Technological Change in Cities and Regions

An Evolutionary Analysis of Knowledge Spaces and Technology Trajectories

Dieter Franz Kogler

School of Geography, Planning & Env. Policy University College Dublin



MUNK School of Global Affairs - University of Toronto Innovation Policy Lab Speaker Series – Frontiers of Research in Global Innovation Toronto, Canada, October 8th, 2014.

KNOWLEDGE [IN] SPACE

While a substantial literature, i.e. Regional Innovation Systems, Learning Regions, Local Knowledge Economies, promotes the idea that different knowledge economies/learning regions produce various subsets of knowledge, which in turn becomes the source of their competitive advantage, systematic evidence of the production of these different kinds of knowledge over space is lacking.

Little is known about how technological change evolves at specific places over time.





KNOWLEDGE PRODUCTION IN AN EVOLUTIONARY ECONOMIC GEOGRAPHY FRAMEWORK



- cumulative,
- path-dependent, and
- interactive process.

Evolutionary Economic Geography Boschma and Frenken (2006)

Kogler (RS SI on EEG, 2015)

Knowledge [in] space

- Knowledge accumulates
- knowledge relationships

Increasing interest in EG Boschma et al. (2012), Rigby (2012), Kogler et al. (2013)

Knowledge acquired in the past provides

- opportunities, and
- sets limits.

Entry, Exit and Selection Rigby and Essletzbichler (2000), Boschma, Balland & Kogler (2014)



WHAT WE KNOW / WHAT WE WANT TO KNOW

Novel technology competencies emerge from the recombination of existing competences and knowledge.

(SCHUMPETER, 1939; ABERNATHY and TOWNSEND, 1975; FLEMING, 2001; Boschma and Frenken, 2011)

Do cities and regions diversify into technologies that are related to their specific knowledge structure and expertise?

If yes, what are the driving forces of this diversification process?





THE TECHNOLOGY/KNOWLEDGE SPACE - OBJECTIVES

Objectives:

- Investigate the long-term evolution of technology portfolios of European regions over a 30-year time period.
- 1. Construct a **knowledge space** that measures the degree of relatedness between distinct technologies
 - a) examine the evolution of the European knowledge space
 - b) analyse how the knowledge space shifts within different regions
- 2. Decompose changes in the technological coherence of individual NUTS regions into the influence of selection (differential growth), entry and exit
- 3. Estimate a fixed-effects conditional logit model of technological entry and exit by technology class and region



Kogler D. F., Rigby D. L. & Tucker I. (2013) Mapping Knowledge Space and Technological Relatedness in US Cities, *European Planning Studies* 21(9), 1374-1391.

EPO DATA - 1981 to 2005

Patent data is an excellent proxy of inventive output.

The advantages of using patents to track knowledge output are clear: long time-series, spatial disaggregation, technological detail and information on inventors, co-inventor relationships and patterns of assignment.

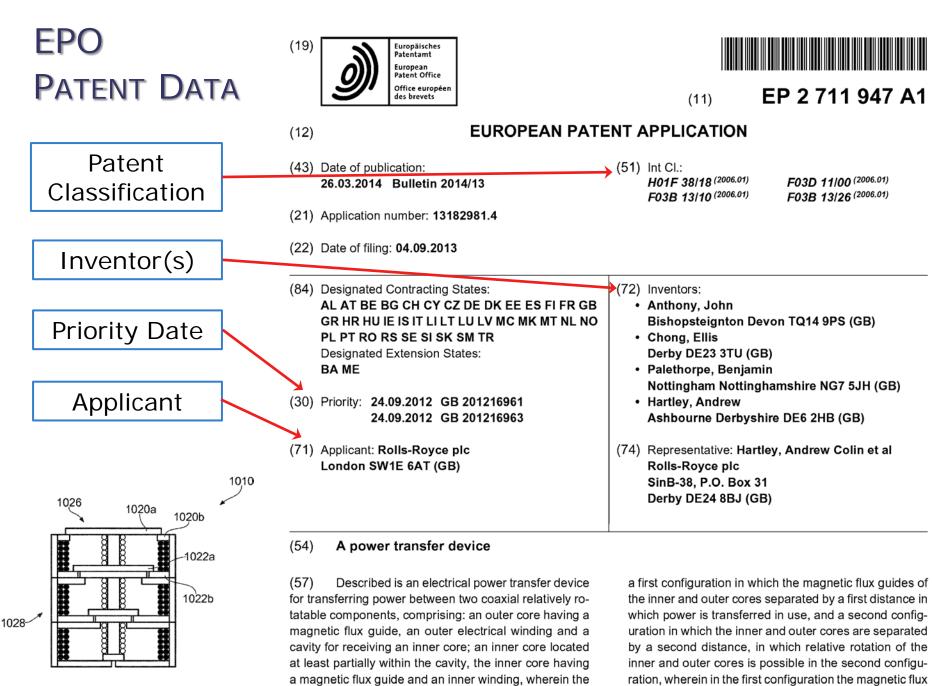
EPO patents

- Each patent that was developed by at least one <u>EU15</u> inventor
- 629 IPC [technology] subclasses
- Timeframe = 1981 to 2005 [priority date]
 - Five 5-year periods:

1981-1985	\rightarrow	1
1986-1990	\rightarrow	2
1991-1995	\rightarrow	3
1996-2000	\rightarrow	4
2001-2005	\rightarrow	5



Geography ???

