



# **Empirical Strategies to Analyze Regional Innovation Dynamics**

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# Structure of the lecture

- 1. Introduction: The importance of geography for innovation dynamics
- 2. Empirical analyses of the relationship between regional innovation and growth
- 3. Empirical analyses of the regional dimension of innovation dynamics

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- Why do we care about the regional dimension of innovation dynamics ?
- On the one hand, since the seminal works by Schumpeter (1912 and 1945), innovation has be regarded as key for economic development.
- From a different perspective, Solow (1957) showed that the residual, i.e. technical progress, is the main responsible of macroeconomic growth.
- Such residual is affected by innovation and technological change.
- However, the generation of technological knowledge, as well as growth dynamics, show a high degree of cross-regional variance even within the same country.
- It is very likely therefore that innovation dynamics can explain economic growth at the regional level

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- On the other hand, the very dynamics of innovation take place at the regional or local level.
- Allen (1983) provides a former contribution on the collective dimension of inventive activities.
- Some years later von Hippel (1988) published his "The sources of innovation", in which he stresses the importance of interaction dynamics and user-producer linkages
- In the same years Lundvall (1992) and Nelson (1993) published edited volumes on Innovation Systems, emphasizing the cumulativeness of knowledge as well as the importance of the interactions amongst a variety of institutional actors directly or indirectly involved in the innovation process

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- The collective and interactive dimension of technological knowledge (see also Foray, 2004) raises the issue of the proximity of innovating agents
- The Regional Innovation Systems (RIS) approach in this perspective stresses the relevance of different institutional assets at the regional level,
- degree of tacitness of the knowledge base, the presence of interface mechanisms among production, technological and scientific contexts, the variety of interaction process among firm (Storper, 1995a and 1995b; Scott and Storper, 1995; Cooke et al., 1997)

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- On complementary grounds, the intrinsic limits of knowledge in terms of appropriability (Arrow, 1962) leads to the issue knowledge spillovers.
- Griliches (1992) proposes the distinction between embodied and disembodied spillovers
- Disembodied spillovers are "[...] ideas borrowed by research teams of industry I from the research results of industry j. It is not clear that this kind of borrowing is particularly related to input purchase flows" (Griliches (1992), p. S36).

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- The distinction between tacit and codified knowledge becomes important in this respect
- Geographic proximity matters in transmitting knowledge, because tacit knowledge is inherently non-rival in nature, and knowledge developed for any particular application can easily spill over and have economic value in very different applications.
- von Hipple (1994) explains that sticky knowledge , is best transmitted via face-to-face interaction and through frequent and repeated contact.
- the marginal cost of transmitting knowledge, especially tacit knowledge, is lowest with frequent social interaction, observation and communication (Audretsch and Feldman, 2003)

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- Knowledge spillovers have proved to be geographically clustered, and firms are likely to base their location choices on the opportunities of taking advantages of the positive feedbacks associated to knowledge externalities (Audretsch and Feldman, 1996; Baptista and Swann, 1998).
- the spatial concentration applies above all when informal rather than formal cooperation ties are at work (Audretsch and Stephan, 1996)

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- Knowledge spillovers have been seen as a case of pure technological externalities, being knowledge available at no costs in local contexts, and freely accessible by everyone "being there".
- The issue proximity needs however to be properly addressed
- For a critical review see Breschi and Lissoni (2001)

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- In view of the twofold dimension of the relationship between geography and innovation, we will discuss:
- Empirical contributions analyzing the effects of innovation on regional growth
- Empirical analyses of the spatial dynamics of innovation

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![](_page_10_Figure_4.jpeg)

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- The theorical approach initiated by Solow has paved the way to a stream of empirical literature focusing on the determinants of economic convergence across countries.
- The hypothesis of conditional convergence (less heroic than the absolute) states that it is important to control for country-specific factors (see the seminal works by Barro and Sala-i-Martin)
- In this stream of literature there has been little or no attention to the role of technology.
- An exception is the work by Bernard and Jones (1996a and b), who proposedan alternative index of productivity, the Total Technological Productivity (TTP), to account also for the changes in technology affecting output elasticities rather than the parameter A in the production function
- No analyses at the regional level (see Quatraro[2006] for an application to the Italian case).

