A quantitative approach of innovation

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Chapter 3. Geography of innovation and Knowledge flows

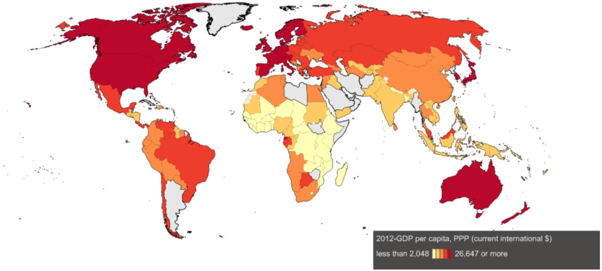
Issues and questions raised in this chapter :

- Knowledge is more localized than production (Feldman and Audretsch, 1999)
- What are agglomeration economies and knowledge spillovers
  - Measurement of agglomeration economies and increasing returns
  - The empirics of localization of knowledge spillovers (Jaffe, Trajtenberg and Henderson, 1993)
- From knowledge spillovers to knowledge flows
- The mechanisms behind knowledge spillovers : knowledge flows and diffusion
  - The role of skilled labor
  - The role of mobility
  - The role of social proximity

1. Agglomeration of economic activities
Why do cities exist ?

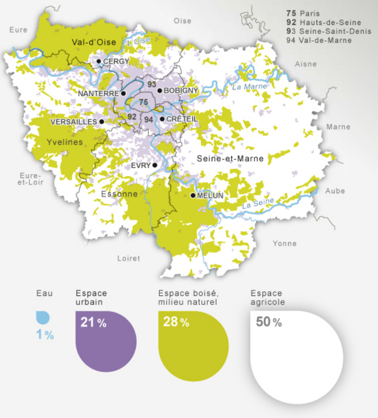
Introduction

- **Why do cities exist ?**
- Paradox : concentration of firms and people in cities despite congestion and increased land prices (rents)
  - 1/2 of world population lives in cities
- **Unequal distribution of economic activities**
  - **In the world** : Unequal distribution of living standards



Introduction

- Unequal distribution of economic activities
  - **In cities** : example of activities in **Ile de France**
    2.8% of French territory, 11.8 millions inhabitants (19% of French population), 28% of GDP, 23% of firms, 40% of researchers



Introduction

- Higher concentration of innovation
  - **In countries and cities** : Unequal distribution of activities in industrial clusters- Biotechnology in Canada (Aharonson, Baum, Plunket, 2008)

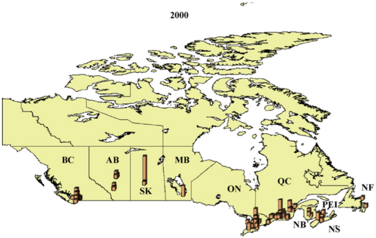


Fig. 1. Geographic location of biotechnology firms in Canada.

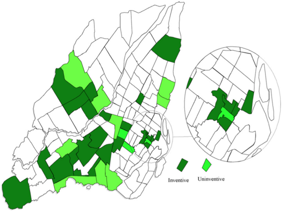


Fig. 2. Inventive productivity of Montreal FSAs.

Introduction

- **Proximity to earlier development** : despite the wide availability of open space, almost all recent development is less than one kilometre away from earlier development.
- The role of **density** : dense areas are more attractive for new developments
- What are the **advantages of cities that offset the costs** and attracts workers and firms ?
  - One cannot make sense of this sort of numbers, of the extent to which people cluster together in cities and towns, without considering some form of **agglomeration economies or localised aggregate increasing returns**.

1.1. Evidence of the magnitude of agglomeration economies

Strategies for evaluating the scope of agglomeration economies

- External economies exist when the scale of the urban environment adds to productivity and/or reduces average production cost
- Hicks neutrality assumption : external economies shift the establishment's/firm's production function

  $$y = g(A)f(x)$$

  where x is a vector of the usual inputs (land, labor, capital, and materials) and A characterizes the establishment's environment.
- An increase in $g(A)$ will lead to higher productivity - increase in y given the same level of inputs

$=$ Agglomeration economies arise from the aggregation of urban external effects

1.1. Evidence of the magnitude of agglomeration economies

Strategies for evaluating the scope of agglomeration economies

- Consider two establishments, j and k. The effect of establishment k on establishment j depends on :
  - on the scale of activity at both establishments x_j and x_k
  - their geographical distance d_{jk}^{G} - they are or not in the same location
  - their industrial distance d_{jk}^{I} - they are or not in the same industry
  - their temporal distance d_{jk}^{T} - impact over time
- The benefits to j from interaction with establishment $k \in K$ equal

$$q(x_j, x_k)a(d_{jk}^{G}, d_{jk}^{I}, d_{jk}^{T})$$

  - $q(x_j, x_k)$: reflects benefits from interaction that depend on the scales of j's and k's activities, denoted by their input vectors x_j and x_k, for example the size of k's workforce.

1.1. Evidence of the magnitude of agglomeration economies

Strategies for evaluating the scope of agglomeration economies

- $a(d^G_{jk}, d^I_{jk}, d^T_{jk})$ captures the effect of attenuation of the interaction as establishments become more distant

- The total benefit of agglomeration enjoyed by establishment $j$is equal to the sum over interaction partners of agglomerative effect as a function of geographic, industrial and temporal distance :

$$A_j = \sum_{k \in K} q(x_j, x_k) a(d^G_{jk}, d^I_{jk}, d^T_{jk})$$

- A varies for each firm since each one belongs to an other industry, another location and another period

1.1. Evidence of the magnitude of agglomeration economies

- **Location decisions of new establishments** (Rosenthal and Strange, 2003) - agglomeration effects decrease rapidly with distance
- **Differences in wages** across areas are a direct evidence of the existence and magnitude of agglomeration economies (Glaeser and Maré, 2001 ; Combes et al. 2010)
  - In competitive markets, labor is paid the value of its marginal product : Higher wages in large/dense urban areas = evidence of higher productivity.
  - For workers, higher wages may be offset by larger commuting and housing costs.
  - However, higher wages and land rents in large cities would lead firms to relocate elsewhere unless there were some significant productive advantages.
    - urban wage premium as evidence of agglomeration economies : If more able workers sort into larger cities, then the urban wage premium may reflect their greater abilities instead of any intrinsic advantage to urban location.

1.1. Evidence of the magnitude of agglomeration economies

- **Differences in productivity** across space as evidence of local increasing returns
  - Local external scale economies imply that plants are able to produce more output with the same inputs in larger, denser, urban environments.
  - A doubling of city size increases productivity by between 3 and 8 percent for a large range of city sizes (Rosenthal and Strange, 2004).
- But higher average productivity in larger cities could result from a survival of the fittest rather than from a productivity boost based on agglomeration economies.
  - **Sorting mechanisms** : the presence of more firms in larger markets makes competition tougher and this leads less productive firms to exit.

