Agglomeration Economies

Urban Economics

Ignacio Sarmiento-Barbieri

Universidad de los Andes

October 15, 2025

Agenda

Agglomeration Economies

- Why do we see such a remarkable clustering of human activity in a small number of urban areas?
- Spatial Eq. Model: cities may form because some places have innate advantages in productivity, housing supply or amenities.
- Or it may be because clusters of people endogenously increase productivity, housing supply or amenities (agglomeration effects)

Agglomeration Economies

- Then cities exist because they are areas with high levels of productivity, which might occur because people come to places that are innately more productive or because density itself enhances productivity because of agglomeration economies

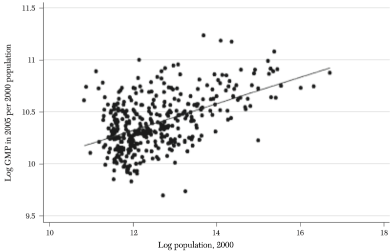


Figure 1. Productivity and City Size

Notes: Units of observation are Metropolitan Statistical Areas under the 2006 definitions. Population is from the Census, as described in the Data Appendix. Gross Metropolitan Product is from the Bureau of Economic Analysis.

The regression line is log *GMP per capita* $= 0.13\ [0.01] \times \log$ *population* $+ 8.8\ [0.1]$.
$R^2 = 0.25$ and $N = 363$.

Evidence of Agglomeration Economies

- Three strategies to identify agglomeration economies

  1. Show there is too much spatial concentration to be random (Duranton and Overman, 2005)
  2. Compare productivity over space (Greenstone et al., 2010; Moretti 2021)
  3. Compare wages and rents across space (Quantitative Spatial Models, Ahlfeldt et al, 2015)

Spatial Concentration

Extremes of Localization and Dispersion

(c) Other Agricultural and Forestry Machinery (SIC2932)

(d) Machinery for Textile, Apparel and Leather Production (SIC2954)

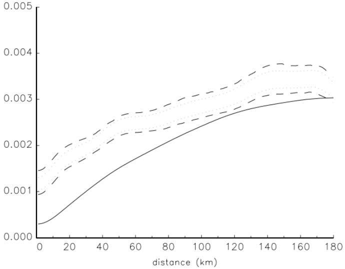
Spatial Concentration
Ambiguous Cases

(a) Basic Pharmaceuticals
(SIC2441)

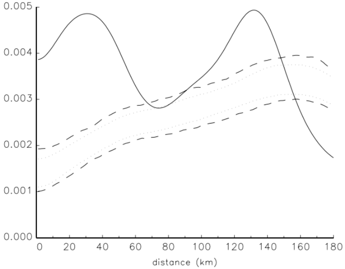
(b) Pharmaceutical Preparations
(SIC2442)

Spatial Concentration

K Density Estimates



(c) Other Agricultural and Forestry Machinery (SIC2932)



(d) Machinery for Textile, Apparel and Leather Production (SIC2954)

Most Localized

sic92	Industry	Γ or Ψ
Most localised		
2214	Publishing of Sound Recordings	0.470
1711	Preparation and Spinning of Cotton-type Fibres	0.411
2231	Reproduction of Sound Recordings	0.403
1760	Manufacture of Knitted and Crocheted Fabrics	0.321
1713	Preparation and Spinning of Worsted-type Fibres	0.319
2861	Manufacture of Cutlery	0.314
1771	Manufacture of Knitted and Crocheted Hosiery	0.290
1810	Manufacture of Leather Clothes	0.203
1822	Manufacture of Other Outerwear	0.181
2211	Publishing of Books	0.178

Most Dispersed

Most dispersed		
1520	Processing and Preserving of Fish and Fish Products	0.200
3511	Building and Repairing of Ships	0.113
1581	Manufacture of Bread, Fresh Pastry Goods and Cakes	0.094
2010	Saw Milling and Planing of Wood, Impregnation of Wood	0.082
2932	Other Agricultural and Forestry Machinery	0.067
1551	Operation of Dairies and Cheese Making	0.064
1752	Manufacture of Cordage, Rope, Twine and Netting	0.062
3615	Manufacture of Mattresses	0.050
1571	Manufacture of Prepared Feeds for Farm Animals	0.049
2030	Manufacture of Builders' Carpentry and Joinery	0.047

Measuring Agglomeration Economies Through Productivity

Measuring Agglomeration Economies Through Productivity

- The most direct approach
  - Measure productivity from output, then relate it to density

Measuring Agglomeration Economies Through Productivity

- The most direct approach
  - Measure productivity from output, then relate it to density
- Problems with this approach?