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- A strategy to analyze the impact of innovation on economic growth relies on Solow's model for what concerns the calculation of the growth of multifactor productivity (MFP) at the regional level
- Then model productivity growth as a function of innovation
- Antonelli, Patrucco and Quatraro (2011, Economic Geography) propose a model to assess the effects of knowledge externalities to MFP growth

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# Innovation and Regional Growth

- MFP can be derived as follows:  $\frac{dA}{A} = \frac{dY}{Y} - (1 - \overline{\beta}) \left(\frac{dK}{K}\right) - \overline{\beta} \left(\frac{dL}{L}\right)$
- The relationship between MFP and knowledge externalities becomes:

$$\frac{dA}{A} = f(\ln A_{i,t-1}, D_{t-1})$$

• the growth rate of MFP is modeled as a function of the density of technological activities, which we call  $D_{it}$ 

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- Measurement problem: how to proxy innovation?
- Measures of input (R&D) and output (patents, trademarks, etc.)
- R&D measures are derived by firms' balance sheets, which are often unreliable in this respect
- It can happen that these figures are inflated in order to obtain special government aids or lower taxation

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- As a measure of output, the most used data are drawn from the Community Innovation Surveys (CIS) or from patent offices.
- the agglomeration of technological activities is measured as the ratio between the regional level of patenting and the total labour force:

$$D_{i,t} = \frac{PAT_{it}}{L_{it}}$$

![](_page_16_Picture_0.jpeg)

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- The baseline equation to be estimated is:  $\frac{dA}{dt} = a + b \ln A_{t-1} + c_1 D_{t-1} + c_2 D_{t-1}^2 + dX_{t-1} + \rho_i + \sum \psi t + \varepsilon_i$
- $\frac{dA}{A} = a + b \ln A_{t-1} + c_1 D_{t-1} + c_2 D_{t-1}^2 + dX_{t-1} + \rho_i + \sum \psi t + \varepsilon_{i,t}$  Problem of spatial dependence: there can be correlation amongst the errors terms of neighbour regions
- Possible biases in the estimates call for the adoption of spatial econometric techiques:
  - Spatial error model
  - Spatial autoregressive model

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# Innovation and Regional Growth

• The new equations to be estimated are:

$$\frac{dA}{A} = \xi W \left(\frac{dA}{A}\right) + b \ln A_{i,t-1} + c_1 D_{t-1} + c_2 D_{t-1}^2 + dX_{t-1} + \rho_i + \sum \psi t + \varepsilon_{i,t}$$
SAR model

and

$$\frac{dA}{A} = b \ln A_{i,t-1} + c_1 D_{t-1} + c_2 D_{t-1}^2 + dX_{t-1} + \rho_i + \sum \psi t + \varepsilon_{i,t} + \phi_t$$
SEM model
$$\phi_t = \delta W \phi_t + \mu_t \quad E(\mu_t) = 0 \qquad E(\mu_t \mu_t) = \sigma^2 I_N$$

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#### Innovation and Regional Growth

			Table	e 2			
Region TFP Growth, Panel Data Fixed Effects Estimates							
Variable :	I	2	3	4	5	6	7
Constant	0.157*** (0.065)	0.178*** (0.066)	-0.039 (0.061)	-0.041 (0.061)	-2.14*** (0.648)	-0.011 (0.061)	-0.001 (0.516)
In A <sub>P1</sub>	-0.051** (0.024)	-0.061*** (0.024)	0.017 (0.022)	0.017 (0.023)	0.032 (0.024)	0.002 (0.022)	0.034 (0.025)
D,	0.191* (0.11)	1.096*** (0.405)	1.484*** (0.356)	(0.459)	1.348*** (0.379)	0.844*** (0.277)	0.717*** (0.287)
$D_{t-1}^2$		-2.441*** (1.030)	-3.52*** (0.903)	_3.509*** (0.907)	-3.294*** (0.961)	-2.051*** (0.707)	- 1.707** (0.707)
SPEC⊢⊤			0.015 (0.012)	0.015 (0.012)	0.009 (0.013)	-0.013 (0.012)	
DenSPECer				0.012 (0.841)			
ACCL-1					0.399*** (0.127)		- 0.081 (0.101)
ശവും					· ·	0.054**	`0.029´ (0.038)
Observations nl	827	827	701	701	633	514	457
n	021	0.22	0.27	0.27	0.50	0.40	0.43

Note: \* p < 0.1; \*\* p < .05; \*\*\* p < .0.01. Unbalanced panel. Standard errors in parentheses. All regressions include time dummy variables.

