scale economies
 - Lower α : higher decrease in marginal cost with each sale

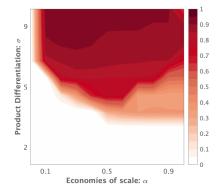
Initial state: non-integrated duopoly.



Comparative Statics

The market degenerates to a monopoly with

- Low σ : high competition
- Low α : high benefits from learning-by-doing



Monopoly Probability (long run)

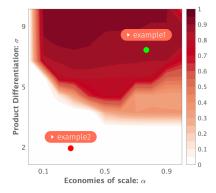
what about welfare?

How do we get there?

Comparative Statics

The market degenerates to a monopoly with

- Low σ : high competition
- Low α : high benefits from learning-by-doing



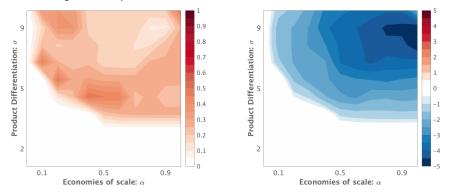
Monopoly Probability (long run)

what about wolfare?

How do we get there?

Bundling and Below-cost pricing

Do firms actually bundle and/or price below cost?



Bundling Probability (short run)

Price - Cost (short run)

Yes, but does it matter?

Parameter grid: 20 × 20 for $\sigma \in [0.1, 1.0]$ and $\alpha \in [0.1, 1]$.

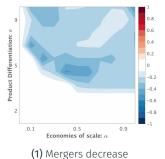
We do two separate experiments

- 1. Shut down the learning-by-doing channel
 - Firm start at the top of the learning curve
- 2. Shut down the **bundling** channel
 - No bundling allowed

Removing Learning-by-doing

What happens if you remove learning by doing?

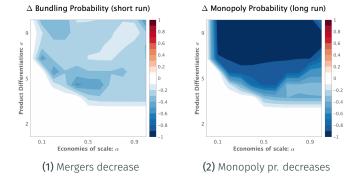
 Δ Bundling Probability (short run)



Parameter grid: 20 × 20 for $\sigma \in [0.1, 1.0]$ and $\alpha \in [0.1, 1]$.

Removing Learning-by-doing

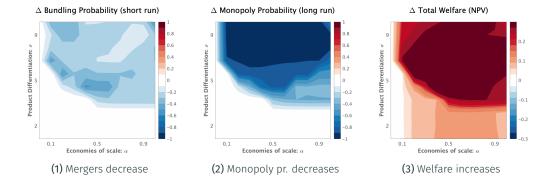
What happens if you remove learning by doing?



Parameter grid: 20 × 20 for $\sigma \in [0.1, 1.0]$ and $\alpha \in [0.1, 1]$.

Removing Learning-by-doing

What happens if you remove learning by doing?



Bundling increases with learning-by-doing.

Parameter grid: 20×20 for $\sigma \in [0.1, 1.0]$ and $\alpha \in [0.1, 1]$.

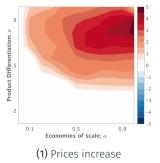
Short run: first 5 periods. Long run: asymptotic. NPV: discounted stream from t = 0 to $t \rightarrow \infty$.

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Removing Bundling

What happens if you remove bundling?

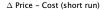
Δ Price – Cost (short run)

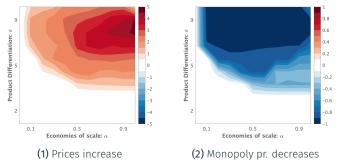


Parameter grid: 20 × 20 for $\sigma \in [0.1, 1.0]$ and $\alpha \in [0.1, 1]$.

Removing Bundling

What happens if you remove bundling?



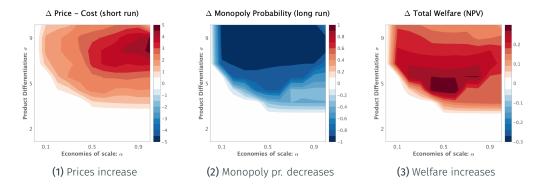


 Δ Monopoly Probability (long run)

Parameter grid: 20 × 20 for $\sigma \in [0.1, 1.0]$ and $\alpha \in [0.1, 1]$.

