Scalable Expertise

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Introduction

Enormous differences in firm size and scale

- Renewed attention of late (rise in concentration, superstar firms)

This paper: 1. New facts

- Larger firms ‘respond’ more to common (i.e. sector-wide) ‘shocks’
- Changes in scope (Num. of units/products/locations) key to this heterogeneity

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2. A theory of firm size

- Scope and size endogenously determined
- Key ingredient: scalable expertise

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3. Model vs data

- A direct measure of scalability based on detailed product-level data
- Model's predictions consistent with patterns in the data

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4. Implications beyond heterogeneity

- Link scalability to diffusion of knowledge → Potential amplification mechanism

Firm Size and Responsiveness to Shocks

Data:

- Two datasets
  - Establishment-level data (NETS)
  - Product-level data (Nielsen)
- Three demand shocks.
  - Change in home prices 2001-2006
  - Change in home prices 2007-2011
  - Change in Chinese import penetration, 2006-2015

Specification:

$$\Delta \ln(Size_{ijt+\tau}) = \beta \; \Delta Shock_{ijt} \; \ln(Size_{ijt}) + \alpha \Delta Shock_{ijt} + \gamma \ln(Size_{ijt}) + \sigma_{j\tau} + \epsilon_{ij\tau}$$

Results: Multi-establishment firms (NETS)

Fact 1: Larger firms respond by more to shocks

	Δ ln($Size$)	Δ ln($Size$)	Δ ln($Size$)
$\Delta Shock \times \ln(Size)$	0.049***	0.047***	0.191***
	(0.001)	(0.001)	(0.049)
Obs.	580,946	569,328	34,583
Sector FE	Y	Y	Y
Shock	Housing	Housing	China
Period	2001-2006	2007-2011	2006-2015
Data	NETS	NETS	NETS

$$\Delta \ln(Size_{ijt+\tau}) = \beta \; \Delta Shock_{ijt} \; \ln(Size_{ijt}) + \alpha \Delta Shock_{ijt} + \gamma \ln(Size_{ijt}) + \sigma_{j\tau} + \epsilon_{ij\tau}$$

Results: Multi-establishment firms (NETS)

Fact 1: Larger firms respond by more to shocks

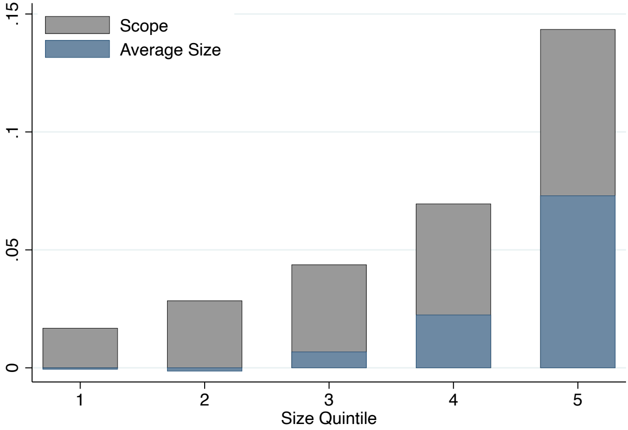
Fact 2: Heterogeneous changes to scope play a significant role

	$\Delta \ln(Size)$	$\Delta \ln(Scope)$	$\Delta \ln(Size)$	$\Delta \ln(Scope)$	$\Delta \ln(Size)$	$\Delta \ln(Scope)$
$\Delta Shock \times \ln(Size)$	0.049***	0.031***	0.047***	0.025***	0.191***	0.036
	(0.001)	(0.000)	(0.001)	(0.001)	(0.049)	(0.023)
Obs.	580,946		569,328		34,583	
Sector	Y		Y		Y	
Shock	Housing		Housing		China	
Period	2001-2006		2007-2011		2006-2015	
Data	NETS		NETS		NETS	

$$\Delta \ln(Size_{ijt+\tau}) = \beta \ \Delta Shock_{ijt} \ \ln(Size_{ijt}) + \alpha \Delta Shock_{ijt} + \gamma \ln(Size_{ijt}) + \sigma_{j\tau} + \epsilon_{ij\tau}$$

$$\Delta \ln(Scope_{ijt+\tau}) = \beta \ \Delta Shock_{ijt} \ \ln(Size_{ijt}) + \alpha \Delta Shock_{ijt} + \gamma \ln(Size_{ijt}) + \sigma_{j\tau} + \epsilon_{ij\tau}$$

Heterogeneous Response to Demand Shocks by Size Quintile



Note: $\Delta Scope_{ij} = \sum_{q=1}^{5} \beta_q d_{q,ij} \times \Delta Shock_{ij} + \sum_{q=1}^{5} \alpha_q d_{q,i} + \gamma_j + \epsilon_{ij}$, where $d_{q,i}$ is a dummy for the size quintile (within industry).