![](_page_19_Picture_0.jpeg)

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#### Innovation and Regional Growth

		Tab	ole 4			
Regional TFP Growth, Spatial Autoregressive Model for Panel Data						
Variable:	I	2	3	4	5	6
W <sup>c</sup> (d'log A/dt)	0.256** (2.054)	0.403*** (3.822)	0.257**	0.399*** (3.757)	0.243** (1.941)	0.380*** (3.53)
In A <sub>P-1</sub>	-0.315*** (-7.77)	-0.288*** (-7.551)	-0.316*** (-7.794)	_0.289*** (-7.57)	-0.327*** (-7.955)	-0.30(*** (-7.824)
D1	2.48*** (4.105)	2.079*** (3.897)	2.49[***	2.103*** (3.939)	3.345*** (4.176)	3.070*** (4.422)
D <sup>2</sup> <sub>1-1</sub>	-5.313*** (-3.435)	-4.389*** (-3.123)	-5.323*** (-3.447)	-4.447*** (-3.161)	-5.608*** (-3.587)	-4.594*** (-3.265)
SPEC1			0.010 (0.436)	0.011 (0.483)	0.018 (0.782)	0.022 (0.942)
D <sub>F1</sub> :SPBC <sub>F1</sub>					-2.417** (-1.72)	-2.990*** (-2.176)
Regional dummy variables	Yes	Yes	Yes	Yes	Yes	Yes
Time dummy variables	No	Yes	No	Yes	No	Yes
Observations	42.4	424	424	42.4	424	424
Log-likelihood	792.083	757.624	792.201	757.583	793.397	761.846
R"	0.27	0.24	0.27	0.24	0.28	0.2.4

Note: \*  $\beta < 0.1$ ; \*\*  $\beta < .05$ ; \*\*\*  $\beta < .0.01$ . Balanced panel. Test of Student in parentheses.

![](_page_20_Picture_0.jpeg)

![](_page_20_Picture_2.jpeg)

- In the same perspective, the relationship between technological knowledge and regional economic growth can be assessed by digging into the heterogenous nature of technological knowledge
- Actually the simple count of patents, or even more sophisticated indexes of knowledge stock, do not allow to grasp the dynamics of leading to the generation of knowledge

![](_page_21_Picture_0.jpeg)

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- We know knowledge is the outcome of a collective effort, in which innovating agents combine pieces of knowledge dispersed in the technology landscape (Fleming and Sorenson, 2001 and 2004; Weitzman, 1998)
- The combinatorial process may put together pieces of knowledge either highly complementary and similar, or loosely related
- The former pattern is mostly observed in periods of exploitation, while the latter in periods of exploration of the technology lifecycle

![](_page_22_Picture_0.jpeg)

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- The information contained in patent applications, namely technological classes, can be used to derive indicators of average complementarity and dissimilarity amongst technologies of patent portfolios at different levels of aggregation
- As for the regions, these indicators of knowledge coherence and cognitive distance allow for assessing the relationship between the stage of the technology lifecycle and the economic performance

![](_page_23_Picture_0.jpeg)

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#### Innovation and Regional Growth

![](_page_23_Figure_4.jpeg)

#### Process for amplifying nucleic acid sequences.

The single cell of the matrix  $\Omega$  is the frequency by which two specific technologies occur together in the k patents of the database. The relatedness index  $\tau$  between technologies is obtained by standardizing the frequency of co-occurrence for each pair of technologies. The idea behind the coherence index is that if two technologies occur together more frequently than the expectation, they are likely to be complementary. The same principle applies to the technological proximity index (S<sub>ij</sub>). The idea is that two technologies I and j are more similar the higher the frequency by which the both of them co-occur with the same technologies m, i.e. the higher the number of co-occurring technologies that they have in common.

![](_page_24_Picture_0.jpeg)

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• In Quatraro (2010, Research Policy) a model is proposed linking the growth of regional MFP to the properties of the knowledge base

 $g_{i,t} = f(K_{i,t-1})$ 

Assume that a region is a bundle of D productive activities, represented by the vector P. Each regional activity p<sub>d</sub> draws mainly upon a core scientific and technological expertise e<sub>d</sub>, so that the regional total expertise is the vector E.

![](_page_25_Picture_0.jpeg)

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- The regional knowledge base emerges out of a local search process aimed at combining different and yet related technologies
- This implies that an activity p<sub>d</sub> may also take advantage of the expertise developed in other activities I (), depending on the level of relatedness τ between the technical expertise e<sub>d</sub> and e<sub>l</sub>.
- It follows that the knowledge base k used by the dth activity is:

• 
$$k_d \equiv e_d + \sum_{l \neq d}^D e_l \tau_{ld}$$

![](_page_26_Picture_0.jpeg)

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- The knowledge base k of each activity d amounts to the sum of its own expertise and the expertise developed by other activities weighted by their associate relatedness.
- Such equation can be generalized at the regional level to define the aggregate knowledge base:
  K ≡ ∑<sub>d</sub><sup>D</sup> e<sub>d</sub> + ∑<sub>d</sub><sup>D</sup> ∑<sub>l≠d</sub><sup>D</sup> e<sub>l</sub>τ<sub>ld</sub>
  K ≡ E[1+(D-1)R]

