Mechanisms of the Urban Productivity Premium: Evidence from Italian Firms

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Motivation

Through history, urbanisation has been associated with economic development and the enhancement of living standards

Nowadays cities contribute to a relevant fraction of global GDP ("large cities" account for $\approx$ 85% of GDP in US; $\approx$ 65% in Europe)

What are the driving forces behind this broad pattern?

The productivity of firms located in urban areas is substantially higher Italy

Urban productivity premium may unfold through two main channels: sorting and agglomeration (oversimplifying)

This paper

In this paper we exploit the fact that we observe firms switching location to perform two exercises:

1. Disentangle sorting and agglomeration economies
   - → Show that better firms sort to bigger/urban areas
   - → Show that agglomeration economies are stronger in bigger/urban areas
2. Shed some light on the way in which firms appropriate the advantage of being located in a city
   - → Document some facts on relocating firms
   - → Show that part of the gains have a static nature, but most of them accrue over time

Related literature

- On urban productivity premium: Henderson (2003), Moretti (2004), Combes et al. (2012), Gaubert(2017)
- On urban wage premium:
  - $\rightarrow$ Sorting: Yankow (2006), Combes et al.(2008), Eeckhout et al. (2014)
  - $\rightarrow$ Assortative matching between firms and workers: Andersson et al. (2007), Dauth et al. (2016)
  - $\rightarrow$ Pattern of wage premium accrual: Glaeser and Maré (2001), D'Costa and Overman (2014)
  - $\rightarrow$ Value of urban experience: De La Roca and Puga (2017)
- On firm relocation: Brouwer at al. (2004), Bergeaud and Ray (2017)

Data description

Archivio Statistico delle Imprese Attive (ASIA): firm-level data on universe of Italian non-agricultural and non-financial firms

- Data span years 2005–2014
- Variables: VA, sales, employees, type of firm, sector (Nace 5 digits), date of birth, location
- We observe firms switching location in every year

Urban productivity premium is apparent in the data...

	Non-urban			Urban		
Year	# firms	VA per worker	# workers per firm	# firms	VA per worker	# workers per firm
2005	1,851,819	35,850	3.33	2,442,237	46,699	4.10
2006	1,866,562	35,986	3.35	2,463,383	48,198	4.14
2007	1,902,740	36,234	3.41	2,496,657	48,770	4.18
2008	1,914,794	34,761	3.44	2,513,636	47,010	4.23
2009	1,890,381	32,107	3.39	2,488,411	43,295	4.20
2010	1,882,643	33,963	3.36	2,484,337	46,970	4.16
2011	1,871,957	34,535	3.36	2,483,459	46,918	4.17
2012	1,869,098	32,774	3.34	2,478,877	45,158	4.15
2013	1,840,623	33,256	3.30	2,455,844	44,665	4.14
2014	1,819,558	33,978	3.27	2,444,285	45,655	4.13

. . . and resists after controlling for firm's observables

	(1)	(2)	(3)
log LLM population	0.0372***		
	(0.0002)		
Urban area		0.0933***	
		(0.0006)	
Small urban area			0.0760***
			(0.0007)
Big urban area			0.1210***
			(0.0009)
Obs.	41,295,232	41,295,232	41,295,232
R^2	0.218	0.216	0.217

Notes: Year, sector and size class fixed effects. Controls for age and age^2.

Disentangling sorting and agglomeration

Abowd, Kramarz and Margolis (1999) framework:

$$\pi_{iy} = X'_{iy}\beta + \delta_c \times \delta_y + \delta_f + \varepsilon_{iy}$$

- π_{iy} is log value added per worker of firm i in year y
- δ_f and δ_c are firm and city fixed effects
- Interested in δ_f (sorting) and $\delta_{cy} = \delta_c \times \delta_y$ (agglomeration)

Table: Correlation table

	π	δ_{cy}
δ_{cy}	0.1591	
δ_f	0.7606	0.0389

Sorting and agglomeration in urban areas

Use δ_{cy} and δ_f as dependent variables to assess that sorting and agglomeration are stronger in urban areas

	δ_c †		δ_f ‡	
log LLM population	0.0191***		0.0239***	
	(0.00527)		(0.000221)	
Small urban area		0.0317***		0.0721***
		(0.0149)		(0.000771)
Big urban area		0.0506***		0.0766***
		(0.0217)		(0.000884)
Obs.	79,404	79,404	6,296,667	6,296,667
R^2	0.042	0.037	0.002	0.002

† Year fixed effects included

‡ Relocating firms dropped from the regressions

Productivity gains from relocation

Analyze relocating firms to learn something about the pattern of productivity accrual

- We observe 522,215 firms switching location (7% of total firms)
- 88% of them move only once
- Half of the moves involve a displacement of 14 km or less Distance histogram
- Relocating firms are significantly larger (employees and sales), more productive, and younger than static firms Descriptives

Two empirical stretegies:

1. Difference-in-differences
2. Synthetic controls

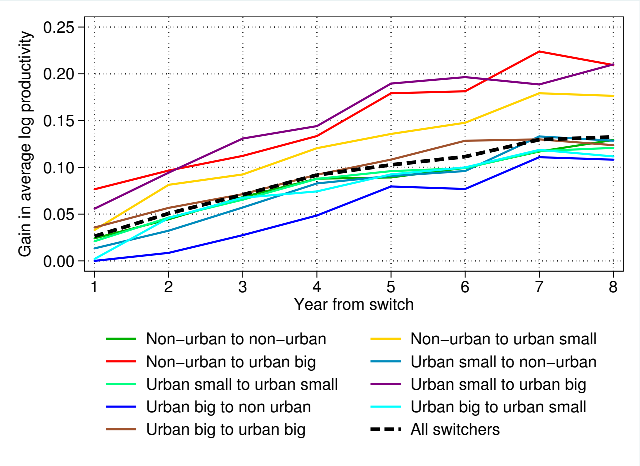
Difference-in-differences

We estimate:

$$\pi_{iy} = \alpha + \sum_{t=0}^{8} \beta_t S_{iy} \times I_{iy}^{t} + \delta_i + \delta_y + \varepsilon_{iy}$$

- Control for time-invariant potential confounders through the inclusion of δ_i
- S_{iy} is a dummy equal to one from the switch year onwards
- I_{iy}^{t} is equal to one if firm i in year y is t years away from a switch

Difference-in-differences - results



- Gain from switching is always positive, on impact and through time
- Concern about parallel trend hypothesis

Synthetic controls

Build on Abadie et al. (2010) to devise a synthetic control exercise involving multiple treated units:

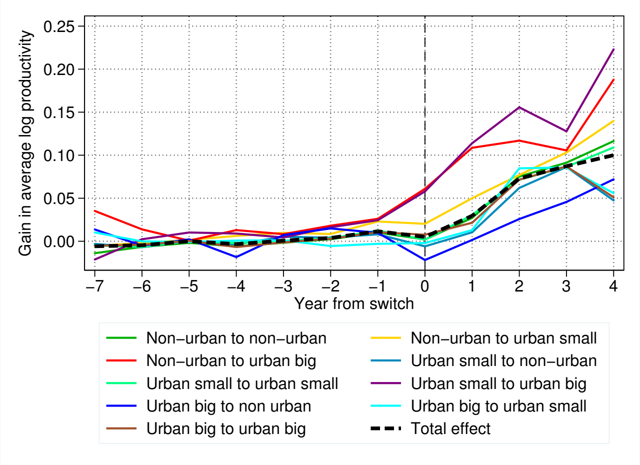
- Define relocations occurring in years 2010–12 as the treatment of interest
- For each moving firm, build an artificial counterfactual from a pool of potential donors
- Matching characteristics (pre-treatment): VA per worker (outcome) + sales, employees, age
- Synthetic control found for 38,345 out of 43,831 switchers Balancing properties
- The profile of productivity gain depends on the year of the switch Results by year of switch

Net from year-specific effects in a regression framework:

$$\Delta\pi_{iy} \equiv \pi_{i(T)y} - \pi_{i(C)y} = \delta_y + \sum_{t=-7}^{4} \gamma_t^G \left(\delta_G \times I_{iy}^t\right) + \varepsilon_{iy}$$

where δ_G are fixed effects that capture the nature of the relocation

Synthetic controls - results



- Size of the gains comparable to D-i-D
- Static productivity advantage only in big urban areas. Most of the gains accrue over time, more rapidly for firms moving to urban areas
- Future work: wider time span, standard errors

Concluding remarks

- Study the determinants of urban productivity premium

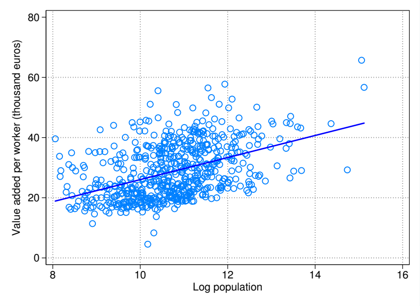
- Distinguish two relevant factors: sorting of more productive firms to cities vs. agglomeration economies:
  - $\rightarrow$ Sorting explains a substantially higher fraction of urban productivity premium, but agglomeration is non-negligible
  - $\rightarrow$ Both show a positive elasticity with respect to city size

- Exploit the episodes of firm relocation to tell something on how the productivity premium accrues through time
  - $\rightarrow$ Bigger gains for firms relocating from non-urban to urban areas
  - $\rightarrow$ For these firms, most of the productivity gains dynamically accrue over time