Removing Bundling

What happens if you remove bundling?



Below-cost pricing increases with bundling.

Parameter grid: 20 × 20 for $\sigma \in [0.1, 1.0]$ and $\alpha \in [0.1, 1]$.

- Without learning, firms have less incentives to bundle products
- Without bundling, firms have more incentives to price below cost
- Together enhance the probability of joint market tipping
- Negative effects on welfare

It seems that they are **complementary**, but why?

Anti-competitive Incentives

Foreclosure

Two potential **foreclosure channels** in this model:

- 1. Bundling
- 2. Pricing

We decompose the incentives in

- Competitive
 - Pricing: scale the learning curve
 - Bundling: internalize cross-market externalities

• Anti-competitive

- Exit-inducing incentives
- Entry-preventing incentives

How?



Anti-competitive Pricing Incentives

Anti-competitive pricing incentives: marginal benefit of price change coming through changes in rivals' entry/exit probability.

How do we quantify them?

1. Take dynamic component of first order condition

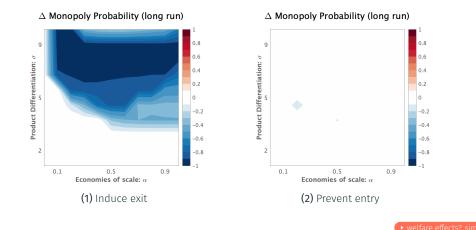
$$\beta \mathbb{E}_{\omega'} \left[\sum_{s} \frac{\partial q_s(\boldsymbol{p})}{\partial p_{A_1}} V_{A_1}^s(\omega') \Big| \Phi \right]$$
(1)

2. Use different future value: value computed with exit (or entry) probabilities unaffected by learning-by-doing

$$\beta \mathbb{E}_{\boldsymbol{\omega}'} \left[\sum_{s} \frac{\partial q_s(\boldsymbol{p})}{\partial p_{A_1}} V_{A_1}^s(\boldsymbol{\omega}') \middle| \Phi_{-X}, \Phi_X^* \right]$$
(2)

3. Compute prices using counterfactual values

Anti-competitive Pricing Incentives



- Anti-competitive incentives are mostly exit-inducing
- Highlights where we can expect policy impact

Anti-competitive Bundling Incentives

Anti-competitive bundling incentives: marginal benefit of bundling coming through changes in rivals' entry/exit probability.

How do we quantify them?

1. Take future value conditional on bundling

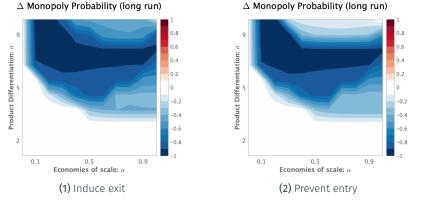
$$\beta \mathbb{E}_{\boldsymbol{\omega}'} \Big[V_n(\boldsymbol{\omega}') \ \Big| \ \text{bundling}, \boldsymbol{\omega}, \boldsymbol{\Phi} \Big]$$
(3)

2. Use different future value: value computed with exit (or entry) probabilities unaffected by bundling

$$\beta \mathbb{E}_{\boldsymbol{\omega}'} \Big[\mathsf{V}_n(\boldsymbol{\omega}') \Big| \text{ bundling}, \boldsymbol{\omega}, \boldsymbol{\Phi}_{-X}, \boldsymbol{\Phi}_X^* \Big]$$
 (4)

3. Compute bundling policy using counterfactual values

Anti-competitive Bundling Incentives



 Δ Monopoly Probability (long run)

- Most of the incentives are exit-inducing
- Highlights where we can expect policy impact

Policy

1. Limit mergers

• Ban mergers between market leaders

2. Limit bundling

 \cdot Allow bundling only when more than one firm can offer the bundle

3. Data sharing

• Leader and follower can be at most 1 level of experience apart

Limit Mergers

Firms that are ahead in the learning curve cannot integrate.