![](_page_27_Picture_0.jpeg)

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Methodology to derive the regional MFP using regional accounting data

$$\ln\left(\frac{A_i(t)}{A_i(t-1)}\right) = \ln\left(\frac{Y_i(t)}{Y_i(t-1)}\right) - (1-\overline{\beta})\ln\left(\frac{C_i(t)}{C_i(t-1)}\right) - \overline{\beta}\ln\left(\frac{L_i(t)}{L_i(t-1)}\right)$$

- MFP growth as a function of E, R and D (knowledge stock, coherence and diversiy)
- Also in this case a check is in order to test whether results are robust also to the application of estimators accounting for spatial dependence

![](_page_28_Picture_0.jpeg)

![](_page_28_Picture_2.jpeg)

#### Innovation and Regional Growth

#### Table 3

Panel data estimates of Eq. (12).

	(1)	(2)	(3)	(4)
Intercept	-0.212** (0.093)	0.203" (0.93)	-0.295 (0.101)	-0.302 (0.102)
$\log A_{t-1}$	0.0315 (0.022)	0.0223(0.021)	0.041* (0.023)	$0.0399^{\circ}(0.022)$
$log(E)_{t-1}$	0.0212** (0.009)	0.028 (0.009)	0.0185** (0.008)	0.0173 (0.010)
$log(R)_{t-1}$	0.0878*** (0.035)	0.0792" (0.035)	0.0911*** (0.035)	0.0929*** (0.035)
$log(TV)_{t-1}$	0.0153" (0.007)			
$log(UTV)_{t-1}$		0.0007 (0.001)		0.0011 (0.002)
$log(RTV)_{t-1}$			0.005** (0.002)	0.005 (0.002)
log(AGGL)t-1	-0.0007 (0.002)	-0.0018 (0.003)	-0.0012(0.003)	-0.0012(0.003)
$log(LOQ)_{t-1}$	-0.1581 <sup>***</sup> (0.032)	-0.1506*** (0.032)	-0.1725 (0.033)	-0.1743 <sup>***</sup> (0.033)
Regional dummies	Yes	Yes	Yes	Yes
Time dummies	Yes	Yes	Yes	Yes
Rsq	0.33	0.32	0.33	0.33
F	6.55***	6.33***	6.61 <sup>***</sup>	6.37***
Ν	395	395	395	395

Dependent variable:  $log(A_t/A_{t-1})$ . Standard errors between parentheses.

p< 0.01.</p>

<sup>•</sup> p < 0.1.

<sup>&</sup>quot; p < 0.05.

![](_page_29_Picture_0.jpeg)

![](_page_29_Picture_2.jpeg)

#### Innovation and Regional Growth

#### Table 4

Results for the estimation of Eq. (14) (Spatial Autoregressive Model).

	(1)	(2)	(3)	(4)
$\log A_{t-1}$	-0.012 (-0.914)	-0.012(-0.92)	-0.005(-0.40)	-0.005(-0.38)
$W[\log(A_t/A_{t-1})]$	0.188 (1.98)	0.188 (1.98)	0.190 (1.99)	0.190 (1.80)
$\log(E)_{t-1}$	0.0145 (1.99)	0.014*** (3.22)	0.006 (1.19)	0.006 (0.87)
$log(R)_{t-1}$	0.081 (2.36)	0.081** (2.28)	0.091 (2.52)	0.091 (2.51)
$log(TV)_{t-1}$	-0.001 (-0.14)			
$log(UTV)_{t-1}$		-0.0002 (-0.11)		0.003 (1.36)
$log(RTV)_{t-1}$			0.003 (1.36)	0.0002 (0.147)
$log(AGGL)_{t-1}$	-0.005 <sup>***</sup> (-4.15)	-0.004 <sup>***</sup> (-4.15)	-0.004**** (-4.22)	-0.004 (-4.21)
$log(LOQ)_{t-1}$	-0.131*** (-4.08)	-0.131 <sup>***</sup> (-4.09)	-0.143*** (-4.32)	-0.144 (-4.31)
Regional dummies	Yes	Yes	Yes	Yes
Time dummies	Yes	Yes	Yes	Yes
Log-likelihood	653.18	653.17	663.4	654.07
N	395	395	395	395

Dependent variable:  $log(A_t/A_{t-1})$ . t of Student between parentheses.

p<0.1.

p < 0.05.

\* p<0.01.