Measuring Agglomeration Economies Through Productivity

- The most direct approach
  - Measure productivity from output, then relate it to density
- Problems with this approach?
  - Natural advantages make a region more productive
  - Greater productivity attracts workers and firms

Agenda

Identifying Agglomeration Spillovers: Evidence from Winners and Losers of Large Plant Openings

Greenstone, Hornbeck, and Moretti (2010)

We quantify agglomeration spillovers by comparing changes in total factor productivity (TFP) among incumbent plants in "winning" counties that attracted a large manufacturing plant and "losing" counties that were the new plant's runner-up choice. Winning and losing counties have similar trends in TFP prior to the new plant opening. Five years after the opening, incumbent plants' TFP is 12 percent higher in winning counties. This productivity spillover is larger for plants sharing similar labor and technology pools with the new plant. Consistent with spatial equilibrium models, labor costs increase in winning

MDP Greenstone, Hornbeck, and Moretti (2010)

Research Design

MDP Greenstone, Hornbeck, and Moretti (2010)
Data

TABLE 1
The Million Dollar Plant Sample

	(1)
Sample MDP openings:[a]	
Across all industries	47
Within same two-digit SIC	16
Across all industries:	
Number of loser counties per winner county:	
1	31
2+	16
Reported year − matched year:[b]	
−2 to −1	20
0	15
1 to 3	12
Reported year of MDP location:	
1981–85	11
1986–89	18
1990–93	18
MDP characteristics, 5 years after opening:[c]	
Output ($1,000s)	452,801
	(901,690)
Output, relative to county output 1 year prior	.086
	(.109)
Hours of labor (1,000s)	2,986
	(6,789)

MDP Greenstone, Hornbeck, and Moretti (2010)

Econometric Model

MDP Greenstone, Hornbeck, and Moretti (2010)

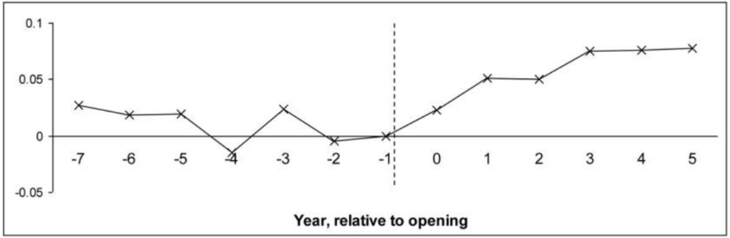
Results

TABLE 4
INCUMBENT PLANT PRODUCTIVITY, RELATIVE TO THE YEAR OF AN MDP OPENING

Event Year	In Winning Counties (1)	In Losing Counties (2)	Difference Col. 1 − Col. 2 (3)
$\tau = -7$	.067	.040	.027
	(.058)	(.053)	(.032)
$\tau = -6$	.047	.028	.018
	(.044)	(.046)	(.023)
$\tau = -5$	.041	.021	.020
	(.036)	(.040)	(.025)
$\tau = -4$	−.003	.012	−.015
	(.030)	(.030)	(.024)
$\tau = -3$	.011	−.013	.024
	(.022)	(.022)	(.021)
$\tau = -2$	−.003	.001	−.005
	(.027)	(.011)	(.028)
$\tau = -1$	0	0	0
$\tau = 0$	.013	−.010	.023
	(.018)	(.011)	(.019)
$\tau = 1$	.023	−.028	.051**
	(.026)	(.024)	(.023)

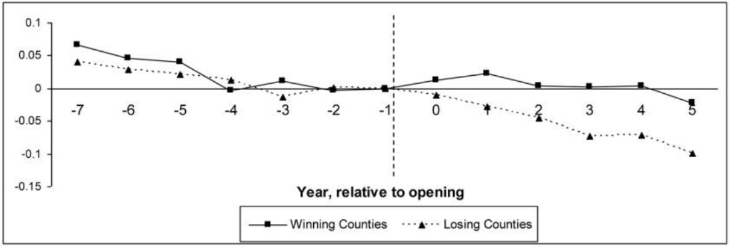
MDP Greenstone, Hornbeck, and Moretti (2010)

Results



MDP Greenstone, Hornbeck, and Moretti (2010)

Results



MDP Greenstone, Hornbeck, and Moretti (2010)