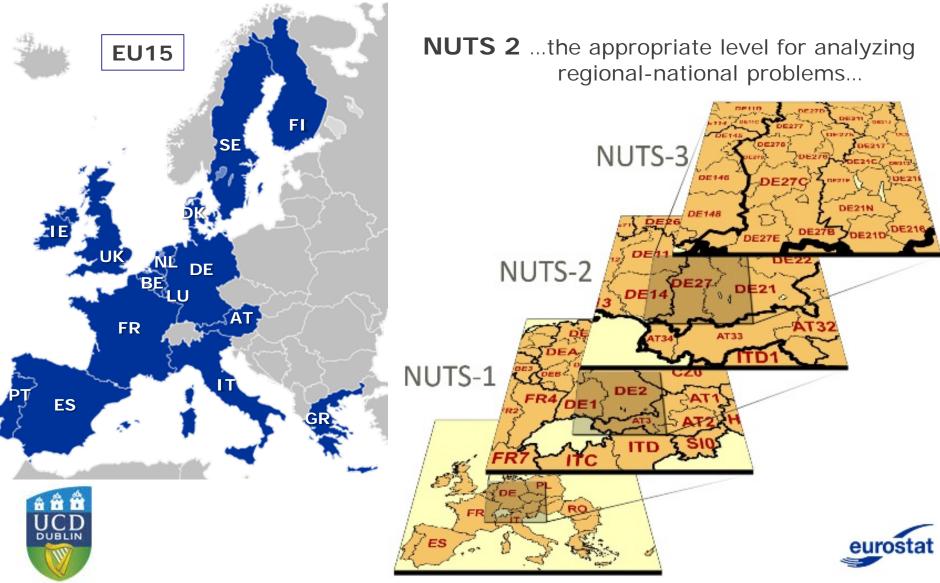


inner and outer core are arranged to be movable between

guides of the inner and outer cores abut one another.

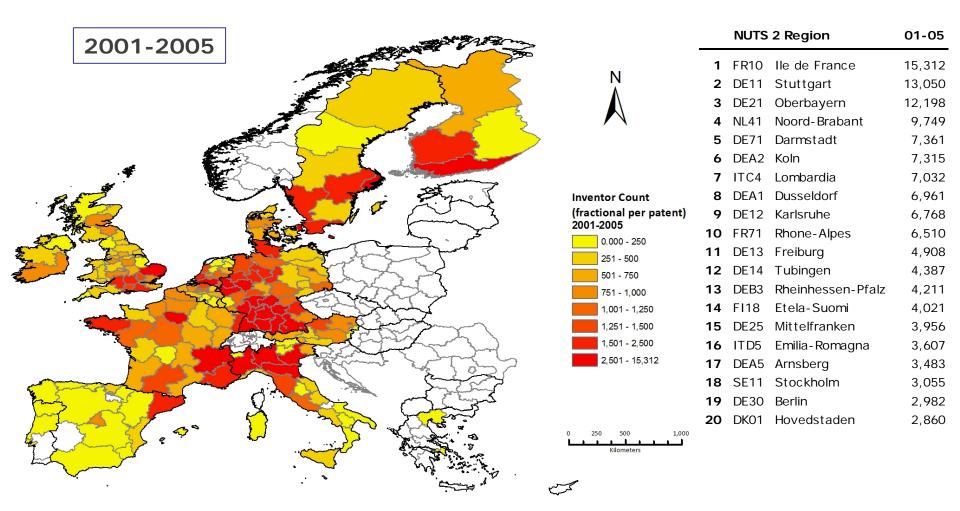
FIG. 10

NUTS REGIONS (NOMENCLATURE OF TERRITORIAL UNITS FOR STATISTICS)



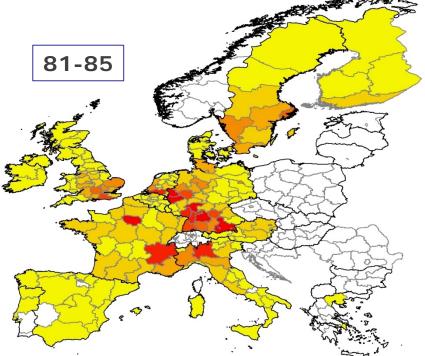
74 regions at NUTS 1, 216 regions at NUTS 2 and 1090 regions at NUTS 3 level for EU15.

REGIONAL INVENTIVENESS [FRACTIONAL INVENTOR COUNTS PER PATENT]



CAREFUL WITH RANDOM RANKING EXERCISES!

Kogler (2014) Intellectual Property and Patents: Knowledge Creation and Diffusion, forthcoming in the Handbook of Manufacturing Industries in the World Economy, Edward Elgar

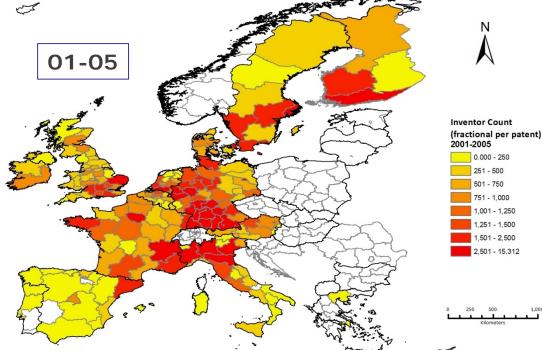


REGIONAL INVENTIVENESS

N

		NUTS	2 Region	81-85			NUTS 2 Region	81-85
Inventor Count (fractional per patent) 1981-1985 0.000 - 250 251 - 500	1 2 3	FR10 DE21 DE71	lle de France Oberbayern Darmstadt	7,745 4,966 4,207	11 12 13		Lombardia Mittelfranken Freiburg	1,912 1,497 1,426
251 - 500 501 - 750 751 - 1,000 1,001 - 1,250	4 5	DEA2		3,741 3,714	14 15	DEA5 UKJ2	Arnsberg Surrey, E&W Sussex	1,296 1,260
1,251 - 1,500 1,501 - 2,500 2,501 - 7,745	6 7 8	DE11 FR71 DE12	Stuttgart Rhone-Alpes Karlsruhe	2,981 2,226 2,130	16 17 18	UKJ1	Stockholm Berks, Bucks & Oxon Tubingen	1,198 1,120 1,003
	9 10	NL41 DEB3	Noord-Brabant Rheinhessen-Pfalz	2,090 2,073	19 20	ITC1 UKI2	Piemonte Outer London	987 896