0.8 9 9 0.2 0.6 Ь Product Differentiation: Product Differentiation: 0.4 0.1 0.2 5 -0.2 -0.1 -0.4 -0.6 -0.2 2 2 -0.8 -0.3 0.1 0.5 0.9 0.1 0.5 0.9 Economies of scale: α Economies of scale: α

 Δ Total Welfare (NPV)

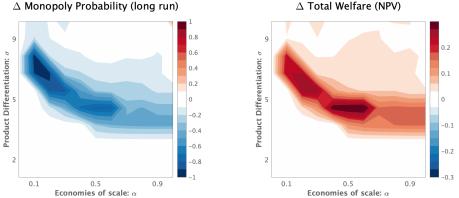
more details

Parameter grid: 20 \times 20 for $\sigma \in [0.1, 1.0]$ and $\alpha \in [0.1, 1]$.

 Δ Monopoly Probability (long run)

Limit Bundling

Firms can only bundle products if also a competitor is able to offer the bundle.



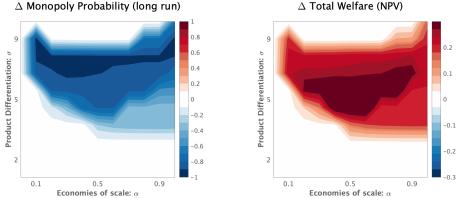
 Δ Total Welfare (NPV)

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Parameter grid: 20 × 20 for $\sigma \in [0.1, 1.0]$ and $\alpha \in [0.1, 1]$.

Data sharing

Firms can be at most 1 level of experience apart in the learning curve: follower inherits the old knowledge/technology from the leader.



 Δ Total Welfare (NPV)

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Parameter grid: 20 × 20 for $\sigma \in [0.1, 1.0]$ and $\alpha \in [0.1, 1]$.

All three policies are effective, but for different reasons.

- 1. Limiting mergers and bundling limits asymmetries along the learning scale
- 2. Data sharing softens IRS incentives

Tackling one foreclosure practice also has an effect on the other!

Conclusion

- Exclusive bundling and predatory pricing seem complementary
 - Risk of domino effects across markets
 - Also if markets are not complementary (coming soon)
- Foreclosure complementarity driven by predatory incentives
 - And welfare decreasing
- Effective policies exist

Conclusion

- Exclusive bundling and predatory pricing seem complementary
 - Risk of domino effects across markets
 - Also if markets are not complementary (coming soon)
- Foreclosure complementarity driven by predatory incentives
 - And welfare decreasing
- Effective policies exist

Thank you!

Appendix 1: Bibliography

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Appendix 2: Model

Learning-by-Doing: Besanko et al. (2014)

- Model: learning-by-doing only in market A (to be relaxed)
- State variable: *e_n*, firm *n* stock of know-how
- Winning a sale increases know-how by 1, with probability q_n (demand)
- Law of motion of know-how:

$$e_n'=e_n+q_n$$

• Concave learning curve for marginal cost:

$$C(e_n) = C_0 \max\{e_n, M\}^{\alpha}$$

where

- c₀: maximum marginal cost
- $\alpha \in [0, 1]$: learning rate¹
- M: know-how upper bound (i.e. size of the learning scale)



¹Interpretation: marginal cost decreases by 100(1 – α)% as the stock of know-how e_n doubles.

Demand of product A₁

$$\begin{aligned} q_{A_1}(\boldsymbol{p}) &= q_{A_1B_1}(\boldsymbol{p}) + q_{A_1B_2}(\boldsymbol{p}) = \\ &= \frac{e^{-(p_{A_1} + p_{B_1})/\sigma} + e^{-(p_{A_1} + p_{B_2})/\sigma}}{e^{-(p_{A_1} + p_{B_1})/\sigma} + e^{-(p_{A_2} + p_{B_1})/\sigma} + e^{-(p_{A_2} + p_{B_2})/\sigma} + e^{-p_{0}/\sigma}} = \\ &= \frac{e^{-p_{A_1}/\sigma}}{e^{-p_{A_1}/\sigma} + e^{-p_{A_2}/\sigma} + e^{-p_{0}/\sigma} \left(e^{-p_{B_1}/\sigma} + e^{-p_{B_2}/\sigma}\right)^{-1}} \end{aligned}$$

Without outside option, it would simplify to $q_{A_1}(\mathbf{p}) = \frac{e^{-p_{A_1}/\sigma}}{e^{-p_{A_1}/\sigma} + e^{-p_{A_2}/\sigma}}$.