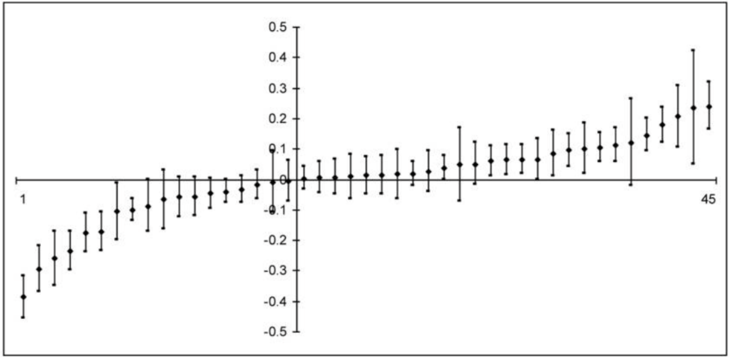
Results

TABLE 5
CHANGES IN INCUMBENT PLANT PRODUCTIVITY FOLLOWING AN MDP OPENING

	All Counties: MDP Winners − MDP Losers		MDP Counties: MDP Winners − MDP Losers		All Counties: Random Winners
	(1)	(2)	(3)	(4)	(5)
	A. Model 1				
Mean shift	.0442*	.0435*	.0524**	.0477**	− 0.0496***
	(.0233)	(.0235)	(.0225)	(.0231)	(.0174)
				[$170 m]	
R^2	.9811	.9812	.9812	.9860	~0.98
Observations (plant by year)	418,064	418,064	50,842	28,732	~400,000
	B. Model 2				
Effect after 5 years	.1301**	.1324**	.1355***	.1203**	−.0296
	(.0533)	(.0529)	(.0477)	(.0517)	(.0434)
				[$429 m]	
Level change	.0277	.0251	.0255	.0290	.0073
	(.0241)	(.0221)	(.0186)	(.0210)	(.0223)
Trend break	.0171*	.0179**	.0183**	.0152*	− 0.0062
	(.0091)	(.0088)	(.0078)	(.0079)	(.0063)
Pre-trend	−.0057	−.0058	−.0048	−.0044	−.0048
	(.0046)	(.0046)	(.0046)	(.0044)	(.0040)
R^2	.9811	.9812	.9813	.9861	~.98
Observations (plant by					

MDP Greenstone, Hornbeck, and Moretti (2010)

Results



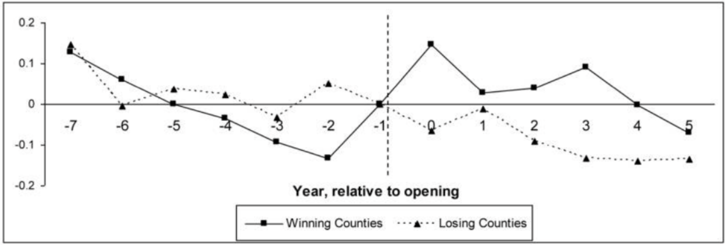
MDP Greenstone, Hornbeck, and Moretti (2010)

Results

TABLE 7
CHANGES IN INCUMBENT PLANT PRODUCTIVITY FOLLOWING AN MDP OPENING FOR INCUMBENT PLANTS IN THE MDP'S TWO-DIGIT INDUSTRY AND ALL OTHER INDUSTRIES

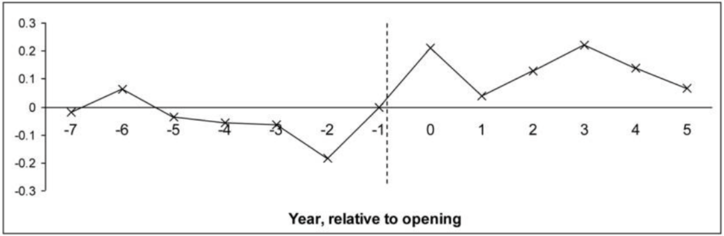
	All Industries (1)	MDP's Two-Digit Industry (2)	All Other Two-Digit Industries (3)
		A. Model 1	
Mean shift	.0477**	.1700**	.0326
	(.0231)	(.0743)	(.0253)
	[$170 m]	[$102 m]	[$104 m]
R^2	.9860	.9861	
Observations	28,732	28,732	
		B. Model 2	
Effect after 5 years	.1203**	.3289	.0889*
	(.0517)	(.2684)	(.0504)
	[$429 m]	[$197 m]	[$283 m]
Level change	.0290	.2814***	.0004
	(.0210)	(.0895)	(.0171)
Trend break	.0152*	.0079	.0147*
	(.0079)	(.0344)	(.0081)
Pre-trend	−.0044	−.0174	−.0026

MDP Greenstone, Hornbeck, and Moretti (2010)
Results



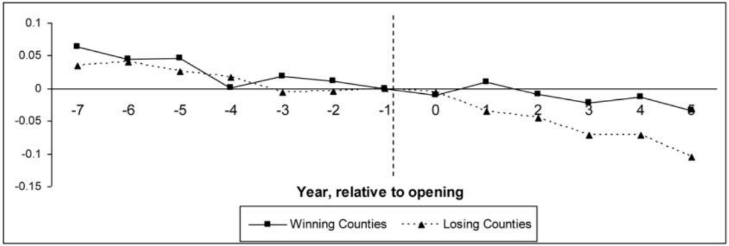
MDP Greenstone, Hornbeck, and Moretti (2010)