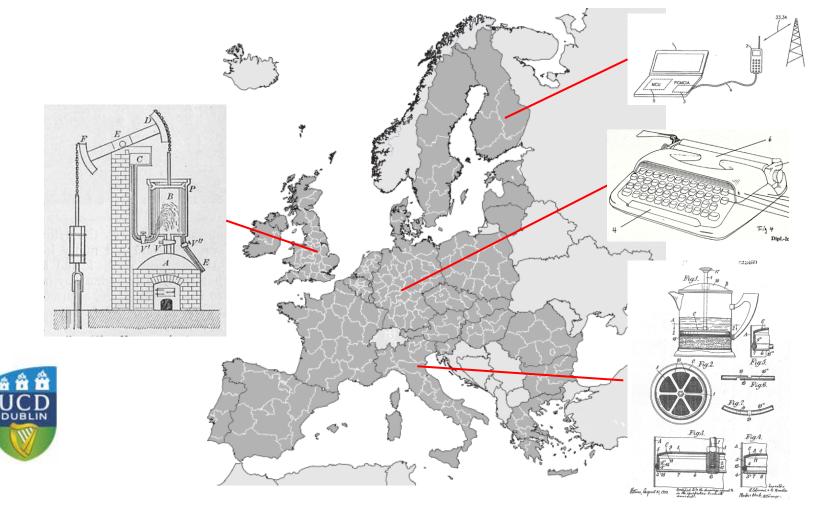
NUTS 2 Region 01-05 **NUTS 2 Region** 01-05 **1** FR10 lle de France 15,312 11 DE13 Freiburg 4,908 13,050 4,387 2 DE11 Stuttgart 12 DE14 Tubingen 3 DE21 Oberbayern 12,198 13 DEB3 Rheinhessen-Pfalz 4,211 **4** NL41 Noord-Brabant 9,749 14 FI18 Etela-Suomi 4,021 7,361 **15** DE25 Mittelfranken 3,956 5 DE71 Darmstadt 6 DEA2 Koln 7,315 16 ITD5 Emilia-Romagna 3,607 7,032 17 DEA5 Arnsberg 3,483 7 ITC4 Lombardia 8 DEA1 Dusseldorf 18 SE11 Stockholm 6,961 3,055 9 DE12 Karlsruhe 6,768 19 DE30 Berlin 2,982 10 FR71 Rhone-Alpes 20 DK01 Hovedstaden 2,860 6,510



TECHNOLOGICAL SPECIALIZATION

We analyze the **technological diversity/coherence** of European NUTS Regions

(629 patent classes; 229 NUTS 2 regions; 1981 to 2005)



THE EU KNOWLEDGE SPACE [CO-OCCURRENCE OF PATENT CLASSES]

The (629 x 629) symmetric technology class co-occurrence matrix...

The following is a matrix for a patent that makes 5 separate knowledge claims in 2 distinct technology classes, i.e. H02B, H02J. There are <u>5 separate knowledge claims</u>, **4 in H02J** and **1 in H02B**, i.e. the patent class field reads: H02J, H02J, H02J, H02J, H02B

	H02A	H02B	H02C	H02D	H02E	H02F	H02G	H02H	H02I	H02J	H02K	H02L	IPC Class Definition:
H02A													Section H = ELECTRICITY
H02B										1			H20 = GENERATION,
H02C													CONVERSION, OR DISTRIBUTION OF ELECTRIC
H02D													POWER
H02E													H02B = BOARDS, SUBSTATIONS, OR
H02F													SWITCHING ARRANGEMENTS
H02G													FOR THE SUPPLY OR DISTRIBUTION OF ELECTRIC
H02H													POWER
H02I													H02J = CIRCUIT
H02J										4			ARRANGEMENTS OR SYSTEMS FOR SUPPLYING OR
H02K													DISTRIBUTING ELECTRIC
H02L													POWER; SYSTEMS FOR STORING ELECTRIC ENERGY



...the **relatedness** of technology classes in a place determines the technological **competency** or **coherence** of a region...

THE EU KNOWLEDGE SPACE [CO-OCCURRENCE OF PATENT CLASSES]

Measuring the proximity, or knowledge relatedness, between patent technology classes.

 $F_{ip} = 1$ if patent record p lists the class code i, otherwise $F_{ip} = 0$

Then, in a given time period, the total number of patents that list technology class *i* is given by: $N_i = \sum_p F_{ip}$

Similar the number of individual patents that list the pair of co-classes *i* and *j* is identified by the count: $N_{ij} = \sum_p F_{ip} F_{jp}$

Repeating this co-class count for all pairs of 629 patent classes yields the (629 x 629) symmetric technology class co-occurrence matrix Cthe elements of which are the co-class counts N_{ij}



Kogler D. F., Rigby D. L. & Tucker I. (2013) Mapping Knowledge Space and Technological Relatedness in US Cities, *European Planning Studies* 21(9), 1374-1391.

THE EU KNOWLEDGE SPACE [CO-OCCURRENCE OF PATENT CLASSES]

The co-class counts measure the technological proximity of all pairs, but they are also influenced by the number of patents found within each individual patent class N_i .

Therefore, the elements of the co-occurrence matrix are standardized by the square root of the product of the number of patents in the row and column classes of each element:

$$S_{ij} = \frac{N_{ij}}{\sqrt{N_i^2 * N_j^2}}$$

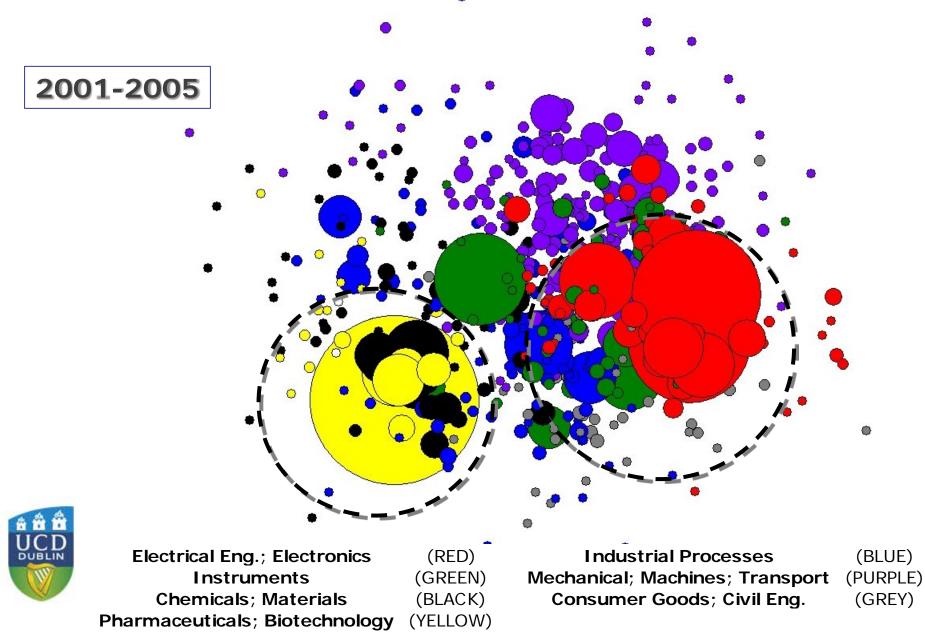
where S_{ij} is an element of the standardized co-occurrence matrix (**S**) that indicates the technological proximity, or knowledge relatedness, between all pairs of patent classes in a given time period