1.2. The causes of agglomeration economies

- **Micro-foundations of agglomeration economies** (Duranton and Puga, 2004) = looking inside the black box that justifies the existence of cities
- Three main classes of mechanisms explain the existence of agglomeration economies
  - **Sharing** : a larger market allows for a more efficient sharing of local infrastructure and facilities, a variety of intermediate input suppliers, or a pool of workers with similar skills
  - **Matching** : a larger market also allows for a better matching between employers and employees, buyers and suppliers, or business partners. This better matching can take the form of improved chances of finding a suitable match, a higher quality of matches, or a combination of both.
  - **Learning** : a larger market can also facilitate learning, for instance by promoting the development and widespread adoption of new technologies and business practices.

1.2.1 Sharing

- **Share indivisible goods and facilities/infrastructures**
  - Airport, Opera House, Olympic swimming pool
- Large indivisibility generates increasing returns because
  - Expensive facility with **substantial fixed costs** ; as it is shared, the larger the population that shares the facility and the lower the cost per user
- The facility is an **excludable good** : it is subject to congestion and increasing crowding which limits the growth of the user base :
  - Capacity constraints when too many people simultaneously try to use the facility
  - As the size of community of users grows, some of those users will be located too far away from the facility

1.2.1 Sharing

Sharing the gains from variety

1 Sharing suppliers

- Advantages for final producers to share a larger common base of suppliers in larger and more specialized cities
- Perfectly competitive final-goods firms use sector-specific intermediate inputs.
- Aggregate production at the city-sector level exhibits **increasing returns**, despite constant returns to scale in perfectly-competitive final production. The reason is that an increase in fi- nal production, by virtue of expanding input sharing across a wider variety of suppliers, requires a less-than-proportional increase in primary factors.

2 Sharing the gains of higher specialization

- Adam Smith's (1776) famous pin factory
- In the pin factory example, having more workers increases output more than proportionately not because extra workers can carry new tasks but because it allows existing workers to specialise on a narrower set of tasks.

1.2.1 Sharing

Sharing the gains from variety

- There are productivity gains from an increase in specialization when workers spend more time on each task : learning by doing, saving on switching tasks and standardisation
- Larger markets forsters specialization

3 Sharing a labor pool

- Marshall emphasized that "a localized industry gains a great advantage from the fact that it offers a constant market for skill" (Marshall, 1890, p. 271).
- Sharing risks
  - A localized industry gains a great advantage from the fact that it o§ers a constant market for skill
- Workers agglomerate to minimise the risk of being unemployed and firms to avoid being constrained by a small workforce when they face a positive shock (Krugman, 1991).

1.2.2. Matching

- Large labor makers enable the better **matching between employers and employees**, matching between buyers and suppliers and between business partners.
- **Matching externality**
  - an increase in the number of agents trying to match improves the expected quality of each match (Helsley and Strange, 1990)
  - as the workforce grows and the number of firms increases the average worker is able to find an employer that is a better match for its skill.
- Costa and Kahn (2000). They show that couples in which both spouses have college degrees are increasingly likely to be located in the largest metropolitan areas, and not just because they meet there. One explanation is that college- educated couples are more likely to **face a co-location problem** and moving to big cities increases the chances that both find suitable matches.

1.2.3. Learning

- Modern economies devote a significant amount of their resources to learning
  - Fundamental feature of learning ; it is a **collective activity** which involves **interactions** with others and interactions are facilitated when they are « face-to-face »
  - Cities, by bringing together a large number of people, may thus facilitate learning.
  - the learning opportunities offered by the cities could provide a strong justification for their own existence.
- **Marshall (1890)** already emphasised how cities favour the diffusion of innovations and ideas.
- **Jacobs (1969)**, numerous authors have stressed how the environment offered by cities improves the prospects for generating new ideas.
- **Lucas (1988)** : the advantages of cities for learning regard not only cutting-edge technologies, but also the acquisition of skills and 'everyday' incremental knowledge creation, diffusion, and accumulation (knowing how, knowing who, etc.)

1.2.4. Agglomeration economies : a black box

- **Marshallian externalities** refer to **intra-industry economies of localization** (Krugman, 1991)
  - **Economies of specialization** : a localized industry can support a greater number of specialized local suppliers of industry-specific intermediate inputs and services, thus obtaining a greater variety at a lower cost
  - **Labour market economies** : Localized industries attract and create pools of workers with similar skills, smoothing the effects of business cycle (both on unemployment and wage) through the effects of large numbers
  - Economies of specialization and labour market economies are refferd to as **« pecuniary » or « rent » externalities** : these allow co-located firms to access traded inputs and labour at a lower price than rivals located elsewhere.

1.2.4. Agglomeration economies : a black box

- **Marshallian externalities refer to intra-industry economies of localization** (Krugman, 1991) (cont'd)
  - **Knowledge spillovers** : information about novelties flows more easily among agents located within the same area, thanks to social bonds that foster reciprocal trust and frequent face-to-face contacts. Therefore geographical clusters offer more « innovation opportunities » than scattered locations. Innovation diffusion is also faster.
  - **Technologies externalities** materialize through non-market interactions and, in principle, are accessible to all members of the local community.
- **Urbanization externalities** occur whenever job or innovation opportunities are enhanced by exchanges and **cross-fertilization** among technologies and sectors, i.e. **inter-industry externalities**, which are most likely to appear within large urban centres.

1.2.4. Agglomeration economies : a black box

Empirical analysis of agglomeration economies at a micro level Martin P., Mayer T. and Mayneris F. (2011), Spatial concentration and plant-level productivity in France, Journal of Urban Economics, 69, 182-195

Martin, Mayer and Mayneris, 2011

- Aim : Empirical investigation of spatial agglomeration of activities on plant-level productivity using French firms from 1996-2004
- The model

$$Y_{it} = A_{it} K_{it}^{\alpha} L_{it}^{\beta} \qquad \text{Production function}$$

A_{it} is Total factor productivity, K_{it} is capital stock and L_{it} is labor-force in terms of employees of plant i at time t

$$A_{it} = (LOC_{it}^{sz})(URB_{it}^{sz})U_{it}$$

  - LOC_{it}^{sz} is a measure of localization economies = intra-industry externalities measured by # of employees in the same sector, same location and
  - URB_{it}^{sz} is urbanization economies = inter-industry externalities measured by # of employees in other sectors, same location

1.2.4. Agglomeration economies : a black box

- Control for industrial diversity and competition (= competition whips up innovation so that more intense competition within clus- ters improves firms' performance, cf Porter, 1998)

Table 2
Summary statistics Département/Naf 3-digit.

Variable	Mean	Std. dev.	Min	Max
Value-added	5104.56	18357.77	1.43	1,440,578
Plant's employment	93.41	256.86	11	19,385
Plant's capital	6554.73	39285.63	10.85	4,283,886
# Employees, other plants, same industry–area	1762.04	3205.69	0	24,475
# Other plants, same industry–area	33.48	76.01	0	874
# Other employees, other industries–same area	44337.15	30867.67	357	135,657
# Other plants, other industries–same area	665.30	509.11	12	2873

Note: Number of observations: 216,340 in all rows. Value-added and capital are expressed in thousands of real euros.