Results: Multi-product firms (Nielsen)

Fact 1: Larger firms respond by more to shocks

Fact 2: Heterogeneous changes to scope play a significant role

	Δ ln($Size$)	Δ ln($Scope$)	Δ ln($Size$)	Δ ln($Scope$)
$\Delta Shock \times \ln(Size)$	0.666***	0.066*	0.126**	0.011***
	(0.145)	(0.036)	(0.012)	(0.004)
Obs.	27,930		23,812	
Sector	Y		Y	
Shock	Housing		China	
Period	2006-2011		2006-2015	
Data	Nielsen		Nielsen	

$$\Delta \ln(Size_{ijt+\tau}) = \beta \; \Delta Shock_{ijt} \; \ln(Size_{ijt}) + \alpha \Delta Shock_{ijt} + \gamma \ln(Size_{ijt}) + \sigma_{j\tau} + \epsilon_{ij\tau}$$

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Model

- A continuum of firms (index: i) in a continuum of sectors (index: j)
- Firm i has a continuum of 'products' $s \in [0, N_{ij}]$
- Linear production function $C_{ij}^s = G_j Z_{ij}^s L_{ij}$ and fixed costs $\mathcal{F}(N_{ij})$
- CES aggregation within (elasticity ϵ) and across (elasticity θ) firms

$$C_{ij}^s = \left(\frac{P_{ij}^s}{P_{ij}}\right)^{-\epsilon} \left(\frac{P_{ij}}{P_j}\right)^{-\theta} C_j$$

$$(P_{ij})^{1-\epsilon} = \int^{N_{ij}} (P_j^s)^{1-\epsilon} ds \qquad (P^s)^{1-\theta} = \int (P_i^s)^{1-\theta} di$$

- Profits of firm i are given by

$$\Pi_{ij} = \int_0^{N_{ij}} \left(P_{ij}^s - \frac{W}{G_j Z_{ij}^s}\right) C_{ij}^s ds - \mathcal{F}(n_{ij})$$

- Sector subscript j suppressed in what follows

Expertise

Productivity of product s of firm i as a function of expertise

$$Z_i^s = \left(x_i^{\frac{\sigma-1}{\sigma}} + (y_i^s)^{\frac{\sigma-1}{\sigma}} \right)^{\frac{\sigma}{\sigma-1}} \qquad 1 < \sigma < \bar{\sigma}$$

where $x_i \equiv$ scalable expertise

$y_i^s \equiv$ product-specific expertise

Cost of acquiring expertise: $\mathcal{C}_i(x_i, \{y_i^s\}_{s\in[0,N_i]})$

Interpretations

- Precision in firm-wide and product-specific operations ▸ Details
- Products as bundles of useful 'services' or 'features'

Special case: $\theta = \epsilon = 2$, $\mathcal{F}(N_i) = FN_i$ $\mathcal{C}_i =$ Capacity constraint

$$\max_{N_i, x_i, y_i} \quad N_i(GZ(x_i, y_i) - F) \quad \text{subject to} \quad \frac{x_i}{a_i^x} + \frac{N_i y_i}{a_i^y} \leq Q$$

FOC x_i :

$$\underbrace{N_i GZ_x(x_i, y_i)}_{mpx} = \frac{\lambda_i}{a_i^x}$$

y_i :

$$\underbrace{GZ_y(x_i, y_i)}_{mpy} = \frac{\lambda_i}{a_i^y}$$

N_i :

$$\underbrace{GZ(x_i, y_i) - F}_{mpn} = y_i \frac{\lambda_i}{a_i^y}$$

$$\boxed{\frac{d \ln N_i}{d \ln G} = \frac{1}{2 - \sigma} \left(\frac{Z_i}{Z_i - 1} \right)}$$

Firms with low rev/product adjust scope by more in response to the same shock

- Fixing (x_i, y_i, N_i), $G \uparrow \rightarrow$ $mpx, mpy \uparrow$ proportionately
- but, $mpn \uparrow$ more than proportionately $\rightarrow$ scope rises (and $Z \downarrow$)
- effect stronger if $GZ(x_i, y_i) - F$ small $\rightarrow$ N rises by more if Z is low

Special case: $\theta = \epsilon = 2$, $\mathcal{F}(N_i) = FN_i$ $\mathcal{C}_i$ = Capacity constraint

$$\max_{N_i, x_i, y_i} \quad N_i(GZ(x_i, y_i) - F) \quad \text{subject to} \quad \frac{x_i}{a_i^x} + \frac{N_i y_i}{a_i^y} \leq Q$$

$$\text{FOC } x_i: \quad \underbrace{N_i GZ_x(x_i, y_i)}_{mpx} = \frac{\lambda_i}{a_i^x}$$

$$y_i: \quad \underbrace{GZ_y(x_i, y_i)}_{mpy} = \frac{\lambda_i}{a_i^y}$$

$$N_i: \quad \underbrace{GZ(x_i, y_i) - F}_{mpn} = y_i \frac{\lambda_i}{a_i^y}$$

$$\boxed{\frac{d \ln N_i}{d \ln G} = \frac{1}{2 - \sigma}\left(\frac{Z_i}{Z_i - 1}\right)}$$

$$\boxed{\frac{GZ_i - F}{GZ_i} = \frac{mpy}{apy} = \left(\left(\frac{x_i}{y_i}\right)^{\frac{\sigma - 1}{\sigma}} + 1\right)^{-1}}$$

Firms with scalable expertise are less profitable (on a per-product basis)

- $mpy \equiv Z_y \rightarrow$ incentives to $\uparrow y$ (and therefore, Z)
- $apy \equiv \frac{Z}{y} \rightarrow$ incentives to $\uparrow N$ (since every new product requires y)
- $\frac{mpy}{apy}$ declines with $\frac{x}{y}$ (since $\sigma > 1$) $\rightarrow$ Z is decreasing in scalability

The general case

$$\max \qquad GN_i^{\phi}\left[\left(x_i^{\frac{\sigma-1}{\sigma}}+y_i^{\frac{\sigma-1}{\sigma}}\right)^{\frac{\sigma}{\sigma-1}}\right]^{\psi}-FN_i^{\omega}-\left(\frac{x_i^{\mu}}{a_i^x}+\frac{N_i y_i^{\mu}}{a_i^y}\right)^{\gamma}\cdot H$$