![](_page_30_Picture_0.jpeg)

![](_page_30_Picture_2.jpeg)

- Evolutionary Economic Geography (EEG)
- What matters of regional economic growth is variety of economic activities
- Regional branching
- New activities emerge out of the sectors in which the region is specialized
- New activities related to those already in place are more likely to persist and to exert a significant effet on growth than unrelated activities

![](_page_31_Picture_0.jpeg)

![](_page_31_Picture_2.jpeg)

- According to the EEG approach, novelty is brought about in the region through different channels:
  - Spinoffs
  - Labour mobility
  - Network linkages
  - Diversification of firms

![](_page_32_Picture_0.jpeg)

![](_page_32_Picture_2.jpeg)

- the higher related variety in a region, the higher regional growth
- Frenken *et al.* (2007) for the Netherlands, confirmed by studies in other countries
- regional growth: may also depend on extra-regional knowledge flows
- Boschma and Iammarino 2009, *Economic Geography*, study on related variety, trade linkages and regional growth in Italy
- inflows of extra-regional knowledge related (but not identical) to the knowledge base in a region do matter for regional growth
- this concerns new knowledge that can be understood and exploited by related sectors in the region and, thus, be transformed into regional growth

![](_page_33_Picture_0.jpeg)

![](_page_33_Picture_2.jpeg)

- through entrepreneurship, new industries emerge, but these do not start from scratch: relatedness is again crucial
- empirical study on the spatial evolution of British automobile sector 1895-1968 (Boschma and Wenting, *Industrial and Corporate Change*, 2007)
- related knowledge and skills are transferred from old sectors (engineering, cycle making, coach making) to the new (automobile) sector: this increased their survival rate, in comparison to other types of entrepreneurs

![](_page_34_Picture_0.jpeg)

![](_page_34_Picture_2.jpeg)

- The creation of new firms is therefore shaped by the characteristics of the local economies
- The EEG approach can be combined with the knowledge spillovers theory of entrepreneurship (KSTE) to deepen the understanding of the features of the local knowledge base which do matter
- Colombelli and Quatraro (2014, WP) analyze the link between the creation of new firms and the structure of knowledge base at the NUTS 3 level in Italy

![](_page_35_Picture_0.jpeg)

![](_page_35_Picture_2.jpeg)

- The idea is that prospective entrepreneurs take advantage of unexploited knowledge available in the local environment
- We raise the basic question as to what extent the creation of new firms is more likely to take advantage of exploitation or exploration phases
- The baseline equations to be estimated are:

• 
$$NEWFIRM_{i,t} = \exp \left(a + \beta_1 KSTOCK_{i,t-3} + \mathbf{Z}\gamma + \rho_i + \sum \psi t + \varepsilon_{i,t}\right)$$
$$NEWFIRM_{i,t} = \exp \left(a + \beta_2 COH_{i,t-3} + \beta_3 CD_{i,t-3} + \beta_4 KV_{i,t-3} + \mathbf{Z}\gamma + \rho_i + \sum \psi t + \varepsilon_{i,t}\right)$$

![](_page_36_Picture_0.jpeg)

![](_page_36_Picture_2.jpeg)

	(1)	(2)	(3)	(4)	(5)	(6)
KSTOCK	0.1860 <sup>***</sup> (0.0507)					0.1014 <sup>*</sup> (0.0601)
сон		-0.1207** (0.0516)	-0.1377*** (0.0524)	-0.0432 (0.0510)	-0.1301** (0.0517)	-0.1535*** (0.0551)
CD		0.7125 <sup>**</sup> (0.3548)	0.7605 <sup>**</sup> (0.3614)	0.7587 <sup>**</sup> (0.3601)	0.7491 <sup>**</sup> (0.3531)	0.7485 <sup>**</sup> (0.3560)
KV		0.2296 <sup>***</sup> (0.0303)				0.2091 <sup>***</sup> (0.0326)
RKV			0.2232*** (0.0302)		0.1932*** (0.0306)	
UKV				0.2355*** (0.0417)	0.1735 <sup>***</sup> (0.0417)	
POP_DENS	0.1822*** (0.0252)	0.1288 <sup>***</sup> (0.0258)	0.1238*** (0.0259)	0.1510*** (0.0261)	0.1261*** (0.0257)	0.1321 <sup>***</sup> (0.0258)
FIRM_DENS	0.8106*** (0.0853)	0.9539*** (0.0874)	0.9482*** (0.0872)	0.9467*** (0.0892)	0.9446*** (0.0865)	0.9444*** (0.0873)
IND_DIV	3.1626*** (0.4635)	3.0434*** (0.4984)	2.6566*** (0.4967)	3.1727*** (0.5117)	3.0022*** (0.4990)	3.0943 <sup>***</sup> (0.4986)
UNEM	0.2152*** (0.0377)	0.2119*** (0.0388)	0.2074*** (0.0387)	0.2003*** (0.0393)	0.2097*** (0.0384)	0.2219*** (0.0391)
INC	0.2423*** (0.0216)	0.2482*** (0.0221)	0.2476*** (0.0221)	0.2566*** (0.0223)	0.2458*** (0.0219)	0.2420*** (0.0223)
DIST	-0.0331*** (0.0085)	-0.0384 <sup>***</sup> (0.0088)	-0.0351*** (0.0088)	-0.0389 <sup>***</sup> (0.0090)	-0.0371*** (0.0088)	-0.0395*** (0.0089)

