Local Agglomeration Spillovers and Startups

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Motivation

- Startups make difficult choices, often constrained and with uncertainty
- Where to open is one of them
  - Home-bias: Figueiredo et al. (2002); Audretsch et al. (2005)
- Policy and industry agree; and encourage firms to locate next to each other
  - 'Big Push' (Murphy et al., 1989), SBIR matching programs (Lanahan and Feldman, 2015), Startup *X*,Y,Z, Co-working and Acceleration labs
- Why? Agglomeration spillovers

Motivation

- Firms co-locate, and evidence shows that this is partly due to agglomeration spillovers
  Ellison and Glaeser (1999); Duranton and Overman (2005); Greenstone, Hornbeck and Moretti (2010)
- Knowledge spillovers and labor pooling stimulate the birth and success of startups
  Porter (1998); Henderson et al. (1995); Chatterji (2009); Chatterji et al. (2014); Glaeser et al. (2015)
- But evidence show that these effect decay rapidly at very local levels
  Rosenthal and Strange (2003); Arzaghi and Henderson (2008); Catalini (2018)
- There is still more to know about if (and if so, how) these spillovers affects startups
  Glaeser, Kerr and Ponzetto (2010); Chatterji, Glaeser and Kerr (2014); Kerr and Kominers (2015)

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This paper studies the role of location choices and very local attributes (including agglomeration spillovers) play on startup outcomes and success.

This paper

- Identifies startups using unique administrative records — Startups
  - workers are followed over time
  - detailed location and ownership structure

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  - attributes of local industrial structure
  - revenues, employment and survivability

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- Estimates the causal impact of local industrial environment on startup outcomes — Blocks
  - attributes of local industrial structure
  - revenues, employment and survivability

- Uses a structural model to account for owner's location sorting — Neighborhoods
  - gender, industry and immigrant status

This paper: Startups

An startup entry in this paper is

- a new active firm
- not the result of older firms restructuring,
- has individual(s) controlling the company,
- has information about their location and industry

This paper: Blocks and Neighborhoods

Problem: location sorting

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  - exclusion restriction: no sorting within neighborhoods
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Allows quantification of the importance of location sorting and local spillovers for startups

Preview of Results

Identifying startups

- do not look like other entrants
- high survival and mobility rates

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- Large block-level **incumbent** agglomeration spillovers for startups
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- Scale is needed in order to overcome benefits of being alone
- Very local spillovers, effects disappear within 75 meters
- No effect on survival but larger moving rates

Contribution

Entrepreneurship	Figueiredo et al. (2002); Delgado et al. (2010); **Dahl and Sorenson (2012)**; Chatterji et al. (2014); **Guzman (2019)**
Urban Economics	**Arzaghi and Henderson (2008); Greenstone et al. (2010); Baum-Snow (2020)**; Ellison et al. (2010); Glaeser et al. (2010); Combes et al. (2012); Combes and Gobillon (2015); Glaeser et al. (2015); Faggio et al. (2017); Rosenthal and Strange (2011)
Areas Delimitation	Duque et al. (2007); **Arribas-Bel et al. (2019); Galdo et al. (2019)**
ML in Economics	Athey and Imbens (2019); Mullainathan and Spiess (2017); **Stambaugh et al. (2015); David et al. (2018)**
Methodology	Ward (1963); Rosenbaum and Rubin (1984); Vella (1998); Dahl (2002)

Outline

Introduction

Data

Local Environment and Startups

Location Sorting and Agglomeration Spillovers (NOT TODAY)

Data

Statistics Canada - Canadian Employer Employee Dynamics Dataset (CEEDD)

- Universe of firms and workers for six major cities in 2001-2017 ($\sim 500k$ p/year)
- Ownership structure (all owners; indiv or corporate; that directly/indirectly owns > 10%)
- Detailed location (at block face level)
- Owners characteristics (Gender, Immigrant status, labor history)
- Firm labour tracking

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DMTI Spatial Inc. CanMap POI dataset (at street address level)

- Amenities (Hotels, Schools, Banks, Hospitals, Attractions, and Police/Fire Stations)
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Other

- Input-Output (StatCan 201X) / Occupational similarity (BLS 2001)

Data: What is a startup?

Measuring entrepreneurship is difficult (Decker et al., 2014)

An startup entry is a firm that appears in the dataset for the first time

1. Active
   - With positive revenues, employment, and/or costs
2. Really new
   - Not for tax purposes, restructuring or a new subsidiary/division
   - Controlled by individual(s) and with concentrated ownership
3. With industry and location information
   - Single Location
   - No NAICS 1 (Mining/Farming), 6 (Schools/Hospitals), 8 (Other services) or 9 (Gov)

Data: What and Who?

- Startups are small, sell less in their first year, have substantially less equity and payroll

	Incumbent	**Startup**	**Inst. Entrant**
Revenue (in millions, 2000 CAD)	2.245	0.158	1.704
Equity (in millions, 2000 CAD)	4.528	0.123	3.485
Payroll (in millions, 2000 CAD)	0.648	0.055	0.287
Employment	6.73	0.75	3.39
Alive within 5 years	0.834	0.415	0.333
Move within 5 years	0.508	0.601	0.594

Table: What?

