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Path dependence and regional lock-in: an analysis using patent self-citations

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Abstract

Patent citation data has been used to track the flow of knowledge between firms and regions. However, patent self-citations are mostly excluded from studies because they do not represent knowledge spillovers. This paper proposes the use of self-citations as indicators of path-dependence and lock-in since they reveal the regional accumulation of knowledge in certain technological areas. The results indicate that regions which have more self-citations may be in a positive or negative lock-in process. Self-citations may measure a natural path dependent trajectory, which is the case of the dynamic and innovative regions but they may also indicate a myopic process of old industrial regions.

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1. Introduction

Regional economics literature focuses on the positive impacts of agglomeration economies on regional development due to the positive externalities. In these industrial agglomerations, the interaction and diffusion of knowledge are favored. Innovations occur as a function of the interactions of different networks of agents of the innovation system (Cooke, 1998). Therefore, in order to promote innovation, the advantages of an environment with many actors have to be considered. Social collaboration in these environments reduces transaction costs, corrects market failures, and reduces operating risks through knowledge spillovers (Cooke and Morgan, 1998).

Knowledge spillovers occur through the imperfect appropriability of knowledge of firms and regions, leveraging innovation in the regions that absorb them. The ability of firms to identify, assimilate and exploit external knowledge, named absorption capacity (Cohen and Levinthal, 1989), is defined in a similar way for regions (Caragliu and Nijkamp, 2008). This can be affected by institutions, geography, and interactions between inventors and firms inside and outside the region (Agrawal, Cockburn and Rosell, 2009).

In general, patent citations track part of the previous knowledge generated by their inventions. This knowledge can be acquired from firms and institutions outside the region (inter-regional knowledge) or from their own previous patents (intraregional). Thus, the analysis of patent citation data demonstrates the dynamics of knowledge over time between geographical units and technological fields (Nagaoka, Motohashi and Goto, 2010).

Patent citations made by the inventor or institutions themselves do not constitute knowledge spillovers (Jaffe, Trajtenberg and Handerson, 1993). However, they may indicate that the region appropriates its own R&D investment returns and that the firm or university in question is carrying out a process of accumulation of knowledge in a certain area of knowledge or technological trajectory (Trajtenberg, Henderson and Jaffe, 1997).

Some authors have used patent self-citations as a way of analyzing firms with path-dependent technologies (Song, Almeida and Wu, 2003; Kim and Song, 2007). Path dependence, lock-in, and related variety are key concepts used by evolutionary theory to deal with the adaptability problems of old industrial regions. These concepts help to explain how some regions lose economic dynamism when faced with a challenge in adaptability (Boschma and Lambooy, 1999; Boschma and Frenken, 2006; Martin and Sunley, 2006).

The decline of old industrial regions has been the subject of regional economic studies since the 1990s (Hassink, 1993; Morgan, 1997; Boschma and Lambooy, 1999; Kaufmann and Tödtling, 2000; Hassink and Shin, 2005; Hudson, 2005; Trippl and Otto, 2009). These studies mainly try to understand the problems of the system of innovation of these regions through the analysis of path dependence and lock-in. Many old industrial regions suffered decline in the 1970s (Norton, 1979; Chisholm, 1990). Most of them had long periods of economic growth driven by their specialization in products that were basic inputs for other sectors, such as chemical products and electronics, and mass consumption goods. The regions' institutions and infrastructure were built to sustain these basic sectors, making them vulnerable due to technological changes (Boschma and Lambooy, 1999).

This paper proposes the use of patent self-citations as a measure of regional path-dependency and lock-in. Path-dependency in some regions may indicate that the region's firms have a limited capacity to access and apply external knowledge that is beyond its current routine and that would allow more innovation (Soyer, 2012). It is therefore argued that the higher the self-citations of patents in the region, the more locked-in the region is. This process can occur in two situations. First, in a given high-tech region which conducts research on the world frontier of a particular field. Second, in less dynamic and/or an old industrial region.

2. Empirical strategy and data

The database used is the OECD Citations Database, which takes into account PCT patent applications. The data cover 44 OECD member countries divided into 645 regions at NUTS2 and TL2 level in the period 1990 to 2015. In addition, EUROSTAT Database data were also used for socio-economic, geographic and science-related data at NUTS level2 from 28 EU countries and others. Table I summarizes all the variables investigated here.

