Network and Spatial Analyses
25. March 2020

Lecture:
Anatomy of Clusters
A journey from the original idea of Marshall (1920) to the latest frontier of cluster research

- Why clusters?
- Characteristics of industry clusters
- Networks and clusters
- Spinoffs and clusters

Seminar:
EconGeo R package and Exponential Random Graph Models

ANET LAB

ELTE ECON

Course Github page: https://github.com/bokae/anet_course

What is a cluster?

Geographic concentration of economic activities that operate in the same or interconnected sectors

(Cooke et al. 2007, Gordon and McCann 2000)

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Why are clusters (still) important?

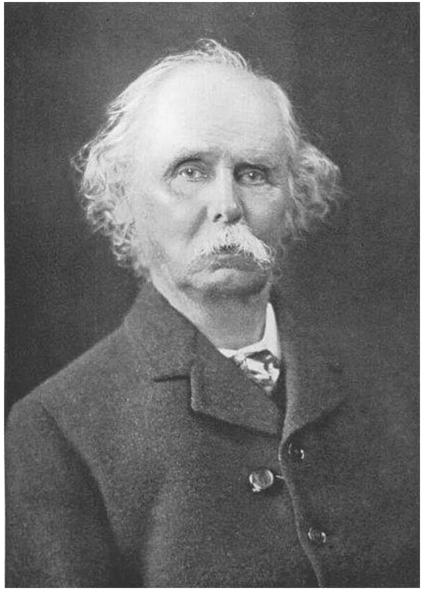
20+ years of consensus about their relevance

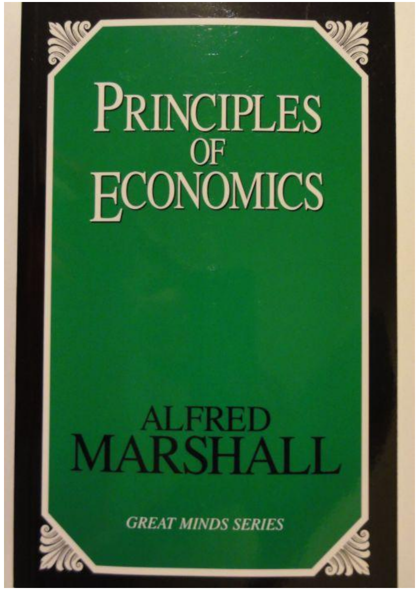
Simple concept for regional development policies

'Petri dish' for research in economic geography

The original idea behind clusters

Alfred Marshall





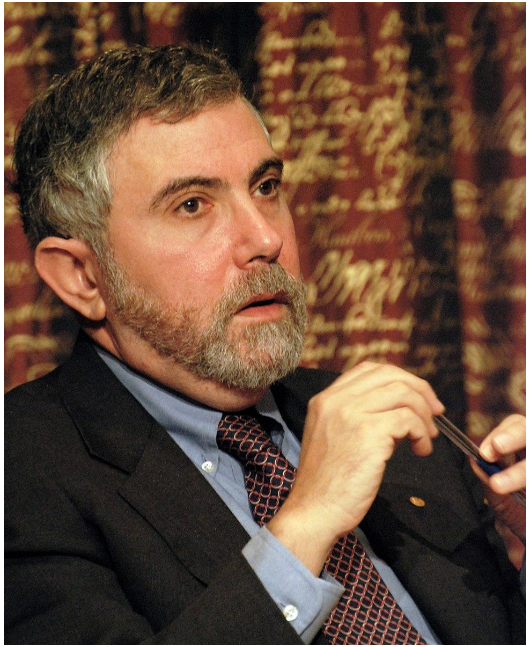
Agglomeration of economic activities

- labour market pooling
- specialized suppliers
- *knowledge spillovers*

Source: Marshall (1920)

Clusters are engines of regional competitiveness and growth

(Mainstream) economics



Paul Krugman **(Nobel prize winner 2008)**

Explanation for spatial concentration of activities by the reinvention of classic models

Forces Affecting Geographical Concentration

Centripetal forces	**Centrifugal forces**
Market-size effects	Immobile factor
Thick labour markets	Land rents
Pure external economies	Pure external diseconomies

Source: Krugman (1991, 1998)

Management ‘science’