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Table: What?

- They are controlled by more female, younger, immigrant and experienced entrepreneurs

	Incumbent	Startup Entrant
Female Controller	0.195	0.262
Immigrant Controller	0.284	0.467
Age of Controller	52.10	42.35
Industry Experience	2.25	1.33
Number of businesses	1.72	1.92

Table: Who?

Data: Where do they go?

- They open at home of one owner (home-bias), or where incumbents in their industry are located

	Incumbents	**Startups**	**Inst. Entrant**
At home*	0.44	0.63	0.82
Firms in Same Industry	16.22	16.18	22.47
Total Employment Same Industry	148.54	148.68	216.62
Total Equity	163	162	230
Total Revenue	48.3	48.1	69.9
Number of Other Entrants	2.00	1.98	3.27
Number of New Startups	4.71	4.70	5.98
Median Area (sq km)	2.43	2.31	4.03

Table: Where?

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Location Sorting and Agglomeration Spillovers (NOT TODAY)

Identification Problem and Strategy

Consider the following outcome equation for startup i in industry j located in block b of neighborhood n

$$y_{bnt}^{(i,j)} = x_t^{(i,j)}\alpha + X_{bnt}^{(-i,j)}\theta + \lambda_t^{(j)} + \epsilon_{bjt}^{(i,j)} \tag{1}$$

$x_t^{(i,j)}$ firm characteristics, $X_{bnt}^{(-i,j)}$ block industrial characteristics, $\lambda_t^{(j)}$ time fixed-effects, $\epsilon_{bnt}^{(i,j)}$ error term

The main identification problem is location sorting

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The main identification problem is location sorting

1. Into neighborhoods
2. Into blocks within neighborhoods
   - exclusion restriction: no sorting within neighborhoods
     Bayer et al. (2008); Liu et al. (2018); Roche (2019)

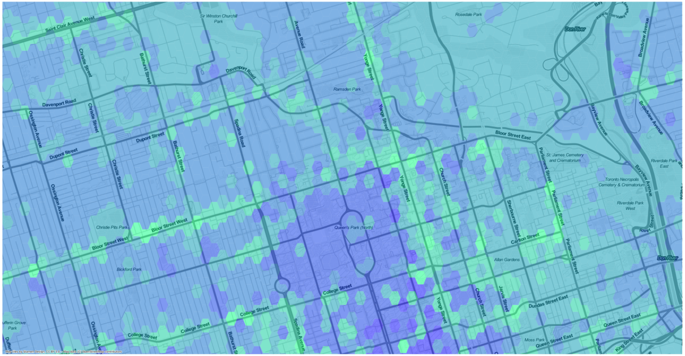
Economic Neighborhoods

(Campusano, 202X)

- Neighborhoods have typically been defined using 'official' boundaries
- These boundaries do not necessarily represent the level at which interactions occur
- Combining machine learning methods with revealed preferences can help

Economic Neighborhoods

Propensity score captures the likelihood that a block is suitable for a new startup (as in Qien and Tan, 2021)



Distribution of Propensity Score

Toronto (Accommodation, Entertainment and Food Services)

Specification is based on ex-ante (2002-2006) startup block choices and block characteristics ▸ Propensity Score Details

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Distribution of Propensity Score and Postal Codes 6 digits (LDU)

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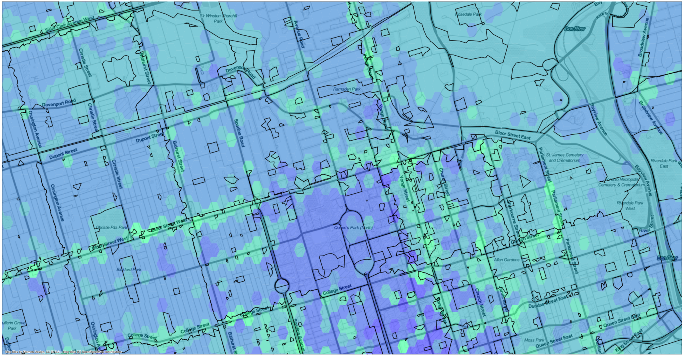

Distribution of Propensity Score and Postal Codes 3 digits (FSA)

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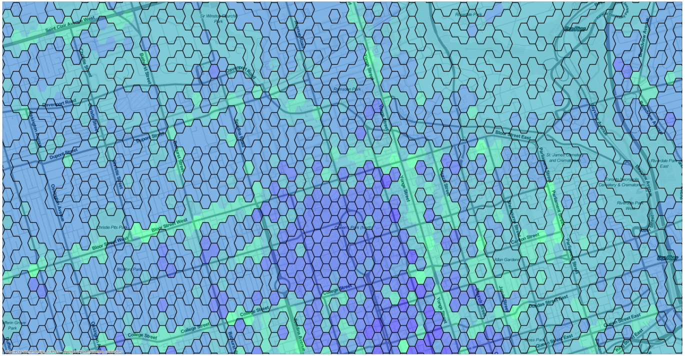
Economic Neighborhoods

