Journal of Evolutionary Economics

Embeddedness and Local Patterns of Innovation: Evidence from Chinese Prefectural Cities

--Manuscript Draft--

Manuscript Number:	JEEC-D-18-00185
Full Title:	Embeddedness and Local Patterns of Innovation: Evidence from Chinese Prefectural Cities
Article Type:	Special Issue:Seoul conference 2018
Corresponding Author:	Federico Frattini, Ph.D. University of Ferrara Ferrara, FE ITALY
Corresponding Author Secondary Information:	
Corresponding Author's Institution:	University of Ferrara
Corresponding Author's Secondary Institution:	
First Author:	Giorgio Prodi, Ph.D.
First Author Secondary Information:	
Order of Authors:	Giorgio Prodi, Ph.D.
	Francesco Nicolli, Ph.D.
	Federico Frattini, Ph.D.
Order of Authors Secondary Information:	
Funding Information:	
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Suggested Reviewers:	Keun Lee, Ph.D. Professor, Seoul National University kenneth@snu.ac.kr Previous research on technological catching up is a pillar of the empirical exercise presented in this manuscript. As Prof. Keun Lee is also editor of the SI, scholars among his research affiliates and co-authors could do in case.
	Maria Luisa Mancusi, Ph.D. Associate Professor, Università Cattolica del Sacro Cuore marialuisa.mancusi@unicatt.it Prof. Mancusi has a strong record of publications on innovation, tech transfer, and internationalization, including papers coauthored with Prof. Franco Malerba and Prof. Stefano Breschi. Journals publishing Prof. Mancusi include Research Policy, Technology Analysis & Strategic Management, and Regional Studies.

Noname manuscript No.
(will be inserted by the editor)

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Giorgio Prodi · **Francesco Nicolli** · **Federico Frattini**

Received: date / Accepted: date

Abstract The diffusion of innovative activities was very fast in China since the mid-1990s. Literature nonetheless suggests that internationally-relevant innovation may have delayed gaining embeddedness in some places, depending on the strategy it was “seeded”. This paper posts that different degrees of embeddedness are linked with different patterns of innovation at a local level and investigates this linkage in Chinese prefectural cities. Four research hypotheses are stated, one for each indicator literature identifies as those to investigate technological catching up. The empirical exercise is set as an ordered logistic regression of data rearranged from the OECD Patent Databases limited to the period 2002 to 2009. Results show that embeddedness is positively linked with innovation that increasingly relies on its own local past and negatively linked with innovative activities more concentrated across patent owners. The evidence of a nexus with technology cycle time is less clear, but the hint is that embeddedness is gained where knowledge paths increase in complexity. Results do not support conclusions about the linkage between the embeddedness and originality of innovative activities, which is required appropriate investigation in future research.

Keywords China · embeddedness · innovation · patent · technological catching up

JEL Classification O33 · O53 · R19

G. Prodi (http://orcid.org/0000-0002-3957-4939)
University of Ferrara, 44121 Ferrara, Italy
E-mail: giorgio.prodi@unife.it

F. Nicolli (https://orcid.org/0000-0001-8109-5969)
European University Institute, 50133 Florence, Italy
E-mail: francesco.nicolli@unife.it
Present address: University of Ferrara, 44121 Ferrara, Italy

F. Frattini (https://orcid.org/0000-0002-8490-4159)
University of Ferrara, 44121 Ferrara, Italy
E-mail: federico.frattini@unife.it

1 Introduction

Technological catching up is essential to economic rise in middle-income countries (Lee, 2013). Laggards are required to accumulate technologically less-vintaged capital to close the gap with the more industrialized economies (Abramovitz, 1986). In these economies, up-to-date capital accumulation is mostly endogenous as it usually happens on the global technological frontier. In those emerging, instead, indigenous capital accumulation can critically benefit from being complemented by capabilities imported from abroad (Lall, 1992).

Despite a debate in literature (De Marchi et al., 2018; Fagerberg et al., 2018; Lee et al., 2018), several channels are reckoned to favor a local absorption of foreign capital and technologies in middle-income countries, such as the import of goods, capital, brains and the involvement in global value chains (GVC). This very absorption is essential for indigenous-innovation patterns to grow less-and-less dependent upon exogenous sources and to "seed" innovation systems (Chung and Lee, 2015; Lee et al., 2018).