- Earlier, special case with $\phi = \omega = \psi = \mu = 1,\ \gamma = \infty$
- Within-firm elasticity > across-firm elasticity $\Rightarrow\ \phi < 1$
- Fixed costs convex in number of products $\Rightarrow\ \omega > 1$
- Curvature in cost of expertise $\Rightarrow\ 1 < \gamma < \infty$
- $\boxed{\frac{\psi}{\phi\mu} \leq 1 \leq \left(1-\frac{\psi}{\mu\gamma}\right)\frac{\omega}{\phi} \leq \mu\omega\frac{\sigma}{\sigma-1}-\omega}$ $\rightarrow$ quasi-concave objective
  - sufficient complementarity between x and y (i.e. σ not too high)
  - sufficient convexity in costs (i.e. $\frac{\omega}{\phi}$ and $\frac{\mu\gamma}{\psi}$ not too low)

Proposition

The elasticity of scope with respect to G is

- *decreasing in revenue/product, conditional on scope.*
- *increasing in scope, conditional on revenue/product.*
- *increasing in scalability.*

Model vs Data: Effect of demand shocks on scope

$$\Delta n_{ij\tau} = \alpha + \beta_0 \Delta g_{ij\tau_0} + \beta_1(\Delta g_{ij\tau} \times n_{ij\tau_0}) + \beta_2(\Delta g_{ij\tau} \times z_{ij\tau_0}) + \gamma_1 \ n_{ij\tau_0} + \gamma_2 \ z_{ij\tau_0} + \Gamma_j + \epsilon_{ij\tau}$$

- Conditional on rev/product, firms with higher scope adjust scope by more ($\beta_1 > 0$)
- Conditional on scope, firms with higher revenue/product adjust scope by less ($\beta_2 < 0$)

	(1)	(2)	(3)	(4)	(5)
Δn					
$\Delta g \times n$	0.022***	0.018***	0.060***	0.104***	0.035***
	(0.000)	(0.000)	(0.013)	(0.039)	(0.004)
$\Delta g \times z$	-0.001	-0.003***	-0.016	0.048	-0.015***
	(0.000)	(0.001)	(0.026)	(0.035)	(0.004)
Observations	580,946	569,328	34,577	28,137	23,812
R^2	0.121	0.114	0.127	0.087	0.137
Sector	Y	Y	Y	Y	Y
Shock	Housing	Housing	China	Housing	China
Period	2001-2006	2007-2011	2006-2015	2006-2011	2006-2015
Data	NETS	NETS	NETS	Nielsen	Nielsen

Measuring Scalability using Product-level Data: An example

Product Module: Lamps, incandescent

Firm	Product	Attribute	
		Style	Use
General Electric	1	Clear	Nite Fixture
General Electric	2	Halogen	Appliance
General Electric	3	Clear	Bath & Vanity
General Electric	4	Clear	Ceiling Fan
General Electric	5	Frost	Chandelier

Style:

$$\boxed{\mathcal{SI}_{Style,GE} \equiv 1 - \frac{\text{Distinct Characteristics}}{\#\text{ of Products}}} = 1 - \frac{3}{5} = 0.4$$

Use:

$$\boxed{\mathcal{SI}_{Use,GE} \equiv 1 - \frac{\text{Distinct Characteristics}}{\#\text{ of Products}}} = 1 - \frac{5}{5} = 0$$

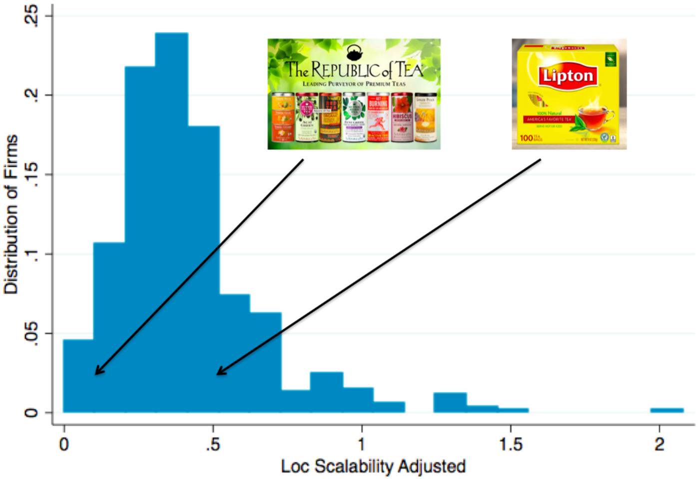
Module:

$$\boxed{\mathcal{SI}_{GE}^{Lamps} \equiv 1 - \frac{\text{Distinct Characteristics}}{\#\text{ of Products} \times \text{Attributes}}} = 1 - \frac{5+3}{5+5} = 0.2$$

$$\boxed{S_{GE}^{Lamps} \equiv \frac{x_i^m}{y_i^m} \equiv \frac{\mathcal{SI}_{GE}^{Lamps}}{1 - \mathcal{SI}_{GE}^{Lamps}}} = \frac{0.2}{1-0.2} = 0.25$$

More examples

Distribution of $\mathcal{SI}$: An example



Model predictions w.r.t. scalability

Cross-section

- Scalability is negatively related to revenue/product, conditional on scope
- Scalability is positively related to scope, conditional on revenue/product