Table I: Variables and description

Variable	Description
self_cit	Number of self-citations
TI	Locational Quotient of high technological patents
gapcit	The gap between citation and publications
Q	Quality of region's patents
O	Originality
G	Generality
GDP_pc	GDP per capita
HC	Tertiary Education (in % of the labour force)
share_employ	Employees (% pop)
pat	Number of patents
abs_cap	Absorptive capacity
LQ	LQ for low-tech manufacturing
size	Size of the firms

Source: Prepared by the authors.

Variables TI, G, O, Q, and Abs_Cap were constructed using the citation patent data. TI is an index of specialization of the regions in 33 highly technological subclasses[1], and is used to separate the sample of regions in more and less technological. The index is calculated as follows:

$$TI_{it} = \frac{\frac{\sum_{n=1}^{33} patents_{n,it}}{\sum patents_{it}}}{\frac{\sum_{n=1}^{33} patents_{n,t}}{\sum patents_t}} \tag{1}$$

where $\sum_{n=1}^{33} patents_{n,it}$ is the sum of the number of patents received by the region *i* at time *t* in the fields (33 high-tech subclasses) and $\sum patents_{it}$ is the total number of patents of region *i* in period *t*. The expression $\sum_{n=1}^{33} patents_{n,t}$ is the sum of the high-tech patents of all regions at time t and $\sum patents_t$ is the sum of all patents in period *t*.

Variables G and O measure the number of the region's inventions in basic technological areas (Jaffe, Trajtenberg and Handerson, 1993; Trajtenberg, Henderson and Jaffe, 1997). The degree of generality is calculated using the forward patent citations in the region, therefore the more patents of a region are cited by more technological areas, the more "basic" the patents of this particular region are. The degree of originality is calculated in a similar way to generality,

[1] Computer and automated business equipment; micro-organism and genetic engineering; aviation; communications technology; semiconductors; and lasers. The classification is available at http://ec.europa.eu/eurostat/cache/metadata/Annexes/pat_esms_an2.pdf.

but using the backward citation concept, i.e., the patents that cited a higher number of technological fields are those with a greater degree of originality. The indexes are given by:

$$G_{it} = 1 - \sum_{n=1}^{n} \left(\frac{RC_{it,n}}{RC_{it}}\right)^2 \tag{2}$$

in which *n* refers to the IPC subclasses of the patents, $RC_{it,n}$ is the number of citations received by region *i* at time *t* from patents in field *n* and RC_{it} is the number of total citations received by the patent *i* in period *t*. To correct the bias of regions that have not been cited, the generality is estimated as follows:

$$\hat{G}_{it} = \left(\frac{RC_{it}}{RC_{it}-1}\right) G_{it} \tag{3}$$

Similarly,

$$O_{it} = 1 - \sum_{n} \left(\frac{MC_{in,t}}{MC_{i,t}}\right)^2 \tag{4}$$

$$\hat{O}_{it} = \left(\frac{MC_{it}}{MC_{it}-1}\right) O_{it} \tag{5}$$

where $MC_{in,t}$ is the number of citations made in region *i* in the *n* IPC subclasses of patents at time *t* and MC_{it} is the total number of citations made in region *i* at time *t*.

The use of originality and generality normalized indexes were proposed by Hall et al. (2002), and used by Belenzon (2006) and Fabrizio (2007, 2009). These measurements are calculated as a normalized Herfindahl–Hirschman index, so that regions with forward citations that are more concentrated in fewer areas have less generality. Regions with more concentrated backward citations, in turn, have less originality.[2]

The Quality Index (Q) of the region's patents was created under the hypothesis that regions that generate more knowledge spillovers, as measured by patent citations, in relation to the number of patents they hold, are those with patents of a higher value. Hence, the index is nothing more than a ratio of the number of forward citations of the region divided by its total number of patents.

Absorptive capacity (abs_cap) is measured as the ratio between the number of patent citations from other regions and the total number of patents of the region. The greater the use of knowledge from other regions in relation to its patent stock, the greater the region's absorption capacity.