The interaction between endogenous and exogenous capabilities may nonetheless produce side effects in the medium–long term, such as the foreign activities to displace some of those indigenous (Lin and Kwan, 2016). For this reason, the strategy that technological catching up is "seeded" is no less than critical for innovative activities to embed at a local level (Prodi et al., 2018). Embeddedness regards the depth innovation takes roots into a local environment. In "mature" innovation systems, for instance, technology creation, absorption and exploitation are supposed as fully anchored and governed at a local level (Cooke et al., 1998). Accordingly, innovative activities gaining embeddedness can be assumed as the result of a local environment gaining strength.

As much as for many other features of innovation, however, a precise measure of embeddedness is unfortunately unattainable. Possible approximations rather rely on observing the input of innovative activities like the amount of the R&D expenditure or personnel, its output like patent applications, or effect like the change in total factor productivity (Keller, 2004). A choice among these alternatives often depends on the aims of the empirical investigation.

Prodi et al. (2018) suggests that the embeddedness of innovative activities in small regions can be proxied comparing the prevalence of patent inventors and applicants (or assignees). Higher is the presence of indigenous applicants in the local pool, more innovative activities are said to be embedded in their local environment. The idea behind is quite simple: innovation is anchored more tightly to where it is promoted, funded, managed and exploited than where it just happens. Let take for instance the theories about multinational corporations (MNC) and global value chains (GVC). Value creation is more distributed to the network "peripheries" as more the resources and competences are dispersed across subsidiaries and suppliers and, there, they are actually governed (Ghoshal and Bartlett, 1990; Gereffi et al., 2005). The same is for innovative activities, on which value creation depends extensively, so that they need more than being just performed in a place to embed.

The approach in Prodi et al. (2018) was set up limited to ranking and mapping the levels that innovative activities are embedded in Chinese prefectural cities. Nonetheless, it is reasonable to assume embeddedness as related to the local patterns of innovation in some ways. More or less anchored innovative activities should reveal indeed fairly different characteristics taking place. And the aim of this paper is to investigate this very linkage.

Literature offers a wide set of patent statistics to investigate the features of innovative activities (Squicciarini et al., 2013). Breschi et al. (2000) first took some of these indicators to qualify different patterns of innovation in separate technological regimes. Park (2006) later enriched and tuned that selection to specifically investigate technological regimes for technological catching up in emerging economies. Lee (2013) finally identified the localization, originality, concentration, and technology cycle time of innovations as the most critical indicators in cross-country comparison. Each one of these indicators is built upon patent information to capture as much features of the innovative environment that can foster technological catching up.

In details, technological catching up is positively related to more original inventions and an increasing localization of the knowledge sources in the same place where innovation is carried out, while it tends to slow down where the concentration of innovative activities across applicants and the technology cycle time increase (Lee, 2013). The main assumption here is that, at a local level, all these patterns but technology cycle time are related to the embeddedness of innovative activities in the same way they are to technological catching up in middle-income countries. Embeddedness is indeed expected to grow along with technological catching up and its highest levels to be found out in mature local innovative environments. For this reason, a higher embeddedness can be also expected to support more complex paths of knowledge creation than those required to boost filling technological gaps in capital accumulation. These hypotheses are tested in an ordered logistic regression where the dependent variable are ranked levels of embeddedness in Chinese prefectural cities and the four indicators of the local patterns of innovation are included as continuous explanatory variables.

The empirical exercise is based on the set of patent applications from China filed at the European Patent Office (EPO) that Prodi et al. (2018) rearranged at a prefectural level from the OECD REGPAT Database (January 2014). The REGPAT database is rich of systematized details about the location of patent inventors and applicants that can be used to build a measure of embeddedness. In addition, patent records in REGPAT are linkable with those in the OECD Citations Database and the OECD Patent Quality Indicators Database, from which the indicators for the local patterns of innovation can be derived. The period considered here is limited to between 2002 to 2009.

For what concerns the selected case, China is one paradigmatic for the purpose of this paper. It is indeed one of the most successful catching up economies experiencing unprecedented economic growth and a specific developmental model since the early 1980s (Brandt and Thun, 2016). Success led the country to the role of "world factory" (Thun, 2014) so that, today, China is a provider of manufacturing activities to many GVC (Sun and Grimes, 2018) and also capable of international technological collaborations and a world leadership in some industries (Ma et al., 2009; Zhang, 2015). Several gaps with industrialization have been then filled, at least in some cities. China's developmental attainments follow in fact from an articulated and unbalanced strategy of technological catching up that mixed indigenous and foreign seeds diversely over time (Fu et al., 2016). As a result, innovative activities are strongly concentrated in some regions (Crescenzi et al., 2012) and variously embedded as well (Prodi et al., 2018).