Demand shock and scope

- Firms with higher scalability adjust scope by more

Demand shock and scalability

- Firms with higher scalability adjust scalability by more
- Firms with higher rev/product adjust scalability by less, conditional on scope
- Firms with higher scope adjust scalability by more, conditional on rev/product

Diffusion

Model vs Data: Scalability in the Cross-section

- Scalability is negatively related to revenue/product, conditional on scope ($\beta_1 < 0$)
- Scalability is positively related to scope, conditional on revenue/product ($\beta_2 > 0$)

ln Scalability	(1)	(2)	(3)
z	0.19***		-0.02***
	(0.002)		(0.002)
n		0.49***	0.50***
		(0.002)	(0.002)
Observations	293,013	293,151	293,013
R-squared	0.155	0.324	0.324
Period × Sector	Y	Y	Y

$$s_{ijt} = \alpha + \beta_1 \; z_{ijt} + \beta_2 \; n_{ijt} + \Gamma_{jt} + \varepsilon_{ijt} \; .$$

Diffusion

Model vs Data: Response of Scope to the China shock

- Firms with higher scalability adjust scope by more $(\beta_1 > 0)$

Δn	(1)	(2)	(3)
Δg	0.026**	0.036***	
	(0.012)	(0.004)	
$\Delta g \times s$		0.024***	0.024**
		(0.004)	(0.009)
Observations	22,822	18,125	18,125
R-squared	0.002	0.031	0.074
Sector	N	N	Y

$$\Delta n_{ij\tau} = \alpha + \beta_0 \, \Delta g_{j\tau} + \beta_1 \, (\Delta g_{j\tau} \times s_{ij\tau_0}) + \gamma \; s_{ij\tau_0} + \Gamma_j + \epsilon_{ij,\tau}$$

▸ Diffusion

Model vs Data: Response of Scalability to the China Shock

- Firms with higher scalability adjust scalability by more ($\beta_1 > 0$)
- Firms with higher revenue/product adjust scalability by less ($\beta_2 < 0$), conditional on scope
- Firms with higher scope adjust scalability by more ($\beta_3 > 0$), conditional on rev/product

Δ ln Scalability	(1)	(2)	(3)
Δg	0.017***		
	(0.002)		
$\Delta g \times s$		0.006***	
		(0.001)	
$\Delta g \times z$			-0.008***
			(0.003)
$\Delta g \times n$			0.006**
			(0.002)
Observations	16,077	16,076	16,076
R-squared	0.003	0.313	0.083
Sector	N	Y	Y

$$\Delta s_{ij\tau} = \alpha + \beta_0 \, \Delta g_{j\tau} + \beta_1 \, (\Delta g_{j\tau} \times s_{ij\tau_0}) + \gamma \, s_{ij\tau_0} + \Gamma_j + \epsilon_{ij\tau}$$

$$\Delta s_{ij\tau} = \alpha + \beta_0 \, \Delta g_{j\tau} + \beta_2 \, (\Delta g_{j\tau} \times z_{ij\tau_0}) + \gamma_1 \, z_{ij\tau_0} + \beta_3 \, (\Delta g_{j,\tau} \times n_{ij\tau_0}) + \gamma_2 \, n_{ij\tau_0} + \Gamma_j + \epsilon_{ij\tau}$$

Robustness

Theory

- Dynamics (potentially with adjustment costs)
  - results hold for a firm in steady state
- Preference for variety $\rightarrow$ reduces the benefit of scalable expertise
  - changes level of $Z(x, y)$; results depend on elasticities

Empirical

- Choice of time horizon, aggregation etc.
  - Results robust to annual differences, firm-level, normalization
- Endogeneity of import penetration
  - Use ΔIP_j for other countries as instruments

Scalable Expertise and Diffusion

Scalable Expertise and Diffusion

Hypothesis: Diffusion within the firm → diffusion outside the firm ($\beta > 0$)

For a new feature c introduced by firm i at time t, define

$$\mathcal{DI}_{c,m,i,t,\tau} \equiv \frac{\text{Num. of new products introduced by other firms between } t \text{ and } t+\tau \text{ with } c}{\text{Num. of new products introduced by other firms between } t \text{ and } t+\tau}$$

Diffusion	(1)	(2)	(3)	(4)
$\mathcal{SI}$	0.0599***	0.0097***		
	(0.000)	(0.001)		
$\widetilde{\mathcal{SI}}$			0.1326***	0.0282***
			(0.000)	(0.001)
n	-0.0292***	-0.0057***	-0.0013***	-0.0028***
	(0.000)	(0.000)	(0.000)	(0.001)
Observations	3,319,518	3,234,863	3,269,030	3,183,439
R-squared	0.808	0.914	0.812	0.913
Firm-Attribute-Module	N	Y	N	Y
Attribute-Module-Time-Age	Y	Y	Y	Y

$$\mathcal{DI}_{cmit\tau} = \alpha + \beta\, \mathcal{SI}_{amit-1} + \gamma\, n_{mit} + \lambda_{amt\tau} + \theta_{ami} + \epsilon_{amit\tau}$$

$$\mathcal{DI}_{cmit\tau} = \alpha + \beta\, \widetilde{\mathcal{SI}}_{amit-1} + \gamma\, n_{mit} + \lambda_{amt\tau} + \theta_{ami} + \epsilon_{amit\tau}$$