- Neighborhoods in the spirit to Rosenbaum and Rubin (1984)'s propensity score *stratas*
- Use ML to groups blocks into economic neighborhoods at the industry level
  Adjacent Hierarchical Clustering Algorithm (Campusano, 202X)
- Neighborhoods are composed by blocks with homogenous industrial characteristics correlated with ex-ante startup location choices

Economic Neighborhoods

Distribution of Propensity Score and Economic Neighborhoods



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▸ Propensity Score Details ▸ Algorithm Details

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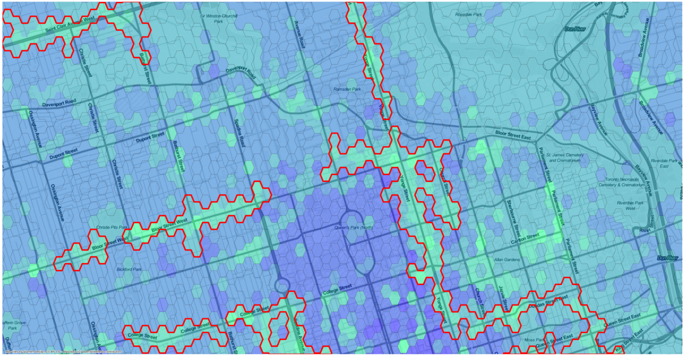

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Local Environment and Startups

Providing random allocation within neighborhoods, adding neighborhood-year fixed effects allow us to identify the causal effects of block level environment β and θ within neighborhoods

$$y_{bnt}^{(i,j)} = x_t^{(i,j)}\alpha + a_{bn}\beta + X_{bnt}^{(-i,j)}\theta + \lambda_t^{(j)} + \delta_{nt}^{(j)} + \epsilon_{bjt}^{(i,j)} \tag{2}$$

- $y_{bnt}^{(i,j)}$ (revenue, employment, exit, move)
- $X_{bnt}^{(-i,j)}$ total revenue, total employment, average revenue/worker
- Owner controls, $x_t^{(i,j)}$, are age, female/immigrant, industry exp, owner exp
- Most startups (63%) open at home, sample only considers those that do not
- High dimensional fixed effects and many zeroes => estimation with PPML-HDFE

Local Environment and Startups: Revenue

Large agglomeration spillovers for startups: competition and scale are important

(Incumbents)	(1)	(2)	(3)	(5)	(6)
	End of Year Revenue				
Log (# Incumbents Same Industry)	-0.156**	-0.172***	-0.156**	-0.132***	-0.169***
	(0.0628)	(0.0513)	(0.0592)	(0.0347)	(0.0500)
Log (Total Incumbent Revenue Same Industry)	0.155***	0.171***	0.150***	0.140***	0.185**
	(0.0351)	(0.0226)	(0.0350)	(0.0192)	(0.0660)
Log (Total Incumbent Employment Same Industry)	0.0220	0.0245	0.0360	0.0469**	0.0310
	(0.0410)	(0.0288)	(0.0406)	(0.0223)	(0.0680)
Observations	36,386	98,044	45,586	157,024	49,278
Sample	Away	Away	Inst.Entrants	Home/Away	Away
Neighborhood Year FE	YES	FSA	YES	YES	NO
Cluster Level	NeighYear	NeighYear	NeighYear	NeighYear	NeighYear

Owner controls, Industry-Year FE and City-Year FE

More Robustness

Local Environment and Startups: Revenue

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	(0.0410)	(0.0288)	(0.0406)	(0.0223)	(0.0680)
1*(# Incumbents Same Industry=0)	-0.146	-0.328***	-0.168	-0.283***	-0.205**
	(0.156)	(0.0769)	(0.155)	(0.0807)	(0.0921)
1*(Total Revenue Same Industry=0)	0.312**	0.251***	0.297*	0.192**	0.273**
	(0.154)	(0.0755)	(0.156)	(0.0623)	(0.115)
1*(Total Employment Same Industry=0)	1.760***	2.183***	1.720***	1.687***	2.184**
	(0.430)	(0.287)	(0.428)	(0.230)	(0.785)
Observations	36,386	98,044	45,586	157,024	49,278
Sample	Away	Away	Inst.Entrants	Home/Away	Away
Neighborhood Year FE	YES	FSA	YES	YES	NO
Cluster Level	NeighYear	NeighYear	NeighYear	NeighYear	NeighYear

