Domestic vs Foreign Superstars: Granular Comparative Advantage, Pro-competitive Effects, and Productivity Spillovers

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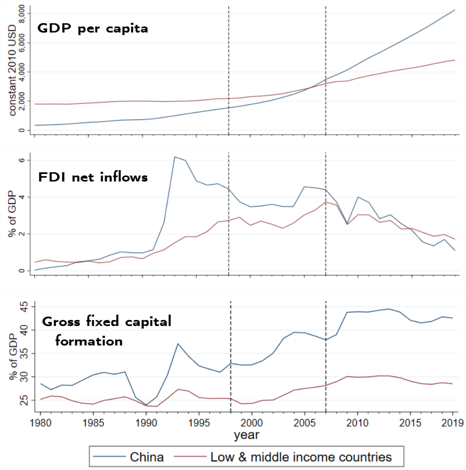
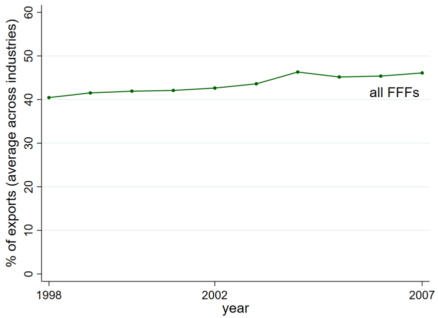
Introduction

Figure: China's Economic Miracle



Superstar exporters in China

Figure: Accounting for China's industry-level exports



- Chinese Industrial Enterprise Survey: 1998 to 2007, 2 million observations, 420 industry codes.
  - Foreign-Funded Firms (FFFs): firms with 50% or more foreign funding (FDI). 15% of observations.
  - Domestically-Funded Firms (DFFs): all other firms.

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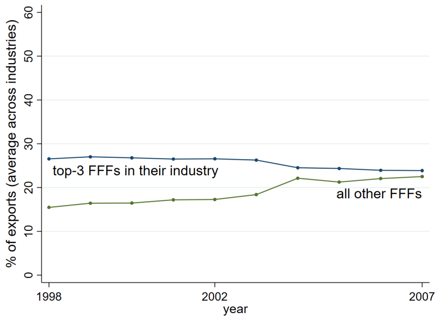

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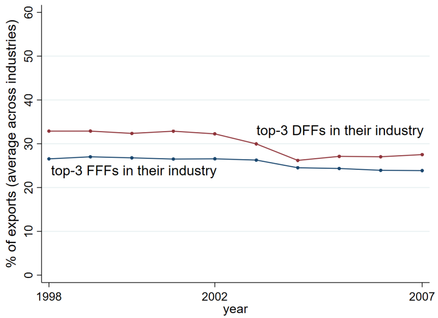

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China's Economic Miracle and FDI

- While most manufacturing FDI aids growth and development (Almfraji and Almsafir, 2014), results are sensitive for less developed economies (Beugelsdijk et al., 2008).
- The case of China is clear: FDI = 30-40% of '03-'04 economic growth (Whalley and Xin, 2006).
  - » Understanding the types of FDI that benefited China the most is crucial for developing countries aspiring to replicate its success.
- FDI spillover effects in China vary (Du et al. (2012), Lu et al. (2017)).
- Recent literature on large, granular firms:
  - Gabaix (2011): Granular Hypothesis
  - Freund and Pierola (2015): Superstar Exporters
  - Gaubert and Itskhoki (2021): Granular Comparative Advantage
  - Amiti et al. (2023): Superstar vertical spillovers on suppliers

This Paper

1. **Are China's export patterns shaped by granular firms (Granular Comparative Advantage), and in what way?**

   Findings:

   - Granularity generally hurts industry export performance
   - Defining granularity by employment shares, an additional 10% of total **employment** concentrated among top-3 **DFFs** associates with a 8.1% decrease in industry exports.
   - An additional 10% of total **employment** concentrated among top-3 **FFFs** associates with a 16.1% increase in industry exports.
     - Stronger effects in pre-mature industries (low TFP, less FDI) with more young firms.
     - Granularity from DFFs still cancels out net effect, but converges towards FFFs over time.

This Paper

2. **Does granularity from FFFs and DFFs impact markups of non-granular firms?**
    - Literature on trade and markups (Edmond et al., 2015), and concentration (De Loecker et al., 2020).
    - Few studies on FDI and market power in host countries, not to mention in the context of granularity.

Findings:

- Results show both granular groups in China indicate a **pro-competitive effect** on other large firms, but only from FFF granularity for all firms.

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   Findings:

   - Results show both granular groups in China indicate a **pro-competitive effect** on other large firms, but only from FFF granularity for all firms.

3. **Is granularity from FFFs a new (and separate) source of horizontal spillovers on productivity of domestic firms?**
   - Horizontal spillovers from FDI (the diffusion of knowledge, technology, and best practices from one firm to another within the same industry), are typically found to be zero or negative for China.

   Findings:

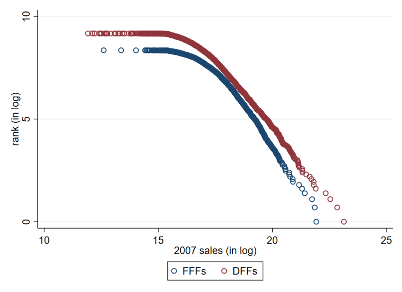
   - FFF granularity induces positive and significant **horizontal spillover effects** on domestic firms, while general FDI penetration does not.

Outline

- Granularity in China
- Granular Comparative Advantage (GCA)
- Pro-competitive effects
- Productivity spillovers
- Conclusion

Two types of granular firms: FFFs and DFFs

Figure: cCDF of sales; 2007 Textile & apparel firms (4-digit industry example)



- Thicker right-tail for set of DFFs (lower Pareto exponent) → higher firm-size inequality. Pareto exponents

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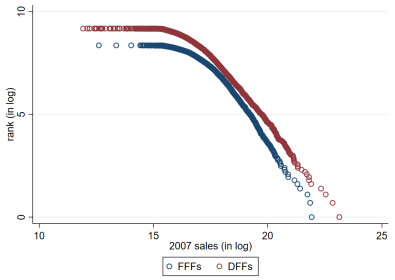
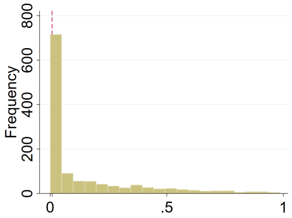


- Thicker right-tail for set of DFFs (lower Pareto exponent) $\rightarrow$ higher firm-size inequality. Pareto exponents
- Define industry-level granularity by the concentration among top-few firms:

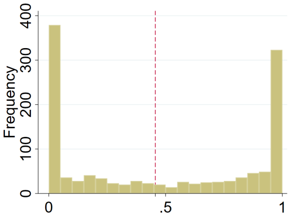
$\sum_{i=1}^{3} \widetilde{s}_{z,i,t}$ for some share $\widetilde{s}$. But which share to use?