1.2.4. Agglomeration economies : a black box

Table 5
Fixed effects approach, Département/Naf 3-digit.

Dep. var.:	ln Levinsohn–Petrin TFP			
Model	(1)	(2)	(3)	(4)
ln(# employees, other plants, same industry–area + 1)	0.024[a]	0.008[a]	0.037[a]	0.007[a]
	(0.002)	(0.002)	(0.002)	(0.002)
ln(# employees, other industries, same area)	0.054[a]	0.017	0.066[a]	0.018
	(0.004)	(0.019)	(0.004)	(0.020)
Competition			−0.038[a]	0.008[c]
			(0.004)	(0.005)
Sectoral diversity			−0.072[a]	0.003
			(0.007)	(0.011)
Time fixed effect	Yes	Yes	Yes	Yes
Plant fixed effects	No	Yes	No	Yes
N	216,340	216,340	216,340	216,340
# Plants	46,855	46,855	46,855	46,855
R^2	0.028	0.018	0.032	0.018

Note: Standard errors in parentheses. Standard errors are corrected to take into account individual autocorrelation.
[a] Significance at the 1% level.
[b] Significance at the 5% level.
[c] Significance at the 10% level.

2. Agglomeration of innovative activities

2.1. Innovation is spatially concentrated

- **Innovation exhibits a pronounced tendency to cluster** both spatially and temporally.
- Innovation is **more geographically concentrated** than inventions
  - Invention is the first stage of the innovation process
  - Patents are geographically concentrated reflecting a concentration of research and development (R&D) activity.
  - Jaffe (1989), Acs et al. (1994) find that new product introductions were more geographically concentrated than patents.
- Innovation is more geographically concentrated than production (Audretsch and Feldman, 1996)
  - **Location matters most at the earliest stage of the industry life cycle**. Once a good is at a mature stage of its life cycle costs of production become more important.
  - Early stages of the industry life cycles are characterized by the importance of **tacit knowledge**. Once a product has become standardized and demand will support mass production, it is easier for an industry to disperse geographically.

2.2. Localized knowledge spillovers

- Growth theories suggest that differences in growth rates result from **increasing returns to knowledge** (Romer, 1986 ; Lucas, 1988, 1992 ; Grossman and Helpman, 1992)
- One source of increasing returns may be agglomeration or geographic concentrations of knowledge that provide means to facilitate
  - information searches, increase search intensity, and ease task coordination
- Specificity of knowledge spillovers due to the characteristics of knowlegde
  - Knowledge is a non-rival production asset (Nelson, 1959, Arrow, 1962)
  - **Knowledge externalities** : a few agents invest in research or technology development and facilitate other agents' innovation efforts intentionally (publications or collaborations) or unintentionally (through imitation)

2.3. The geographic knowledge production function

- Innovative activities are strongly concentrated geographically, both in the US and in Europe
- **Firms in certain areas are systematically more productive** than firms located elsewhere
  - Firms located in regions with high flows (or stocks) of both private and public **R&D and academic research** are more likely to be innovative than firms located elsewhere, since they benefit from knowledge « leaking out » form these sources.
  - **Distance matters** in determining the beneficiaries of knowledge spillovers is found in the distinction between « tacit » knowledge and information », the latter being a synonym of « codified « knowledge
- The propensity for innovative activity to cluster spatially will be the greatest in industries where **tacit knowledge** plays an important role... it is tacit knowledge, as opposed to information which can only be transmitted informally, and typically demands direct and repeated contacts.

2.3. The geographic knowledge production function

- **The knowledge production function** relates innovative inputs such as R&D to innovation output measures, such as patents or innovation counts
  - Local and distant external innovation inputs, i.e. between inputs coming from outside the observation unit, but within its geographical area and those originating from outside the area
  - Significant differences between the estimated parameters of the two kinds of R&D are then interpreted as evidence of the existence and the localization of R&D spillovers
- **The knowledge production function approach** was introduced by **Griliches (1979)** to account for spatial and product dimensions

$$\text{Innovation}_{si} = \alpha IRD^{\beta_1} * RDE_{si}^{\beta_2} * \epsilon_{si}$$

IRD : private corporate expenditures on R&D

RDE : external research expenditures

2.4. Empirical evidence of LKS : aggregate data

- **Pioneering work of Jaffe (1989)** : assess the real effects of academic research : how the number of patents of each US state of each technological area is a positive function of the R&D performed by local universities
  - The relationship between patents and university R&D is interpreted as a sign of the existence of localized technological spillovers from the academic institutions into the local business realm
- **Pioneering work of Jaffe, Trajtenberg and Henderson (1993)** to study knowledge flows based on patent citations
- **Bottazzi and Peri (2003)** : Consider knowledge spillover decay on aggregated data

2.4. Empirical evidence of LKS : aggregate data

Empirical analysis of LKS Paper 1 based on the knowledge production function and knowledge externalities

Jaffe, A.B., 1989. Real Effects of Academic Research. The American Economic Review, 79(5), pp.957–970.

2.4. Empirical evidence of LKS : aggregate data

Jaffe (1989)

- **Aim of the paper** : Study the existence of geographically mediated « spillovers » **from university research to commercial innovation at the state-level**.
  - Mechanisms of informal conversations : The pool of graduates, the ideas generated by faculty and research facilities ease the process of commercial innovation in their neighborhood ⇒ **Notion of proximity**
  - Relate the production of corporate patents to industry R&D and university research ⇒ Evidence of the existence of geographically mediated spillovers.
- **Data** : 39 US state-level R&S data (NSF R&D Census), USPTO Patent data.
- Technological areas : Drugs and medical technology ; Chemicals, Electronics, optics and Nuclear Technology, Mechanical arts, Others

2.4. Empirical evidence of LKS : aggregate data

Jaffe (1989)

- Based on the **knowledge production function approach** which R&D to innovation output measures
- Dependent variable : P_{ikt} **corporate patents**, as proxy for new economically useful knowledge at the state i, technological area k and time t level

$$\log(P_{ikt}) = \beta_{1k}\log(I_{ikt}) + \beta_{2k}\log(U_{ikt}) + \beta_{3k}\log[(U_{ikt})\log(C_{ikt})] + \epsilon_{ikt}$$

- Independent variables :
  - I_{ikt} R&D performed by industry
  - U_{ikt} University research
  - C_{ikt} Measure of **geographic coincidence** of university and industry research activity within the state : the degree of overlap between university research and industry lab in a State

2.4. Empirical evidence of LKS : aggregate data

Jaffe (1989)

- **Estimation strategy : simultaneous system**
  Some university research is industry funded and firms may favor local universities in this funding or contribute to attract funding. Conversely, research universities may contribute to industrial R&D lab location decisions.
  - University research depends on industry R&D and certain state characteristics Z

$$\log(U_{ikt}) = \beta_{4k} \log(I_{ikt}) + \delta_{ik} Z_1 + \xi_{ikt}$$

  - Industry R&D depend depends on university research and state characteristics

$$\log(I_{ikt}) = \beta_{5k} \log(U_{ikt}) + \delta_{2k} Z_2 + \mu_{ikt}$$

- Controls for private inputs and state size, measured by population
- Estimation strategy : Instrumental variable / Generalized least squares = three stage least squares based on 29 observations

2.4. Empirical evidence of LKS : aggregate data

Jaffe (1989), Results

- Jaffe reclassifies patents into a restricted number of technological areas and shows that the # of patents of each US state for each technological area is a positive function of the R&D performed by local universities
- **Drawbacks**
  - **US states are too large** as units of analysis for assuming that inventors, entrepreneurs and managers living in one state will have more chances of having face-to-face contacts with each other than with people living elsewhere : state boundaries are very poor proxy for the geographical units within which knowledge ought to circulate
  - Technological areas (6 areas) are far too broad to presume any serious matching beween firms' technological competencies, corporate R&D objectives, and university research or expertise.