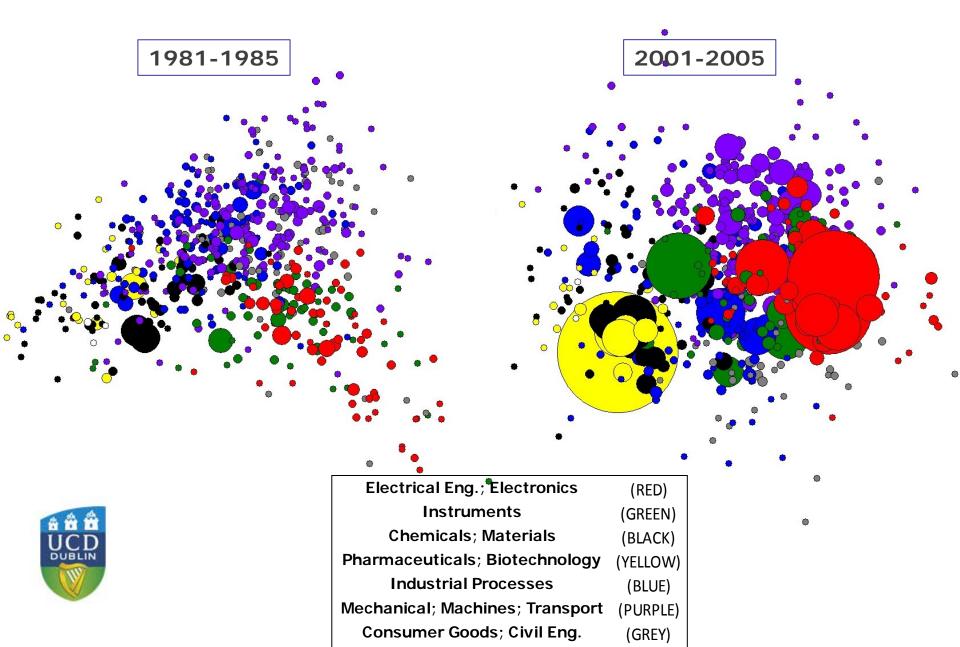
Note: We apply a fractional count of technology classes and also weight by the spatial distribution of co-inventors

THE EUROPEAN KNOWLEDGE SPACE

Gower, 1971)



THE EUROPEAN KNOWLEDGE SPACE



	RAGE RI	Time Period	Ave	erall erage edness			
Ove		0095					
=	steady incr	ease (incre	easing spec	ialization)	1986-9		0097
Sec	storal Ave	a Doloto	dinaaa		1991-9 1996-0		0102 0115
				ation	2001-0		0129
= variations		avg	high ↓	high t	avg	low 1	low 1
Time Period	Electrical	Instru- ments	Chemicals Materials	Pharma- ceuticals	Industrial Processes	Mechanical Machines	Consumer Goods &
Period	Eng. & Electronics	ments	water lais	Biotech.	FIUCESSES	Transport	Civil Eng.
1981-85	0.045	0.054	0.078	0.290	0.041	0.017	0.035
1986-90	0.045	0.055	0.072	0.299	0.042	0.018	0.038
1991-95	0.047	0.054	0.069	0.336	0.044	0.018	0.039
1996-00 2001-05	0.059 0.071	0.060 0.065	0.063 0.067	0.350 0.347	0.043 0.043	0.020 0.020	0.040 0.042

REGIONAL AVERAGE RELATEDNESS

The average relatedness value for a region r in time period t is calculated as:

$$AR^{rt} = \frac{\sum_{j} s_{ij}^{t} * D_{j}^{rt}}{N^{rt}}$$

 S_{ij}^{t} represents the (row or column) vector of the standardized cooccurrence matrix noted previously

 D_{j}^{rt} is the count of the number of patents in technology class j in NUTS2 region r in year t

 N^{rt} is a count of the total number of patents in region r in year t

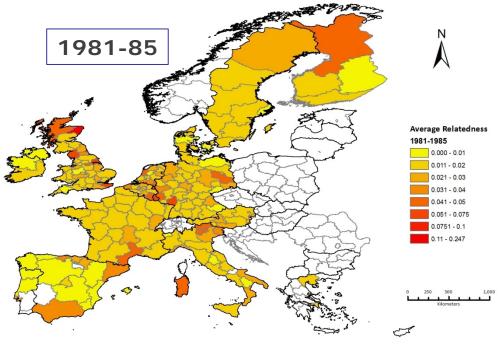


Note: We apply a fractional count of technology classes and also weight by the spatial distribution of co-inventors

REGIONAL AVERAGE RELATEDNESS

n arltdn	inv
land 0.137	282
ide 0.120	396
s and Isl. 0.119	74
Suomi 0.085	522
0.080	696
e 0.078	653
e 0.075	1,721
0.074	929
0.071	789
xemb. (B) 0.070	124
· : -	:
5	1,186
	2,777
-	962
	435
	98
,	3,483
	2,783
	1,050
	2,848
ire and Std 0.010	388
	and 0.137 de 0.120 s and Isl. 0.119 Suomi 0.085 0.080 e 0.078 e 0.075 0.074 0.071 kemb. (B) 0.070 : - g 0.012 0.012 yern 0.012 0.011 & Isl. of S. 0.011 0.011