The China Shock and Diffusion

Hypothesis: Higher demand $\Rightarrow$ more scalable expertise $\Rightarrow$ diffusion $\uparrow$ ($\beta_2 > 0$)

Δ Diffusion	(1)	(2)	(3)
Δs	0.201***	0.100***	0.100***
	(0.039)	(0.038)	(0.038)
Observations	8,433	8,433	8,432
Sector	N	N	Y
Controls	N	Y	Y
Shock	China	China	China
Estimator	IV	IV	IV

$$\Delta s_{ij\tau} = \alpha + \beta_0 \, \Delta g_{j\tau} + \beta_1 \, \Delta g_{j\tau} \times s_{ij\tau_0} + \gamma \, s_{ij\tau_0} + \Gamma_j + \epsilon_{ij\tau}$$

$$\Delta \ln \mathcal{DI}_{ij\tau} = \alpha + \beta_2 \, \Delta\widehat{s}_{ij\tau} + \gamma_1 \, z_{ij\tau_0} + \gamma_2 \, \Delta g_{j\tau} \times z_{ij\tau_0} + \Gamma_j + \epsilon_{ij\tau}$$

Conclusion

A tractable model of scope, size and productivity

- key: scalability of knowledge

Cross-sectional predictions consistent with product-level data

- next: aggregate implications?

Dynamic Model: Expertise as Precision

Firm's operations modeled as a tracking problem (expertise = more precision)

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- Each product j has a 'target' action with 2 ind components

$$\tilde{v}_{it}^{*} = \underbrace{v_{it}^{*}}_{\text{Firm-wide}} + \underbrace{v_{ist}^{*}}_{\text{Product-specific}}$$

Dynamic Model: Expertise as Precision

Firm's operations modeled as a tracking problem (expertise = more precision)

- Each product j has a 'target' action with 2 ind components

$$\tilde{v}^*_{it} = \underbrace{v^*_{it}}_{\text{Firm-wide}} + \underbrace{v^*_{ist}}_{\text{Product-specific}}$$

- Firm chooses actions $\{v_{it}, v_{ijt}\}$ and operating profit of product j

$$\Pi_{ist} = \frac{G_t}{\mathbb{E}\left[\left((v_{it} + v_{ist}) - (v^*_{it} + v^*_{ist})\right)^2\right]} = G_t \quad Z_{ist} \qquad \text{where}$$

$$\underbrace{Z_{ist} \equiv \left(\frac{1}{x_{it}} + \frac{1}{y_{ist}}\right)^{-1}}_{\text{Expertise}} \qquad \underbrace{x_{it} \equiv \frac{1}{\mathbb{E}\left[\left(v_{it} - v^*_{it}\right)^2\right]}}_{\text{Scalable}} \qquad \underbrace{y_{ist} \equiv \frac{1}{\mathbb{E}\left[\left(v_{ist} - v^*_{ist}\right)^2\right]}}_{\text{Non-scalable}}$$

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$$\underbrace{Z_{ist} \equiv \left(\frac{1}{x_{it}} + \frac{1}{y_{ist}}\right)^{-1}}_{\text{Expertise}} \qquad \underbrace{x_{it} \equiv \frac{1}{\mathbb{E}\left[\left(v_{it} - v_{it}^{*}\right)^2\right]}}_{\text{Scalable}} \qquad \underbrace{y_{ist} \equiv \frac{1}{\mathbb{E}\left[\left(v_{ist} - v_{ist}^{*}\right)^2\right]}}_{\text{Non-scalable}}$$

Total profit of the firm $\Pi_{it} \equiv \int_0^{N_{it}} (G_t Z_{ist} - F_t) dj$ Details

- No cannibalization within or across firms (for now)

Back

Dynamic Model: Expertise as Precision

Target actions $\{v^*_{it}, v^*_{ist}\}$ are mean-reverting Gaussian processes

Firm chooses number of signals $q^x_{it}, \{q^y_{ist}\}$ at a cost $C_i(q^x_{it}, \{q^y_{ist}\};\ x_{it}, \{y_{ist}\})$

Special case

$$\frac{1}{a^x_i} q^x_{it} + \frac{1}{a^y_i} \int q^y_{ist} ds \leq 1$$

where a^x_i and a^y_i are (firm-specific) skill parameters

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$$\frac{1}{a^x_i} q^x_{it} + \frac{1}{a^y_i} \int q^y_{ist} ds \leq 1$$

where a^x_i and a^y_i are (firm-specific) skill parameters

Evolution of expertise (in continuous time),

$$\dot{x}_{it} = -\delta x_{it} + q^x_{it}$$

$$\dot{y}_{ist} = -\delta y_{ist} + q^y_{ist}$$

Dynamic Model: The Special Case

Assume

- $\theta = \epsilon = 2, \quad \sigma = 0.5, \quad \mathcal{F}_t(n_{it}) = F_t n_{it} \quad C_i(\cdot) \rightarrow$ capacity constraint

$$\max_{n_{it}, x_{it}, \{y_{ist}\}} \quad \int_0^\infty e^{-rt} \left[\int_0^{n_{it}} (G_t Z_{ist} - F_t) ds \right] dt \qquad \text{s.t.}$$

$$\frac{q_{it}^x}{a_i^x} + \frac{\int q_{ist}^y dj}{a_i^y} \leq 1$$

$$Z_{ist} = \left(\frac{1}{x_{it}} + \frac{1}{y_{ist}} \right)^{-1} \qquad \dot{x}_{it} = -\delta x_{it} + q_{it}^x \qquad \dot{y}_{ist} = -\delta y_{ist} + q_{ist}^y$$