Granular FFFs: Pure domestic market sellers and pure exporters

Figure: Export intensities of granular FFFs in 2007



(a) the 3 biggest FFFs by **domestic market sales**



(b) the 3 biggest FFFs by **employment**

- Most granular FFFs either only export or only focus on local market (graph b) DFFs

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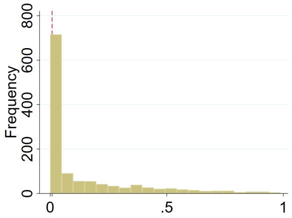

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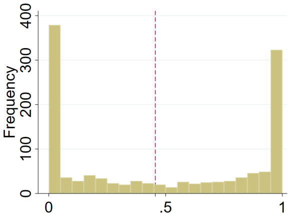

(b) the 3 biggest FFFs by **employment**

- Most granular FFFs either only export or only focus on local market (graph b) DFFs
- Defining granularity by domestic market sales creates **horizontal FDI (domestic market access)** bias
- Defining granularity by employment is more neutral

$$\sum_{i=1}^{3} \tilde{s}_{z,i,t} = \sum_{i=1}^{3} domestic\ market\ sales\ share_{z,i,t} \quad or \quad \sum_{i=1}^{3} employment\ share_{z,i,t}$$

How do granular and other large firms compare?

Table: Characteristics of granular and other large firms (defining $\tilde{s}$ by employment)

	(1)	(2)	(3)	(4)	(5)
Dependent variable:	export intensity	ln markups	ln KL ratio	ln labor productivity	ln mean wage rate
Top-3 FFF dummy	0.260***	-0.017***	0.297***	0.184***	0.268***
Top-3 DFF dummy	-	-	-	-	-
Other large FFF dummy	0.219***	-0.072***	0.200***	0.021	0.176***
Other large DFF dummy	-0.057***	-0.086***	-0.289***	-0.126***	-0.119***
Constant	0.239***	0.355***	3.678***	3.907***	2.472***
State-owned dummy	Y	Y	Y	Y	Y
Firm age	Y	Y	Y	Y	Y
Industry & Year FEs	Y	Y	Y	Y	Y
Observations	1058852	1058852	1058852	1058852	1058852

Note: Regresses firm level metrics on four funding-size dummies, with Granular DFFs as the reference group. Other large firms are those with $\geq$ 100 employees but not among the top-3. Not controlling for state-owned firms leads to a doubling of the labor productivity coefficient on the dummy for granular FFFs, but all other coefficients see only minor adjustments (not shown). Industry clustered errors, *** $p<0.001$.

Granular Residual: Accounting Framework

Following Gaubert and Itskhoki (2021) model of Granular Comparative Advantage (GCA):

For industry z, industry exports X_z, and domestic industry expenditure Y_z:

- Export ratio $\Lambda_z = \frac{X_z}{Y_z}$ varies one-to-one with CA variation across industries for a within-country analysis.
- This export ratio decomposes into contribution to exports of finite firms:

$$\Lambda_z = \sum_{i=1}^{N_z} s_{zi}\lambda_{zi} = \mathbf{s}_\mathbf{z}'\boldsymbol{\lambda}_\mathbf{z} \quad \textit{with } (\lambda, \mathrm{s}) \sim F_z(\cdot)$$

$s_{z,i} = \frac{d_{z,i}}{Y_z}$ is firm level domestic market share and $\lambda_{z,i} = \frac{x_{z,i}}{d_{z,i}}$ is the ratio of firm exports to domestic sales

Granular Residual: Accounting Framework

Decomposition of Λ_z into an expected value plus a granular residual (finiteness):

$$\Lambda_z = \Phi_z + \Gamma_z \quad \text{where} \quad \Phi_z = \mathbb{E}_z\{\Lambda_z\} = \int s'\lambda \, dF_z(\lambda, s).$$

- Φ_z, Fundamental Comparative Advantage (FCA):
  - industry characteristics embodied in the distribution function Fz common to all firms.
- $\Gamma_z = \Lambda_z - \Phi_z$ is the granular residual, or GCA.
  - departures from population mean due to granular firms

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Taking account of systematic differences between home and foreign firms in a host country, Γ_z splits into two parts:

$$\Gamma_z^{DFF} + \Gamma_z^{FFF}$$

$$var\ (\Lambda_z) = var\ (\Phi_z) + var\ (\Gamma_z^{DFF}) + var\ (\Gamma_z^{FFF}).$$

Detecting GCA: specification

Baseline regression with two sources of granularity, $X_{z,t}$:

$$exports_{z,t} = \alpha + \beta^{DFF} \sum_{i=1}^{3} \tilde{s}_{z,i,t}^{FFF} + \beta^{FFF} \sum_{i=1}^{3} \tilde{s}_{z,i,t}^{DFF} + \log D_{z,t} + \varepsilon_{z,t}, \tag{1}$$

- where $\sum_{i=1}^{3} \tilde{s}_{z,i,t}$ is the **concentration** ratio among the **top-3 firms** in industry z (domestic sales or employment) and the first sum is across the **top-3 FFFs** while the second among the **top-3 DFFs**.
- $\log D_{z,t}$ is a control for industry scale (total domestic sales or total employment).
- Poisson regression required as 47/4200 industry-years have zero exports and to address Heterogeneity (Santos Silva and Tenreyro, 2006).

Baseline Results

Table: Granular Comparative Advantage and FDI

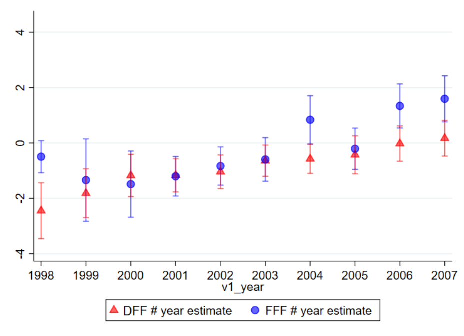
	Defining $\widetilde{s}$ by domestic sales			Defining $\widetilde{s}$ by employment		
Dependent variable: $exports_{z,t}$	(1)	(2)	(3)	(4)	(5)	(6)
$\sum_{i=1}^{3} \widetilde{s}_{z,i,t}$	-0.814***			0.120		
	(0.24)			(0.29)		
$\sum_{i=1}^{3} \widetilde{s}^{FFF}_{z,i,t} + \sum_{i=1}^{3} \widetilde{s}^{DFF}_{z,i,t}$		-0.809***			0.272	
		(0.23)			(0.27)	
$\sum_{i=1}^{3} \widetilde{s}^{FFF}_{z,i,t}$			-0.471			1.495***
			(0.34)			(0.40)
$\sum_{i=1}^{3} \widetilde{s}^{DFF}_{z,i,t}$			-1.194***			-0.807**
			(0.29)			(0.39)
$D_{z,t}$	0.396***	0.384***	0.359***	0.793***	0.795***	0.728***
Industry & Year FEs	Y	Y	Y	Y	Y	Y
Observations	4200	4200	4200	4200	4200	4200

Note: Columns (1) - (3) define granularity by domestic sales shares, (4) - (6) define it by employment shares. All are Poisson regressions. Industry clustered errors; ** p$<$0.05, *** p$<$0.01.