2.4. Empirical evidence of LKS : aggregate data

TABLE 3—SIMPLE STATISTICS

	Regression Sample				All States
	Mean	Standard Deviation	Minimum	Maximum	Mean
University R&D					
Drugs&Medical	28.50	35.34	1.39	203.53	20.01
Chem. Exc. Drugs	5.69	9.73	0.16	55.45	4.12
Electronics, etc.	20.95	49.16	0.08	385.39	14.02
Mechanical	12.68	25.63	0.15	174.45	9.12
Total	98.76	143.95	7.33	980.68	69.60
Total R&D Performed By Industry	582.89	823.52	3.76	4,328.87	n.a.
Geographic Coincidence Index	0.63	0.35	0.03	1.00	n.a.
Population (Thousands)	5,955.92	4,853.05	946	24,265	4,318.03
Total Number of Public Universities	7.88	6.02	1	30	4.60
Total Number of Private Universities	6.63	8.16	0	37	3.27
Total Number of FFRDC's	0.55	0.94	0	4	0.29
Corporate Patents					
Drugs&Medical	71.70	99.43	0	549	43.92
Chem. Exc. Drugs	201.24	249.00	1	948	131.55
Electronics, etc.	225.01	295.29	2	1,222	142.88
Mechanical	300.78	319.90	15	1,144	191.83
Total	879.37	975.70	36	3,447	564.70

Note: All dollar figures are millions of 1972 dollars. The "All States" column corresponds to the mean for the 50 states and D.C. for the 8 years (1972–77, 1979, and 1981) of the regression sample.

2.4. Empirical evidence of LKS : aggregate data

TABLE 5—OLS ON THE FULL PATENT MODEL; POOLED DATA

Variable (Parameters)	Dependent Variable: Log of Corporate Patents by Area				
	All Areas	Drugs	Chemicals	Electronics Etc.	Mechanical Arts
$\log(I_{it})$	0.713	0.892	0.758	0.714	0.628
(β_1)	(0.035)	(0.064)	(0.062)	(0.051)	(0.042)
$\log(U_{ikt})$	0.084	0.332	0.207	0.305	0.085
$(\beta_2 + \beta_1\gamma)$	(0.047)	(0.123)	(0.108)	(0.067)	(0.061)
$\log(U_{ikt})^*$	0.109	0.153	0.167	0.043	0.080
$\log(C_i)$	(0.041)	(0.079)	(0.056)	(0.034)	(0.040)
(β_3)					
$\log(U_{it})$		−0.095	−0.103	−0.161	−0.122
$(-\beta_2\gamma)$		(0.127)	(0.149)	(0.135)	(0.089)
(β_2)	0.084	0.237	0.104	0.144	−0.042
	(0.047)	(0.125)	(0.113)	(0.071)	(0.111)
(γ)		0.107	0.136	0.225	0.194
		(0.155)	(0.172)	(0.164)	(0.151)
$\log(Pop_{it})$	0.179	0.131	0.476	−0.033	0.348
	(0.068)	(0.136)	(0.117)	(0.104)	(0.076)
$\hat{\sigma}$	0.380	0.698	0.657	0.524	0.437
R^2	0.915	0.828	0.801	0.879	0.870

Notes: 232 observations. All equations include year dummies. Standard errors are in parentheses.

2.4. Empirical evidence of LKS : aggregate data

Empirical analysis of LKS Paper 2 based on patent citations = knowledge flows

Jaffe, A.B., Trajtenberg, M. & Henderson, R., 1993. Geographic Localization of Knowledge Spillovers as Evidenced by Patent Citations. The Quarterly Journal of Economics, 108(3), pp.577–598.

2.4. Empirical evidence of LKS : aggregate data

Jaffe et al. 1993

- **Aim of the paper** : Track direct knowledge flows from academic research into corporate R&D
  - Respond to Krugman (1991,p.53) : « knowledge flows... are invisible ; thy leave no paper trail by which they may be measured and tracked, and there is nothing to prevent the theorist from assuming anything about them that she likes »
- **Knowledge flows do leave paper trail** in the form of **citations**
  - Patent citations can be used to track knowledge spill-overs If one patent is citing another patent, JTH interpret this link as knowledge spill-over
  - patents provide information on the localization of the inventor
- Main hypotheses
  - If knowledge spill-overs are localized within countries, then citations of patents generated within the US should come disproportionately from within the US.
  - To the extent that regional localization of spill-overs is important, citations should come disproportionately from the same state of metropolitan area as the original document.

2.4. Empirical evidence of LKS : aggregate data

Jaffe et al. 1993

- **Empirical problem** : if a large fraction of citations to Stanford patents comes from the Silicon valley, it could be attributed to localization of spillovers **BUT** since a lot of Stanford patents related to semiconductors, and a disproportionate fraction of people in semiconductors happen to be in the Silicon valley, we would observe a correlation even without spilovers
- **Solution** : construct « control samples » of patents that :
  - do no cite the original patents
  - Are as similar as possible to the citing patents
- Test for localization based on controls
  - Calculate geographic matching frequency between citing patents and original patents
  - Calculate geographic matching frequency between controls and original patents
  - If there's geographic localization these frequencies should be different !