Dynamic Model: The Special Case

Assume

- $\theta = \epsilon = 2, \quad \sigma = 0.5, \quad \mathcal{F}_t(n_{it}) = F_t n_{it} \quad C_i(\cdot) \rightarrow$ capacity constraint

$$\max_{n_{it}, x_{it}, \{y_{ist}\}} \quad \int_0^\infty e^{-rt} \left[\int_0^{n_{it}} (G_t Z_{ist} - F_t) ds \right] dt \qquad \text{s.t.}$$

$$\frac{q_{it}^x}{a_i^x} + \frac{\int q_{ist}^y dj}{a_i^y} \leq 1$$

$$Z_{ist} = \left(\frac{1}{x_{it}} + \frac{1}{y_{ist}} \right)^{-1} \qquad \dot{x}_{it} = -\delta x_{it} + q_{it}^x \qquad \dot{y}_{ist} = -\delta y_{ist} + q_{ist}^y$$

- interior optima $\Rightarrow$ reduces to a sequence of static problems

$$(n_{it}^*, x_{it}^*, y_{it}^*) = \arg\max_{n,x,y} \quad n(G_t Z(x,y) - F_t) \quad ,$$

$$\text{subject to} \quad \frac{x}{a_i^x} + \frac{ny}{a_i^y} \leq \frac{1 - e^{-\delta(t-\tau_i)}}{\delta} \equiv Q_{it}$$

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Data Description

- Two interpretations of scope: establishments and products

Data I: Establishments (NETS)

- Establishment-level longitudinal microdata covering universe of U.S. businesses.
- Each establishment has a DUNS identifier, a HQ number, and a sector.
- Average of 8 and 19 million each year, 1990-2017
- Information on sales, employment, industry, and location.
  - Given certain restrictions NETS mimics official employer data sets.

Data II: Products (Nielsen Retail Measurement Services scanner dataset)

- 2006-2015, covers CPG sector ($\approx$ 4.4% of Agg Consumption)
- Matched to firms using GS1 codes, $\approx$ 34K active during sample Statistics
- Products uniquely identified by a 12-digit Universal Product Code (UPC)
  - 100 product groups (e.g, toasters, light bulbs, razors, milk, etc)
  - 300K active every quarter
  - Information on attributes: color, style, size, flavor, etc.

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The 'China shock'

Extend framework to include imported varieties

- Sectoral import prices $\rightarrow G^s$

The 'China shock'

Extend framework to include imported varieties

- Sectoral import prices $\rightarrow G^s$

Following Autor et. al (2013) and Acemoglu et. al. (2015)

- Change in import penetration ratio in *sector j* at period τ: Details

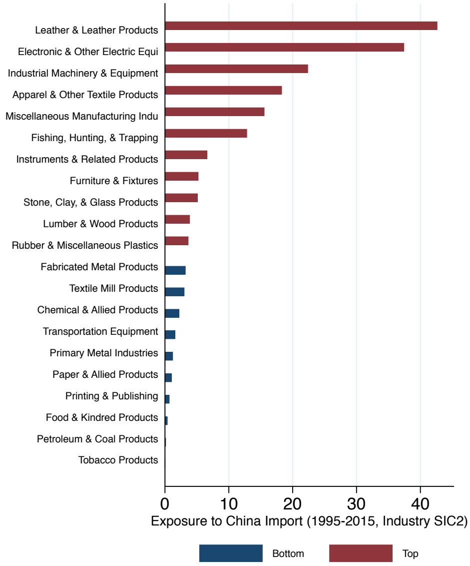
$$\Delta IP_{j\tau} = \frac{\Delta M_{j\tau}}{Y_{j\tau_0} + M_{j\tau_0} - E_{j\tau_0}} \quad \text{where}$$

$$\Delta M_{j\tau} \equiv \text{change in imports from China in period } \tau$$

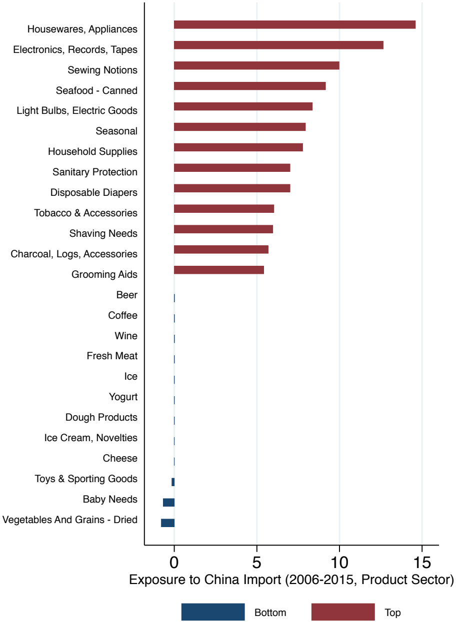
$$Y_{j\tau_0} + M_{j\tau_0} - E_{j\tau_0} = \text{industry shipments + imports - exports (base year)}$$

- Assumption: Higher $\Delta IP_{j\tau} \Rightarrow$ lower $\Delta \ln G_{j\tau}$
- Map sectors to Nielsen product groups – follow Bai and Stumpner (2019)

The ‘China shock’: NETS



The 'China shock': Nielsen



Measuring Scalability: Bootstrap-adjusted

Concern

- Mechanical relationship between size and our scalability measure

Strategy

- Assign products randomly to firms within a product group $\rightarrow S^{bootstrap}$
- Adjusted scalability measure: $\frac{S}{S^{bootstrap}}$