Michael Porter

“geographic concentrations of interconnected companies, specialized suppliers, services providers, firms in related industries, training institutions and support organizations linked around technologies or end product within a local area or region” (Porter 1990)

Strategic decisions of globally competing firms necessarily lead to industrial clustering

Successful clusters are the key for regional competitiveness (and development)

Famous examples

Italian industrial districts

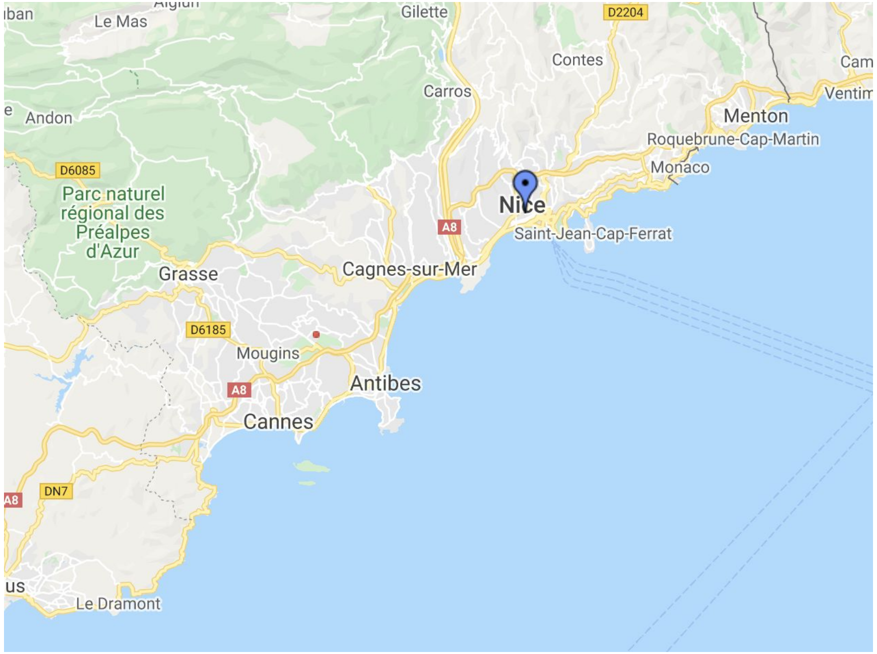
Mainly around Emilia Romagna region
Classic manufacturing industries with high quality products for world-wide export
Small and medium size enterprises collaborate to organize common services

Textil/clothing cluster - Carpi, Prato, Biella and Como

Ceramic cluster - around Sassuro

Italian Chair District - around Manzano

Famous examples



Sophia Antipolis

‘Artificial’ created after the success of Silicon Valley between Cannes and Nice (south of France)

Started by a science and technology park and it is a leading IT and life-science cluster in Europe by now

Identification of industry clusters

Revealed comparative advantage

Region (r) has comparative advantage in an industry (i), if $RCA_{r,i} > 1$

Also known as Location Quotient (LQ)

Easy to apply on many different data types (e.g. export, employment, registered firms, patent counts)

$$RCA_{r,i} = \frac{E_{r,i} / \sum_i E_{r,i}}{\sum_r E_{r,i} / \sum_r \sum_i E_{r,i}}$$

r - regions in country
i - industries in country

Source: Balassa (1965)

Characteristics of industry clusters

Characteristics	Pure agglomeration	Industrial complex	Social network	
			New SN	Old SN
Nature of technical knowledge	Codified, explicit and mobile	Mixed, systemic, routinised, R&D-intensive	Tacit, new, generic, non-systemic, sticky and leaky	Mixed, mature, incremental
	Transmitted by way of information	Specific, based on non-transferable experience	Transmitted within cognitive networks	Transmitted within localised networks
Technological trajectory	Oriented to processes, problem-solving	Oriented to complex products, cost-cutting	Oriented to radically new products	Oriented to processes, customer-driven
Dynamics	Stochastic	Strategic	Mixed	Mixed
Sources of innovation	External to the firm	Internal to the firm	Mixed	External to the firm
Appropriability of innovation returns	Low, perfect or monopolistic competition	High, private creation of new knowledge, oligopolistic competition	Mixed, public-private creation of new knowledge	Low, collaboration and competition
Technological opportunities	Medium	Low	Very high, uncertain	Low
Degree of cumulativeness	Low	High	Low	High
Knowledge-base	Diversified	Specialised	Research-based	Specialised along the filière
Modes of governance	Market	Hierarchies	Relational and cognitive networks	Social and historical networks
Examples of industrial specialisation	Finance, banking, insurance, business services, retailing	Steel, chemicals, automotive, pharmaceuticals, machine tools, medical instruments, ICT hardware	SME high-tech clusters in general purpose technologies	Customised traditional goods textiles, footwear, furniture, tourism
Example of cluster	'Silicon Valley' (California)	'Silicon Glen' (Scottish Electronics Industry)	'Silicon Fen' (Cambridge UK)	Italian industrial districts (Emilia-Romagna)
Pavitt classification	Information intensive, Supplier Dominated firms	Production Intensive Firms (Scale Intensive & Specialised Suppliers)	Science-based firms	Supplier dominated firms