2.4. Empirical evidence of LKS : aggregate data

Jaffe et al. 1993 ; results and conclusion

- Knowledge spillovers leave paper trails in the form of citations and these are geographically localized
- Sample construction :

1. JTH start off with a two samples of "originating" patents
   - Cohort of 950 patents applied for in 1975
   - Cohort of 1450 patents applied for in 1980
   - Cohorts contains patents belonging to Universities, Top-10 applicants (corporate) and remaining companies
2. Identification of citing patents
   - 1975 cohort received about 4750 citations
   - 1980 cohort received about 5200 citations

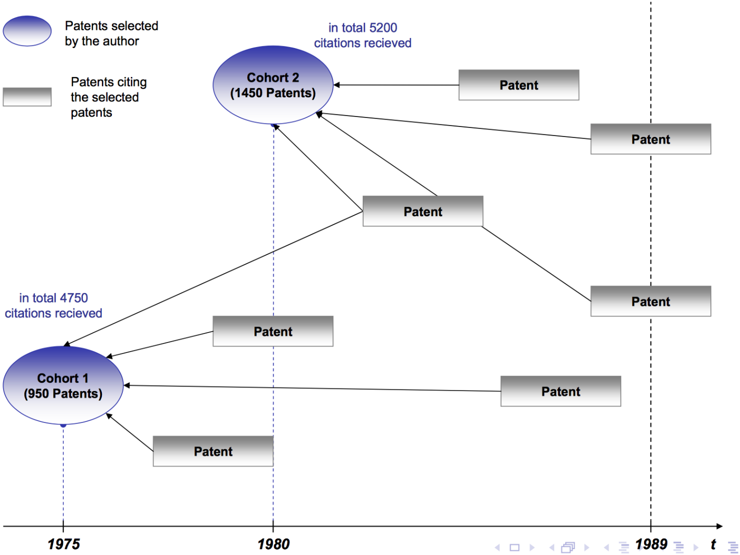
2.4. Empirical evidence of LKS : aggregate data

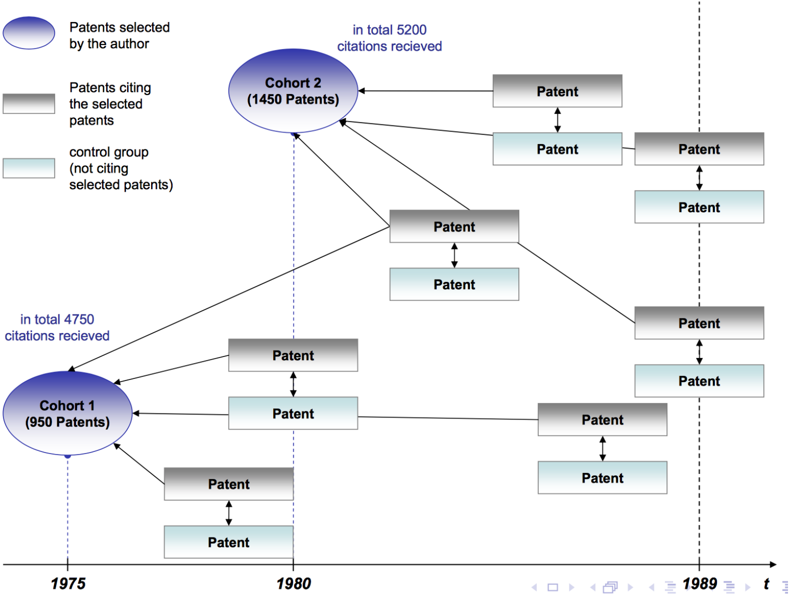
Jaffe et al. 1993 ; results and conclusion

3 Identification of control patents

- Strategy : Find for each citing patent a patent that is as similar as possible but DOES NOT cite the originating patent
- Matching via
  - Technological area (3-digit US classification system) $\rightarrow$ patents are supposed to have the same main technological area
  - Time of application

Sample construction




Patents selected by the author
Patents citing the selected patents
control group (not citing selected patents)
in total 5200 citations recieved
Cohort 2 (1450 Patents)
in total 4750 citations recieved
Cohort 1 (950 Patents)
Patent
1975
1980
1989
t

2.4. Empirical evidence of LKS : aggregate data

Jaffe et al. 1993 ; results and conclusion

- Results for 1975
  - At the SMSA level, 9 to 17 % of total citations are localized
  - This drops significantly when self-citations are excluded but 4.3. % of university citations, 4.5% of other corporate citations are localized excluding self cites
  - Regarding control matching proportions, only about 1% of citations are localized and differences are highly significant
- Results for citations of 1980 patents are stronger and more significant
- For every dataset, for every geographic level, the citations are quantitatively and statistically significantly more localized than controls

TABLE III
GEOGRAPHIC MATCHING FRACTIONS

	1975 Originating cohort			1980 Originating cohort		
	University	Top corporate	Other corporate	University	Top corporate	Other corporate
Number of citations	1759	1235	1050	2046	1614	1210
		Matching by country				
Overall citation matching percentage	68.3	68.7	71.7	71.4	74.6	73.0
Citations excluding self-cites	66.5	62.9	69.5	69.3	68.9	70.4
Controls	62.8	63.1	66.3	58.5	60.0	59.6
t-statistic	2.28	−0.1	1.61	7.24	5.31	5.59
		Matching by state				
Overall citation matching percentage	10.4	18.9	15.4	16.3	27.3	18.4
Citations excluding self-cites	6.0	6.8	10.7	10.5	13.6	11.3
Controls	2.9	6.8	6.4	4.1	7.0	5.2
t-statistic	4.55	0.09	3.50	7.90	6.28	5.51
		Matching by SMSA				
Overall citation matching percentage	8.6	16.9	13.3	12.6	21.9	14.3
Citations excluding self-cites	4.3	4.5	8.7	6.9	8.8	7.0
Controls	1.0	1.3	1.2	1.1	3.6	2.3
t-statistic	6.43	4.80	8.24	9.57	6.28	5.52

Number of citations is less than in Table I because of missing geographic data for some patents The t-statistic tests equality of the citation proportion excluding self-cites and the control proportion See text for details

2.4. Empirical evidence of LKS : aggregate data

Jaffe et al. 1993 ; critic

- Citations do not capture non-codified knowledge flows and embodied knowledge flows, which could be important sources of localized spillovers, as Saxenian (1991) and Audretsch and Feldman (1996) argue.
- Matching patents on Three-digit patent class level
  - Thompson and Fox-kean (2005) in American Economic review, argue that 3-digit level controls are misleadingly broad since there is a great deal of technological heterogeneity within classes and instead construct controls at the patent subclass level ... however Find similar results at the MSA level

2.4. Empirical evidence of LKS : aggregate data

Jaffe et al. 1993 ; critic

- Breschi and Lissoni (2005) in Annales d'Economie et Statistiques, « cross-firm inventors and social networks »,
  - Jaffe et al. results hold only for patents whose inventors are socially connected, and that short social distances greatly enhances the probability to observe co-location between cited and citing patents.
  - This is taken as evidence that geographical proximity is not a sufficient condition for accessing spillovers, as long as these circulate only within tightly knitted social networks.

2.4. Empirical evidence of LKS : aggregate data

Empirical analysis of LKS Paper 3 : knowledge externalities and spillover decay

Bottazzi L., Peri G. (2003), Innovation and spillovers in regions : Evidence from European patent data, European Economic Review, 47

2.4. Empirical evidence of LKS : aggregate data

Bottazzi L., Peri G. (2003)

- Aim of the paper : Estimate the impact of R&D resources in a representative region on innovation done in other regions at di erent geographical distances.
- This stock of knowledge increases in a region as local inventors discover new ideas. It diffuses mostly via personal contacts and face-to-face interactions.
- Spatial decay : The stock of knowledge is conceived as a "Local public good" as it benefits scientists within the region or its neighborhoods but it fades farther away as contacts and interactions decrease.
  - Localized R&D spillovers exist if the productivity of R&D in a region is a ected by the amount of R&D resources used in other regions in spatial proximity.
- Data : 86 european regions from 1977 - 1995 - Eurostat data at the NUTS 1 or NUTS 2 level of aggregation (NUTS - Nomenclature Units Territory Statistics)
- Average a period of almost 20 years to capture the long-run relationship between R&D and patenting.
- Capture intra-sector and inter-sector spillovers accros regions.