Where v_i is the value of a product for consumer *i*, p_{A_1} is A_1 's price, $\varepsilon_{iA_1B_1}$ is consumer *i* shock for system A_1B_1 .

Entry, Exit

Value function of firm n in state ω

$$V_n(\boldsymbol{\omega}) = \pi_n^*(\boldsymbol{\omega}) + \beta \mathbb{E}_{\boldsymbol{\omega}'} \Big[V_n(\boldsymbol{\omega}') \mid \boldsymbol{\omega}, \Phi \Big]$$

The firm compares expected benefit and cost of entry/exit.

• The exit policy function

$$\Phi_n^{\chi}(\boldsymbol{\omega},\phi^{\chi}|\omega_n>0) = \arg\max\ \left\{\phi^{\chi}\ ,\ \beta\ \mathbb{E}_{\boldsymbol{\omega}'}\Big[\mathsf{V}_n(\boldsymbol{\omega}')\ \Big|\ \boldsymbol{\omega},\Phi\Big]\right\}.$$

• The entry policy function

$$\Phi_n^{\mathsf{E}}(\boldsymbol{\omega},\phi^{\mathsf{E}}|\omega_n=0) = \arg\max \left\{0\;,\; -\phi^{\mathsf{E}} + \beta \; \mathbb{E}_{\boldsymbol{\omega}'}\Big[\mathsf{V}_n(\boldsymbol{\omega}') \; \Big| \; \boldsymbol{\omega},\Phi\Big]\right\}.$$

where Φ is the vector of policy functions of all firms and ϕ^X and ϕ^E are the realized exit scrap value and entry cost.



Mergers

Value function of firm n in state ω

$$V_n(oldsymbol{\omega}) = \pi_n^*(oldsymbol{\omega}) + eta \mathbb{E}_{oldsymbol{\omega}'} \Big[V_n(oldsymbol{\omega}') \; \Big| \; oldsymbol{\omega}, \Phi \Big]$$

How to split the future value among merging firms? Nash bargaining.

$$\tau_{n_{B},n_{S}}^{*}(\boldsymbol{\omega}) = \lambda \underbrace{\left[V_{n_{B}}^{M}(\boldsymbol{\omega}') - V_{n_{B}}(\boldsymbol{\omega}) - \phi^{M}\right]}_{\text{reservation value of the buyer}} + (1 - \lambda) \underbrace{\left[V_{n_{S}}^{M}(\boldsymbol{\omega}') - V_{n_{S}}(\boldsymbol{\omega})\right]}_{\text{reservation value of the seller}}$$

With symmetrical bargaining power $\lambda = 0.5$, the merger policy function is $\Phi_n^M(\omega, \phi^M) = \arg \max \left\{ \phi^M, \beta \mathbb{E}_{\omega'} \left[V_{n_B}^M(\omega') + V_{n_S}^M(\omega') - V_{n_B}(\omega) - V_{n_S}(\omega) \mid \omega, \Phi \right] \right\}$

where ϕ^{M} is the realized merger cost.



Bundling

Value function of firm n in state ω

$$V_n(oldsymbol{\omega}) = \pi_n^*(oldsymbol{\omega}) + eta \mathbb{E}_{oldsymbol{\omega}'} \Big[V_n(oldsymbol{\omega}') \; \Big| \; oldsymbol{\omega}, \Phi \Big]$$

The firm compares expected benefit and cost of entry/exit

$$\begin{split} \Phi_n^{\scriptscriptstyle B}(\boldsymbol{\omega}, \phi^{\scriptscriptstyle B}) &= \arg \max \ \Big\{ \beta \ \mathbb{E}_{\boldsymbol{\omega}'} \Big[V_n(\boldsymbol{\omega}') \ \Big| \ \boldsymbol{\omega}, \Phi \Big] \ , \\ &- \phi^{\scriptscriptstyle B} + \beta \ \mathbb{E}_{\boldsymbol{\omega}'} \Big[V_n(\boldsymbol{\omega}') \ \Big| \ \text{bundling}, \boldsymbol{\omega}, \Phi \Big] \Big\}. \end{split}$$

where Φ is the vector of policy functions of all firms and ϕ^{B} is the realized bundling cost.