This paper offers a threefold contribution to the innovation studies applied to development economics. First, it reinforces the bridge between two streams of research, one focusing on the political economy of developmental upgrading in China (among others: Naughton (2007); Brandt et al. (2008); Jin et al. (2008); Brandt and Thun (2016); Chen and Naughton (2016); Brandt and Thun (2016)) and the other on the relevance of technological catching up to that change (among others: Lee and Lim (2001); Park (2006); Lee (2013); Lee et al. (2017)). Second, the empirical exercise somehow validates the methodology to approximate embeddedness proposed in Prodi et al. (2018), as it offers evidence of theoretically consistent linkages between embeddedness and previous findings in literature. Third, the findings here provide additional support to the idea that technology cycle time actually works in different ways in the experience of technological catching up and that one of pushing on the frontier (Lee, 2013). In doing this, the remainder of the paper is outlined as follows.

Section 2 illustrates the diffusion and dispersion of innovative activities in China, also showing how they are variously embedded across Chinese prefectural cities. Section 3 describes the indicators capturing the local patterns of innovation that are relevant to the analysis here and reports summary statistics at the prefectural level. Section 4 is devoted to introducing the empirical test of the linkages between embeddedness and the local patterns of innovation and, then, to report and discuss the results. Section 5 makes finally room for conclusive remarks highlighting the main findings, their limitations and implications.

2 Embeddedness of innovative activities in China

Innovative activities have grown very fast in China since the mid-1990s. Domestic patent applications to the State Intellectual Property Office of the People's Republic of China (SIPO) rose on average 24.6% a year from 7.7 to 207 per million inhabitants between 1995 to 2010.[1] Although the counts are much smaller, the growth pace is even steeper where the applications to international

[1] Compound Annual Growth Rate. Counts consider domestic applications for creations and inventions from China's National Bureau of Statistics, China Statistical Yearbooks. Editions referred for data collection are 1996, 1998 to 2003 and 2005 to 2011, available at the National Bureau of Statistics of China, Annual Data: http://www.stats.gov.cn/english/Statisticaldata/AnnualData. Population data are from the United Nations, Department of Economic and Social Affairs, Population Division, World

patent offices are considered. As an example, the number of patent applications from China to the EPO rose on average 34.5% a year from 0.03 to 2.5 per million inhabitants during the same period.[2] Several factors are mentioned in literature as fostering that upsurge of patents, such as the amendments to the national law on intellectual property rights (Hu and Jefferson, 2009), a competition between local authorities (Li, 2012) and, of course, a reinforcement of technological capabilities (Lee et al., 2017).

The rise of innovative activities is tightly intertwined with economic development and strongly concentrated where it cumulated first (Crescenzi et al., 2012). In 1995, around 55% of patent applications from China to the EPO were actually located in Beijing, the capital city, and they amounted up to 71% including those from Shanghai and the provinces of Guangdong, Jiangsu and Zhejiang. Concentration further increased afterwards, with the EPO applications from these regions reaching 86% in 2010. Nonetheless, the distribution has substantially changed over years with Beijing counting about 10% of the total national patent applications, Guangdong 62% and Shenzhen in Guangdong almost 57% its own.[3] Evidence is mitigated but not confuted by referring to the domestic applications to the SIPO: 31% of innovative activities in China were located in the same regions as above in 1995, then grown to 60% in 2010.[4]

These figures are the product of a specific, multilayered and evolving set of science, technology and innovation (STI) policies at a national level, as well as of more local drivers of development (Fu et al., 2016; Zhang, 2010). Major cities like Beijing and Shanghai, for instance, were better endowed of local R&D capacity to attract seeds of local innovation systems in the origin (Zhang, 2010). Other cities like Shenzhen differently took advantage of dramatically rescaling alongside country's development since the early 1980s (Zeng, 2010). It was in the very post-Mao strategy of transition and industrialization to favor indeed foreign direct investments (FDI), and so also new imported capabilities, to start agglomerating in a limited number of places, such as the special economic zones (SEZ), where to open to and experiment on market economy (Heilmann, 2008). Then, a number of STI initiatives, like the Torch Programme launched

Population Prospect 2017: https://esa.un.org/unpd/wpp. Hong Kong, Macao and Taiwan are not included for statistical consistency. Data extracted on May 21, 2018.

[2] Compound Annual Growth Rate. Patent counts refer to the priority date and applicant location based on fractional counts from the OECD.Stat: http://stats.oecd.org. Population data are from the United Nations, Department of Economic and Social Affairs, Population Division, World Population Prospect 2017: https://esa.un.org/unpd/wpp. Hong Kong, Macao and Taiwan are not included for statistical consistency. Data extracted on May 21, 2018.