![](_page_37_Picture_0.jpeg)

![](_page_37_Picture_2.jpeg)

- Spatial dependence may affect the dynamics of new firm creation (Andersson, 2005; Plummer, 2010).
- Former treatment of spatial econometric issues can be found in Anselin (1988), subsequently extended by Le Sage (1999).
- There are different ways to cope with this issue:
  - one may apply spatial filters to the sample data, so as to remove the spatial structure and then apply traditional estimation techniques.
  - Second, the relationship can be reframed by using different kinds of models for panel data

![](_page_38_Picture_0.jpeg)

![](_page_38_Picture_2.jpeg)

- i) the spatial autoregressive model (SAR), which consists of including the spatially lagged dependent variable in the structural equation;
- ii) the spatial autocorrelation model (SAC), in which not only the spatially lagged dependent variables is included in the right hand side of the equation, but also the error term is further decomposed so as to include a spatial autocorrelation coefficient;
- iii) the spatial Durbin model (SDM), which includes the spatial lag of one or more exogenous variables in the matrix Z of covariates (Varga, 1998; Elhorst, 2003 and 2010).

![](_page_39_Picture_0.jpeg)

![](_page_39_Picture_2.jpeg)

#### Innovation and Regional Growth

	(1)	(2)	(3)	(4)	(5)	(6)
	SAR	SAR	SAC	SAC	SDM	SDM
кѕтоск	0.2039***		0.2010***		0.1906***	
	(0.0491)		(0.0496)		(0.0506)	
СОН		-0.1719***		-0.1622***		-0.1600***
		(0.0450)		(0.0456)		(0.0471)
CD		1.4084***		1.4647***		1.5981***
		(0.4530)		(0.4562)		(0.4705)
кv		0.2089***		0.2084***		0.2195***
		(0.0270)		(0.0271)		(0.0278)
POP_DENS	0.2614***	0.2216***	0.2599***	0.2222***	0.2597***	0.2229***
	(0.0225)	(0.0221)	(0.0227)	(0.0222)	(0.0227)	(0.0220)
IND_DIV	2.5606***	2.6810***	2.8667***	2.9976***	2.5404***	2.7811***
	(0.4647)	(0.4591)	(0.4722)	(0.4633)	(0.4678)	(0.4616)
INC	0.2599***	0.2653***	0.2671***	0.2732***	0.2580***	0.2679***
	(0.0222)	(0.0217)	(0.0229)	(0.0222)	(0.0224)	(0.0216)
MANEMPL	0.4892***	0.4589***	0.5032***	0.4706***	0.4940***	0.4579***
	(0.0235)	(0.0229)	(0.0245)	(0.0238)	(0.0236)	(0.0229)
Spatial						
rho	-0.3753**	-0.3331**	-0.1453	-0.1366	-0.3551**	-0.3837**
	(0.1609)	(0.1576)	(0.1746)	(0.1691)	(0.1684)	(0.1745)
lambda			-0.9906***	-0.9512***		
			(0.3043)	(0.2939)		
		Spati	ally lagged regre	essors		
KSTOCK					-0.1903	
					(0.3833)	
СОН						0.1989
						(0.4742)

6.3987 (4.5657)

CD

![](_page_40_Picture_0.jpeg)

![](_page_40_Picture_2.jpeg)

- An increasing body of literature analyzing the spatial dimensions of innovative activities are based on the model of the knowledge production function (Griliches, 1979) applied at spatial units of observation
- One of the most important and perhaps most influential contribution re-focusing the knowledge production function (KPF) is the one by Jaffe (1989):

$$I_{si} = \alpha IRD^{\beta_1} * UR_{si}^{\beta_2} * (UR_{si} * GC_{si}^{\beta_3}) * \varepsilon_{si}$$

![](_page_41_Picture_0.jpeg)

![](_page_41_Picture_2.jpeg)