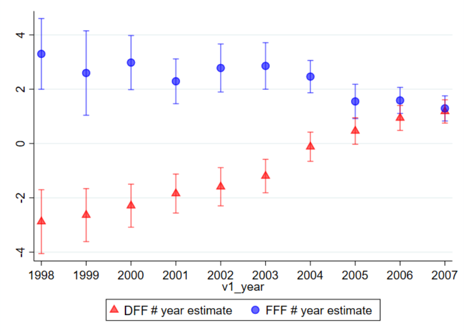
- Opposite results in column 1 compared to Gaubert and Itskhoki (2021), but all from DFFs (column 3).
- An additional 10% of total **employment** concentrated among top-3 **FFFs** associates with a 16.1% ([exp(1.495x0.10)-1]) increase in industry exports.

Convergence in GCA as China develops

Figure: GCA from DFFs and FFFs converges over time



(a) defining $\tilde{s}$ by domestic sales



(b) defining $\tilde{s}$ by employment

Note: Plots coefficients of a single Poisson regression equivalent to column (3) and (6) in previous table with added year interactions on each of the two granularity proxies. Granularity is proxied for using staff shares. Industry and year fixed effects included. Robust errors with solid fill indicates significance past the 90 percent level.

Robustness, Endogeneity and Heterogeneity

Robustness & Endogeneity

- Removing state firms - no change. Here
- Alternative reasons for association: more skewed distribution encourages more exports:
  - IV approach - Invested capital shares (equity) as IVs for granularity proxies strengthens results: Here
  - Predictive power of key variables - evidence against reverse causality: Here

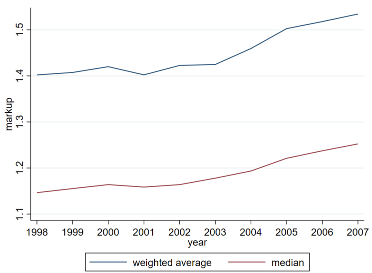
Heterogeneity

- GCA from DFFs more positive in low-tech or high-growth industries; more negative in ratio of young firms, state-owned firms, or FFFs.
- GCA from FFFs more positive in mid-tech or ratio of young firms; more negative in ratio of FFFs and industry TFP
- Heterogeneity from granular firm characteristics behaves similarly for DFFs and FFFs Here

Markups of non-granular firms

- International trade reduces markups when there is both missallocation and an increase in competitive pressure, i.e the additional activity is not only along the extensive margin (Edmond et al., 2015).
- Much dispersion in markups, with granular DFFs highest, then granular FFFs. details
- Granular firms indeed compete head-to-head with non-granular firms and signs point to granular FFFS inducing relatively more effective competitive pressure. details

Figure: Estimated Markups (De Loecker and Warzynski (2012))



Markups of non-granular firms: specification

Do granular FFFs bring more pro-competitive effects than granular DFFs?

$$mu_{z,i,t+1} = \alpha + SS_{z,i,t} + \sum_{i=1}^{3} \widetilde{s}_{z,i,t}^{FFF} + \sum_{i=1}^{3} \widetilde{s}_{z,i,t}^{DFF} + SS_{z,i,t} * \sum_{i=1}^{3} \widetilde{s}_{z,i,t}^{FFF} + SS_{z,i,t} * \sum_{i=1}^{3} \widetilde{s}_{z,i,t}^{DFF} + \mathrm{X}_{z,i,t} + \varepsilon_{z,i,t} \quad (2)$$

- All variables lagged one year.
- $SS_{z,i,t}$ = firm-level industry sales share. $\widetilde{s}$ = *employment shares*.
- Additional firm controls: labor productivity, price of labor, capital intensity, and export intensity.
- Industry controls: price of labor, capital intensity, number of firms, and export intensity.
- Industry and Year fixed effects

Results

Table: Granular pro-competitive effects

Dependent variable: Estimated Markup (log), $mu_{z,i,t+1}$	(1)	(2)	(3)	(4)
$SS_{z,i,t}$;		0.631***	1.577***	1.172***
		(0.06)	(0.11)	(0.11)
$\sum_{i=1}^{3} \tilde{s}_{z,t}^{FFF}$	-0.060***		-0.072***	-0.056**
	(0.02)		(0.02)	(0.02)
$\sum_{i=1}^{3} \tilde{s}_{z,t}^{DFF}$	0.033***		0.026***	-0.006
	(0.01)		(0.01)	(0.01)
$SS_{z,i,t} \times \sum_{i=1}^{3} \tilde{s}_{z,t}^{FFF}$			-1.496***	-1.114***
			(0.35)	(0.33)
$SS_{z,i,t} \times \sum_{i=1}^{3} \tilde{s}_{z,t}^{DFF}$			-2.085***	-1.467***
			(0.20)	(0.17)
$FDI_{z,t}$; % of firms that are FFFs				-0.005***
				(0.00)
Other firm & industry controls	N	N	N	Y
Firm & Year FEs	Y	Y	Y	Y
Adjusted R_sq	0.861	0.861	0.861	0.862
Observations	1220553	1220553	1220553	1218377

Note: $\tilde{s}$ = employment share. SS = sales share. The top-3 granular FFFs and DFFs per industry by employment share are excluded. All explanatory variables are lagged one year. Industry×Year clustered errors. Other control variables for Column (4) here. Robust to changing granularity definition and including non-granular FDI penetration here.

Granular FDI Spillovers

- Literature on FDI in China find zero (Du et al., 2012), or negative horizontal spillovers (Lu et al., 2017).
- Difficulty of identifying spillovers due to endogenous selection by foreign firms.

Is the granular component of FDI a new source of horizontal spillovers on domestic firms?