2001 - 2005



REGIONAL AVG RLTD

1981 - 1986

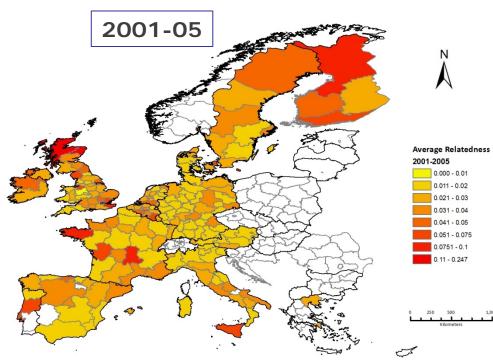
NUTS 2	2 Region	arltdn	inv
1 UKM5 I	NE Scotland	0.127	68
2 UKD5 1	Merseyside	0.083	247
3 UKE1 I	E. Yorkshire & N. Lincs	0.069	148
4 UKD1 (Cumbria	0.069	63
5 LUOO I	Luxemb. (GrDuche)	0.059	167
6 UKJ4 H	Kent	0.056	390
7 DEB3	Rheinhessen-Pfalz	0.054	2,073
8 UKM6 I	Highlands and Isl.	0.049	5
9 UKE3 S	South Yorkshire	0.048	167
10 FR81 l	Languedoc - Roussillon	0.047	250

		2001 - 2005			
NUTS	S 2 Region	arltdn	inv		
1 UKM5	NE Scotland	0.137	282		
2 UKD5	Merseyside	0.120	396		
3 UKM6	Highlands and Isl.	0.119	74		
4 FI1A	Pohjois-Suomi	0.085	522		
5 UKJ4	Kent	0.080	696		
6 FR72	Auvergne	0.078	653		
7 FR52	Bretagne	0.075	1,721		
8 UKH3	Essex	0.074	929		
9 UKD2	Cheshire	0.071	789		

0.070

124

10 BE34 Prov. Luxemb. (B)





DECOMPOSING REGIONAL CHANGES IN TECHNOLOGICAL SPECIALIZATION

According to our theory of knowledge and technology evolution:

- The process of technological diversification and abandonment is shaped by the region's technological structure at the beginning of the period.
- How do regions become more or less technologically cohesive (related)?

The need to examine:

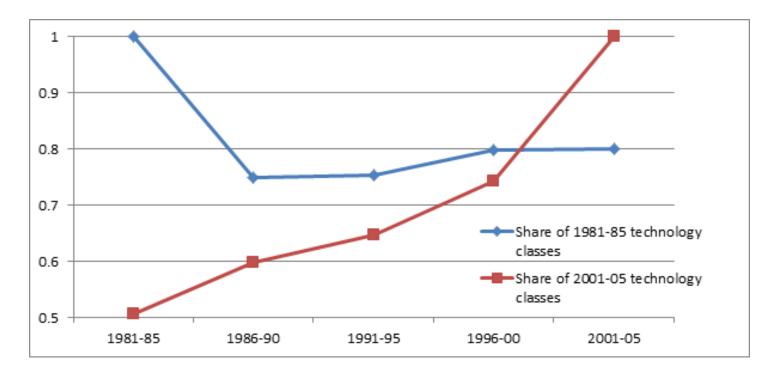
- the impact of changes in technology classes present in a region (incumbent technologies)
- technologies added to the regional portfolio (entry); and
- abandoned technologies (exit).



REGIONAL TECHNOLOGICAL DIVERSIFICATION AND ABANDONMENT

Out of a total of 133,977 (213x629) possible region-technology classes, 34,005 (25.4%) existed in the period 1981-1985, increasing to 53,606 (40%) by 2001-05.

In other words, regions started to fill a lot of empty technology niches over the period examined.





DECOMPOSING REGIONAL CHANGES

Following the literature on productivity decomposition (FOSTER *et al.*, 1998), the change in technological cohesion in region r and between times t and t+1 can then be decomposed as follows

$$C_{r}^{t+1} - C_{r}^{t} = \sum_{ij \in INC} (p_{ijr}^{t+1} - p_{ijr}^{t}) s_{ijr}^{t} + \sum_{ij \in INC} (s_{ijr}^{t+1} - s_{ijr}^{t}) (p_{ijr}^{t} - C_{r}^{t})$$

$$\sum_{ij \in INC} (SC_{ir}^{t+1} - SC_{ir}^{t}) (s_{ir}^{t+1} - s_{ir}^{t}) + \sum_{ij \in N} (p_{ijr}^{t+1} - C_{r}^{t}) s_{ijr}^{t+1} - \sum_{ij \in X} (p_{ijr}^{t} - C_{ijr}^{t}) s_{ijr}^{t}$$

where the subscript *INC* denotes incumbent links, i.e. links between patents in technology classes that exist in year t and t+1,



N represent new links to entering technology classes that exist in t+1 but were not part of the regional portfolio in year t, and

X denotes abandoned links to technology classes that leave the region between t and t+1

DECOMPOSING REGIONAL CHANGES

$$C_{r}^{t+1} - C_{r}^{t} = \sum_{ij \in INC} (p_{ijr}^{t+1} - p_{ijr}^{t}) s_{ijr}^{t} + \sum_{ij \in INC} (s_{ijr}^{t+1} - s_{ijr}^{t}) (p_{ijr}^{t} - C_{r}^{t})$$

$$\sum_{ij \in INC} (SC_{ir}^{t+1} - SC_{ir}^{t}) (s_{ir}^{t+1} - s_{ir}^{t}) + \sum_{ij \in N} (p_{ijr}^{t+1} - C_{r}^{t}) s_{ijr}^{t+1} - \sum_{ij \in X} (p_{ijr}^{t} - C_{ijr}^{t}) s_{ijr}^{t}$$

Incumbent classes (INC)

- 1. Change in relatedness values among incumbent classes assuming that the shares of those links on the total number of links remains const.
- Selection effect positive if classes with relatedness values higher than average reg. relatedness expand their patent shares relative to those links with lower than avg. values.
- 3. Covariance term positive if tech. classes that have become more related also expand market shares.