[3] Shares are computed on fractional counts of patent applications to the EPO by priority date and applicant location. Data are collected from the OECD.Stat: http://stats.oecd.org. Hong Kong, Macao and Taiwan are not included for statistical consistency. Data extracted on May 21, 2018.

[4] Shares are computed on domestic applications for creations and inventions from China's National Bureau of Statistics, China Statistical Yearbooks available at the National Bureau of Statistics of China, Annual Data: http://www.stats.gov.cn/english/Statisticaldata/AnnualData. Hong Kong, Macao and Taiwan are not included for statistical consistency. Data extracted on May 21, 2018.

in 1988 to create new industry and technology parks, worked as a connection between separate governmental layers (Heilmann, 2013) and as an additional boost for local economic growth (Hu, 2007).

Concentration is the most immediate but not the one side effect of unbalanced growth. Structural differences may also emerge over time as much for income as for innovative activities. Especially where the seeds vary across regions, innovative activities can grow to feature place-specific institutional and structural traits, which include embeddedness (Prodi et al., 2017, 2018). To gain an insight into this aspect of the diffusion of innovative activities in China, the discussion now focuses on the patent applications from China to the EPO. Patentability is usually more binding and patenting costs higher than to national patent offices, so that referring to one or more international patent offices is advantageous as it introduces an implicit quality threshold to the analysis (Dernis and Khan, 2004). In other words, patent applications feature higher opportunity costs *ex ante*, so that their counts *ex post* tend to be smaller and so, magnify the evidence. Some very recent literature also suggests that this issue should be carefully considered in the case of China where international patents are shown to be far more reliable than domestic patents to measure the quality and relevance of innovative output (Prud'homme and Zhang, 2017; Long and Wang, 2018).

Figure 1 starts from reporting the overall trends of the EPO patent applications from China between 1995 to 2010.[5] Two separate trends are drawn in the figure. The black solid line counts the patents located in China by applicant (a) and the black dashed line those located by inventor (b). The pair of lines exhibit a fast growth but the gap in the between (g) highlights that the count by applicant location is 15 to 25% smaller. In this sense, internationally relevant innovation appears to be more frequently performed than appropriated in Chinese prefectural cities. The question is now whether this evidence is homogeneously distributed or not all over the local innovative centers in China.

Data on the EPO patent applications as rearranged at a prefectural level from the OECD REGPAT Database (January 2014) in Prodi et al. (2018) can help get an answer. Based on these data, it is possible indeed to quantify the gap ($g{-}i = b_i{-}a_i$) between the counts of EPO patent applications by applicant (a_i) and inventor (b_i) in Chinese prefectural cities i. Figure 2 focuses on the period between 2002 to 2009, that is, the latest period considered in Prodi et al. (2018) and, of course, where the number of cities hosting at least one EPO-patent inventor or applicant is the largest (187 over 345 total). As innovative activities have been said strongly concentrated in some of these cities, the gap measure is rescaled on the overall number of the EPO patent applications considered for each city (f_i), that is, the combination of the applicant- and inventor-based counts: $f_i = a_i + b_i - c_i$, where c_i are patent documents which applicants and inventors are located in the very same city i. Put into a different

[5] Data are collected from the OECD.Stat: http://stats.oecd.org. Hong Kong, Macao and Taiwan are not included for statistical consistency. Data extracted on May 21, 2018.

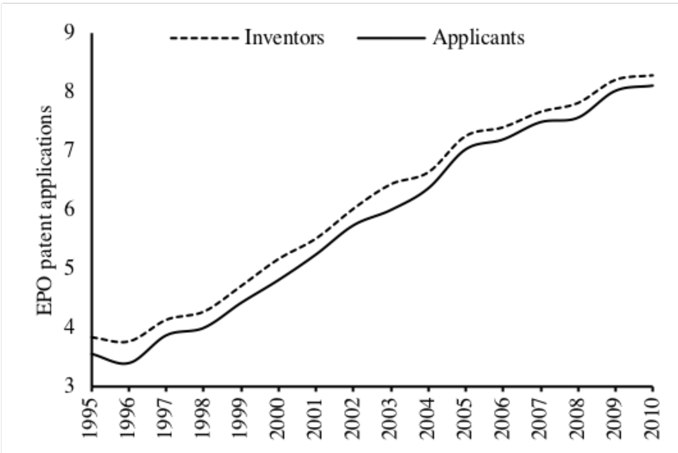

Fig. 1 Diffusion of innovative activities in China by inventor and applicant location, 1995-2010, fractional counts, log scale. Source: authors' arrangement from the OECD.Stat.