Dynamic Pricing Incentives

Firm *n* value function is

$$V_{n}(\boldsymbol{\omega}) = \max_{p_{n}} q_{n}(\boldsymbol{p})(p_{n} - c_{n}) + \beta \mathbb{E}_{\boldsymbol{\omega}'} \left[\sum_{s} q_{s}(\boldsymbol{p}) V_{n}^{s}(\boldsymbol{\omega}') \middle| \Phi \right], \quad (5)$$

Taking the first order condition we can isolate dynamic pricing incentives

$$0 = \underbrace{\frac{\partial q_{A_1}(\boldsymbol{p})}{\partial p_{A_1}}(p_{A_1} - c_{A_1}) - q_{A_1}(\boldsymbol{p})}_{\text{static incentives}} + \underbrace{\beta \mathbb{E}_{\boldsymbol{\omega}'}\left[\sum_{s} \frac{\partial q_s(\boldsymbol{p})}{\partial p_{A_1}}V_{A_1}^s(\boldsymbol{\omega}')\right]}_{\text{dynamic incentives}}, \quad (6)$$

Anti-competitive pricing incentives are dynamic incentives coming from changes in rivals' exit probability.

Internalizing Externalities - Mergers

Assume the same firm produces A_1 and B_1 .

Objective function:

$$\pi_{A_1}(\boldsymbol{p}) + \pi_{B_1}(\boldsymbol{p}) = (p_{A_1} - c_{A_1})q_{A_1}(\boldsymbol{p}) + (p_{B_1} - c_{B_1})q_{B_1}(\boldsymbol{p})$$

FOC:

$$\frac{\partial q_{A_1}(\boldsymbol{p})}{\partial p_{A_1}}(p_{A_1} - c_{A_1}) - q_{A_1} + \underbrace{\frac{\partial q_{B_1}(\boldsymbol{p})}{\partial p_{A_1}}(p_{B_1} - c_{B_1})}_{\text{partial internalization}} = 0$$

- Firm internalizes the fact that lowering the price of product in market A increases demand (and profits) for product in market B
- But only for *joint product* A_1B_1



Internalizing Externalities - Bundling

Assume the same firm produces A_1 and B_1 and bundles.

Objective function:

$$\pi_{A_1}(p) + \pi_{B_1}(p) = (p_{A_1} - c_{A_1} - c_{B_1})q_{A_1B_1}(p)$$

Assume A_1 and B_1 are produced by the same firm and bundled together²:

$$\frac{\partial q_{A_1B_1}(\boldsymbol{p})}{\partial p_{A_1B_1}}(p_{A_1}-c_{A_1}-c_{B_1})-q_{A_1B_1}=0$$

- Higher margin: $(p_{A_1} c_{A_1}) \rightarrow (p_{A_1} c_{A_1} c_{B_1})$
- Now firms sell only the *joint product*
- Firms fully internalizes impact on profits in the other market

▲ back

 $^{{}^{2}}p_{B_{1}}$ normalized to zero, i.e. $p_{A_{1}B_{1}} \equiv p_{A_{1}}$.

What is predatory?

- Ordover & Willig (1981): "[p]redatory behavior is a response to a rival that sacrifices part of the profit that could be earned under competitive circumstances were the rival to remain viable, in order to induce exit and gain consequent additional monopoly profit."
- Cabral & Riordan (1997): "an action predatory if (1) a different action would increase the probability that rivals remain viable and (2) the different action would be more profitable under the counterfactual hypothesis that the rival's viability were unaffected."



Anti-competitive Pricing Incentives, Exit

Anti-competitive exit-inducing incentives are the dynamic pricing incentives driven by a change in rivals' exit probability.