Entry (N) – positive if entering tech. classes are more closely related to the reg. tech. portfolio than average

Exit (X) – negative if technology classes less closely related to the reg. portfolio than avg. relatedness exit the region

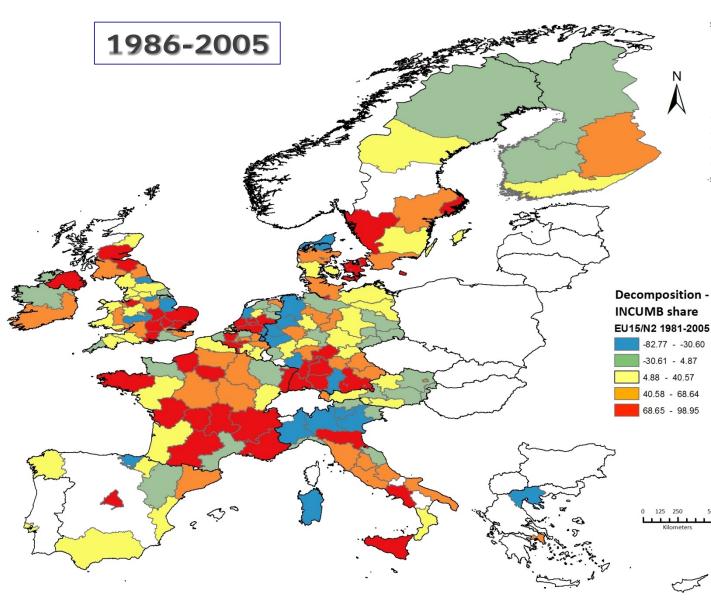
COMPONENTS OF CHANGE IN REGIONAL TECHNOLOGICAL SPECIALIZATION

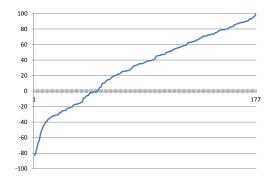
Period	Regional change - Avg. Relatedness	Incumbent, Selection, Covariance	Entry	Exit
1981/90	-0.00003	0.00053	-0.00247	-0.00191
	%	10.8	-50.3	-38.9
1986/95	0.00177	0.00185	-0.00191	-0.00183
	%	33.1	-34.2	-32.7
1991/00	0.00232	0.00289	-0.00216	-0.00159
	%	43.5	-32.5	-23.9
1996/05	0.00103	0.00109	-0.00176	-0.00169
	%	24.0	-38.8	-37.2)

Note: The values are weighted means for all regions with more than 50 patents. The weights are the number of patents at the beginning of each period. The percentages reflect the share of each component divided by the sum of their absolute values.



DECOMPOSITION – SHARE OF INCUMBENT, SELECTION AND COVARIANCE

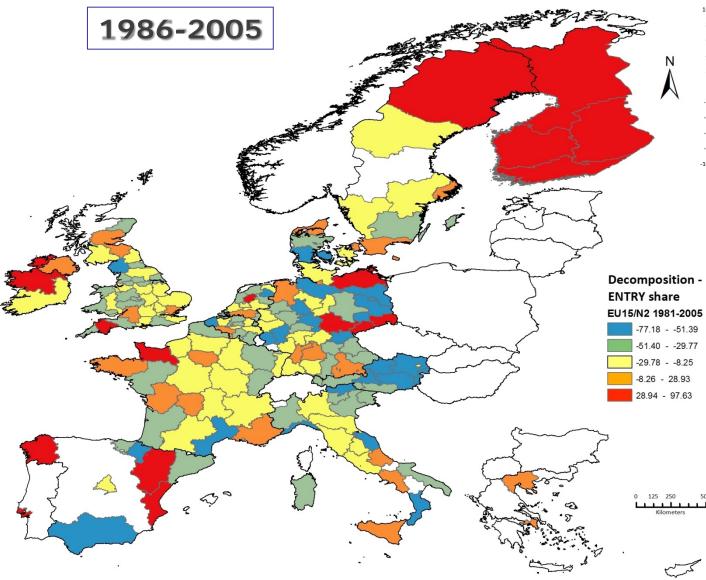


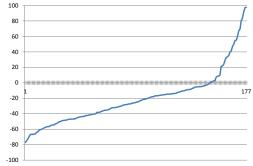


Rank	ID	NUTS Region	ISC %		
1	FR10	lle de France	98.947		
2	SE11	Stockholm	96.532		
3	DE11	Stuttgart	95.220		
4	FR52	Bretagne	93.378		
5	DE21	Oberbayern	92.952		
:	:	-:-	:		
173	DEA1	Dusseldorf	-63.331		
174	DE94	Weser-Ems	-66.496		
175	ITC4	Lombardia	-73.523		
176	DEA2	Koln	-80.768		
177	DEB3	RheinhPfalz	-82.769		

In about 2/3 of all regions incumbents increase technological cohesion

DECOMPOSITION – SHARE OF ENTRY

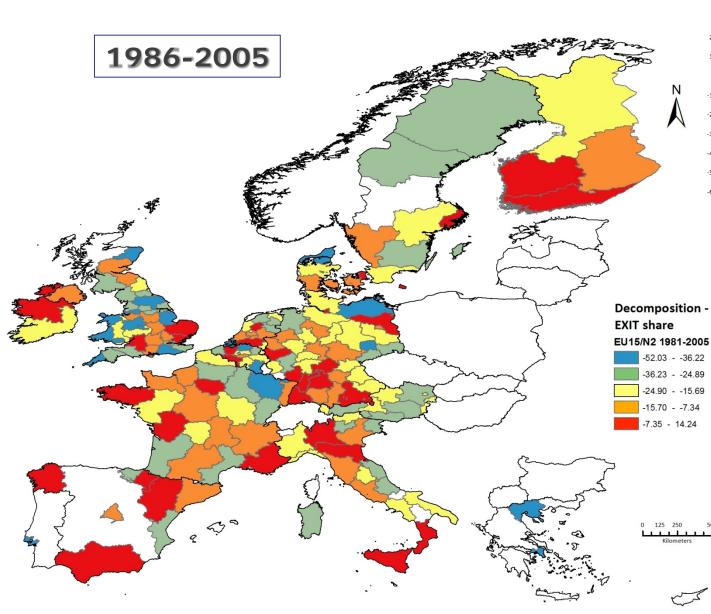


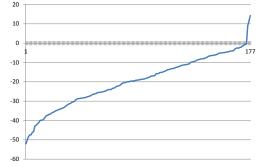


Rank	ID	NUTS Region	ENTRY %		
1 IE01		Border, Midl.	97.624		
2	ES24	Aragon	97.330		
3	FI19	Lansi-Suomi	92.057		
4	FR25	Basse-Normand.	83.697		
5	ES11	Galicia	80.398		
:	:	-:-	:		
173	ES22	Com. Foral d.N.	-66.856		
174	AT22	Steiermark	-69.652		
175	AT11	Burgenland (A)	-72.726		
176	DE93	Luneburg	-75.075		
177	ES61	Andalucia	-77.179		

In all, but 29 regions, entry lowers technological cohesion → Does this contradict the theory?