Specialization in low technology industries (LQ) is measured as a Locational Quotient of jobs in low technology industries as follows:

$$LQ_{it} = \frac{\dfrac{\sum employ\_lowtech_{it}}{\sum employ_{it}}}{\dfrac{\sum employ\_lowtech_{t}}{\sum employ_{t}}} \tag{6}$$

[2] A concept that can be related to basicness measures is that of General Purpose Technology (GPT). These are technologies that connect to different applications and allow the emergence of multiple lines of innovation and diffusion of knowledge. Examples are the late 19th and early 20th century electric motor industry and late 20th century information technology (Hall and Trajtenberg, 2004).

where $\sum employ\_lowtech_{it}$ is the sum of the number of employees in low-tech manufactures in region i in period t and $\sum employ\_lowtech_t$ is the sum of all regions employees in low-tech manufacturing industries. $\sum employ_{it}$ is the total number of employees in region i in period t and $\sum employ_t$ is the sum of all employees of all regions in period t.

The proxy for the average size of firms in the region (size) is given by the ratio between the number of employees and the number of firms in the region.

The dependent variable is a counting variable - the number of self-citations made by the region. In this paper, self-citation made by the region is considered a measure of regional lock-in bias.

The estimated panel data model for the regional lock-in effect is given by:

$$Y_{it} = \beta_0 + \beta_1 G_{it} + \beta_2 O_{it} + \beta_3 Q_{it} + \beta_4 gapcit_{it} + \beta_5 KC_{it} + \beta_6 GDPpc_{it} + \beta_7 share\_employ_{it} + \beta_8 pat_{it} + \beta_9 abs\_cap_{it} + \beta_{10} LQ_{it} + \beta_{11} size_{it} + a_i + \varepsilon_{it} \quad (7)$$

Where the subscript *i* indicates the NUTS-2 region and the subscript *t* indicates the year of analysis; β_0 to β_{11} are the parameters to be estimated; $G_{it}, O_{it}, Q_{it}, Gapcit_{it}, HC_{it},, PIBpc_{it}, Share\_Employ_{it},\ pat_{it},\ abs\_cap_{it}, size_{it}, LQ_{it}$ are the explanatory variables; a_i are the individual effects; and ε_{it} represents the error term.

The dependent variable in our model is a positive and discrete count variable, the number of self-citations made by the region. The use of a linear model may not provide good estimates in that case. The alternative would be to use Nonlinear Least Squares, however, this approach does not treat the heteroscedasticity of counting data (Wooldridge, 2002). The models indicated for the counting data case are Poisson and Negative Binomial.

The Poisson model has the restriction that the conditional variance must equal the conditional mean. [3] In counting data, the problem of overdispersion is very common, making the use of the Poisson model impracticable. The Binomial Negative Model, unlike Poisson, is designed to explicitly handle overdispersion in data, which makes its use here more appropriate to increase estimation efficiency (Cameron and Trivedi, 2009).

In the case of panel data, the heterogeneity and variance of the unobserved term may cause serial autocorrelation and overdispersion, which makes the use of a method to control these effects necessary. Hausman, Hall and Griliches (1984) proposed a conditional likelihood method for a Binomial Negative Regression to consider some of the fixed effects. However, according to Allison and Waterman (2002), this method is not a true fixed effects method. Allison (2005) proposes the estimation of a negative binomial random effects model with all time-varying covariates expressed as deviations from their individual mean.

3. Findings

3.1. Descriptive statistics

The descriptive statistics are shown in Table II. The number of self-citations ranges from 0 to 3,966, while the mean value is 13.6 indicating a very right-skewed distribution.

[3] The results point to overdispersion condition at the 1% of significance level, with û statistic = 0.611 and p-value = 0.000.

Table II: Descriptive statistics

Variable	Obs	Mean	Std.Dev.	Min	Max
Self-citations	4175	13.626	81.141	0	3966.000
LQ of high technological patents	4175	0.003	0.009	0	0.158
Gap between application and citation	4175	2.112	1.702	0	5.000
Quality of region's patents	4175	0.212	0.52	0	21.500
Originality	4175	0.892	0.369	0	2.000
Generality	4175	0.251	0.381	0	2.000
GDP per capita	3714	26816.590	14803.320	658.000	172000.000
Tertiary Education (in % of labour force)	3359	28.083	11.060	4.600	78.800
Employees (% pop)	3865	54.986	8.113	16.200	87.800
Number of patents	4175	38.055	79.446	1	1234.000
Absorptive capacity	4175	1.736	3.046	0	138.000
LQ for low-tech manufacturing	2679	1.070	0.490	0.088	3.976
Size of the firms	2624	16.801	125.939	0.054	4054.813

Source: Prepared by the authors.