Results



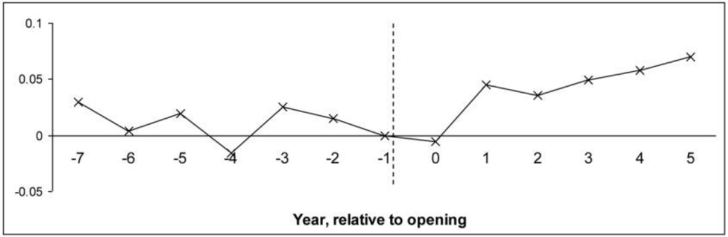
MDP Greenstone, Hornbeck, and Moretti (2010)

Results



MDP Greenstone, Hornbeck, and Moretti (2010)

Results



MDP Greenstone, Hornbeck, and Moretti (2010)

Results

TABLE 8
CHANGES IN INCUMBENT PLANT PRODUCTIVITY FOLLOWING AN MDP OPENING, BY MEASURES OF ECONOMIC DISTANCE BETWEEN THE MDP'S INDUSTRY AND INCUMBENT PLANT'S INDUSTRY

	(1)	(2)	(3)	(4)	(5)	(6)	(7)
CPS worker transitions	.0701***						.0374
	(.0237)						(.0260)
Citation pattern		.0545***					.0256
		(.0192)					(.0208)
Technology input			.0320*				.0501
			(.0173)				(.0421)
Technology output				.0596***			.0004
				(.0216)			(.0434)
Manufacturing input					.0060		−.0473
					(.0123)		(.0289)
Manufacturing output						.0150	−.0145
						(.0196)	(.0230)
R^2	.9852	.9852	.9851	.9852	.9851	.9852	.9853
Observations	23,397	23,397	23,397	23,397	23,397	23,397	23,397

MDP Greenstone, Hornbeck, and Moretti (2010)

Results

CHANGES IN COUNTIES' NUMBER OF PLANTS, TOTAL OUTPUT, AND SKILL-ADJUSTED WAGES FOLLOWING AN MDP OPENING

	A. CENSUS OF MANUFACTURES		B. CENSUS OF POPULATION
	Dependent Variable: Log(Plants) (1)	Dependent Variable: Log(Total Output) (2)	Dependent Variable: Log(Wage) (3)
Difference-in-difference	.1255**	.1454	.0268*
	(.0550)	(.0900)	(.0139)
R^2	.9984	.9931	.3623
Observations	209	209	1,057,999

Agenda

The Effect of High-Tech Clusters on the Productivity of Top Inventors

Moretti (2021)

The high-tech sector is concentrated in a small number of cities. The ten largest clusters in computer science, semiconductors, and biology account for 69 percent, 77 percent, and 59 percent of all US inventors, respectively. Using longitudinal data on 109,846 inventors, I find that geographical agglomeration results in significant productivity gains. When an inventor moves to a city with a large cluster of inventors in the same field, she experiences a sizable increase in the number and quality of patents produced. The presence of significant productivity externalities implies that the agglomeration of inventors generates large gains in the aggregate amount of innovation produced in the United States. (*JEL* D62, J24, L60, O31, 034, R32)

We know from ordinary experience that there are group interactions that are central to individual productivity. We know this kind of external effect is common to all the arts and sciences—the 'creative professions'

(Lucas 1988)

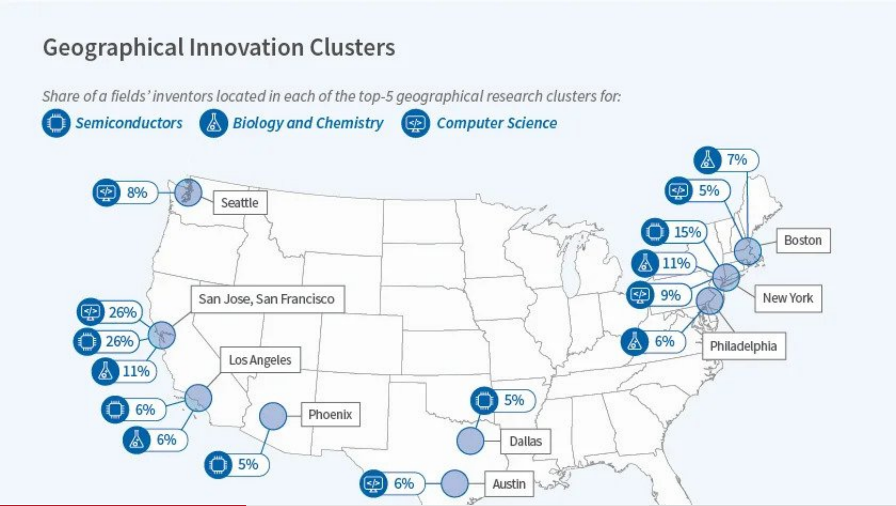
The Effect of High-Tech Clusters on the Productivity of Top Inventors