2.4. Empirical evidence of LKS : aggregate data

Bottazzi L., Peri G. (2003)

- The model

$$\Delta A_i = B(\text{R\&D})_i^{e_R} A_i^{e_0} \prod_{j \neq i} A_j^{e(dist_{ij})}, \quad i = 1, 2, \ldots, 86. \tag{1}$$

- Variables
  - A is R&D resources and existing ideas ; ΔA is the variation of the knowledge stock originated in region i measured by the number of new patents granted to researchers in that region.
  - Ideas generated in region i depends on R&D ressources in region i, on the ideas generated in other regions (A_j) depending on the distance between region i and region j.
  - Country dummies capture unobserved factors

$$\begin{aligned}\ln(\Delta A)_i &= \beta + \varepsilon_0 \ln(\text{R\&D})_i + \varepsilon_{[dist_0, dist_1)}[\underline{m}'_{i1} \ln \underline{(\text{R\&D})}] + \cdots \\ &+ \varepsilon_{[dist_n, K)}[\underline{m}'_{iK} \ln \underline{(\text{R\&D})}] + u_i, \quad i = 1, 2, \ldots, 86, \end{aligned} \tag{2}$$

2.4. Empirical evidence of LKS : aggregate data

Bottazzi L., Peri G. (2003)

- Full model

The basic specification of Eq. (2) that we estimate is the following:

$$\begin{aligned}\ln(Patent)_i = \beta &+ \varepsilon_0 \ln(R\&D)_i + \varepsilon_1 [\underline{m}'_{i[0-300]} \ln(\underline{R\&D})] \\ &+ \varepsilon_2 [\underline{m}'_{i[300-600]} \ln(\underline{R\&D})] \\ &+ \varepsilon_3 [\underline{m}'_{i[600-900]} \ln(\underline{R\&D})] + \varepsilon_4 [\underline{m}'_{i[900-1300]} \ln(\underline{R\&D})] \\ &+ \varepsilon_5 [\underline{m}'_{i[1300-2000]} \ln(\underline{R\&D})] \\ &+ D_i * (Country)_i + u_i.\end{aligned}$$

- Results : spillovers are very localized and exist only within a distance of 300 km. However the size of these spillovers is small.
- Doubling R&D spending in a region would increase the output of new ideas in other regions within 300 km only by 2–3%, while it would increase the innovation of the region itself by 80–90%.

2.4. Empirical evidence of LKS : aggregate data

Bottazzi L., Peri G. (2003) : results

Table 3
Basic specifications using R&D spending

Variables	I	II	III	IV	V	VI
$\ln(R\&D)_i$	0.95**	0.83**	0.82**	0.82**	0.82**	0.80**
	(0.05)	(0.06)	(0.06)	(0.06)	(0.06)	(0.06)
$m'_{[-300]} \ln(\underline{R\&D})$		0.030**	0.028**	0.029**	0.026**	0.025**
		(0.010)	(0.001)	(0.011)	(0.011)	(0.011)
$m'_{[30-600]} \ln(\underline{R\&D})$			0.004	0.003	0.002	−0.007
			(0.01)	(0.011)	(0.012)	(0.013)
$m'_{[60-900]} \ln(\underline{R\&D})$				(0.004)	0.005	−0.004
				(0.012)	(0.013)	(0.012)
$m'_{[90-1300]} \ln(\underline{R\&D})$					−0.010	−0.007
					(0.010)	(0.012)
$m'_{[130-2000]} \ln(\underline{R\&D})$						−0.018
						(0.012)
12 Country dummies	Yes	Yes	Yes	Yes	Yes	Yes
R^2	0.81	0.88	0.88	0.88	0.89	0.89
Observations	86	86	86	86	86	86

R&D = Regional real spending (1985 ECU) in research and development (private and public).
Dependent variable: ln(yearly patent applications).
Cross-section using 1977–1995 averages. Heteroskedasticity robust std. errors in parentheses.
*Significant at 10% level.
**Significant at 5% level.

2.5. Empirical evidence of LKS : micro data

Empirical analysis of LKS at the micro level Aharonson B., Baum J. and Feldman M. (2007), Desperately seeking spillovers ? Increasing returns, industrial organization and the location of new entrants, Industrial and Corporate Change, 2007

2.5. Empirical evidence of LKS : micro data

- Aharonson, Baum and Feldman (2007) explore the geographic scope of knowledge spillovers on entrants' locations and find
  - Knowledge spillovers are highly localized, with entrants attracted to incumbents' R&D employees and spending within 500m, but not further.
  - There increasing returns in the sense that areas concentrated in a technological domains will attract more firms in that domain.
- Data : 675 firms in biotechnology in Canada between 1991 and 2000 - 206 entrants
- Dependent variable : 0/1 for entrance in a location in a year
- Independent variables : R&D expenses and # of employees in the area at distance 0-500m, 500m-2km, 2-10km.

2.5. Empirical evidence of LKS : micro data

Table 1 Rare event logistic regression models of biotech firm entry—spillover seeking and avoidance

	Inventive activity: R & D employees						Inventive activity: R & D expenses					
	Model 1a			Model 1a(2)			Model 1b			Model 1b(2)		
	β	S.E.	P	β	S.E.	P	β	S.E	P	β	S.E.	P
Inventive activity—entrant's specialization												
<500 m	0.785	0.188	***	0.771	0.244	**	0.162	0.037	***	0.208	0.055	***
<500 m²				−0.005	0.026					−0.002	0.001	+
500 m to 2 km	0.279	0.153	*	0.278	0.160	*	0.033	0.026		0.033	0.026	
2 to 10 km	−0.051	0.043		−0.052	0.045		−0.014	0.009	+	−0.014	0.009	+
Inventive activity—other specializations												
<500 m	0.358	0.062	***	0.656	0.120	***	0.086	0.013	***	0.128	0.024	***
<500 m²				−0.023	0.008	**				−0.001	0.000	**
500 m to 2 km	−0.018	0.038		−0.021	0.039		0.001	0.008		0.000	0.008	
2 to 10 km	−0.024	0.019		−0.019	0.019		−0.002	0.004		−0.002	0.004	
Number of universities												
<500 m	3.858	0.805	***	3.729	0.801	***	3.641	0.751	***	3.583	0.757	***
500 m to 2 km	0.925	0.566	+	0.997	0.527	*	1.110	0.527	*	1.167	0.535	*
2 km to 10 km	0.355	0.298		0.420	0.301	+	0.560	0.349	+	0.651	0.350	*
Fixed effects												
Entry group	incl.			incl.			incl.			incl.		
Region	incl.			incl.			incl.			incl.		
Technological specialization	incl.			incl.			incl.			incl.		
Year	incl.			incl.			incl.			incl.		
Log likelihood	−448.30			−442.99			−447.38			−443.90		
Likelihood ratio test				10.620	* (2 df)					6.960	* (2 df)	

Notes: *P*-level: + <0.01; *<0.05; **<0.01; ***<0.001; the sample included 1236 0bservations (206 entry postal codes; 1030 random non-entry postal codes); Incl. Included.