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Identification:

- 2002 China updated guidelines on encouragement of FDI (previously set in 1997).
- Matching each line to industry codes:
  - 121 industries become more encouraging of FDI (treatment group)
    - Example: Dairy products was previously restricted but became an encouraged category of FDI.
  - 283 industries have no change (control group)
  - 16 with at least some new discouraging of FDI (excluded)
- Only $\sum_{i=1}^{3}$ *domestic sales share*$_{z,t}^{FFF}$ (FFF dom granularity) correlates strongly with the 2002 shock. details

Granular FDI Spillovers: specification

First stage:

$$\sum_{i=1}^{3} \widetilde{s}_{z,i,t}^{FFF} = \alpha + treatment_z \times post_t + \mathrm{X}_{z,i,t} + \delta_z + \delta_t + \varepsilon_{z,i,t}. \quad (3)$$

Second stage:

$$y_{z,i,t} = \alpha + \sum_{i=1}^{3} \widetilde{s}_{z,i,t}^{FFF} + \mathrm{X}_{z,i,t} + \delta_z + \delta_t + \varepsilon_{z,i,t}, \quad (4)$$

- $\widetilde{s} = domestic\ sales\ share$
- Firm controls: output, KL ratio, state dummy, exporter dummy.
- Industry controls: 1998 values interacted with year dummies (to control for time path of outcomes) for import tariffs, export tariffs, import penetration, FDI penetration, export intensity, new product output intensity, mean firm age, number of firms, state-firm penetration, DFF domestic sales granularity.

Results

Table: Granular FDI and Horizontal Spillovers

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	1st stage		IV		OLS	
	(1)	(2)	(3)	(4)	(5)	(6)
Dependent variable:	FDI dom penetration	FFF dom granularity	ln TFP	ln labor productivity	ln TFP	ln labor productivity
$treatment_z \times post_t$	-0.001	0.010***				
	(0.006)	(0.003)				
$\sum_{i=1}^{3} \tilde{s}_{k,i,t}^{FFF}$ (FFF dom granularity)			3.570*	3.697*	-0.012	0.154***
			(2.089)	(2.065)	(0.064)	(0.040)
$\sum_{i=1}^{N_z} \tilde{s}_{k,i,1998}^{FFF}$ * yr (FDI dom pen.)		0.000***	-0.001***	-0.000**	-0.000**	-0.000***
		(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
$\sum_{i=1}^{3} \tilde{s}_{k,i,1998}^{DFF}$ * yr	0.000	0.000***	-0.000**	-0.000*	-0.000**	-0.000
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
Kleibergen-Paap Wald rk F statistic			12.34	12.34		
Anderson-Rubin Wald test			4.95**	5.13**		
Firm & Year FEs	Y	Y	Y	Y	Y	Y
Industry controls $\times$ year dummies	Y	Y	Y	Y	Y	Y
Time-varying firm controls	Y	Y	Y	Y	Y	Y
Observations	1200640	1200640	1200640	1200640	1200640	1200640

Note: Column (2) shows the first stage estimation of 3 for the IV regressions of 4 presented in column (3) for TFP and column (4) for labor productivity. Industry-clustered errors; * p<0.10, ** p<0.05, *** p<0.01.

- An additional 1% concentrated among the top-3 **FFFs** sees a 3.7% increase in local firm labor productivity.

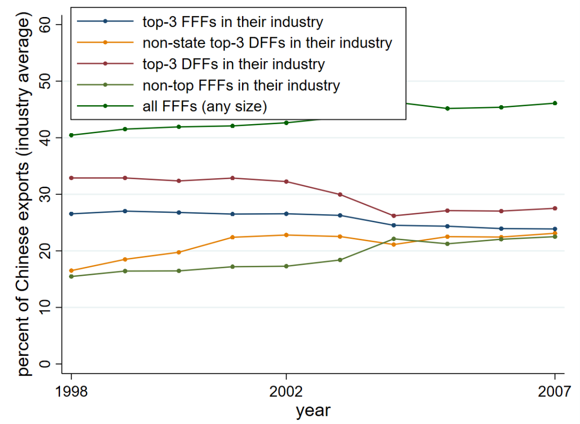
Conclusion

- Granularity and industry exports in China had a negative relationship in general for '98 to '07
  - Large firms with home country bias dampen China's GCA
  - Relief from efficiency-seeking (vertical) FDI, but not from market-seeking FDI
  - much heterogeneity according to industry characteristics and characteristics of the granular firms themselves.
- Granularity form FDI has more pro-competitive effects than granularity from domestic firms.
- While existing literature usually indicates negative horizontal spillover effects from FDI, there are positive horizontal spillover effects on firm-level labor productivity and TFP coming from granular FDI.
- These results are important for policymakers looking to promote or restrict the activity of superstar firms.

Thank you

Superstar exporters in China

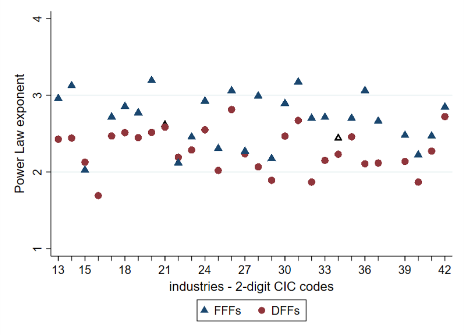
Figure: Accounting for China's industry-level exports



back

Granularity in China: Differing distributions

Figure: Power-law (Pareto) exponent estimates by firm funding type within 29 2-digit industries



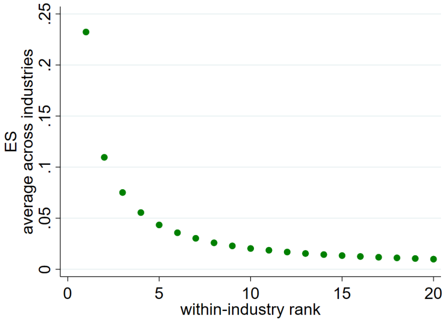
Note: $\hat{\alpha}$ values and corresponding lower bound of Power-law behavior (x_{min}) in density function $p(x) = \frac{-x}{x_{min}}(\frac{x}{x_{min}})^{-\alpha}$ found by MLE a la Clauset et al. (2009). Goodness-of-fit p-values > 0.10 indicated by solid fill.

- FFFs have a power law exponent 0.387 higher on average with a t-stat of 4.74.

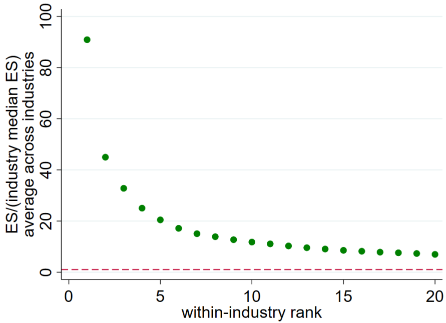
back

Stylized facts: Granularity in China

Figure: Granularity in export shares (ES) across top firms in 2007



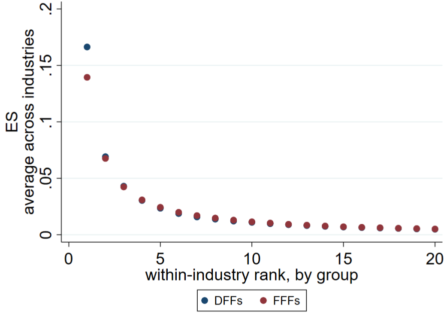
(a) Export share of the i^{th} ranked exporter (ES_{zi}), averaged.