Moretti (2021)

- Data
  - Location
  - Patents
  - Inventors

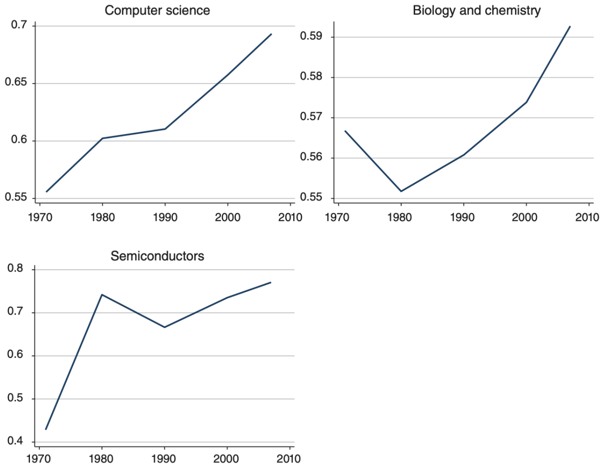
The Effect of High-Tech Clusters on the Productivity of Top Inventors

Moretti (2021)



The Effect of High-Tech Clusters on the Productivity of Top Inventors

Moretti (2021)



The Effect of High-Tech Clusters on the Productivity of Top Inventors

Moretti (2021)

The Effect of High-Tech Clusters on the Productivity of Top Inventors

Moretti (2021)

The Effect of High-Tech Clusters on the Productivity of Top Inventors

Moretti (2021)

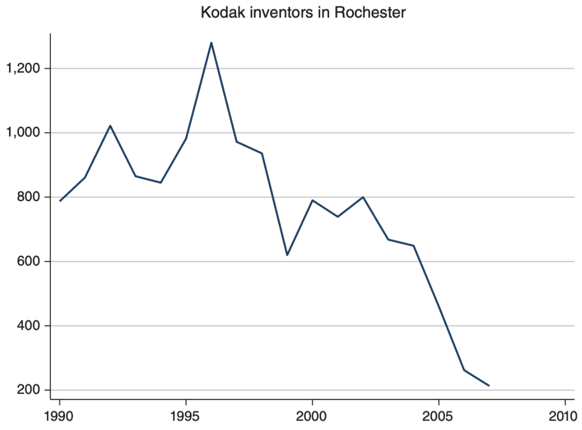


FIGURE 2. KODAK'S DECLINE

The Effect of High-Tech Clusters on the Productivity of Top Inventors

Moretti (2021)

FIGURE 3. AVERAGE INVENTOR PRODUCTIVITY IN ROCHESTER OUTSIDE KODAK

Note: Controls include research field dummies.

The Effect of High-Tech Clusters on the Productivity of Top Inventors

Moretti (2021)

TABLE 2—DIFFERENCE-IN-DIFFERENCE ESTIMATES: 1996–2007 PRODUCTIVITY CHANGE OF NON-KODAK INVENTORS IN ROCHESTER COMPARED TO OTHER CITIES

					Weighted
	(1)	(2)	(3)	(4)	(5)
Panel A					
Rochester × 2007	−0.0641	−0.0673	−0.0805	−0.0916	−0.0947
	(0.00757)	(0.00674)	(0.00631)	(0.00665)	(0.00860)
Rochester	−0.0148	−0.0364	−0.0317		
	(0.0105)	(0.0101)	(0.00987)		
2007	−0.190	−0.189			
	(0.00757)	(0.00713)			
Observations	194,120	194,120	194,120	194,120	193,331
Field		Yes	Yes	Yes	Yes
Field × year			Yes	Yes	Yes
Field × city				Yes	Yes

The Effect of High-Tech Clusters on the Productivity of Top Inventors

Moretti (2021)

Panel B. Within-inventor difference-in-difference estimates					
Rochester × 2007	−0.206	−0.222	−0.257	−0.309	−0.363
	(0.0772)	(0.0782)	(0.0825)	(0.0609)	(0.0387)
2007	−0.205	−0.206			
	(0.0190)	(0.0193)			
Observations	16,430	16,430	16,430	16,430	16,379
Inventor	Yes	Yes	Yes	Yes	Yes
Field		Yes	Yes	Yes	Yes
Field × year			Yes	Yes	Yes
Field × city				Yes	Yes

The Effect of High-Tech Clusters on the Productivity of Top Inventors

Moretti (2021)