Table III shows the regions that made more self-citations in the period of 2000 to 2010. The regions were divided into the quartile with the highest degree of technological intensity and the lowest degree of technological intensity. The regions that self-cite and have the highest technological intensity are more dynamic and innovative. Their self-citations are probably due to the dominance of their research in certain fields. Regions of low technological intensity that most self-cite are characterized by being relatively less dynamic and innovative. Some of these belong to the former Soviet Union and had specialized in traditional industries such as metallurgy.

3.2. Results of Estimations

Table IV presents the results of the negative binomial random effects model. The sample was divided by quartiles of the variable specialization in high-technology patents (TI). The first column presents the results of a sample of lower specialization index in the high-technology fields. The second column shows the regions of the fourth quartile of the sample, with the regions with the highest rates of IT. A third column presents the full sample of regions.

The quality of patents in the region (Q) is negatively related to self-citations in the full sample. This indicates that the more patents in the region are cited, i.e. the greater the quality of the region’s patents, the less technologically locked in the region will be.

The control variable that measures the time gap between citation and patent publication (gapcit) is positively related to self-citation in the full sample, as expected, indicating that time increases the chances of self-citation.

Table III: Regions with the highest number of self-citations by the technological intensity in the period 2000-2010

Order	Regions in the lowest technological intensity quartile				Regions in the highest technological intensity quartile			
	Cod NUTS-2	Country	Region	Self-citations	Cod NUTS-2	Country	Region	Self-citations
1	NL12	Netherlands	Friesland	12	US06	United States	California	11670
2	BR23	Brazil	Santa Catarina	10	JPD0	Japan	Southern-Kanto	2575
3	CZ07	Czech Republic	Střední Morava	6	DK01	Denmark	Hovedstaden	1961
4	ZA02	South Africa	Free State	6	DE71	Germany	Darmstadt	1530
5	ITI2	Italy	Toscana	5	US25	United States	Massachusetts	1526
6	HU21	Hungary	Közép-Dunántúl	3	JPG0	Japan	Kansai region	1517
7	HR03	Croatia	Jadranska Hrvatska	3	DEB3	Germany	Rheinhessen-Pfalz	1209
8	PL21	Poland	Małopolski e	3	FR10	France	Île de France	1201
9	ME22	Mexico	Querétaro	2	NL41	Netherlands	North Brabant	1193
10	PL41	Poland	Wielkopols kie	2	US48	United States	Texas	1155
11	RU24	Russia	Kaliningrad Oblast	2	US34	United States	New Jersey	1144
12	ES70	Spain	Canarias	2	DEA1	Germany	Düsseldorf	1083
13	CN03	China	Hebei	1	DEA2	Germany	Köln	881
14	MT00	Malta	Malta	1	US27	United States	Minnesota	863
15	NL23	Netherlands	Flevoland	1	FR71	France	Rhône-Alpes	790

Source: Prepared by the authors.

The Locational Quotient for industries that are less technologically based (LQ) is negatively related to self-citations in the full sample. The more specialized in traditional industries the region is, the fewer the number of self-citations. This could be related to the low propensity to patent in such low-tech industries.

The percentage of people employed in the region (share_employ) is negatively related to self-citations in the full sample. This may indicate that manufacturing regions are more likely to produce patents that cite patents from other regions.

In the sample of less technological regions, as well as in the full sample, the degree of generality (G) of the region's patents is positive and significant, indicating that the higher the level of basicness of a region’s technology, the more self-citations will be made.

The size of firms in the region (size), while negative in all models, is significant only for the sample of less technological regions. The presence of bigger firms in less technological regions is negatively associated with patent self-citations possibly indicating greater access to external resources.

Table IV: Estimation of the negative binomial regression model for the NUTS-2 patent self-citations by regions according to their technological intensity in the period 2000-2010

	(1) Low tech regions	(2) High tech regions	(3) Full sample
Quality of region's patents	0.123	0.062	-0.177*
	(0.188)	(0.155)	(0.096)
Generality	0.364**	0.102	0.174**
	(0.156)	(0.120)	(0.069)
Originality	0.030	2.530***	0.245*
	(0.162)	(0.759)	(0.132)
Number of patents	4.591***	0.385***	0.419***
	(0.485)	(0.021)	(0.018)
Gap between citation and publication	0.001	0.040	0.083***
	(0.040)	(0.046)	(0.022)
Employees (% pop)	-0.086	-0.057	-0.123**
	(0.089)	(0.072)	(0.050)
Tertiary Education (in % of labour force)	-0.222**	-0.157**	-0.197***
	(0.089)	(0.076)	(0.059)
GDP per capita	0.470***	0.325***	0.652***
	(0.134)	(0.106)	(0.085)
Size of firms	-2.941***	-0.000	-0.012
	(0.796)	(0.062)	(0.050)
External absorptive capacity	0.058	0.125***	0.106***
	(0.041)	(0.034)	(0.020)
LQ for low-tech manufacturing	0.032	-0.100	-0.226**
	(0.153)	(0.159)	(0.103)
_cons	2.248***	1.110***	0.982***
	(0.331)	(0.146)	(0.088)
Obs.	509	315	1297
Log likelihood	-650.86824	-1174.6883	-3062.3333