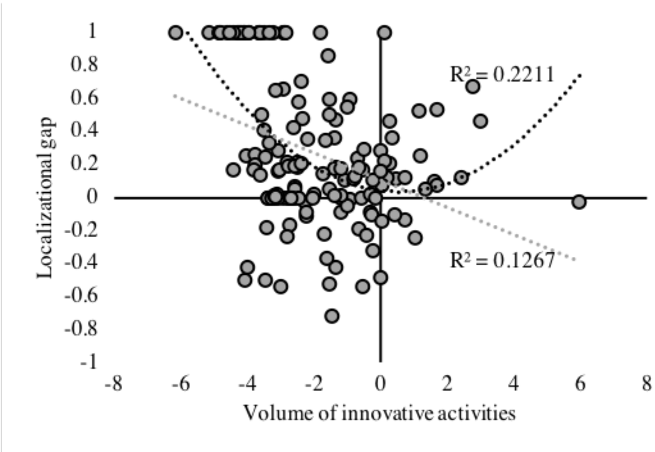

Fig. 2 Gaps between applicant- and inventor-located EPO patent applications (rescaled counts) and total number of EPO patent applications considered in Chinese prefectural cities (patent per million inhabitants, log scale), 2002-2009, period pooled counts. Source: authors' arrangement from the OECD REGPAT Database, January 2014 and China Data On Line.

perspective, the overall number of patent applications (f_i) is a union of two sets $f_i = a_i \cup b_i$, that is, the usual count of total patent applications by applicant location a_i and the usual count of total patent applications by inventor location b_i, which intersect in the subset $c_i = a_i \cap b_i$. By definition, f_i is never less than a_i neither than b_i ($f_i \geq a_i, b_i \forall i$) and the rescaled gaps (g_i/f_i), which are scattered against the total number of EPO patent applications per million inhabitants (f_i/pop_i) in Figure 2, therefore range between −1 and +1 ($-1 \leq g_i/f_i \leq +1$).[6]

The feedback from Figure 2 is straightforward: the gaps (g_i/f_i) weight differently across cities and it appears to be weakly related to the volume of innovative activities performed in cities. Prodi et al. (2018) interpreted this picture as the evidence that innovative activities are variously embedded across cities and, going a step further, as a sort of trace of the mix seeding technological catching up locally. In this sense, more (less) embedded innovative activities are expected to come from more endogenous (exogenous) seeds. Innovative activities were found indeed to have increased faster although they have delayed gaining embeddedness in places like the SEZ where imported capabilities agglomerated the most in the origin.

The key to that evidence was of course to get a measure of embeddedness. The method proposed in Prodi et al. (2018) is to perform a grouping of cities into clusters based on the values of the three rescaled indicators. The substance of clustering is to separate observations into groups according to some measure of association in order to summarize their multidimensional variability (Hair et al., 2009). Records are separated here into three locational sets: applications that the applicants only are from a city i ($d_i = a_i - c_i$); those that the inventors only are from a city i ($e_i = b_i - c_i$); those that both the applicants and inventors are from the same city i (c_i). Counts are then rescaled on the total number of the EPO patent documents considered ($f_i = c_i + d_i + e_i = a_i + b_i - c_i$) and taken their period-average values.

The resulting groups are classes of observations, and they are orderable where a motivated criterion exists. In this specific case, the motivation is intrinsic into how innovative activities are supposed to evolve along they gain embeddedness, that is, those patents located by applicant come to weight more while those located by inventor do less. Table 1 reports the results as obtained by Prodi et al. (2018) for the period between 2002 to 2009 (letters amended as above). Among the 187 cities for which EPO patent records have been found, the 130 grouped into class 1 are those where embeddedness is assumed to be the lowest because innovative activities are mostly or even exclusively associated to these cities by inventor. Applicants are therefore located elsewhere in China or abroad. Embeddedness is then expected to increase climbing up the classes, and the 38 cities in class 2 are indeed those that EPO patent documents show also hosting innovative activities in which inventors and applicants are both local. This very set of innovative activities is the one most relevant among the 14 cities in class 3, while it emerges together with innovative activities located by the applicant only among the 5 cities in class 4. These results therefore suggest that internationally relevant innovative activities are far from reaching high levels of embeddedness in a large majority of the Chinese prefectural cities where they are performed. About 70% of cities predominantly host only inventors of EPO patent applications (class 1) and

[6] Data on population in prefectural cities (pop) are from China Data On Line, City statistics, http://chinadataonline.org/member/city/. Data extracted on February 18, 2016.

Table 1 Classes of prefectural cities by prevailing patent indicator, Chinese prefectural cities, 2002-2009. Source: authors' arrangement from Prodi et al. (2018), Table 5 (partial), p. 91.