2.5. Empirical evidence of LKS : micro data

Table 2 Rare event logistic regression models of biotech firm entry—controlling for increasing returns

	Model 2a			Model 2b		
	R&D employees			R&D expenses		
	β	S.E.	P	β	S.E.	P
Inventive activity—Entrant's specialization						
<500 m	1.961	0.539	***	0.484	0.153	**
<500 m²	−0.266	0.116	**	−0.016	0.008	*
500 m to 2 km	0.300	0.165	*	0.036	0.029	
2–10 km	−0.042	0.047	*	−0.012	0.010	
Concentration—entrant's specialization						
<500 m	74.841	25.664	**	47.465	19.277	**
× Inventive Activity <500m	−74.221	28.095	**	−13.493	3.864	***
× Inventive Activity <500m²	11.260	4.884	**	0.539	0.241	*
Inventive activity—other specializations						
<500 m	0.653	0.124	***	0.128	0.025	***
<500 m²	−0.022	0.008	**	−0.001	0.000	**
500 m to 2 km	−0.021	0.040		0.001	0.008	
2–10 km	−0.018	0.019		−0.002	0.004	
Number of universities						
<500 m	3.717	0.786	***	3.626	0.744	***
500 m to 2 km	0.923	0.570	+	1.096	0.537	*
2–10 km	0.396	0.293		0.616	0.352	*

2.6. Localized Knowledge Spillovers : a black box

- **LKS is no more than a « black box »**
  - Knowledge spillovers or knowledge externality is a summary variable for a number of knowledge flows
  - Too little attention devoted to the origin of the LKS concept, which is a by-product of the production function view of innovation processes
  - Fuzzy concept when associated with « tacitness » and intended as an intrinsic property of scientific and/or technical knowledge, and said to require physical proximity for knowledge to be exchanged.
- All studies on LKS (Feldman, 1999, Audretsch and Feldman, 2004) are unanimous in concluding that knowledge spillovers, either intra-industry or inter-industry are important and **strongly bounded in space.**

2.6. Localized Knowledge Spillovers : a black box

- **The unverified story** usually told assumes that employees and managers of firms near to universities and other innovative firms will be the first to be acquainted with the results of important discoveries
  - Knowledge generated within innovative firms and/or universities is somehow transmitted to other firms
  - Knowledge that spills over is a (pure) public good, it is freely available to those wishing to invest in searching for it (non-excludablility) and may be exploited by more than a few users at the same time (non-rivalry)
  - The knowledge that spills over is mainly « tacit », i.e. highly contextual and difficult to codify, and is therefore easily transmitted through face-to-face contacts and personal relationships, which require spatial proximity ; in other words it is a public good, but a local one.
- Need for better analysis of knowledge flows and underlying mechanisms

3. Knowledge flows/diffusion mechanisms

3. Knowledge flows/diffusion mechanisms

- Localized knowledge spillovers is a black box
- None of the previous studies address the mechanisms by which knowledge spillovers are realized.
  - **Ideas are embodied in individuals** who have the skill, knowledge and know-how to engage in technological advance (Zucker and Darby, 1996 ; 1997).
    - The role of Star scientists as mechanisms of knowledge diffusion from university to industry
  - **Inter-firm mobility** as a mean to trace the transfer of ideas. Almeida and Kogut (1997,1999), using patent citations, show that mobility affects positively the innovation rate of local firms
  - **The role of interpersonal ties** and networks as means of knowledge diffusion (Singh, 2005 ; Cassi and Plunket, 2015).

3.1. Skilled workers mobility as carriers of knowledge

- Labour mobility must help spreading knowledge from one firm to another, from one place to another
- Labour mobility generates **pure knowledge spillovers** if and only if, as workers move from one firm to another, they help in **creating a common pool of knowledge** from which all their previous employers are capable of drawing
- Patent data provide a mean to test whether skilled mobility can explain the observed concentration of knowledge flows in space
- **Pioneering study : Almeida and Kogut (1999)** in Management science :
  - Interfirm mobility of inventors in US semiconductor industry influences the local transfer of knowledge across firms
  - Geographical coincidence of the top25% most highly cited patents and citing patents.
  - For each citing patent, they identify a control patent
  - Suggests that **knowledge spillovers go along with mobility within spatially defined labor markets**

3.1. Skilled workers mobility as carriers of knowledge

- **Breschi and Lissoni (2009)** in Journal of Economic Geography, consider the role of spatial and social distance between inventors on US data
  - **Social distance between two inventors** is measured by the # of collaboration ties that separate them
  - The role of **spatial proximity is lowered when social proximity is controlled for**. This argues against knowledge spillovers ! !
  - Knowledge flows are not in the air but follow formel channels (= mobility and co-invention)

3.1. Skilled workers mobility as carriers of knowledge

Breschi and Lissoni (2009)

- **Data :** Citations to patents from inventors in the US in pharmaceuticals, organic chemicals and biotechnology.
- 66.349 patents, 5.820 organizations, 63.188 inventors
- Patent citing-cited and control - cited (same year and same technology)
- 2 variables
  - geographic co-localization based on inventors adress
  - Type of links between inventors - 3 groups
    - Mobility : The citing and cited patent are produced by the same inventor but organizations are different
    - Connected : Inventors from the cited and citing patents are linked within a co-inventor network with finite distance
    - Non connected : Inventors are not connected within the network.

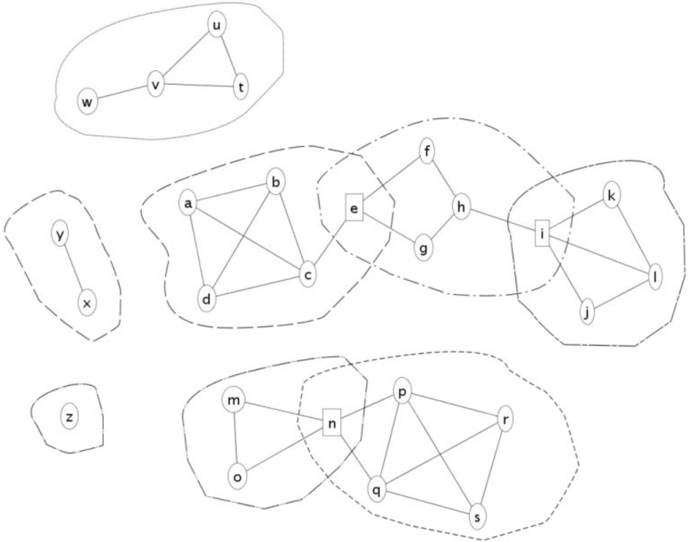


Figure 1. A snapshot of the network of inventors at time t.