DECOMPOSITION - SHARE OF EXIT

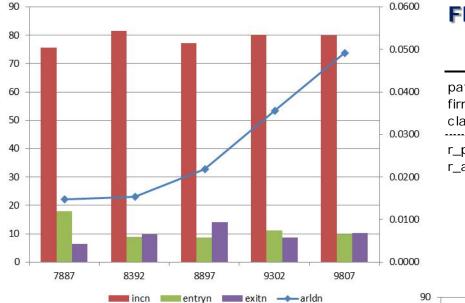




Ran	k	ID	NUTS Region	EXIT %
	1 ITF6		Calabria	14.238
	2	ES22	Com. Foral d.N.	11.465
	3	ES11	Galicia	8.930
	4	IE01	Border, Midl.	-0.376
	5	FR10	Ile de France	-0.612
	:	:	-:-	:
17	3	UKG3	West Midlands	-47.432
17	4	UKG2	Shrop. & Staff.	-47.457
17	5	BE21	Prov. Antwerpen	-48.361
17	6	UKJ2	Surrey, E&W SX	-50.143
17	7	GR12	Kentriki Maked.	-52.030

In all regions, other than 3, exit increase tech. specialization

CHANGE IN REGIONAL TECHNOLOGICAL COHERENCE



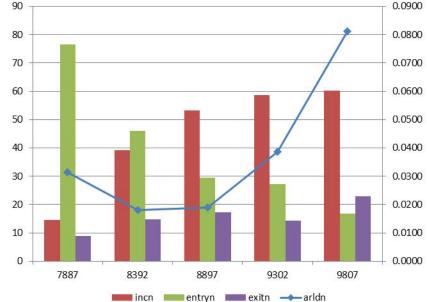
FR10 – Ile de France

	78-82	83-87	88-92	93-97	98-02	03-07
patents firms classes	5,942 1,100 527			1,862	2,241	
r_pat r_arltdn	1 171	1 187	1 187	1 168	1 130	1 136

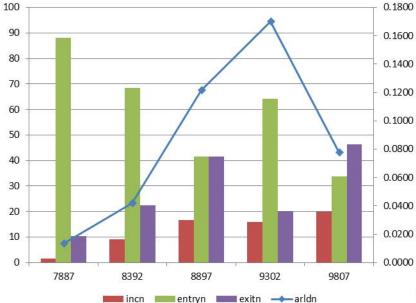
FI18 – Etela-Suomi

DUBLIN

	78-82	83-87	88-92	93-97	98-02	03-07
patents	193	615	1,249	2,313	3,945	3,827
firms	72	207	322	494	709	730
classes	155	305	383	415	450	433
r_pat	75	43	26	16	12	16
r_arltdn	57	154	171	97	41	39



CHANGE IN REGIONAL TECHNOLOGICAL COHERENCE



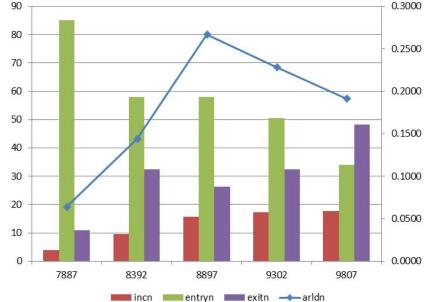
ITG1 – Sicilia

	78-82	83-87	88-92	93-97	98-02	03-07
patents	22	62	123	212	337	340
firms	6	26	41	35	70	105
classes	27	74	116	116	173	156
r_pat	151	141	133	128	129	134
r_arltdn	50	24	7	7	20	33

UKM5 – North Eastern Scotland

		78-82	83-87	88-92	93-97	98-02	03-07
1	patents	29	86	123	212	324	340
	firms	20	55	78	116	139	142
	classes	29	71	90	119	139	123
	r_pat	145	132	132	126	134	135
	r_arltdn	11	6	3	3	4	2

DUBLIN



ENTRY & EXIT OF TECHNOLOGIES IN REGIONS

 $\tilde{Y}_{i}^{rt} = \alpha + \beta_{1} \tilde{T}echProx_{i}^{rt-1} + \beta_{2} \tilde{G}eogProx_{i}^{rt-1} + \beta_{3} \tilde{S}ocialProx_{i}^{rt-1} + \beta \tilde{C}ov_{i}^{rt-1} + \beta T + \tilde{\varepsilon}_{i}^{rt}$

where the binary dependent variable assumes the value 0 or 1, and represents the probability of region r in year t exhibiting relative technological specialization in technology class i.

TechProx is the time-lagged value of the total distance (in units of technological relatedness) between each technology class *i* and all other technology classes where the city exhibits relative technological specialization.

GeogProx is a time-lagged and spatially weighted measure of knowledge flows to region *r* from all NUTS2 regions that have relative technological specialization in technology class *i*.

SocialProx is a time-lagged measure of the strength of co-inventor linkages between a region and its neighbors within each technology class.

Cov is a matrix of region and time specific covariates and **T** is a time fixed effect.



The final term is an error assumed to possess the usual properties. The \sim indicates that each of the variables have been demeaned with respect to time. The fixed effects specification has the advantage of eliminating unobserved fixed effects that are swept out of the model, along with other fixed effects (region and technology class).

Boschma R., Balland P.-A. & Kogler D. F. (2014) Relatedness and technological change in cities: The rise and fall of technological knowledge in U.S. metropolitan areas from 1981 to 2010, *Industrial and Corporate Change*, doi: 10.1093/icc/dtu012.