Source: Iammarino and McCann (2006)

Collaboration is the basic ingredient for clusters

Networks in clusters

Elisa Giuliani

Knowledge is ‘not in the air’

Firms need to connect in social networks to exploit locally concentrated knowledge

Advanced capabilities are needed to cooperate in knowledge networks

Source: Giuliani and Bell (2005), Giuliani (2007)

Current research frontier

Evolution of collaboration networks in clusters

The aim is to understand the evolution of clusters through the evolution of social networks in clusters

(Giuliani 2013, Balland et al. 2016, Juhász and Lengyel 2018)

Multiplex networks in clusters

Different network layers (e.g. business relationships, technical knowledge sharing, ownership ties or friendships) co-evolve

How do different network layers influence the circulation of knowledge in another layer?

(Capone and Lazzeretti 2018)

Knowledge spillovers

vs

Inheritance of capabilities

Spinoff companies and the inheritance theory

Steven Klepper

Clusters are the result of spinoff company formation

Successful firms are training grounds for employees

Organizational reproduction (locally) and the inheritance of capabilities and routines are behind the survival and success of firms in clusters

Source: Klepper (2007, 2010), Buenstorn and Klepper (2009, 2010)

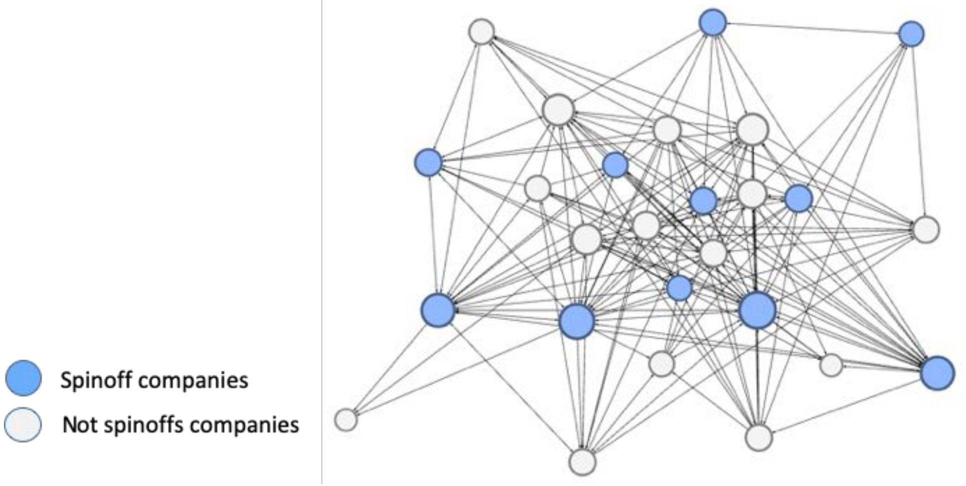
Spinoffs in cluster networks (case study)

Do Spinoffs cooperate and form more ties in cluster knowledge networks?

Main idea: inherited capabilities of spinoff enable them to cooperate and exchange knowledge more easily and to gain more from positive knowledge externalities in clusters

Context
The printing and paper product cluster of Kecskemét

Data
Fim level advice network (on knowledge sharing) collected through face-to-face interviews in 2012



Source: Juhász (2019) SBE

Spinoffs in cluster networks

Method - Exponential random graph models (ERGMs)

In our particular case: *Do spinoff companies form more ties than we would expect by chance?*

- Why do we not use a simple t-test or correlation to figure out the relationship between spinoff background and network degree?
- Network data is inherently relational, it violates the assumptions of independence and identical distribution of standard statistical models like linear regression.