Embeddedness (classes)	Description	# obs
4	Prevalence of c/f and d/f	5
3	Prevalence of c/f	14
2	Prevalence of c/f and e/f	38
1	Prevalence of e/f	130
Total grouped		187
Total excluded for no activity recorded at the EPO		158

c = number of EPO patent applications with local inventor and applicant
d = number of EPO patent applications with local inventor only
e = number of EPO patent applications with local applicant only
$f = c + d + e$ = total number of EPO patent applications counted

less than 3% record a sizeable presence of local applicants (class 4). For the remainder 27% of cities, the local pool of innovative activities is in the between (classes 2-3).[7]

3 Local patterns of innovation across Chinese prefectural cities

Embeddedness is just one of the qualities of local innovative activities that can be detected by patent statistics. As mentioned above, literature offers several patent quality indicators aimed to reveal manifold characteristics of innovation (Squicciarini et al., 2013). Some of these indicators have been adopted to investigate the patterns of innovation that are relevant to identify separate technological regimes (Breschi et al., 2000) and later, to estimate how technological catching up appear to foster economic growth (Lee, 2013). These indicators include the originality of innovation, the localization of its knowledge base, the concentration of innovation across innovators, and the cycle time of technologies (Lee, 2013).

First, an originality index (O_p) focuses on "the breath of the technology fields on which a patent relies" (Squicciarini et al., 2013, 49). Based on the seminal contribution by Trajtenberg et al. (1997), it is defined as

$$O_p = 1 - \sum_{k \in K_p} s_{pk}^2$$

where p is a patent document, k a four-digit class of technologies in the International Patent Classification (IPC) and s the share of citations to a technological class k reported in the document p. A higher variety of the referred technological fields then corresponds to more originality. But, as the analysis

[7] A rank 5, that is, a prevalence of d/f, may additionally result from grouping in theory. It is hard (not impossible), however, to find out that innovators largely agglomerate in a place while their activities are mostly performed elsewhere. The results presented in Prodi et al. (2018) actually report this hypothetical rank 5 as an empty group.

here is put into a regional perspective, the single-patent indicators ($p \in P_i$) are summarized taking the average value for cities:

$$O_i = \frac{1}{|P_i|} \sum_{p \in P_i} O_p \tag{1}$$

within the set of patents P_i relating to each city i. Indicator values can range between 0 and 1 included ($0 \leq O_i \leq 1$) corresponding to the lowest and the highest level of originality respectively.

Second, the localization of knowledge creation and diffusion (L_i) is based on the idea "to compare the probability of a patent matching the originating patent by geographic area, conditional on it citing the originating patent, with the probability of a match not conditioned on the existence of a citation link" (Jaffe et al., 1993, 581). Following from this idea, Lee and Yoon (2010) proposed to measure localization as the ratio between the propensity to regional self-citation and the citations from other regions. Lee (2013) then amended the indicator as follows:

$$L_i = \frac{c_{ii}}{c_i} - \frac{\sum_{j \in J} c_{ij}}{\sum_{j \in J} c_j} \tag{2}$$

where: c_{ii} is the number of citations to patents in a region i by patents from the same region; c_{ij} is the number of citations to patents in the region i from another region $j \neq i$; c_i is the total number of citations by patents in the region i; c_j is the total number of citations in a region $j \neq i$. The set J is restricted here to the Chinese prefectural cities so that the value of L_i is the percentage points that a city i is exceeding or failing the other cities j to reference its very knowledge base. In other words, L_i increases as innovative activities tend to build more and more on their own local past. Indicator can take both positive and negative values theoretically ranging between -1 and $+1$ included ($-1 \leq L_i \leq +1$).

Third, "high technological opportunities allow for the entry of new innovative firms, thereby reducing concentration" (Breschi et al., 2000, 393). Accordingly, the concentration of innovative activities (H_i) is negatively related to technological catching up (Lee, 2013). It can be approximated as the same as market concentration by a Herfindahl-Hirschman index and, more precisely here, as follows:

$$H_i = \sum_{a:p_i} (\frac{\pi_a}{\pi_i})^2 \tag{3}$$

where π is the count of patent applications located in the region i by inventor that are attributable to the same applicant a. Indicator values can range between 0 and 1 included ($0 \leq H_i \leq 1$) corresponding to the lowest and the highest level of concentration respectively.

The fourth indicator taken into account is technology cycle time (T_i). It was introduced to measure how knowledge differs "in its obsolescence over time" (Park, 2006, 726) based on patent-citation lags, that is, the approximation

Table 2 Indicators of local patterns of innovation, Chinese prefectural cities, 2002–2009, summary statistics. Source: authors' arrangement from the OECD REGPAT Database, January 2014, the OECD Citations Database, March 2018, and the OECD Patent Quality Indicators, March 2018.