- Where I is the innovation output, IRD is private corporate expenditures on R&D, UR is the research expenditures undertaken at universities, and GC measures the geographic coincidence of university and corporate research.
- The unit of observation for estimation was at the spatial level, *s*, a state, and industry level, *i*.
- Implicit assumption that innovative activity should take place in those regions where the direct knowledgegenerating inputs are the greatest
- Link between patent as an output measure and R&D as an input measure

![](_page_42_Picture_0.jpeg)

![](_page_42_Picture_2.jpeg)

- A wide range of applications, adopting both different output and input measures
- See Audrestch and Feldman (2004: Handbook of Regional and Urban Economics, Chapter 61) for a critical survey
- Recent contributions include the estimation of the impact of academic knowledge spilloers on regional innovation (Ponds, van Oort and Frenken, 2010)
- Estimation of the differential impacts of geographical, technological and institutional proximity on innovation (Marrocu, Paci and Usai, 2013)

![](_page_43_Picture_0.jpeg)

![](_page_43_Picture_2.jpeg)

- KPF provides an assessment of input-output relationship in knowledge production at the regional level
- More in depth analysis of dynamics of innovation focus on pattern of collaborations amongst innovating agents
- Focus on co-invention, cooperation and knowledge flows

![](_page_44_Picture_0.jpeg)

![](_page_44_Picture_2.jpeg)

- The micro-founded analyses of innovation activities rely to a great extent on patent data.
- In particular, the exchange of knowledg, often called knowledge flow, is measured by looking at citation and co-invention patterns
- Different empirical approaches are available to investigate these issues

![](_page_45_Picture_0.jpeg)

![](_page_45_Picture_2.jpeg)

- Social network analysis provdes a useful set of indicators and tools to appreciate the relationships between innovating agents and their relative importance in innovation networks
- Moreover, the dynamic analysis allows to assessing the evolution of the network structure over time, so as to link it with the evolution of specific sectoral characteristics
- The recent works by Holger Graf and Anne ter Wal provide insightiful applications of these tools
- Balconi, Breschi and Lissoni (2004) applies SNA to investigate the role of academic inventors in innovation networks

![](_page_46_Picture_0.jpeg)

![](_page_46_Picture_2.jpeg)

- Besides SNA, microeconometric studies investigate the determinants of citation or coinvention patterns so as to assess the impact of the different kinds of proximity
- Gravity equation models are widely used in this context
- The idea is that knowledge flows are function of a set of attracting forces, e.g. regional variables like GDP, employment, etc (the mass of corps in Newton's equation), and of distance

![](_page_47_Picture_0.jpeg)

![](_page_47_Picture_2.jpeg)

- An important contribution in this area is: Peri, G., (2005). Determinants of Knowledge Flows and Their Effect on Innovation. The Review of Economics and Statistics 87(2), 308-322.
- More recent contributions are:
- Guellec, D., and Van Pottelsberghe, B., (2001). The internationalization of technology analyzed by patent data. Research Policy 30(8), 1253-126
- Picci, L., (2010). The Internationalization of Inventive Activity: A Gravity Model Using Patent Data. Research Policy39(8), 1070-1081.
- Montobbio, F. and Sterzi, V. (2013). The globalization of technology in emerging markets : a gravity model on the determinants of international patent, *World Development*, forthcoming.

![](_page_48_Picture_0.jpeg)

![](_page_48_Picture_2.jpeg)

- Quatraro and Usai (2014) compare the dynamics concerning three types of knowledge flows across regions in Europe in the last decade,
  - citations,
  - applicant-inventor links
  - co-inventorships
- Secondly, we look for evidence on the moderating role of different kinds of proximity on the impact of geographical distance.
- Finally, we follow the intuition by Lafourcade and Paluzie (2010), who show that border regions, which often appear to be disadvantaged areas because of their peripheral position within the country, may experience a counter effect due to the fact that they are the closest regions to other countries.

![](_page_49_Picture_0.jpeg)

![](_page_49_Picture_2.jpeg)

- We measure knowledge flows by using all information contained in the OECD RegPat Database, and in particular data on coinventorships, applicant-inventor links, and citation flows for 276 European regions in 29 countries (EU27+2).
- The empirical strategy builds upon the traditional gravity model applied to knowldge flows as in Maurseth and Verspagen (2002), Usai and Paci (2009), Picci (2010), Maggioni et al. (2011).