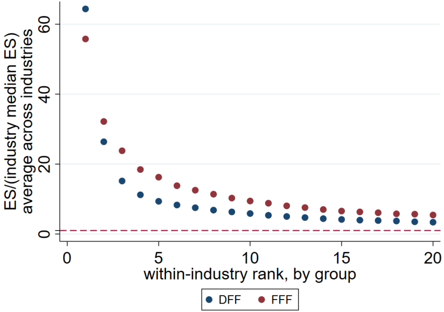
(b) The number of times larger ES_{zi} is than the industry median among exporters, averaged.

Stylized facts: Granularity in China

Figure: Granularity in export shares (ES) across top FFFs and DFFs in 2007



(a) Export share of the i^{th} ranked exporter (ES_{zi}), averaged.

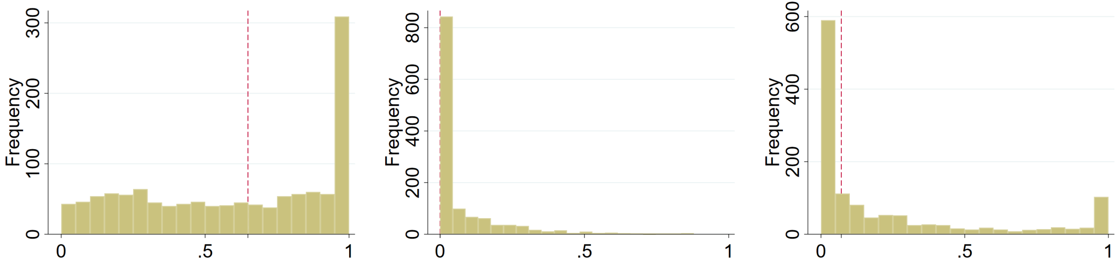


(b) The number of times larger ES_{zi} is than the industry median among exporters, averaged.

back

Capturing Granularity in China

Figure: Export intensities of top-3 DFFs in 2007



(a) Ranked by exports (b) Ranked by domestic sales (c) Ranked by workers

Note: The red dashed line indicates the median among the top firms.

back

Poisson 2sls using invested capital shares as IVs

Table: Poisson 2sls using invested capital shares as IVs

	Defining $\widetilde{s}$ as dom sales share			Defining $\widetilde{s}$ as employment share			
	(1)	(2)	(3)	(4)	(5)	(6)	(7)
$\sum_{i=1}^{3} \widetilde{s}_{z,i,t}$	-3.236**			-0.778			
$\sum_{i=1}^{3} \widetilde{s}^{FFF}_{z,i,t} + \sum_{i=1}^{3} \widetilde{s}^{DFF}_{z,i,t}$		-4.874**			-1.337		
$\sum_{i=1}^{3} \widetilde{s}^{FFF}_{z,i,t}$			-2.810			3.053*	3.002*
$\sum_{i=1}^{3} \widetilde{s}^{DFF}_{z,i,t}$			-3.921**			-1.537	
$\sum_{i=1}^{3} \widetilde{s}^{DFF}_{z,i,t}$; private only							-1.531**
$D_{z,t}$	0.387***	0.393***	0.348**	0.753***	0.703***	0.698***	0.710***
s1 v	2.623*			1.007			
s1 v		4.344*			1.732		
FFFs s1 v			2.571			-1.668	-1.459
DFFs s1 v			3.050*			0.874	1.423*
Industry & Year FE	Y	Y	Y	Y	Y	Y	Y
Observations	4200	4200	4200	4200	4200	4200	4200

Note: Poisson IV with fixed effects procedure from Lin and Wooldridge (2017); estimates the reduced form (first stage) for endogenous variables and includes the residuals as controls (s1 v) in a Poisson regression. Robust errors; * p<0.10, ** p<0.05, *** p<0.01

- Granularity form FFFs boosts industry exports. DFFs still no.
- Replacing the DV with industry TFP (not shown) shows both types of granularity contribute positively, but FFFs twice as much.

back

OLS 2sls using invested capital shares as IVs

Table: Poisson 2sls using invested capital shares as IVs

	Defining $\widetilde{s}$ as dom sales share			Defining $\widetilde{s}$ as employment share			
	(1)	(2)	(3)	(4)	(5)	(6)	(7)
$\sum_{i=1}^{3} \widetilde{s}_{z,i,t}$	-3.236**			-0.778			
$\sum_{i=1}^{3} \widetilde{s}_{z,i,t}^{FFF} + \sum_{i=1}^{3} \widetilde{s}_{z,i,t}^{DFF}$		-4.874**			-1.337		
$\sum_{i=1}^{3} \widetilde{s}_{z,i,t}^{FFF}$			-2.810			3.053*	3.002*
$\sum_{i=1}^{3} \widetilde{s}_{z,i,t}^{DFF}$			-3.921**			-1.537	
$\sum_{i=1}^{3} \widetilde{s}_{z,i,t}^{DFF}$; private only							-1.531**
$D_{z,t}$	0.387***	0.393***	0.348**	0.753***	0.703***	0.698***	0.710***
s1 v	2.623*			1.007			
s1 v		4.344*			1.732		
FFFs s1 v			2.571			-1.668	-1.459
DFFs s1 v			3.050*			0.874	1.423*
Industry & Year FE	Y	Y	Y	Y	Y	Y	Y
Observations	4200	4200	4200	4200	4200	4200	4200

Note: Underidentification test rejection of the null with a p-value $<$ 0.001 all indicates that the instruments are relevant, and the model is identified. Cragg-Donald Wald F stat of above 100 imply instruments are not weak. As regression is not Poisson here, log exports excludes zero export industry-years. Robust errors; * p$<$0.10, ** p$<$0.05, *** p$<$0.01

- Granularity form FFFs boosts industry exports. DFFs still no.
- Replacing the DV with industry TFP (not shown) shows both types of granularity contribute positively, but FFFs twice as much.