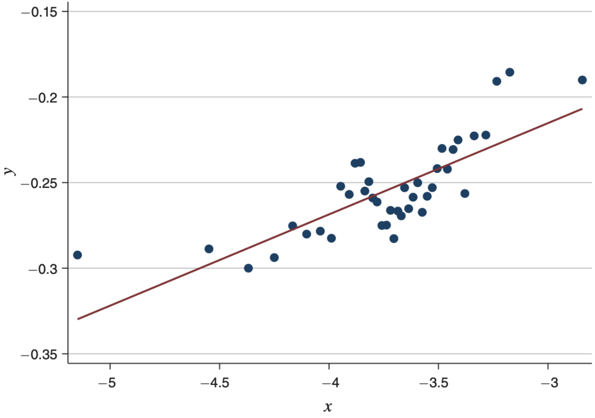


FIGURE 4. AVERAGE LOG NUMBER OF PATENTS PER INVENTOR PER YEAR AND LOG CLUSTER SIZE: ALL YEARS AND FIELDS

The Effect of High-Tech Clusters on the Productivity of Top Inventors

Moretti (2021)

TABLE 3—EFFECT OF CLUSTER SIZE ON INVENTOR PRODUCTIVITY: BASELINE MODELS

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
log size	0.0518							
	(0.00815)							
Observations	932,059							
Year	Yes							
City	Yes							
Field	Yes							
Class	Yes							
City × field								
City × class								
Field × year								
Class × year								
Inventor								
City × year								
Firm								

Notes: Each column is a separate regression. The level of observation in the regressions is inventor-year. The dependent variable is log of number of patents filed in a year. The model estimated is equation (1). Standard errors are clustered by city × research field.

The Effect of High-Tech Clusters on the Productivity of Top Inventors

Moretti (2021)

TABLE 3—EFFECT OF CLUSTER SIZE ON INVENTOR PRODUCTIVITY: BASELINE MODELS

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
log size	0.0518	0.0762						
	(0.00815)	(0.0167)						
Observations	932,059	932,059						
Year	Yes	Yes						
City	Yes	Yes						
Field	Yes	Yes						
Class	Yes	Yes						
City × field		Yes						
City × class								
Field × year								
Class × year								
Inventor								
City × year								
Firm								

Notes: Each column is a separate regression. The level of observation in the regressions is inventor-year. The dependent variable is log of number of patents filed in a year. The model estimated is equation (1). Standard errors are clustered by city × research field.

The Effect of High-Tech Clusters on the Productivity of Top Inventors

Moretti (2021)

TABLE 3—EFFECT OF CLUSTER SIZE ON INVENTOR PRODUCTIVITY: BASELINE MODELS

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
log size	0.0518	0.0762	0.0881					
	(0.00815)	(0.0167)	(0.0187)					
Observations	932,059	932,059	932,059					
Year	Yes	Yes	Yes					
City	Yes	Yes	Yes					
Field	Yes	Yes	Yes					
Class	Yes	Yes	Yes					
City × field		Yes	Yes					
City × class			Yes					
Field × year								
Class × year								
Inventor								
City × year								
Firm								

Notes: Each column is a separate regression. The level of observation in the regressions is inventor-year. The dependent variable is log of number of patents filed in a year. The model estimated is equation (1). Standard errors are clustered by city × research field.

The Effect of High-Tech Clusters on the Productivity of Top Inventors

Moretti (2021)

TABLE 3—EFFECT OF CLUSTER SIZE ON INVENTOR PRODUCTIVITY: BASELINE MODELS

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
log size	0.0518	0.0762	0.0881	0.0907				
	(0.00815)	(0.0167)	(0.0187)	(0.00926)				
Observations	932,059	932,059	932,059	932,059				
Year	Yes	Yes	Yes	Yes				
City	Yes	Yes	Yes	Yes				
Field	Yes	Yes	Yes	Yes				
Class	Yes	Yes	Yes	Yes				
City × field		Yes	Yes	Yes				
City × class			Yes	Yes				
Field × year				Yes				
Class × year								
Inventor								
City × year								
Firm								

Notes: Each column is a separate regression. The level of observation in the regressions is inventor-year. The dependent variable is log of number of patents filed in a year. The model estimated is equation (1). Standard errors are clustered by city × research field.

The Effect of High-Tech Clusters on the Productivity of Top Inventors

Moretti (2021)

TABLE 3—EFFECT OF CLUSTER SIZE ON INVENTOR PRODUCTIVITY: BASELINE MODELS

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
log size	0.0518	0.0762	0.0881	0.0907	0.0677			
	(0.00815)	(0.0167)	(0.0187)	(0.00926)	(0.00862)			
Observations	932,059	932,059	932,059	932,059	932,059			
Year	Yes	Yes	Yes	Yes	Yes			
City	Yes	Yes	Yes	Yes	Yes			
Field	Yes	Yes	Yes	Yes	Yes			
Class	Yes	Yes	Yes	Yes	Yes			
City × field		Yes	Yes	Yes	Yes			
City × class			Yes	Yes	Yes			
Field × year				Yes	Yes			
Class × year					Yes			
Inventor								
City × year								
Firm								

Notes: Each column is a separate regression. The level of observation in the regressions is inventor-year. The dependent variable is log of number of patents filed in a year. The model estimated is equation (1). Standard errors are clustered by city × research field.