Table 3. Sample of citing, cited and control patents

Patent pairs	Number	Type of links (% of all pairs)		
		Connected		Not connected
		Mobility (social distance $= 0$)	Co-invention network (social distance > 0)	(social distance $\to \infty$)
Citing-cited	3700	5	25.9	69.1
Control-cited	3700	0.2	19.6	80.2

Table 4. Distance between connected patent pairs (co-invention network)

Distance	Citing-cited	Control-cited
1	5.2	1.1
2–5	17.1	13.4
6–10	46.3	32.6
10–20	28.3	40.5
>20	3	4.3
Average	9.2	10.5
Median	8.5	9.5
Std deviation	10.5	11.7

Table 5. Geographical matching at the MSA and state levels

	Number of observations	Citing cited	Control cited	z-test ($P > z$)	Odds ratio
MSA level					
All patent pairs (JTH experiment)	3700	17.4	10.8	8.1 (0.00)	1.73
All pairs except those linked by mobility (social distance = 0)	3512	13.5	10.8	3.5 (0.00)	1.29
All pairs except those connected at social distance ≤ 5	3217	11.8	9.9	2.5 (0.01)	1.22
Only not connected pairs	2299	11.7	9.4	2.5 (0.01)	1.21
State level					
All patent pairs (JTH experiment)	3700	20.8	14	7.8 (0.00)	1.62
All pairs except those linked by mobility (social distance = 0)	3512	17.2	13.8	3.9 (0.00)	1.3
All pairs except those connected at social distance ≤ 5	3217	15.5	13	3.0 (0.00)	1.24
Only not connected pairs	2299	15.1	12.5	2.5 (0.01)	1.24

Table 7. Citing patents' probability of co-location with cited ones, at the MSA and state level: Logit regressions

	MSA			State		
	(1)	(2)	(3)	(4)	(5)	(6)
Intercept	−2.06***	−2.12***	−2.01***	−1.80***	−1.84***	−1.75***
	(0.07)	(0.060)	(0.055)	(0.060)	(0.060)	(0.0512)
Control-cited co-location	0.67***	0.68***	0.72***	0.73***	0.76***	0.7707***
	(0.142)	(0.138)	(0.135)	(0.118)	(0.114)	(0.113)
	[1.5–2.5]	[1.5–2.6]	[1.6–2.7]	[1.6–2.6]	[1.7–2.7]	[1.7–2.7]
Citing-cited social distance = 0	4.40***			4.08***		
	(0.271)			(0.270)		
	[48.1–139.3]			[34.9–100.5]		
Citing-cited social distance = 1	2.11***			1.77***		
	(0.295)			(0.294)		
	[4.6–14.7]			[3.3–10.4]		
Citing-cited social distance = 2	1.56***			1.48***		
	(0.35)			(0.344)		
	[2.4–9.4]			[2.2–8.6]		
Citing-cited social distance = 3	1.63***			1.38***		
	(0.449)			(0.447)		
	[2.1–12.3]			[1.7–9.6]		
Citing-cited social distance = 4	1.21***			1.20***		
	(0.354)			(0.338)		
	[1.7–6.7]			[1.7–6.5]		
Citing-cited social distance = 5	0.91***			0.59*		
	(0.308)			(0.306)		
	[1.4–4.5]			[0.99–3.3]		
Citing-cited social distance = 6	1.11***			0.98***		
	(0.260)			(0.250)		
	[1.8–5.0]			[1.6–4.3]		

	[illegible]			[illegible]		
More social distance dummies[a]						
Citing-cited inverted soc. distance		2.35***			2.06***	
		(0.269)			(0.265)	
		[6.2–17.8]			[4.7–13.4]	
Control-cited inverted soc. distance		0.63			0.456	
		(0.557)			(0.527)	
		[0.6–5.6]			[0.6–4.4]	
Mobile inventor btw. citing-cited		2.07***			2.04***	
		(0.366)			(0.364)	
		[3.9–16.3]			[3.8–15.7]	
Mobile inventor btw. control-cited		−2.31			−2.34	
		(1.727)			(1.639)	
		[0.003–2.9]			[0.01–2.4]	
Citing-cited social proximity			4.53***			4.17***
			(0.276)			(0.270)
			[53.9–159.2]			[38.3–110.4]
Control-cited social proximity			−0.02			−0.49
			(1.018)			(1.034)
			[0.1–7.2]			[0.08–4.7]
L-ratio test	693.99***	625.15***	602.43***	630.81***	559.70***	541.76***
Aikake information criterion	2807.7	2800.5	2819.3	3241.8	3236.9	3250.9
Bayesian information criterion	3081.2	2837.8	2844.1	3515.3	3274.2	3275.8
Nagelkerke R-square	0.284	0.258	0.249	0.245	0.219	0.213
Obs	3700	3700	3700	3700	3700	3700

Note: Std error in brackets; 95% confidence odds ratios in square brackets.[a]Citing-cited soc. distance dummies from 7 to 20 and control-cited from 1 to 20 (none significant). Significant at ***99%, **95%, *90%.

3.1. Skilled workers mobility as carriers of knowledge

- **Breschi and Lissoni (2009)** show that
  - Mobility of inventors across firms occurs largely within the same locations because **individuals are little mobile in space**
  - Many citations occurring between firms are in fact personal self-citations by mobile inventors
  - ⇒ The same inventors by joining different teams, **end up building a localized collaboration networks** which explains citations flows
- **Agrawal, Cockburn and McHale, (2006)**, « Gone but not forgotten » in Journal of Economic geography show that
  - Citations to mobile inventors' patents filed after their transfer from one city to another **come disproportionately from their prior locations.**
  - Mobile inventors do not only transfer knowledge from their original location to their destinations, but also allow for the **opposite flows**, thanks again to social networks

3.2. The role of interpersonal ties and other proximities

- **Social or professional networks** may facilitate knowledge flows between individuals because it lowers the cost of accessing knowledge between members (Sorenson et al. 2006).
- Membership in multiple overlapping networks helps reinforce the bonds of trust that facilitate exchange of tacit knowledge (Coleman, 1988).
- Singh (2005) in Management Science use USPTO data
  - Existence of interpersonal ties in the form of co-patents increases the probability of knowledge flows, as measured by patent citations
  - Ties are critical to explain knowledge flows within regions and within firms' boundaries, as opposed to inter-regional and inter-organizational flows
  - Geography matters only because interpersonal networks tend to be regional in nature = the effect of regional or firm boundaries on knowledge flow decreases once interpersonal ties are accounted for

Conclusions

- Innovation is geographically localized
- Geographical proximity plays an important role besides other forms of proximity (industrial, technological, social.)
- Knowledge is not in the air but follows specific formal and informal channels.
- Policy recommendations : Favor collaborations inter-firm and inter-region within and across technological domains.

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