Owner controls, Industry-Year FE and City-Year FE

▸ More Robustness

Local Environment and Startups: Employment

Large agglomeration spillovers for startups: competition and scale are important

(Incumbents)	(1)	(2)	(3)	(4)	(5)
	End of Year Employment				
Log (# Firms Same Industry)	-0.170**	-0.127***	-0.142**	-0.145***	-0.251***
	(0.0580)	(0.0217)	(0.0569)	(0.0363)	(0.0332)
Log (Total Revenue Same Industry)	-0.0152	-0.00745	-0.0245	-0.00329	0.0133
	(0.0339)	(0.0164)	(0.0328)	(0.0173)	(0.0243)
Log (Total Employment Same Industry)	0.161***	0.147***	0.156***	0.176***	0.170***
	(0.0474)	(0.0203)	(0.0464)	(0.0260)	(0.0343)
Observations	25,866	77,769	37,142	121,375	49,627
Sample	Away	Away	Inst Entrants	Home/Away	Away
Neighborhood Year FE	YES	FSA	YES	YES	NO
Cluster Level	NeighYear	NeighYear	NeighYear	NeighYear	NeighYear

Owner controls, Industry-Year FE and City-Year FE

More Robustness

Local Environment and Startups: Employment

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	(0.0474)	(0.0203)	(0.0464)	(0.0260)	(0.0343)
1*(# Firms Same Industry=0)	0.00276	-0.0393	0.0232	-0.199***	0.0264
	(0.124)	(0.0752)	(0.120)	(0.0575)	(0.0871)
1*(Total Revenue Same Industry=0)	-0.126	-0.101	-0.160	-0.0391	-0.0930
	(0.110)	(0.0660)	(0.108)	(0.0507)	(0.0998)
1*(Total Employment Same Industry=0)	0.0320	0.0683	-0.101	0.227	0.272
	(0.354)	(0.203)	(0.345)	(0.188)	(0.269)
Observations	25,866	77,769	37,142	121,375	49,627
Sample	Away	Away	Inst Entrants	Home/Away	Away
Neighborhood Year FE	YES	FSA	YES	YES	NO
Cluster Level	NeighYear	NeighYear	NeighYear	NeighYear	NeighYear

Owner controls, Industry-Year FE and City-Year FE

More Robustness

Local Environment and Startups: Spatial Decay

However agglomeration spillovers are very local, and decay rapidly within 75 meters

	(1)	(2)	(3)	(4)
1 "block" Away	EOY Revenue		EOY Employment	
Log (# Incumbents Same Industry)	-0.0200	0.0180	-0.0982	-0.0834
	(0.0985)	(0.0973)	(0.0626)	(0.0639)
Log (Total Revenue Same Industry)	-0.00407	-0.00845	0.00740	0.00513
	(0.0352)	(0.0342)	(0.0263)	(0.0265)
Log (Total Employment Same Industry)	0.0552	0.0655*	0.0246	0.0276
	(0.0350)	(0.0343)	(0.0379)	(0.0383)
1*(# Incumbents Same Industry=0)	0.202	0.205	0.118	0.0941
	(0.135)	(0.130)	(0.134)	(0.138)
1*(Total Revenue Same Industry=0)	0.306**	0.325**	-0.0246	-0.0162
	(0.134)	(0.133)	(0.113)	(0.112)
1*(Total Employment Same Industry=0)	-0.275	-0.345	0.147	0.140
	(0.480)	(0.464)	(0.319)	(0.320)
Observations	36,386	36,386	25,866	25,866
Sample	Away	Away	Away	Away
Neighborhood Year FE	YES	YES	YES	YES
Cluster Level	NeighYear	NeighYear	NeighYear	NeighYear
Include Block Characteristics	NO	YES	NO	YES

Owner controls, Industry-Year FE and City-Year FE

▸ Full Results ▸ Rings

Local Environment and Startups: Survival and Mobility

Agglomeration spillovers affects mobility of firms but not survivability

	Survive		Move	
	+1 Year	+4 Year	+1 Year	+4 Year
Log (# Incumbents Same Industry)	-0.00134	-0.0147	0.0537**	0.0927**
	(0.00278)	(0.0104)	(0.0226)	(0.0415)
Log (Total Revenue Same Industry)	-0.00236*	0.00402	-0.0325**	0.0104
	(0.00139)	(0.00450)	(0.0104)	(0.0202)
Log (Total Employment Same Industry)	0.00284	0.00911	-0.0895***	0.0800**
	(0.00176)	(0.00606)	(0.0149)	(0.0255)
1*(# Incumbents Same Industry=0)	0.000247	-0.0184	0.0896*	0.0858
	(0.00651)	(0.0262)	(0.0531)	(0.0934)
1*(Total Revenue Same Industry=0)	-0.00134	0.0264	-0.0217	-0.166**
	(0.00458)	(0.0165)	(0.0370)	(0.0738)
1*(Total Employment Same Industry=0)	-0.0304*	0.0530	-0.401**	0.289
	(0.0174)	(0.0584)	(0.127)	(0.257)
Observations	35,638	23,337	24,228	9,768
Sample	Away	Away	Away	Away
Neighborhood Year FE	YES	YES	YES	YES
Cluster Level	NeighYear	NeighYear	NeighYear	NeighYear