The Effect of High-Tech Clusters on the Productivity of Top Inventors

Moretti (2021)

Table 3—Effect of Cluster Size on Inventor Productivity: Baseline Models

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
log size	0.0518	0.0762	0.0881	0.0907	0.0677	0.0923		
	(0.00815)	(0.0167)	(0.0187)	(0.00926)	(0.00862)	(0.00990)		
Observations	932,059	932,059	932,059	932,059	932,059	932,059		
Year	Yes	Yes	Yes	Yes	Yes	Yes		
City	Yes	Yes	Yes	Yes	Yes	Yes		
Field	Yes	Yes	Yes	Yes	Yes	Yes		
Class	Yes	Yes	Yes	Yes	Yes	Yes		
City × field		Yes	Yes	Yes	Yes	Yes		
City × class			Yes	Yes	Yes	Yes		
Field × year				Yes	Yes	Yes		
Class × year					Yes	Yes		
Inventor						Yes		
City × year								
Firm								

Notes: Each column is a separate regression. The level of observation in the regressions is inventor-year. The dependent variable is log of number of patents filed in a year. The model estimated is equation (1). Standard errors are clustered by city × research field.

The Effect of High-Tech Clusters on the Productivity of Top Inventors

Moretti (2021)

TABLE 3—EFFECT OF CLUSTER SIZE ON INVENTOR PRODUCTIVITY: BASELINE MODELS

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
log size	0.0518	0.0762	0.0881	0.0907	0.0677	0.0923	0.0545	
	(0.00815)	(0.0167)	(0.0187)	(0.00926)	(0.00862)	(0.00990)	(0.0116)	
Observations	932,059	932,059	932,059	932,059	932,059	932,059	932,059	
Year	Yes	Yes	Yes	Yes	Yes	Yes	Yes	
City	Yes	Yes	Yes	Yes	Yes	Yes	Yes	
Field	Yes	Yes	Yes	Yes	Yes	Yes	Yes	
Class	Yes	Yes	Yes	Yes	Yes	Yes	Yes	
City × field		Yes	Yes	Yes	Yes	Yes	Yes	
City × class			Yes	Yes	Yes	Yes	Yes	
Field × year				Yes	Yes	Yes	Yes	
Class × year					Yes	Yes	Yes	
Inventor						Yes	Yes	
City × year							Yes	
Firm								

Notes: Each column is a separate regression. The level of observation in the regressions is inventor-year. The dependent variable is log of number of patents filed in a year. The model estimated is equation (1). Standard errors are clustered by city × research field.

The Effect of High-Tech Clusters on the Productivity of Top Inventors

Moretti (2021)

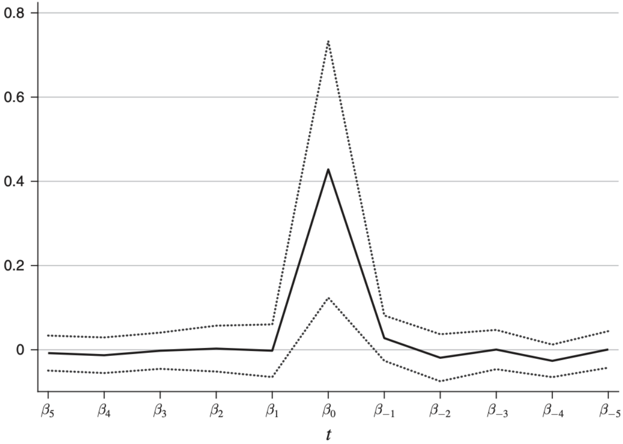
TABLE 3—EFFECT OF CLUSTER SIZE ON INVENTOR PRODUCTIVITY: BASELINE MODELS

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
log size	0.0518	0.0762	0.0881	0.0907	0.0677	0.0923	0.0545	0.0676
	(0.00815)	(0.0167)	(0.0187)	(0.00926)	(0.00862)	(0.00990)	(0.0116)	(0.0139)
Observations	932,059	932,059	932,059	932,059	932,059	932,059	932,059	823,375
Year	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
City	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Field	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Class	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
City × field		Yes	Yes	Yes	Yes	Yes	Yes	Yes
City × class			Yes	Yes	Yes	Yes	Yes	Yes
Field × year				Yes	Yes	Yes	Yes	Yes
Class × year					Yes	Yes	Yes	Yes
Inventor						Yes	Yes	Yes
City × year							Yes	Yes
Firm								Yes

Notes: Each column is a separate regression. The level of observation in the regressions is inventor-year. The dependent variable is log of number of patents filed in a year. The model estimated is equation (1). Standard errors are clustered by city × research field.