$$\underbrace{\beta \mathbb{E}_{\boldsymbol{\omega}'} \left[\sum_{s} \frac{\partial q_{s}(\boldsymbol{p})}{\partial p_{A_{1}}} V_{A_{1}}^{s}(\boldsymbol{\omega}') \middle| \Phi \right]}_{\text{true pricing incentives}} - \underbrace{\beta \mathbb{E}_{\boldsymbol{\omega}'} \left[\sum_{s} \frac{\partial q_{s}(\boldsymbol{p})}{\partial p_{A_{1}}} V_{A_{1}}^{s}(\boldsymbol{\omega}') \middle| \Phi_{-X}, \Phi_{X}^{*} \right]}_{\text{counterfactual pricing incentives}}$$

where Φ_X^* is such that

$$\Phi_{X,i}^{*}(\omega_{1},\omega_{2},\omega_{3},\omega_{4},\omega_{bundling}) = \Phi_{X,i}^{*}(1,1,1,1,\omega_{bundling}) \qquad \forall i,\omega_{bundling}$$

For entry, it is the same but keeping the entry policy unaffected by the learning scale, instead of the exit policy.

Anti-competitive Bundling Incentives

Anti-competitive exit-inducing bundling are the bundling incentives driven by a change in rivals' exit probability.

$$\underbrace{\beta \mathbb{E}_{\boldsymbol{\omega}'} \left[V_n(\boldsymbol{\omega}') \mid \text{bundling}, \boldsymbol{\omega}, \boldsymbol{\Phi} \right]}_{\text{true bundling incentives}} - \underbrace{\beta \mathbb{E}_{\boldsymbol{\omega}'} \left[V_n(\boldsymbol{\omega}') \mid \text{bundling}, \boldsymbol{\omega}, \boldsymbol{\Phi}_{-X}, \boldsymbol{\Phi}_X^* \right]}_{\text{counterfactual bundling incentives}}$$

where Φ_X^* is such that

 $\Phi_{X,i}^{*}(\omega_{1:4},\omega_{bundling}) = \Phi_{X,i}^{*}(\omega_{1:4},\omega_{nobundling}) \qquad \forall i,\omega_{bundling}$

For entry, it is the same but keeping the entry policy unaffected by the learning scale, instead of the exit policy.

Appendix 3: Results

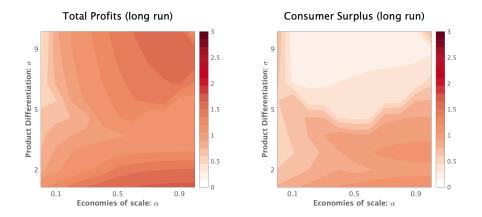
Model Parametrization

Parameter Description	Parameter	Value
Learning rate	α	0.5
Discount factor	β	0.95
Marginal cost	<i>C</i> ₀	1
Maximum experience level	М	5
Price of the outside option	p_0	1.5
Price elasticity	σ	5
Exit scrap value	$F(\phi^X)$	<i>U</i> [0, 1]
Entry cost	$F(\phi^{E})$	<i>U</i> [0, 10]
Merger cost	$F(\phi^M)$	<i>U</i> [0, 1]
Bundling cost	$F(\phi^{B})$	<i>U</i> [0, 1]

Table 1: Model Parametrization

Profits and Consumer Surplus

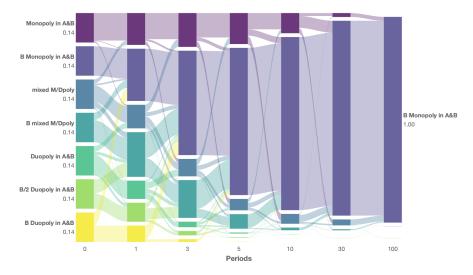
Higher profits and lower consumer surplus when markets degenerate to monopoly.



Parameter grid: 20 × 20 for $\sigma \in [0.1, 1.0]$ and $\alpha \in [0.1, 1]$.

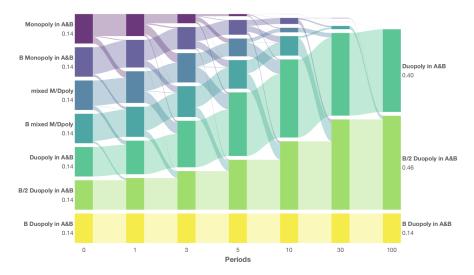


Example 1: Tipping Equilibrium



Transition Flows

Example 2: Competitive Equilibrium

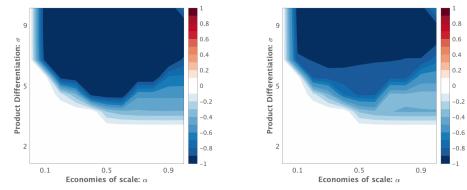


Transition Flows

Removing Learning-by-doing: Market A and B

Market A does not tip, hence market B neither.