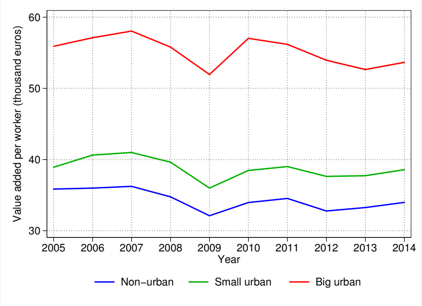
Additional Material

As in other developed countries, in Italy there evidence of a sizable urban productivity premium

a) Productivity vs. city size



b) Productivity across urban areas



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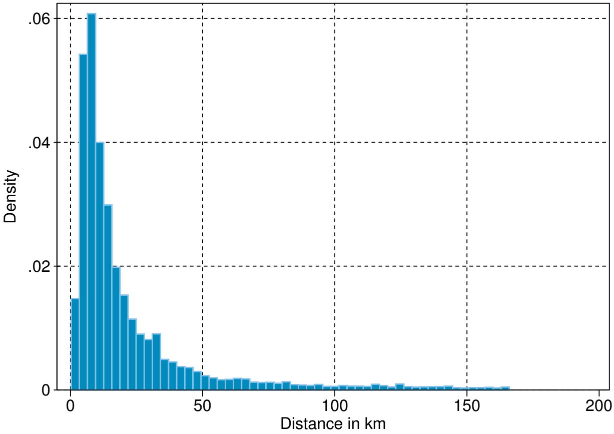
Histogram of relocation distances



Notes: Data have been truncated at the 90th percentile of the observed distribution of distances.

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Descriptive statistics for relocating firms

	Averages		
	Movers	Stayers	Difference
Employees	6.03	3.64	2.39***
Sales	1,489	629	860***
Age	9.37	13.60	-4.22***
VA per worker	35.67	26.76	8.91***

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Balancing properties for synthetic controls

	Averages		
	Movers	Synthetic controls	Difference
log VA per worker $(t-1)$	10.292	10.285	0.0074
log VA per worker $(t-5)$	10.312	10.312	-0.0004
Employees $(t-1)$	7.95	7.21	-0.7358
Wage bill $(t-1)$	26,852	25,467	1,386*
Age $(t-1)$	15.79	17.05	-1.26***
log sales $(t-1)$	12.21	12.12	0.0898
Obs.	37,578	37,578	

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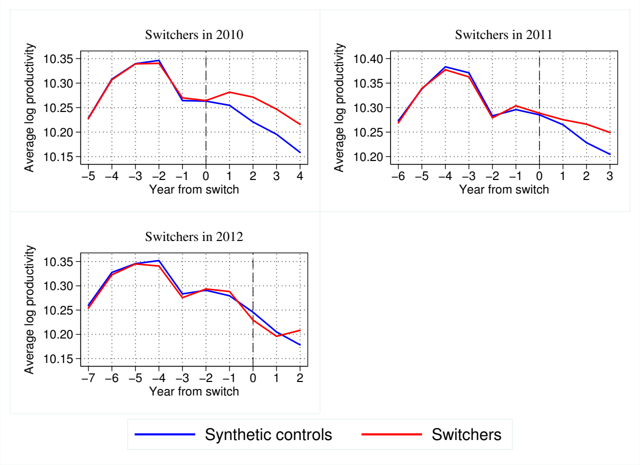
Synthetic controls, by year of switch



Notes: Observations are weighted by the inverse of the Root Mean Square Prediction Error (RMSPE). Data trimmed from the top and bottom 1% of the RMSPE distribution.

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Accounting for firm experience in cities

We restrict the sample to the firms born from 2005 onward and model urban experience as in De La Roca and Puga (2016):

$$\begin{aligned}\pi_{iy} =&\alpha_1 US_{iy} + \alpha_2 UB_{iy} + \beta_0 age_{iy} + \beta_1 ExpUS_{iy} + \beta_2 ExpUB_{iy} + \\ &+\gamma_0 age^2_{iy} + \gamma_1 ExpUS_{iy} \times age_{iy} + \gamma_2 ExpUB_{iy} \times age_{iy} + \\ &+\delta_y + \delta_s + \delta_e + \delta_i + \varepsilon_{iy}\end{aligned}$$

where:

- $ExpUB_{iy}$ if the number of years of experience that firm i has accrued in a big urban area; other variables are defined alike
- $ExpUB_{iy} + ExpUS_{iy} + ExpNU_{iy} \equiv \text{age}_{iy}$
- The interaction captures the curvature in experience profile

Accounting for firm experience in cities (2)

	(1)	(2)	(3)
Urban Small	0.0831***	0.0453***	0.00855**
	(0.00192)	(0.00169)	(0.00344)
Urban Big	0.122***	0.0729***	0.0327***
	(0.00217)	(0.00193)	(0.00432)
age	0.0474***	0.0376***	0.000887**
	(0.000444)	(0.000402)	(0.000391)
age^2	-0.00137***	-0.00103***	-0.00121***
	(0.0000325)	(0.0000292)	(0.0000253)
Experience Urban Big	0.0128***	0.0112***	0.0133***
	(0.000795)	(0.000709)	(0.000684)
age $\times$ Experience Urban Big	-0.000405***	-0.000390***	-0.000653***
	(0.0000584)	(0.0000520)	(0.0000451)
Experience Urban Small	0.00935***	0.00600***	0.00603***
	(0.000684)	(0.000608)	(0.000589)
age $\times$ Experience Urban Small	-0.000337***	-0.000227***	-0.000279***
	(0.0000494)	(0.0000440)	(0.0000384)
Firm FE	N	N	Y
Obs.	16,544,078	16,544,076	15,887,432
R^2	0.021	0.194	0.657

Notes: Industry, size and year fixed effects included.