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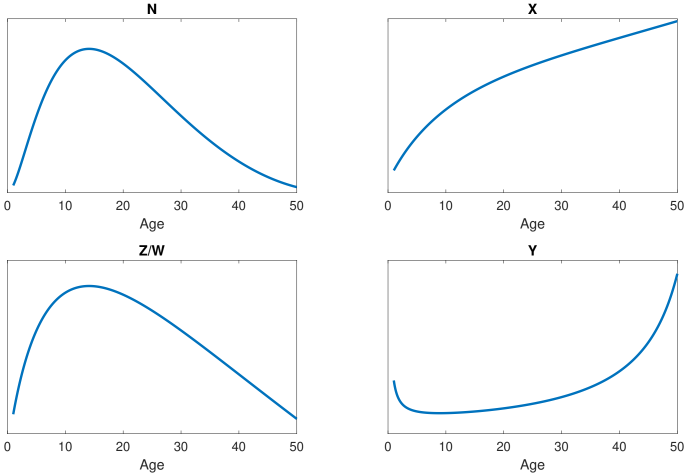
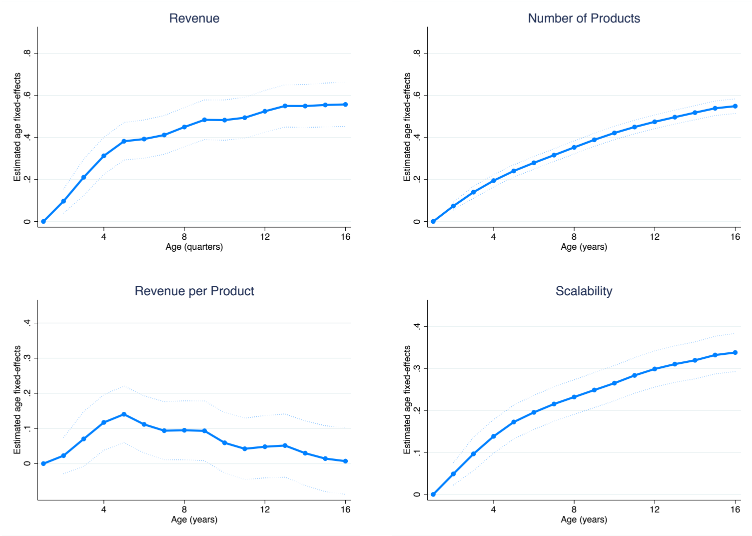
Expertise and replication over the life cycle



- Firms start small, grow by increasing both expertise and scope
- Eventually, $n \downarrow$, but Z continues to $\uparrow$, though slower than W

Life-Cycle of the Firm



Details | Alt: Including Left-Censored | Alt: By Duration | Alt: Other defs of n

Summary Statistics of Firm × Groups by Censoring

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	All	By Censoring Type				By Sample	
		Complete	Right	Left	Right&Left	Balanced	Semi
Total # of firms	65,525	8,154	15,812	17,341	24,218	6,213	23,373
average	6.7	3.7	5.2	4.8	10	7.3	4.3
less than 1y	13	31	16	19	0	0	25
less than 4y	41	83	56	64	0	0	73
above 7y	42	0	11	10	100	22	5.9
Revenue (quarterly, $1,000)							
mean	2,241	23	38	292	5,821	412	221
25th percentile	.6	.1	0	1.4	9.1	3.1	.6
median	8.8	.7	.6	11	68	19	5.6
75th percentile	92	6.2	7.2	72	566	105	43
90th percentile	765	31	43	372	3,943	543	244
95th percentile	2,760	82	121	979	14,329	1,376	679
Products (quarterly)							
mean	11	1.9	2.6	4.6	23	5.8	3.9
25th percentile	1	1	1	1	2	1.4	1
median	2.3	1	1.5	2	5.1	2.7	2
75th percentile	5.7	2	3	4.7	14	5.6	4
90th percentile	16	4	5.2	9	41	11	7.5
95th percentile	32	5	7.6	14	79	18	12

Estimation of the life cycle profile of firms

- **age**: time since a firm first appeared on the market.
- Estimation using **age-period-cohort** empirical model
  - *Baseline*: outcome of interest Y of firm i in sector j at time t, as function of age (a), sector-period (jt) and cohort (c) effects:

$$\ln Y_{ijt} = \alpha + \sum_{a=2}^{A} \beta_a D_a + \lambda_{jt} + \tilde{\theta}_c + u_{ijt}$$

    We use a balanced sample of cohorts of firms born between 2006q2 and 2011q4, that have at least 16 quarters of activity.

  - *Alternative*: accounting for selection by allowing for β_a's to vary with the duration of a firm.