Modeling a network by ERGMs?

- to capture regularities in the network, while recognizing the uncertainties surrounding tie formation
- to test hypothesis about structural features in probabilistic manner

Spinoffs in cluster networks

(Actually) Exponential-family random graph models (ERGMs)

A general class of models based on exponential-family theory for specifying the probability distribution for a set of random graphs

By this framework we can obtain maximum-likelihood estimations for the parameters of a specified model for a given network with the help of random graph generation

Test goodness-of-fit of specific models, compare various model settings and simulate additional networks with the underlying probability distribution implied by that model

Spinoffs in cluster networks

Exponential-family random graph models (ERGMs)

General form for an ERGM:

$$P(Y = y) = \frac{exp(\theta' g(y))}{k(\theta)}$$

Where:

Y is a random network on n nodes

y is the observed network

$g(y)$ is a vector of network statistics

θ is the vector of coefficients for those statistics

$k(\theta)$ is a normalizing constant to ensure probabilities sum to 1
(typically constrained to be all networks with the same node set as y)

Source: Robins (2007a, 2007b)

Spinoffs in cluster networks

Exponential-family random graph models (ERGMs)

Can be re-expressed as a conditional logit, where the dependent variable is all *i,j* pairs of edges in the network

$$logit(Y_{ij} = 1 | y_{ij}^c) = \theta' \delta(y_{ij})$$

y_{ij}^c is the complement of y_{ij} (i.e. all dyads in the network other than y_{ij})

$\delta(y_{ij})$ contains the 'change statistics' for each model term. It records how $g(y)$ term changes if the y_{ij} tie is on/off

Therefore, θ can be interpreted as the log-odds of an individual tie conditional on all others.

Spinoffs in cluster networks

Exponential-family random graph models (ERGMs)

ISSUE - some terms we model are dyad independent (e.g. node attributes)
BUT - some terms are dyad dependent (e.g. mutuality, degree terms, triad terms), which require different estimation algorithm

Estimation
Ideally use MLE to find the estimates of θ that make the observed network y most likely

Difficulty of estimation lies in the normalizing constant, as we need to know something about the distribution of graph statistics across all possible networks with n nodes

$$P(Y = y) = \frac{exp(\theta' g(y))}{k(\theta)}$$

In case we use dyad dependent terms, we use Markov Chain Monte Carle MLE

Spinoffs in cluster networks

Findings

Spinoffs form more knowledge sharing ties in clusters, than not spinoffs

Pre-entry experience, inherited routines and capabilities of spinoff companies indeed influence their ability to cooperate in networks

This can help them to better exploit the positive externalities of co-location

	Main model		Refined model	
	Coefficient	(SE)	Coefficient	(SE)
Spinoff	0.3699 **	(0.124)	0.4272 ***	(0.1286)
Ownership group	0.5120 ***	(0.1536)	0.4939 ***	(0.1442)
Extra-regional knowledge ties	0.0128 *	(0.0063)	0.0149 *	(0.0062)
Age (experience)	0.0204	(0.0434)		
Employment (log)	0.0204	(0.0434)	0.0133	(0.0474)
Geographical proximity	0.1059 **	(0.0355)	0.1214 ***	(0.0361)
Cognitive proximity	0.0121	(0.0436)	0.0171	(0.0422)
GWESP (fixed 0.32)	1.7159 ***	(0.4722)	1.9596 ***	(0.4640)
GWDSP (fixed 1.725)	−0.1769 ***	(0.0487)	−0.1858 ***	(0.0491)
GWIDEGREE (fixed 0.1325)	−0.7690	(0.5415)		
MUTUAL ties	1.6632 ***	(0.2737)	1.5988 ***	(0.2681)
EDGES	−4.2661 ***	(0.7913)	−4.6813 ***	(0.7526)
AIC	733.6		731.9	
BIC	787.3		776.7	

Source: Juhász (2019) SBE

Related seminar

Basic concentration measures

How to identify potential clusters?

We will use the EconGeo R package to estimate RCA values

Exponential random graph models

Determinants of social network formation?

We will use ERGMs to search for factors that influence network formation

Literature

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