Note: Standard errors are in parenthesis.
**** p<0.01, ** p<0.05, * p<0.1*
Source: Authors' elaboration.

Absorptive capacity is positively related to self-citations (abs_cap), though not significant for the sample of less technological regions. This result corroborates the hypothesis that firms and regions are naturally path-dependent in relation to their innovative process, as raised by Mancusi (2008). This author considers that self-citations may indicate absorption capacity as the firm or region has performed previous research in the area. In our case, absorptive capacity increases self-citations as a complementary process mainly in higher technological regions.

In the case of the sample of regions of higher technological intensity, the Degree of Originality (O) is positive and significant. Originality measures how much the region's patents are based on different technological areas, which indicates that regions with a higher degree of originality are more related to various technological areas. This may point to a positive lock-in process in which regions of higher technological intensity are more likely to cite their previous technological outputs.

The following control variables such as percentage of the workforce with tertiary education (HC), patents in the region (pat), and GDP per capita (GDP_pc) are significant in all models. The qualification of the workforce negatively affects self-citation, which may point to the fact that the higher the educational level, the more research is carried out in the region and therefore the greater the chances of access, identification and use of external knowledge. The region's number of patents and GDP per capita are positively related to self-citations in all models.

4. Conclusions

Regions with a higher number of patent self-citations produce patents with knowledge which is more "basic" and of a lower quality level. This can be due to a failure in using external knowledge available resulting in a negative technological myopic process.

The originality of a region's patents, another basicness measure, positively affects the occurrence of self-citations as well, mostly for the high technological regions. As Originality is based on the citations of different technological fields made by the region, it can indicate the diversity of fields in which the region has expertise.

The absorption capacity positively affects self-citation in high-tech regions and in the full sample model, pointing to the fact that the more knowledge a region produces, the more they have capacity to identify, assimilate and apply external knowledge, as in the theoretical proposition of the two faces of R&D made by Cohen and Levinthal (1989). This corroborates Mancusi (2008), in the sense that self-citations are also indicative of previous research carried out by the region.

Our findings may point to the determinants of negative and positive regional lock-in. Old industrial areas with proportionally more self-citations may be experiencing innovative stagnation, and consequently productivity stagnation, which can drive these regions to a loss of economic dynamism. On the other hand, there are high tech regions, with high levels of technological diversity, related variety and absorptive capacity that perform many self-citations in a natural path-dependent process, which can be described as positive lock-in.

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Appendix

Matrix of correlations

Variables	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)
(1) LQ of high-tech patents	1.000											
(2) Gap between citation and publication	0.187	1.000										
(3) Quality of region’s patents	-0.001	0.383	1.000									
(4) Originality	0.004	0.027	-0.062	1.000								
(5) Generality	0.164	0.477	0.449	0.017	1.000							
(6) GDP per capita	0.176	0.322	0.079	0.038	0.216	1.000						
(7) Tertiary Education (% of labor force)	0.093	0.008	0.026	-0.071	0.052	0.310	1.000					
(8) Employees (% pop)	0.071	0.001	0.018	0.051	-0.028	0.213	0.031	1.000				
(9) Number of patents	0.647	0.285	0.073	0.032	0.294	0.313	0.073	0.030	1.000			
(10) Absorptive capacity	0.015	0.020	0.010	0.087	0.036	0.298	0.161	0.086	0.086	1.000		
(11) LQ for low-tech manufacturing	-0.055	0.029	0.035	0.002	0.007	-0.020	-0.042	-0.013	-0.052	-0.021	1.000	
(12) Size of the firms	-0.008	0.010	0.017	0.070	-0.008	-0.021	-0.052	0.023	0.005	-0.035	-0.007	1.000

Source: Prepared by the authors.