Owner controls, Industry-Year FE and City-Year FE

▸ Future Revenue ▸ Future Employment

Local Environment and Startups: Survival and Mobility

Agglomeration spillovers affects mobility of firms but not survivability

	Survive		Move	
	+1 Year	+4 Year	+1 Year	+4 Year
Log (# Incumbents Same Industry)	-0.00134	-0.0147	0.0537**	0.0927**
	(0.00278)	(0.0104)	(0.0226)	(0.0415)
Log (Total Revenue Same Industry)	-0.00236*	0.00402	-0.0325**	0.0104
	(0.00139)	(0.00450)	(0.0104)	(0.0202)
Log (Total Employment Same Industry)	0.00284	0.00911	-0.0895***	0.0800**
	(0.00176)	(0.00606)	(0.0149)	(0.0255)
1*(# Incumbents Same Industry=0)	0.000247	-0.0184	0.0896*	0.0858
	(0.00651)	(0.0262)	(0.0531)	(0.0934)
1*(Total Revenue Same Industry=0)	-0.00134	0.0264	-0.0217	-0.166**
	(0.00458)	(0.0165)	(0.0370)	(0.0738)
1*(Total Employment Same Industry=0)	-0.0304*	0.0530	-0.401**	0.289
	(0.0174)	(0.0584)	(0.127)	(0.257)
Observations	35,638	23,337	24,228	9,768
Sample	Away	Away	Away	Away
Neighborhood Year FE	YES	YES	YES	YES
Cluster Level	NeighYear	NeighYear	NeighYear	NeighYear

Owner controls, Industry-Year FE and City-Year FE

▸ Future Revenue ▸ Future Employment

Conclusions

- Startups have benefits and costs of agglomeration
  - Benefits are important in employment and revenues
  - Competition plays a role offset by benefits
  - But scale is important
  - Costs do not kill but displace
- Benefits are constrained to the block and decay quickly in space

Outline

Introduction

Data

Local Environment and Startups

Location Sorting and Agglomeration Spillovers (NOT TODAY)

What's next?

- Sorting into neighborhoods accounts for neighborhoods heterogeneous treatment effects
- Estimating a model like this require imposing severe restrictions in the sorting process, specially since neighborhoods choice set is large
  Lee and Salanié (2018)

What's next?

- Sorting into neighborhoods accounts for neighborhoods heterogeneous treatment effects
- Estimating a model like this require imposing severe restrictions in the sorting process, specially since neighborhoods choice set is large
  Lee and Salanié (2018)
- I adapt Dahl (2002)'s semi-parametric selection correction approach
  - correction: unknown function of the **first best and staying at home** selection probabilities
  - probabilities: recovered from a 'dynamic' location choice model and estimated with neural networks
  - exclusion restriction: location preferences does not affect profits
    Michelacci and Silva (2007); Dahl and Sorenson (2012); Rosenthal and Strange (2012)

Local Agglomeration Spillovers and Startups

Rolando Campusano

University of Toronto (Rotman)

Canadian Summer Conference in Real Estate and Urban Economics
May 26, 2021 p.t.

Appendix

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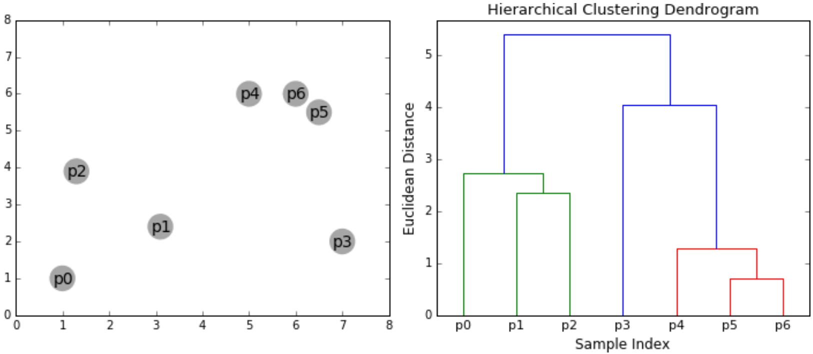
Adjacent Hierarchical Clustering Algorithm



back

Adjacent Hierarchical Clustering Algorithm

The loss of information when grouping blocks into a neighborhood $N \subset \mathcal{P}$

$$I(N) = \sum_{\mathrm{P}_t^u} \| \mathrm{P}_t^u - \overline{\mathrm{P}}_N \|^2$$

where $\overline{\mathrm{P}}_N = n^{-1} \sum_{u=1}^{n} \mathrm{P}_t^u$ is the *centre of gravity* of N and n is the number of blocks in the neighborhood.

Starting from a partition $\{N_1, ..., N_l\}$ of $\mathcal{P}$, the loss of information when merging two neighborhoods N_u and N_v is quantified by:

$$\delta\left(N_u, N_v\right) = I(N_u \cup N_v) - I(N_u) - I(N_v)$$

That, when minimized, it is equal to minimizing the variation of *within-cluster sum of squares* after merging two clusters (Ward, 1963)

back

Adjacent Hierarchical Clustering Algorithm

For a given $\mathcal{P} = \{\mathrm{P}_t^u\}_{u=1}^{\mathbf{B}}$ set of all block-level probabilities to be clustered.