The Effect of High-Tech Clusters on the Productivity of Top Inventors

Moretti (2021)



The Effect of High-Tech Clusters on the Productivity of Top Inventors

Moretti (2021)

Table 5—Models in Differences: Effect of Changes in Cluster Size on Changes in Inventor Productivity: OLS and IV Estimates

	(1)	(2)	(3)	(4)	(5)	(6)
Panel A. OLS						
Δlog size	0.0141	0.0145	0.0153	0.0164	0.0162	0.0159
	(0.00394)	(0.00392)	(0.00376)	(0.00397)	(0.00392)	(0.00385)
Panel B. 2SLS						
Δlog size	0.0422	0.0630	0.0502	0.0496	0.0502	0.0491
	(0.0186)	(0.0211)	(0.0189)	(0.0131)	(0.0137)	(0.0144)
First stage	1.109	1.076	1.096	1.431	1.475	1.488
	(0.151)	(0.170)	(0.167)	(0.214)	(0.189)	(0.185)
F-statistic	53.8	40.2	43.0	44.5	60.8	64.2
Observations	419,596	419,596	419,565	405,111	405,111	403,955
Year	Yes	Yes	Yes	Yes	Yes	Yes
Field		Yes	Yes	Yes	Yes	Yes
Class			Yes	Yes	Yes	Yes
Firm				Yes	Yes	Yes
Field $\times$ year					Yes	Yes
Class $\times$ year						Yes

The Effect of High-Tech Clusters on the Productivity of Top Inventors

Moretti (2021)

	(1)	(2)
Panel A. Heterogeneity by cluster size		
First quartile (smallest)	0.0556	0.0702
	(0.0114)	(0.0137)
Second quartile	0.0596	0.0760
	(0.0120)	(0.0143)
Third quartile	0.0574	0.0743
	(0.0123)	(0.0148)
Fourth quartile (largest)	0.0633	0.0821
	(0.0137)	(0.0163)
Observations	932,059	823,375
p-value equal elasticities	0.157	0.080
Firm		Yes
Panel B. Heterogeneity by firm productivity		
First quartile (least productive)	0.0539	0.0583
	(0.0122)	(0.0142)
Second quartile	0.0568	0.0731
	(0.0117)	(0.0140)
Third quartile	0.0534	0.0713
	(0.0116)	(0.0145)
Fourth quartile (most productive)	0.0558	0.0744
	(0.0118)	(0.0141)
Observations	932,059	823,375
p-value equal elasticities	0.785	0.003
Firm		Yes

The Effect of High-Tech Clusters on the Productivity of Top Inventors

Moretti (2021)

PRODUCTIVITY: COMPUTER SCIENCE IN 2007

	Percent change
Examples of losers	
San Jose-San Francisco-Oakland, CA	−22.76
New York-Newark-Bridgeport, NY-NJ-CT-PA	−17.81
Seattle-Tacoma-Olympia, WA	−16.52
Austin-Round Rock, TX	−14.76
Boston-Worcester-Manchester, MA-NH	−13.45
Minneapolis-St. Paul-St. Cloud, MN-WI	−11.48
Raleigh-Durham-Cary, NC	−10.42
San Diego-Carlsbad-San Marcos, CA	−9.10
Portland-Vancouver-Beaverton, OR-WA	−8.84
Pittsburgh-New Castle, PA	−2.64
Boise City-Nampa, ID	−2.54
Examples of winners	
Miami-Fort Lauderdale-Miami Beach, FL	1.36
Kansas City-Overland Park-Kansas City, MO-KS	2.66
Buffalo-Niagara-Cattaraugus, NY	6.88
Omaha-Council Bluffs-Fremont, NE-IA	13.42
Des Moines-Newton-Pella, IA	14.60
Portland-Lewiston-South Portland, ME	17.76
Scranton-Wilkes-Barre, PA	21.53
Toledo-Fremont, OH	23.36
Memphis, TN-MS-AR	23.36
Oklahoma City-Shawnee, OK	25.76
New Orleans-Metairie-Bogalusa, LA	35.36

Note: Entries are estimates of the percent difference between mean inventor productivity in the counterfactual scenario and observed productivity.

The Effect of High-Tech Clusters on the Productivity of Top Inventors

Moretti (2021)

	Percent change
0–25th percentile	27.53
25th–50th percentile	18.49
50th–75th percentile	9.41
75th–90th percentile	−0.50
90th–95th percentile	−8.18
95th–100th percentile	−14.73

The Effect of High-Tech Clusters on the Productivity of Top Inventors

Moretti (2021)

	Constant elasticity (percent) (1)	Heterogeneous elasticity (percent) (2)
Computer science	−13.34	−14.54
Biology and chemistry	−10.06	−11.27
Semiconductors	−14.83	−16.05
Other engineering	−7.71	−8.61
Other science	−9.75	−10.93
All fields	−11.20	−12.35