ENTRY & EXIT OF TECHNOLOGIES IN REGIONS

(TECHNOLOGICAL, SOCIAL & SPATIAL PROXIMITY)

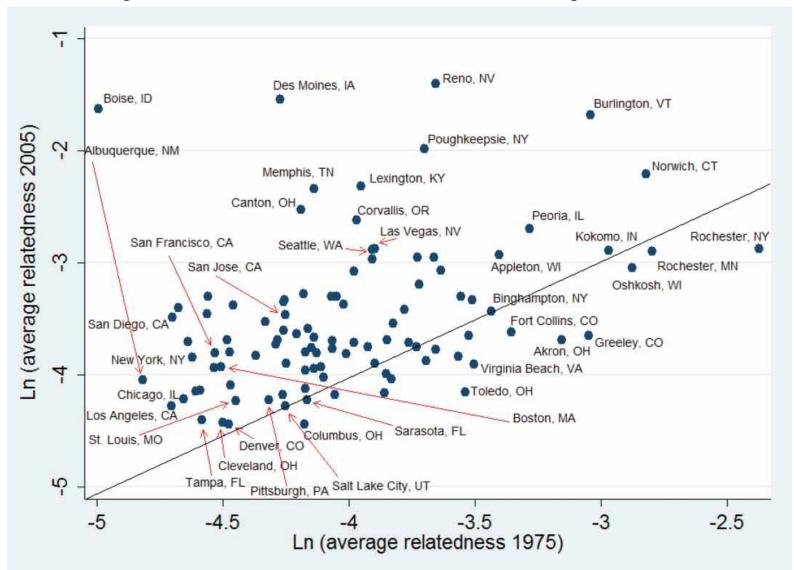
	EN	NTRY	EXIT		
Independent Variables	FE Logit	FE Logit	FE Logit	FE Logit	
L. Tech Proximity	2.5180*** (0.0969)	2.3278*** (0.0978)	-1.5073*** (0.1310)		
L. Geog Proximity		0.0670*** (0.0027)		-0.0990*** (0.0055)	
L. Social Proximity		0.0405*** (0.008)		0.0041 (0.0063)	
L. Inventor Count	0.0039 (0.0047)	-0.0031 (0.0046)	(0.0071)		
No. observations LL	88,449	88,449	31,360	31,360	



Notes: FE is fixed effects. * represents significant at the 0.1 level, ** significant at the 0.05 level, *** significant at the 0.01 level. The L prefix shows that the independent variables are lagged one time period.

AVERAGE RELATEDNESS IN US CITIES, 1975 AND 2005

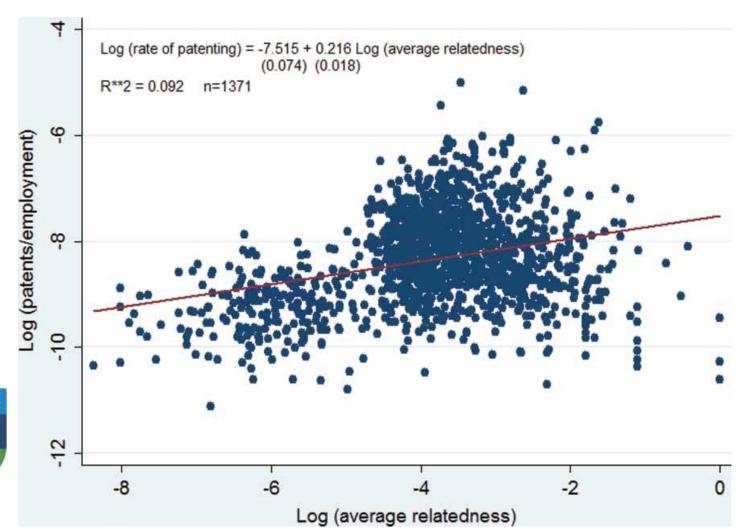
Mean knowledge relatedness value in 1975 = 0.0207, and in 2005 = 0.0391Variance among metro relatedness values was three times greater in 2005 than 1975



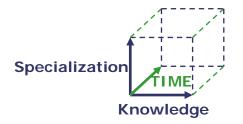
DUBLIN

DOES SPECIALIZATION IMPACT THE PRODUCTION OF KNOWLEDGE ACROSS US CITIES?

The estimated slope coefficient suggests that doubling a city's relatedness score, cetris paribus, will increase the rate of patenting by approximately 22%



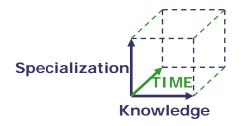
SUMMARY - CONCLUSIONS



- The European and US Knowledge Space is evolving
- Average Relatedness values increase overall, but vary substantially between technology sectors and regions
- Changes in the technological coherence (specialization/diversification) of individual regions and cities are driven by entry, exit, and differential growth; the patterns point to specific regional technology trajectories
- The entry and exit of regional technological knowledge is conditioned by technological and spatial proximity to existing knowledge cores, and to some extent also by social proximity and the number of inventors in a specific technology class.



POLICY IMPLICATIONS - FOLLOW-UP



- The Smart Specialisation Thesis weak empirical basis so far; the present research project should provide further insights.
- Interpreting Results difficult at times, e.g. entry decreases average relatedness, but on a second look the new technology classes that actually enter a place are closer to the regional knowledge space than the ones that don't.
- Follow-up and Next Steps further analysis of the 'actors' (inventors/firms) of change, the 'type' of change (incremental/radical, and branching processes), and the link to policy initiatives, i.e. attracting vs. home grown.



Potential Avenue – drawing upon Ireland as a 'laboratory' to gain further insight into the evolutionary processes that potentially drive technological change/upgrading.

THANK YOU! QESTIONS?

Dieter Franz Kogler

School of Geography, Planning & Env. Policy University College Dublin





MUNK School of Global Affairs - University of Toronto Innovation Policy Lab Speaker Series – Frontiers of Research in Global Innovation Toronto, Canada, October 8th, 2014. The research presented is joined work with:

Jürgen Essletzbichler University College London



David L. Rigby

University of California, Los Angeles; UCLA



For further information and papers please visit: https://www.researchgate.net/profile/Dieter_Kogler or https://ucd.academia.edu/DieterFranzKogler

Kogler D. F., Rigby D. L. & Tucker I. (2013) **Mapping Knowledge Space and Technological Relatedness in US Cities**, *European Planning Studies* 21(9), 1374-1391.

Boschma R., Balland P.-A. & Kogler D. F. (2014) Relatedness and technological change in cities: The rise and fall of technological knowledge in U.S. metropolitan areas from 1981 to 2010, *Industrial and Corporate Change*, doi: 10.1093/icc/dtu012.

Feldman M. P., Kogler D. F. & Rigby D. L. (2014) **rKnowledge - The Spatial Diffusion & Adoption of rDNA Methods**, *Regional Studies*, forthcoming March 2015.



The research presented is part of the "International Knowledge Flows and Spillovers and the Evolution of National Technology Trajectories" Project. Financial support from the Regional Studies Association through the Early Career Grant Scheme, Ref.No. R13455, is gratefully acknowledged.