1. Initialize with set of neighborhoods to be $\{N_1, ..., N_B\}$ where $N_u = \{\mathrm{P}_t^u\}$ for all $u = 1, ..., B$

back

Adjacent Hierarchical Clustering Algorithm

For a given $\mathcal{P} = \{\mathrm{P}_t^u\}_{u=1}^{\mathbf{B}}$ set of all block-level probabilities to be clustered.

1. Initialize with set of neighborhoods to be $\{N_1, \ldots, N_B\}$ where $N_u = \{\mathrm{P}_t^u\}$ for all $u = 1, \ldots, B$
2. Compute the dissimilarity between all pairs, that is, compute $\delta(N_u, N_v)$ for all $u < v \in \{adjacent_u\}$

back

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2. Compute the dissimilarity between all pairs, that is, compute $\delta\left(N_u, N_v\right)$ for all $u < v \in \{adjacent_u\}$
3. While there is more than one neighborhood in the original set:
   3.1 Merge a pair which have minimal dissimilarity

   $$\delta\left(N_{u'}, N_{v'}\right) = \min_{u' < v'} \delta\left(N_u, N_v\right)$$

   set $N_{u'} = N_{u'} \cup N_{v'}$ and remove $N_{v'}$ from the set of neighborhoods

   3.2 Compute dissimilarity between $N_{u'}$ and the remaining neighborhoods in original set

back

Adjacent Hierarchical Clustering Algorithm

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   3.2 Compute dissimilarity between $N_{u'}$ and the remaining neighborhoods in original set
4. The final set of neighborhoods $\{N\}$ is defined as the subset of $\mathcal{P}$ in which the dissimilarity within (across) neighborhoods is minimized (maximized)

back

Propensity Score Specification

- The propensity score captures the probability that a given incumbent firm chooses block cell b based on its characteristics

$$
\begin{aligned}
\#\text{Startups}_{bjt} = \beta + \sum_{POI} \beta_{POI}\text{POI}_{bt} + \sum_{POI} \beta_{\text{MA}POI}\text{MA\_POI}_{bt} + \\
\sum_{POI} \beta_{LAND}\text{LAND}_{bt} + \sum_{LAND} \beta_{\text{MA}LAND}\text{MA\_LAND}_{bt} + \\
\sum_{POI} \beta_{X} X_{bjt} + \sum_{POI} \beta_{\text{MA\_}X}\text{MA\_}X_{bjt} + \epsilon_i
\end{aligned}
$$

  - *POI* are points of interest, *LAND* are land uses
  - X_{bjt}: attributes and composition of nearby firms and workers with
    - *Up*, *Down*, *Eq*, *Oc* based on Input-Output and Occupational Similarity weights
  - $MA(*)$ are measures within 1 km with distance exp decay (rho=1)
- Sample: 2002-2006

back

Testing Neighborhoods

back

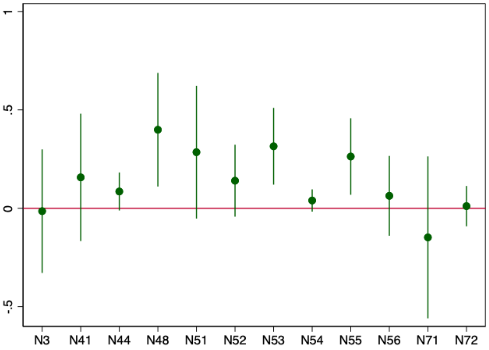
Local Environment and Startups: Revenue

	(1)	(2)	(3)	(4)
		End of Year Revenue		
Log (# Incumbents Same Industry)	-0.156**	-0.0632	-0.156**	-0.189**
	(0.0628)	(0.0442)	(0.0631)	(0.0584)
Log (Total Revenue Same Industry)	0.155***	0.0824***	0.155***	0.164***
	(0.0351)	(0.0188)	(0.0371)	(0.0326)
Log (Total Employment Same Industry)	0.0220	-0.0341	0.0220	0.0817**
	(0.0410)	(0.0245)	(0.0421)	(0.0387)
1*(# Incumbents Same Industry=0)	-0.146	-0.236**	-0.146	-0.354**
	(0.156)	(0.119)	(0.147)	(0.151)
1*(Total Revenue Same Industry=0)	0.312**	0.0834	0.312**	0.372**
	(0.154)	(0.0561)	(0.159)	(0.158)
1*(Total Employment Same Industry=0)	1.760***	0.972***	1.760***	1.986***
	(0.430)	(0.248)	(0.437)	(0.395)
Observations	36,386	101,279	36,386	36,386
Sample	Away	Home	Away	Away
Owner Controls	YES	YES	YES	NO
Neighborhood Year FE	YES	YES	YES	YES
Cluster Level	NeighYear	NeighYear	Neigh	NeighYear