	# obs	mean	sd	$z(W)$	min	25%	50%	75%	max
O_i	159	0.7173	0.1312	5.617***	0.000	0.670	0.732	0.791	0.932
L_i	159	0.0174	0.0863	10.068***	–0.000	0.000	0.000	0.000	0.714
H_i	159	0.4399	0.3528	5.176***	0.012	0.124	0.356	1.000	1.000
T_i	159	13.1913	7.7075	5.863***	2.000	8.133	11.665	16.333	43.000

p-value: $^{*} < 0.1$;$^{**} < 0.05$;$^{***} < 0.01$

of the time span between the appearance of a predecessor and a successor technology (Jaffe and Trajtenberg, 2002). The indicator is amended here to investigate the differences not across technological classes k but regions i, so that:

$$T_i = \frac{1}{|P_i|} \sum_{p \in P_i} t_{pc} \tag{4}$$

where p are citing patent documents (those collected), c are cited patent documents, t the citation lag in years, and P_i the set of patent applications in a city i. By definition, the technology-cycle-time indicator for a single patent document can take only non-negative integer values ($T_p \in 0, 1, 2, \ldots, t, \ldots, t_p - t_c$).

All the indicators are computed looking at the inventor side as it is recommended to use the inventors' location to "compile patent statistics aimed at reflecting inventive activities" (OECD, 2009, 63). Each indicator is taken its average value for the period between 2002 to 2009 based on the patent citations collected in the OECD Citations Database, March 2018, and the indicators collected in the OECD Patent Quality Indicators, March 2018. Application numbers are used to link patent records across databases and their releases. Complete records were collected for 159 out of 187 Chinese prefectural cities.

Table 2 reports summary statistics for each indicator. It is worth to note that their distribution is mostly not well-behaved. As an example, distribution is negatively skewed in the case of originality O_i and positively in the others, as well as there are many zeros in the case of localization L_i. The Shapiro-Wilk test $z(W)$ confirms that the (null) hypothesis of normal distribution should be rejected for all the indicators. As a consequence, quartile thresholds are to be preferred to mean values as meaningfully representative of regressors in the empirical exercise presented in the next section (Filed et al., 2012).

4 Linking embeddedness with local patterns of innovation

The core of this paper is to test whether innovative activities exhibit local patterns which are linked with their degree of embeddedness. The idea is that separate levels of embeddedness gained by local innovative activities correspond to different patterns. The research hypotheses are specified as follows: (H1) embeddedness is positively correlated with the originality of local innovation; (H2) embeddedness is positively correlated with the localization of the knowledge sources referenced by local innovation; (H3) embeddedness is negatively correlated with the concentration of local innovative activities; (H4) embeddedness is not negatively correlated with the technological cycle time of local innovation. No assumption is posted on the nature of these linkages, and no causal relation is implied as well.

As the measure of embeddedness reported in Section 2 is in the form of ranked classes which Chinese prefectural cities are grouped into, the most appropriate model to test the hypotheses above is an ordered logistic regression. This technique belongs to a set of models based on Maximum Likelihood Estimators (MLE), that is, non-linear functions of the dependent variable. In the empirical exercise presented here, nonlinearity arises from the categorical nature of the dependent variable and regression parameters are to be interpreted as the effects of regressors on a latent continuous variable y^* entailed by the classes of the dependent one (Cameron and Trivedi, 2005). Model specification is as follows:

$$y_i^* = \beta X_i + u_i \tag{5}$$

where y_i^* is a one-dimensional array of 159 observations for the response variable that "crosses a series of increasing unknown thresholds [moving] up the ordering of alternatives" (Cameron and Trivedi, 2005, 519). X_i is then a two-dimensional array of 159 observations for each one of the four regressors and u_i the usual one-dimensional array of error terms that are assumed as logistic distributed.

Table 3 reports the distribution of observations by class of the dependent variable. The most of them fall into the class $Y_i = 1$ (about 64%) and frequency decreases fast climbing up alternatives. Just a few observations are grouped into the class $Y_i = 4$ (3%), which size is so small that it can be questioned to bring potential problems into the regression. Table 4 gives an insight into this very point reporting the representative values of regressors by class of the dependent variable. Regardless these values are means or medians, regressors tend to behave homogeneously (increase or decrease) across classes but class $Y_i = 4$. Observations in this class are then expected to exert a countervailing influence on the estimated coefficients, although it will be unlikely strong given that their small number could miss to represent a true alternative of Y_i. It will be worth to take account of this issue when discussing test statistics.