 Δ Monopoly Probability A (long run)



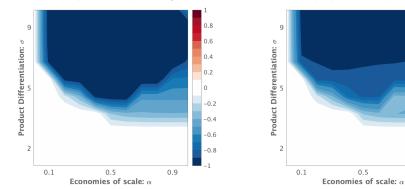
 Δ Monopoly Probability B (long run)

back

Parameter grid: 20 × 20 for $\sigma \in [0.1, 1.0]$ and $\alpha \in [0.1, 1]$.

Removing Bundling: Market A and B

Not only market B does not tip, but also market A is less likely to tip!



Δ Monopoly Probability A (long run) Δ Monopoly Probability B (long run)

Parameter grid: 20 \times 20 for $\sigma \in [0.1, 1.0]$ and $\alpha \in [0.1, 1]$.

Short run: first 5 periods. Long run: asymptotic. NPV: discounted stream from t = 0 to $t \to \infty$.

back

0.8

0.6

0.4

0.2

-0.2

-0.4

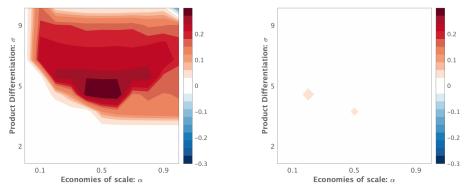
-0.6

-0.8

0.9

Anti-competitive Pricing

Basically mirrors the probability of market tipping.



 Δ Total Welfare (NPV)

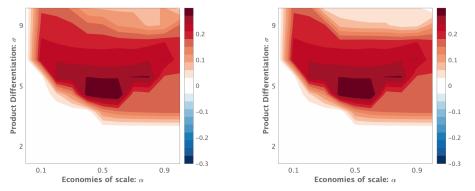
 Δ Total Welfare (NPV)

back

Parameter grid: 20 × 20 for $\sigma \in [0.1, 1.0]$ and $\alpha \in [0.1, 1]$.

Anti-competitive Bundling

Basically mirrors the probability of market tipping.



Δ Total Welfare (NPV)

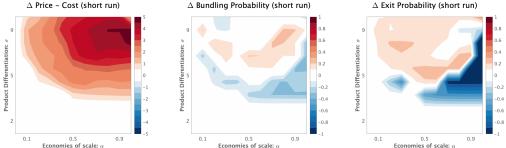
 Δ Total Welfare (NPV)

back

Parameter grid: 20 × 20 for $\sigma \in [0.1, 1.0]$ and $\alpha \in [0.1, 1]$.

Limit Mergers

Firms that are ahead in the learning curve cannot integrate.

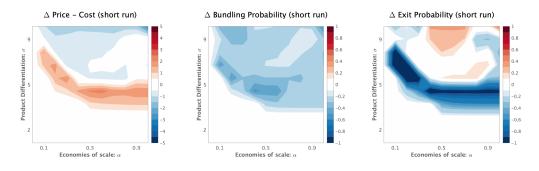


 Δ Exit Probability (short run)

Parameter grid: 20×20 for $\sigma \in [0.1, 1.0]$ and $\alpha \in [0.1, 1]$.

Limit Bundling

Firms can only bundle products if also a competitor is able to offer the bundle.

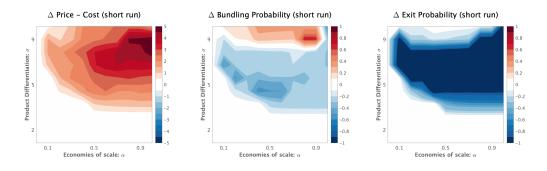


▲ back

Parameter grid: 20 × 20 for $\sigma \in [0.1, 1.0]$ and $\alpha \in [0.1, 1]$.

Data Sharing

Firms can be at most 1 level of experience apart in the learning curve: followerinherits the old knowledge/technology from the leader.



back

Parameter grid: 20 × 20 for $\sigma \in [0.1, 1.0]$ and $\alpha \in [0.1, 1]$.