Industry Year FE City Year FE

back

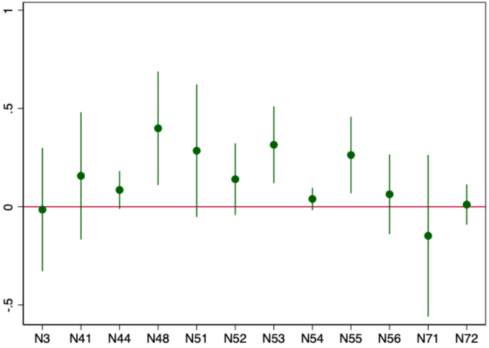
Local Environment and Startups: Revenue



# of Incumbents in the Block

◂ back

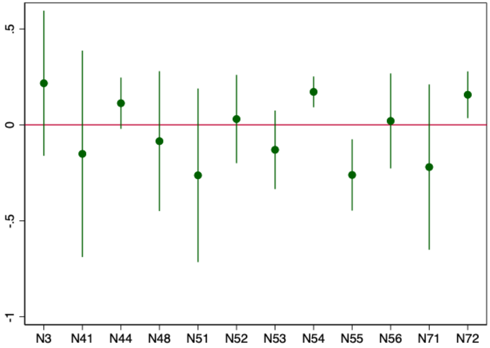
Local Environment and Startups: Revenue



Total Incumbents Revenue in the Block

back

Local Environment and Startups: Revenue



Total Incumbents Employment in the Block

back

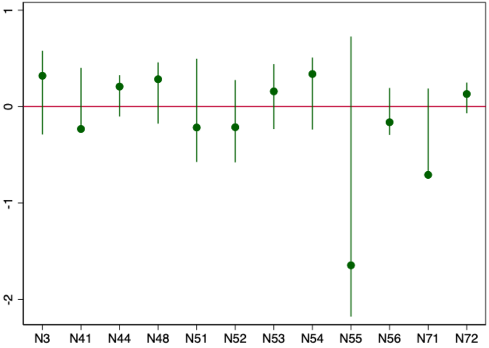
Local Environment and Startups: Employment

	(1)	(2)	(3)	(4)
		End of Year Employment		
Log (# Incumbents Same Industry)	-0.170**	-0.112**	-0.170**	-0.204***
	(0.0580)	(0.0510)	(0.0535)	(0.0571)
Log (Total Revenue Same Industry)	-0.0152	-0.0211	-0.0152	-0.00285
	(0.0339)	(0.0216)	(0.0349)	(0.0315)
Log (Total Employment Same Industry)	0.161***	0.122***	0.161***	0.203***
	(0.0474)	(0.0337)	(0.0473)	(0.0433)
1*(# Incumbents Same Industry=0)	0.00276	-0.212**	0.00276	-0.0914
	(0.124)	(0.0756)	(0.122)	(0.125)
1*(Total Revenue Same Industry=0)	-0.126	-0.107*	-0.126	-0.0848
	(0.110)	(0.0568)	(0.109)	(0.119)
1*(Total Employment Same Industry=0)	0.0320	0.00973	0.0320	0.254
	(0.354)	(0.244)	(0.371)	(0.336)
Observations	25,866	76,507	25,866	25,866
Sample	Away	Home	Away	Away
Owner Controls	YES	YES	YES	NO
Neighborhood Year FE	YES	YES	YES	YES
Cluster Level	NeighYear	NeighYear	Neigh	NeighYear

Industry Year FE City Year FE

back

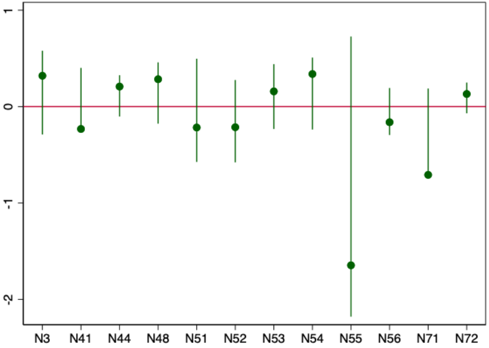
Local Environment and Startups: Employment



# of Incumbents in the Block

back

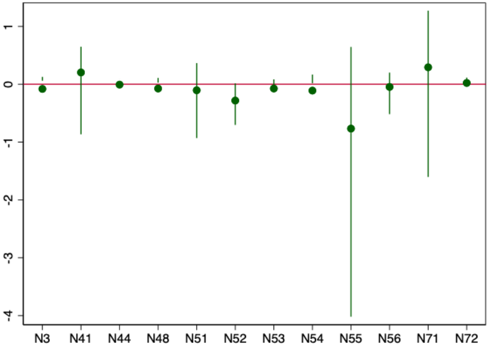
Local Environment and Startups: Employment