back

Robustness: Excluding granular firms from export figures

Table: Excluding the granular firms from industry exports

	Defining $\tilde{s}$ by domestic sales			Defining $\tilde{s}$ by employment		
	(1)	(2)	(3)	(4)	(5)	(6)
$\sum_{i=1}^{3} \tilde{s}_{z,i,t}$	-0.952***			-0.028		
	(0.241)			(0.289)		
$\sum_{i=1}^{3} \tilde{s}^{FFF}_{z,i,t} + \sum_{i=1}^{3} \tilde{s}^{DFF}_{z,i,t}$		-0.953***			0.098	
		(0.229)			(0.270)	
$\sum_{i=1}^{3} \tilde{s}^{FFF}_{z,i,t}$			-0.650*			1.352***
			(0.344)			(0.389)
$\sum_{i=1}^{3} \tilde{s}^{DFF}_{z,i,t}$			-1.297***			-1.048***
			(0.297)			(0.390)
$D_{z,t}$	0.391***	0.378***	0.355***	0.817***	0.815***	0.746***
	(0.068)	(0.070)	(0.071)	(0.040)	(0.041)	(0.036)
Industry & Year FE	Y	Y	Y	Y	Y	Y
pseudo-R-sqr	0.968	0.968	0.968	0.978	0.978	0.980
Observations	4180	4180	4180	4190	4190	4190

Note: This table repeats the exercise for the base regression, changing the dependent variable to industry-aggregate exports minus all exports from the granular firms used to construct the granularity variables. Industry and year fixed effects included. Robust errors; * $p<0.10$, ** $p<0.05$, *** $p<0.01$

back

Robustness: Using export shares for granularity proxies

Table: Granularity via export shares - negative bias

	Proxying by export shares					
	(1)	(2)	(3)	(4)	(5)	(6)
$\sum_{i=1}^{3} \tilde{s}_{z,i,t}$	-0.603***			0.063		
	(0.21)			(0.18)		
$\sum_{i=1}^{3} \tilde{s}_{z,i,t}^{FFF} + \sum_{i=1}^{3} \tilde{s}_{z,i,t}^{DFF}$		-0.999***			-0.233	
		(0.22)			(0.18)	
$\sum_{i=1}^{3} \tilde{s}_{z,i,t}^{FFF}$			-0.893***			0.116
			(0.27)			(0.18)
$\sum_{i=1}^{3} \tilde{s}_{z,i,t}^{DFF}$			-1.140***			-0.609***
			(0.22)			(0.20)
ind. dom sales	0.350***	0.328***	0.326***			
	(0.07)	(0.07)	(0.07)			
ind. employment				0.802***	0.778***	0.796***
				(0.05)	(0.05)	(0.05)
pseudo-R-sqr	0.971	0.971	0.971	0.979	0.979	0.980
Observations	4200	4200	4200	4200	4200	4200

Note: All are Poisson regressions, include industry and year fixed effects and show robust errors. The dependent variable is industry exports. The granularity proxies are computed from export shares only). The ind. size control is log of industry-aggregate domestic sales of all DFFs and FFFs for columns (1) to (3) and the log of the industry-aggregate number of workers for columns (4) – (6). Robust errors; * p<0.10, ** p<0.05, *** p<0.01

back

Separating state-owned firms from granularity variables

	By dom market shares		By wage bill shares		By worker shares	
	(1)	(2)	(3)	(4)	(5)	(6)
$\sum_{i=1}^{3} \widetilde{s}_{z,i,t}^{FFF}$	-0.109	-0.601*	0.204	-0.110	1.642***	1.400***
	(0.41)	(0.33)	(0.36)	(0.35)	(0.40)	(0.40)
$\sum_{i=1}^{3} \widetilde{s}_{z,i,t}^{FFF}$, private	-0.598**	-1.168***	-0.811***	-1.452***	-0.476**	-0.843***
	(0.25)	(0.25)	(0.18)	(0.24)	(0.24)	(0.29)
$\sum_{i=1}^{3} \widetilde{s}_{z,i,t}^{FFF}$, state		-1.396***		-1.320***		-1.024**
		(0.40)		(0.31)		(0.44)
$D_{z,t}$	0.358***	0.358***	0.788***	0.786***	0.729***	0.716***
	(0.07)	(0.07)	(0.05)	(0.04)	(0.04)	(0.04)
pseudo-R-sqr	0.970	0.971	0.980	0.981	0.980	0.980
Obs	4200	4200	4200	4200	4200	4200

Note: All are Poisson regressions. Industry and year FE included. Industry-clustered robust errors.

- Coefficients are largely unchanged when separating state DFFs
- 1,030 firms that were among the top-6 largest in their industry for at least one year changed dominate funding from state to private.

back

Predictive power of key variables

Table: Predictive power of key variables

Dependent Variable:	$gDFFs_{z,07} - gDFFs_{z,98}$	$gFFFs_{z,07} - gFFFs_{z,98}$			$X_{z,07} - X_{z,98}$		
	(1)	(2)	(3)	(4)	(5)	(6)	(7)
$X_{z,98}$	-0.005	0.004	-0.001	0.002	-0.501***	-0.489***	-0.568***
	(0.003)	(0.002)	(0.003)	(0.004)	(0.043)	(0.059)	(0.060)
$\sum_{i=1}^{3} \tilde{s}^{FFF}_{z,i,98}$	0.031	-0.741***	-0.755***	-0.768***	1.644*	1.530*	6.207***
	(0.073)	(0.046)	(0.047)	(0.048)	(0.909)	(0.898)	(2.022)
$\sum_{i=1}^{3} \tilde{s}^{DFF}_{z,i,98}$	-0.455***	0.044*	0.045*	0.060**	0.341	0.647	1.128**
	(0.042)	(0.026)	(0.027)	(0.027)	(0.532)	(0.523)	(0.523)
$log\ workers_{z,98}$	0.008	-0.017***	-0.012**	-0.013***	0.311***	0.174*	0.310***
	(0.006)	(0.004)	(0.005)	(0.005)	(0.078)	(0.095)	(0.097)
$export\ intensity_{z,98}$			0.141	0.168		-12.574***	-10.813***
			(0.153)	(0.157)		(2.958)	(2.944)
$\times X_{z,98}$			-0.006	-0.008		0.841***	0.733***
			(0.010)	(0.010)		(0.187)	(0.187)
$X_{z,07} - X_{z,98}$				0.004			
				(0.008)			
$\times X_{z,98}$				0.000			
				(0.001)			
$FDI\ cap\ share_{z,98}$							1.971***
							(0.477)
$\times \sum_{i=1}^{3} \tilde{s}^{FFF}_{z,i,98}$							-11.200***
							(3.394)
2-digit industry FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes
R-sqr	0.453	0.481	0.487	0.509	0.431	0.462	0.490
Observations	413	413	413	412	412	412	412
dfres	380	380	378	375	379	377	375

Note: All include 2-digit fixed effects. Granularity defined by employment shares. Regresses 1998 values on 10-year change for indicated DV. Standard errors in parentheses; * p<0.10, ** p<0.05, *** p<0.01.

back

Heterogeneity in industry tech level

Table: Interacting with industry tech dummies

	$\widetilde{s}$ by dom sales	$\widetilde{s}$ by wage bill	$\widetilde{s}$ by employment
	(1)	(2)	(3)
$\sum_{i=1}^{3} \widetilde{s}_{z,i,t}^{FFF}$	-0.245	0.761***	2.532***
x high-tech	-0.628	-1.137**	-1.044
x low-tech	0.864*	-0.167	-1.725***
$\sum_{i=1}^{3} \widetilde{s}_{z,i,t}^{DFF}$	-1.157***	-1.381***	-1.765***
x high-tech	-1.001	-0.355	1.635**
x low-tech	1.829***	0.956*	1.994***
$D_{z,t}$	0.356***	0.810**	0.760***
Industry & Year FE	Y	Y	Y
R-sqr	0.972	0.981	0.981
Obs	4200	4200	4200

Note: Of the 420 industries, 131 are classified at low-tech and 53 are classified as high-tech, leaving 236 as mid-tech.