![](_page_50_Picture_0.jpeg)

![](_page_50_Picture_2.jpeg)

- Co-inventorship collaboration
  - a collaboration between the region *i* and the region *j* is identified when, in a patent developed by more than one inventor, at least one co-inventor is resident in region *i* and at least one co-inventor is resident in region *j*.
- Applicant-inventors relationships
  - An applicant-inventor link is identified whenever a patent has (at least) one inventor in region *i* and one applicant (which is usually a firm) resident in another region *j*
- Citation flows
  - citation from region *j* to region *i* occurs when the citing patent has at least one inventor residing in the region *j* and the cited patent has at least one inventor residing in the region *i*

![](_page_51_Picture_0.jpeg)

![](_page_51_Picture_2.jpeg)

 $kf_{ij}^{s} = f(distances_{ij}, contiguities_{ij}),$ 

regional features, regional features,)

- <u>kf</u>: citations flows, applicant-inventors links, coinventorships
- *distances*: geographical, technological, relational, institutional
- *contiguities*: cross-border, within border
- regional features: rd expenditure, patent stock, tertiary education, population density

![](_page_52_Picture_0.jpeg)

![](_page_52_Picture_2.jpeg)

Variable	Definition
1	Natural logarithm of patents with inventors in the region i and in the region j
Incomv	(average value 2002-2004)
Inonniny	Natural logarithm of patents with applicant from region i and inventor from
паррпі	region j (average value 2002-2004)
Ingit	Natural logarithm of patent citations between region i and j (average value
	2002-2004)
dist	Distance (in kilometers)
tachenov	Technological proximity between regions i and j, calculated on the basis of
techprox	Jaffe's cosine index.
instprox	Samecountry dummies
cd	Country dummies
dens	Ratio between population and area (land use)
lo abl	Natural logarithm of people with tertiary education attainment (average value
lognk	1999-2001)
logpat	Natural logarithm of patent applications (average value 1999-2001)
logrdexp	Natural logarithm of R&D expenditure (average value 1999-2001)

![](_page_53_Picture_0.jpeg)

![](_page_53_Picture_2.jpeg)

- geographical distance (*geodist<sub>i,j</sub>*) is measured by logarithm of the row-normalized distance between regions *i* and *j*
- contiguity (*cont*<sub>ij</sub>) between regions *i* and *j*
- contiguity of regions belonging to the same country (*wtbrd*<sub>ii</sub>)
- contiguity of regions belonging to different countries (crossbrd<sub>ii</sub>)
- inner<sub>ij</sub> which is equal to 1 if regions i and j are not contiguous but belong to two contiguous countries, and 0 otherwise

![](_page_54_Picture_0.jpeg)

![](_page_54_Picture_2.jpeg)

- Another important topic related innovation networks concerns technology alliances.
- The investigations have been mostly at the sectoral and country level, as well as the firm level from a strategic management perspective
- Analyses focusing on the geographical dimensions of technology alliances hard to be found
- Marrocu, Paci and Usai (2013) marks a step forwards in this respect

![](_page_55_Picture_0.jpeg)

![](_page_55_Picture_2.jpeg)

	Baseline specification					
	Ln(Cit)	Ln(AppInv)	Ln(Coinv)			
geodist	-0.114***	-0.097***	-0.124***			
techprox	0.056***	0.035***	0.033***			
instprox	0.118***	0.291***	0.308***			
crsbrd	0.022***	0.036***	0.074***			
wtnbrd	0.063***	0.172***	0.271***			
inner	0.000	-0.012**	-0.056***			
Ν	74256	74256	37128			

![](_page_56_Picture_0.jpeg)

![](_page_56_Picture_2.jpeg)

#### Conclusions and avenues

- This lecture aimed at providing an overview upon the possible avenues to undertake the investigation of innovation dynamics from a regional perspective
- A variety of issues have been identified, along with a variety of available methodologies
- This is far from being exhaustive, and most focused on econometric methodologies

![](_page_57_Picture_0.jpeg)

![](_page_57_Picture_2.jpeg)

#### Conclusions and avenues

- Recent interest in the emergence of new industries and technologies at the regional level (Boschma et al, 2013; Colombelli et al., 2014)
- Regional technological trajectories are shaped by competencens accumulated over time
- Product-space approach applied to investigate the impact of 'proximity' between new and existing technological activities
- Smart specialization and key enabling technologies (KETs) (Montresor and Quatraro, in progress)

![](_page_58_Picture_0.jpeg)

![](_page_58_Picture_2.jpeg)

#### Conclusions and avenues

- However, the most original contributions stem from cross-fertilization and combination of different methodologies and theories.
- From this viewpoint, the regional focus to the analyses of the effects and determinants of eco-innovation can be especially interesting
- Work is in progress in this direction: see Horbach (2013) and Ghisetti and Quatraro (2014) (both available at the SEEDS web page).