Total Incumbents Revenue in the Block

◂ back

Local Environment and Startups: Employment



Total Incumbents Employment in the Block

back

Local Environment and Startups: Decay

One "block" away	(1)	(2)	(3)	(4)
	EOY Revenue		EOY Employment	
Log (# Incumbents Same Industry)	-0.0200	0.0180	-0.0982	-0.0834
	(0.0985)	(0.0973)	(0.0626)	(0.0639)
Log (Total Revenue Same Industry)	-0.00407	-0.00845	0.00740	0.00513
	(0.0352)	(0.0342)	(0.0263)	(0.0265)
Log (Total Employment Same Industry)	0.0552	0.0655*	0.0246	0.0276
	(0.0350)	(0.0343)	(0.0379)	(0.0383)
1*(# Incumbents Same Industry=0)	0.202	0.205	0.118	0.0941
	(0.135)	(0.130)	(0.134)	(0.138)
1*(Total Revenue Same Industry=0)	0.306**	0.325**	-0.0246	-0.0162
	(0.134)	(0.133)	(0.113)	(0.112)
1*(Total Employment Same Industry=0)	-0.275	-0.345	0.147	0.140
	(0.480)	(0.464)	(0.319)	(0.320)
Observations	36,386	36,386	25,866	25,866
Sample	Away	Away	Away	Away
Neighborhood Year FE	YES	YES	YES	YES
Cluster Level	NeighYear	NeighYear	NeighYear	NeighYear
Include Block Characteristics	NO	YES	NO	YES

Owner controls, Industry-Year FE and City-Year FE

back

Local Environment and Startups: Decay

- The city is divided in a 75-meter hexagon grid cell
- Each firm is assigned to this grid cell
- Industrial characteristics, and then neighborhoods are computed

Figure: Hexagon Grid Cell and Rings Around

back

Local Environment and Startups: Future Revenue

Effects are persistent over time and affects future revenue and employment

	(1) EOY	(2) +1	(3) +2	(4) +3	(5) +4	(6) +5
Log (# Incumbents Same Industry)	-0.156**	-0.207***	-0.205***	-0.228**	-0.283**	-0.345**
	(0.0628)	(0.0544)	(0.0582)	(0.0741)	(0.0908)	(0.110)
Log (Total Revenue Same Industry)	0.155***	0.100**	0.112**	0.140***	0.166**	0.128**
	(0.0351)	(0.0334)	(0.0356)	(0.0389)	(0.0513)	(0.0480)
Log (Total Employment Same Industry)	0.0220	0.0996**	0.0685	0.0491	0.0263	0.0499
	(0.0410)	(0.0388)	(0.0444)	(0.0428)	(0.0575)	(0.0648)
1*(# Incumbents Same Industry=0)	-0.146	-0.0883	-0.294*	-0.244	-0.148	0.0996
	(0.156)	(0.141)	(0.154)	(0.177)	(0.201)	(0.221)
1*(Total Revenue Same Industry=0)	0.312**	0.218*	0.184	0.292*	0.242	0.114
	(0.154)	(0.118)	(0.135)	(0.159)	(0.212)	(0.254)
1*(Total Employment Same Industry=0)	1.760***	1.247**	1.570***	1.637***	1.939**	1.401**
	(0.430)	(0.398)	(0.396)	(0.473)	(0.607)	(0.548)
Observations	36,386	32,422	25,218	19,409	14,677	10,967
Sample	Away	Away	Away	Away	Away	Away
Neighborhood Year FE	YES	YES	YES	YES	YES	YES
Cluster Level	NeighYear	NeighYear	NeighYear	NeighYear	NeighYear	NeighYear

Owner controls, Industry-Year FE and City-Year FE

◂ back

Local Environment and Startups: Future Employment

Effects are persistent over time and affects future revenue and employment

	(1) EOY	(2) **+1**	(3) **+2**	(4) **+3**	(5) **+4**	(6) **+5**
Log (# Incumbents Same Industry)	-0.170**	-0.182***	-0.156**	-0.187**	-0.191**	-0.314***
	(0.0580)	(0.0522)	(0.0516)	(0.0582)	(0.0629)	(0.0685)
Log (Total Revenue Same Industry)	-0.0152	-0.0168	0.0142	-0.0292	-0.0289	0.0538
	(0.0339)	(0.0314)	(0.0360)	(0.0436)	(0.0496)	(0.0360)
Log (Total Employment Same Industry)	0.161***	0.189***	0.136***	0.184***	0.169***	0.121**
	(0.0474)	(0.0430)	(0.0389)	(0.0418)	(0.0477)	(0.0471)
1*(# Incumbents Same Industry=0)	0.00276	0.0250	-0.0358	-0.0394	-0.0416	0.0362
	(0.124)	(0.134)	(0.140)	(0.119)	(0.149)	(0.173)
1*(Total Revenue Same Industry=0)	-0.126	-0.152	-0.136	-0.00488	-0.0142	-0.0832
	(0.110)	(0.0969)	(0.0991)	(0.0963)	(0.117)	(0.139)
1*(Total Employment Same Industry=0)	0.0320	0.0845	0.404	-0.252	-0.304	0.576
	(0.354)	(0.369)	(0.473)	(0.541)	(0.615)	(0.437)
Observations	25,866	28,192	24,119	19,112	14,616	11,076
Sample	Away	Away	Away	Away	Away	Away
Neighborhood Year FE	YES	YES	YES	YES	YES	YES
Cluster Level	NeighYear	NeighYear	NeighYear	NeighYear	NeighYear	NeighYear

Owner controls, Industry-Year FE and City-Year FE

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