- Granular DFFs see stronger industry exports in low-tech industries.
- Granular FFFs see stronger industry exports when vertically motivated (employment shares) and in the middle of the tech-spectrum.

back

Which industry characteristics are relevant?

Table: Interacting with various industry level controls

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
$\sum_{i=1}^{3} \tilde{s}^{FFF}_{z,i,t}$	1.495***	1.284**	0.730*	4.189***	1.156***	6.205***	0.708	-7.302***	2.470**
$\sum_{i=1}^{3} \tilde{s}^{DFF}_{z,i,t}$	-0.807**	1.296**	0.974***	-1.694***	-0.832**	-4.704***	-2.706	5.366***	3.644***
$D_{z,t}$ (staff)	0.728***	0.765***	1.015***	0.788***	0.734***	0.681***	0.193***	0.559***	0.975***
ind. ratio $<$ 5 yrs		1.399***						0.514**	0.681**
x $\sum_{i=1}^{3} \tilde{s}^{FFF}_{z,i,t}$		2.892**						3.444**	1.938
x $\sum_{i=1}^{3} \tilde{s}^{DFF}_{z,i,t}$		-5.675***						-7.527***	-6.051***
ind. ratio state			-1.061***					-0.807***	-0.912***
x $\sum_{i=1}^{3} \tilde{s}^{FFF}_{z,i,t}$			4.088***					1.293	1.045
x $\sum_{i=1}^{3} \tilde{s}^{DFF}_{z,i,t}$			-8.015***					-7.145***	-7.701***
ind. ratio FFFs				2.763***				1.514***	2.035***
x $\sum_{i=1}^{3} \tilde{s}^{FFF}_{z,i,t}$				-7.857***				-6.613***	-5.307***
x $\sum_{i=1}^{3} \tilde{s}^{DFF}_{z,i,t}$				4.104***				-2.877**	-2.306**
ind. dom. growth					-0.047			-0.073**	
x $\sum_{i=1}^{3} \tilde{s}^{FFF}_{z,i,t}$					0.009			-0.037	
x $\sum_{i=1}^{3} \tilde{s}^{DFF}_{z,i,t}$					0.135*			0.273***	
ind. TFP						0.417***		0.350***	
x $\sum_{i=1}^{3} \tilde{s}^{FFF}_{z,i,t}$						-0.822***		-0.782***	
x $\sum_{i=1}^{3} \tilde{s}^{DFF}_{z,i,t}$						0.526***		0.082	
ind. real FA (log)							0.660***	0.342***	
x $\sum_{i=1}^{3} \tilde{s}^{FFF}_{z,i,t}$							0.078	0.886***	
x $\sum_{i=1}^{3} \tilde{s}^{DFF}_{z,i,t}$							0.134	-0.132	
Industry & Year FE	Y	Y	Y	Y	Y	Y	Y	Y	Y
R-sqr	0.980	0.982	0.984	0.982	0.982	0.983	0.983	0.989	0.986
Obs	4200	4200	4200	4200	3780	4168	4200	3751	4200

- Granularity from FFFs is more conducive to exports in startup environments that are not already flooded by FDI, and when there is a relatively lower initial industry productivity level.
- Granularity from DFFs relatively worse for exports in slow-growth industries or with a high ratio of young firms or state-owned firms.

back

Which characteristics of the granular firms relevant?

Table: Interacting with various firm level controls

	(1)	(2)	(3)	(4)	(5)	(6)	(7)
$D_{z,t}$ (staff)	0.731***	0.739***	0.853***	0.750***	0.753***	0.815***	1.002***
$\sum_{i=1}^{3} \tilde{s}_{z,i,t}^{FFF}$	1.714***	1.657***	1.738***	2.479***	1.260***	0.126	0.095
$\sum_{i=1}^{3} \tilde{s}_{z,i,t}^{DFF}$	-1.326***	-1.514***	-4.907***	-0.872***	-2.217***	-3.785***	-2.487***
inputs/assets x $\sum_{i=1}^{3} \tilde{s}_{z,i,t}^{FFF}$	-0.013					0.124***	0.163***
inputs/assets x $\sum_{i=1}^{3} \tilde{s}_{z,i,t}^{DFF}$	0.155***					0.133***	0.118***
VA/assets x $\sum_{i=1}^{3} \tilde{s}_{z,i,t}^{FFF}$		0.059*				0.124***	0.067*
VA/assets x $\sum_{i=1}^{3} \tilde{s}_{z,i,t}^{DFF}$		0.483***				0.090	0.047
labor productivity x $\sum_{i=1}^{3} \tilde{s}_{z,i,t}^{FFF}$			0.232**			0.371***	0.438***
labor productivity x $\sum_{i=1}^{3} \tilde{s}_{z,i,t}^{DFF}$			1.065***			0.564***	0.335***
wages/assets x $\sum_{i=1}^{3} \tilde{s}_{z,i,t}^{FFF}$				-1.014***		-2.178***	-1.525***
wages/assets x $\sum_{i=1}^{3} \tilde{s}_{z,i,t}^{DFF}$				0.480		-1.498***	-1.329***
wages/workers x $\sum_{i=1}^{3} \tilde{s}_{z,i,t}^{FFF}$					0.002	0.014***	0.015***
wages/workers x $\sum_{i=1}^{3} \tilde{s}_{z,i,t}^{DFF}$					0.039***	0.029***	0.018***
ind. ratio firms age $<$ 5 yrs							-0.034***
x $\sum_{i=1}^{3} \tilde{s}_{z,i,t}^{FFF}$							0.062
x $\sum_{i=1}^{3} \tilde{s}_{z,i,t}^{DFF}$							0.135**
ind. ratio firms state-owned							-0.807***
x $\sum_{i=1}^{3} \tilde{s}_{z,i,t}^{FFF}$							1.607
x $\sum_{i=1}^{3} \tilde{s}_{z,i,t}^{DFF}$							-5.803***
ind. ratio FFFs							2.058***
x $\sum_{i=1}^{3} \tilde{s}_{z,i,t}^{FFF}$							-7.021***
x $\sum_{i=1}^{3} \tilde{s}_{z,i,t}^{DFF}$							-0.091
Industry & Year FE	Y	Y	Y	Y	Y	Y	Y
R-sqr	0.980	0.981	0.981	0.981	0.982	0.983	0.987
Observations	4061	4061	3985	4060	4060	3984	3984