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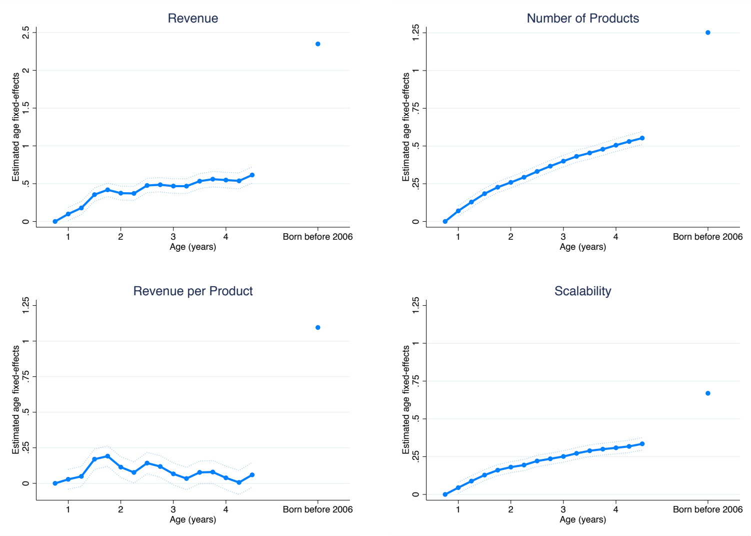
Life-Cycle of the Firm: Including Left-Censored Firm



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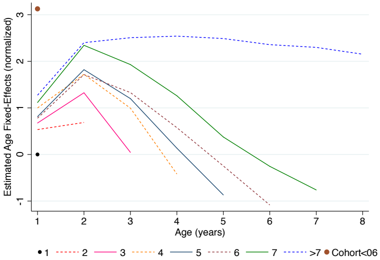
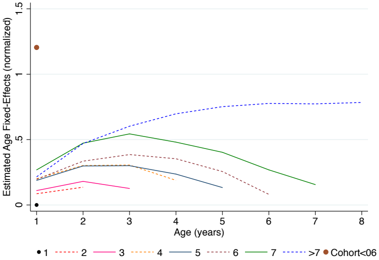
Life-Cycle of the Firm: by Firm Age



(a) Revenue



(b) Products

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Measuring Scalability: An example

Group: Razors, disposable

Firm	Product	Type	Skin Type
Procter & Gamble	1	Razor	Sensitive
Procter & Gamble	2	Razor	Dry
Procter & Gamble	3	Shaver	Normal
Procter & Gamble	4	Razor/Shave Cream in Handle	Ultra Sensitive
Procter & Gamble	5	Shaver/Shave Cream in Handle	Normal to Dry

Style: $$\boxed{S_{Type,PG} \equiv 1 - \frac{\text{Distinct Characteristics}}{\#\text{ of Products}}} = 1 - \frac{4}{5} = 0.2$$

Use: $$\boxed{S_{Skin\,Type,PG} \equiv 1 - \frac{\text{Distinct Characteristics}}{\#\text{ of Products}}} = 1 - \frac{5}{5} = 0$$

Firm level: $$\boxed{S_{PG} \equiv 1 - \frac{\text{Distinct Characteristics}}{\#\text{ of Products} \times \text{Attributes}}} = 1 - \frac{5+4}{5+5} = 0.1$$

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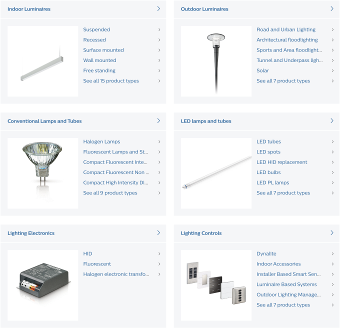
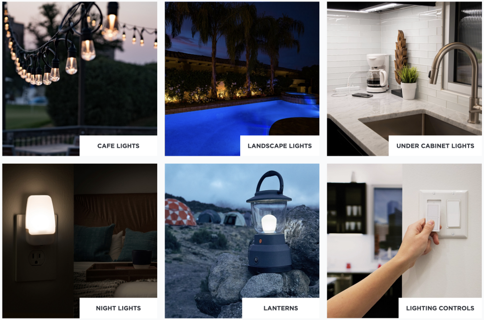
Lamps and light bulbs

Philips Lighting



Jasco



- $\text{Scope}_{\text{Philips},2006} \approx \text{Scope}_{\text{Jasco},2006}$
- $\text{Scalability}_{\text{Philips},2006} < \text{Scalability}_{\text{Jasco},2006}$
- $\text{Expertise}_{\text{Philips},2006} > \text{Expertise}_{\text{Jasco},2006}$
- $\text{Scope}_{\text{Philips},2015} > \text{Scope}_{\text{Jasco},2015}$

Scalable Expertise and Diffusion: Bootstrap adjusted

Hypothesis: Diffusion within the firm $\rightarrow$ diffusion outside the firm

$$D_{c,a,i,t,\tau} \equiv \frac{\text{Num. of times } c \text{ introduced by firm } i \text{ appears in products by } -i \text{ between } t \text{ and } t+\tau}{\text{Num. of products introduced by } -i \text{ between } t \text{ and } t+\tau}$$

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	(1)	(2)	(3)	(4)
Diffusion				
$\ln \frac{Scalability}{Scalability^{\text{Bootstrap}}}$	0.013***	0.0020***		
	(0.000)	(0.000)		
$\ln \frac{Scalability(alt)}{Scalability(alt)^{\text{Bootstrap}}}$			0.0474***	0.0071***
			(0.000)	(0.000)
Total Products	-0.0290***	-0.0077***	-0.0243***	-0.0053***
	(0.000)	(0.000)	(0.000)	(0.000)
Observations	2,176,553	2,128,543	3,061,259	2,969,366
R-squared	0.800	0.8938	0.808	0.890
Firm-Attribute	N	Y	N	Y
Attribute-Time-Horizon	Y	Y	Y	Y

$$D_{c,a,i,t,\tau} = \alpha + \beta\ S_{a,i,t-1,\tau} + \gamma\ n_{i,t-1} + FE + \epsilon_{c,a,i,t,\tau}$$

Cross-section