- Higher granularity from firms that more intensively use inputs or add more value relative to fixed assets, or pay higher wages, associate more positively with GCA.
- Higher granularity from labor intensive firms, measured as total wages bill to fixed assets, is negatively associated with GCA.

back

2002 FDI encouragement shock

Table: 2002 FDI encouragement shock correlations with granularity and FDI penetration

	(1)	(2)	(3)	(4)	(5)	(6)
Dependent variable:	FFF dom granularity	FFF worker granularity	FFF exp granularity	DFF dom granularity	FDI dom penetration	non-granular FDI dom pen.
$treatment_z \times post_t$	0.017**	0.004	0.001	0.003	0.012	-0.004
	(0.007)	(0.006)	(0.020)	(0.013)	(0.009)	(0.005)
Constant	0.087***	0.064***	0.247***	0.230***	0.174***	0.083***
	(0.001)	(0.001)	(0.003)	(0.002)	(0.001)	(0.001)
Industry & Year FEs	Y	Y	Y	Y	Y	Y
Pseudo R-sqr	0.115	0.111	0.099	0.097	0.108	0.113
Observations	4040	4040	3990	4040	4040	4020

Note: The DV for columns (1) - (3) are different measures of FFF granularity. Column (4) repeats column (1) for DFFs, while the repetition of columns (2) and (3) for DFFs is excluded (similar insignificant result). Column (5) is the FDI weighted share of domestic sales. Column (6) repeats column (5) but excludes granular FFFs. Industry clustered errors; * p<0.10, ** p<0.05, *** p<0.01

- Only $\sum_{i=1}^{3}$ *domestic sales share*$_{z,t}^{FFF}$ (FFF dom granularity) correlates strongly with the 2002 shock.

back

Competitive Pressure

Table: Competitive Pressure from granular firms

Dependent Variable:	change in ind sales of non-granular firms	change in observations
	(1)	(2)
Change in FFF sales granularity	-1.932***	-0.496***
	(0.55)	(0.12)
Change in DFF sales granularity	-1.310***	-0.861***
	(0.38)	(0.12)
Constant	0.199***	0.075***
	(0.00)	(0.00)
Industry & Year FEs	Y	Y
Adj R-sqr	0.168	0.413
Observations	3758	3780

Note: Regresses industry change in log sales of non-granular firms (1) and change in log observations (2) on change in FFF and DFF sales granularity. The negative coefficients indicate granular market shares are at the expense of non-granular activity, implying head-to-head competition. While more FFF sales granularity associates with a bigger decline in the number of observations than does DFF granularity, it also associates with a smaller decline in sales from non-granular firms. Industry clustered errors, *** $p<0.001$. back

Firm markups and granular influences (continued)

	(1)	(2)	(3)	(4)
$lp_{z,i,t}$; labor productivity, log				0.011***
				(0.00)
$w_{z,i,t}$; price of labor, log				0.002***
				(0.00)
$w_{z,t}$; ind price of laobr, log				0.005
				(0.00)
$ci_{z,i,t}$; capital intensity, log				-0.013***
				(0.00)
$ci_{z,t}$; ind capital intensity, log				0.000***
				(0.00)
$obs_{z,t}$; number of firms, log				0.000
				(0.00)
$EI_{z,i,t}$; export intensity				0.006***
				(0.00)
$EI_{z,t}$; ind export intensity				-0.039***
				(0.01)
$IP_{z,t}$; import penetration				0.004
				(0.01)
Constant	0.263***	0.262***	0.261***	0.257***
	(0.00)	(0.00)	(0.00)	(0.02)

Note: Dependant variable is log of firm estimated markup. All explanatory variables are lagged one year. Firm and year FE included in all. Industry $\times$ Year clustered errors. Column (4) implements the main regression. back

Robustness

Table: Granular pro-competitive effects - Domestic sales shares and general FDI

	shares by dom sales			shares by employment	
Dependent variable: Estimated Markup, $mu_{z,i,t+1}$	(1)	(2)	(3)	(4)	(5)
$SS_{z,i,t}$	1.349***	1.189***	1.452***	0.945***	0.900***
	(0.16)	(0.19)	(0.20)	(0.18)	(0.19)
$\sum_{i=1}^{3} \tilde{s}_{z,t}^{FFF}$	-0.044**		-0.060***		-0.075**
	(0.02)		(0.02)		(0.03)
$\sum_{i=1}^{3} \tilde{s}_{z,t}^{DFF}$	0.005	-0.027*	-0.041**	-0.084***	-0.082***
	(0.02)	(0.02)	(0.02)	(0.02)	(0.02)
$SS_{z,i,t} \times \sum_{i=1}^{3} \tilde{s}_{z,t}^{FFF}$	-1.887***		-1.849***		-1.670***
	(0.33)		(0.43)		(0.45)
$SS_{z,i,t} \times \sum_{i=1}^{3} \tilde{s}_{z,t}^{DFF}$	-1.548***	-1.609***	-1.870***	-1.245***	-1.070***
	(0.22)	(0.25)	(0.27)	(0.25)	(0.25)
$FDI_{z,t}$; % of firms that are FFFs	-0.027***				
	(0.01)				
$\sum_{i=1}^{Nf} \tilde{s}_{z,t}^{FFF}$		0.000		-0.105***	
		(0.00)		(0.02)	
$SS_{z,i,t} \times \sum_{i=1}^{Nf} \tilde{s}_{z,t}^{FFF}$		-0.000		-0.146	
		(0.00)		(0.47)	
$\sum_{i=4}^{Nf} \tilde{s}_{z,t}^{FFF}$			0.000*		-0.116***
			(0.00)		(0.02)
$SS_{z,i,t} \times \sum_{i=4}^{Nf} \tilde{s}_{z,t}^{FFF}$			-0.000		2.696***
			(0.00)		(1.01)
Adjusted R_{sq}	0.861	0.863	0.864	0.863	0.863
Other firm & industry controls	Y	Y	Y	Y	Y
Firm & Year FEs	Y	Y	Y	Y	Y
Observations	1283695	1066785	1065600	1075763	1075763

Note: $\tilde{s}$ = domestic market shares in columns (1) - (3), and employment shares in columns (4) and (5). SS = sales share. The top-3 granular FFFs and DFFs per industry by employment share are excluded, and all FFFs are excluded when concentration term is over all FFFs (1 - Nf). Explanatory variables lagged one year. Industry×Year clustered errors. back

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