The output of regressing the classes of embeddedness against the four pattern indicators in Chinese prefectural cities is reported in Table 5, both in the form of scores and percentage. Scores quantify the effect one unit increase in regressors x_i produces on the response variable y_i^*. More precisely, this effect is an increase in the log odds that the response variable moves from values below to values above a threshold τ_y. Scores here suggest that the odds are

Table 3 Distribution of observations by class of the dependent variable.

Y_i	Frequency	Percentage	Cumulative percentage
1	102	64.15	64.15
2	38	23.90	88.05
3	14	8.81	96.86
4	5	3.14	100.00
Total	159	100.00	

Table 4 Representative values of regressors by class of the dependent variable.

	Mean				Median			
Y_i	O_i	L_i	H_i	T_i	O_i	L_i	H_i	T_i
1	0.72279	0.00899	0.60085	12.8993	0.75237	0.00000	0.51827	10.5500
2	0.70579	0.01365	0.17161	14.3318	0.71617	0.00000	0.13026	12.4028
3	0.68920	0.09566	0.09509	12.0158	0.70743	0.02000	0.05696	11.5501
4	0.77415	0.00000	0.16354	13.7723	0.74392	0.00000	0.14940	14.4159

affected (H1) negatively and nonsignificantly by an increase of the originality of innovative activities O_i, (H2) positively and significantly by an increase in the localization of knowledge creation and diffusion L_i, (H3) negatively and significantly by an increase of the concentration of innovative activities across applicants H_i, (H4) positively and non-significantly by an increase of technology cycle time T_i.

The quantification of these effects is nonetheless easier where the scores are transformed. The transformations reported in Table 5 are the percentage change in the odds that the response variable crosses a threshold τ_y due to one standard-deviation increase of regressors. Based on this arrangement, the odds of moving up classes of embeddedness are (H1) decreasing by 4.9% where the value of originality O_i increases by one standard deviation (0.131), (H2) increasing by 35.6% with one standard-deviation increase of localization L_i (0.086), (H3) decreasing by 91.7% with one standard-deviation increase of concentration H_i (0.352), (H4) increasing by 26.1% where technology cycle time T_i increases by one standard deviation (7.707). Of course, the estimates for originality O_i and technology cycle time T_i remain statistically non-significant.

Despite two single coefficients fail to meet the assumptions of a consistent linkage specification, test statistics suggest that the assumption of correct specification is met overall. The estimates actually converge to a log likelihood (–107.9) and, second, the log likelihood ratio test between the constrained and unconstrained model (LR) is statistically significant. Nonetheless, the overall fit appears to be substantially improved by excluding the five observations grouped into the class $Y_i = 4$. Although these observations represent just 3.4% of the sample, the log likelihood decreases by about 21% (–85.1) and also the explanatory power of the model increases by five percentage points from 28% to 33% as measured by the pseudo R^2.

Table 5 Regression output (scores for unit and percentage for standard-deviation increase of regressors).

	$Y_i = 1, 2, 3, 4$		$Y_i = 1, 2, 3$	
	Scores	% for sd change	Scores	% for sd change
O_i	–0.3861	-4.9	–2.0903	-24.2
	(1.9584)		(2.0385)	
L_i	3.5276*	35.6	6.5975**	78.4
	(1.9479)		(2.6908)	
H_i	–7.0556***	–91.7	–7.4357***	–92.8
	(1.1787)		(1.2542)	
T_i	0.0301	26.1	0.0198	16.7
	(0.0337)		(0.0357)	
τ_1	–1.4453		–2.7630	
	(1.6072)		(1.6887)	
τ_2	0.6583		–0.3316	
	(1.5973)		(1.6704)	
τ_3	2.2751			
	(1.6380)			
# obs	159		154	
$LR\chi^2(4)$	86.14***		87.28***	
Pseudo R^2	0.2853		0.3389	
Log Likelihood	-107.9168		-85.1303	

p-value: $^* < 0.1$;$^{**} < 0.05$;$^{***} < 0.01$
standard errors in brackets

The results then confirm that the observations grouped into class $Y_i = 4$ bring some noise into the regression, although it is not enough to motivate the two coefficients estimated for originality O_i and technology cycle time T_i to be statistically non-significant. Rather, the comparison of the two estimations suggests that the indicator of concentration of innovative activities across applicants H_i is the most robust to subsetting, being the one associated to coefficients (and related standard errors) that do not relevantly change depending on the sample (the estimated effect is respectively 91.7 and 92.8% including and excluding $Y_i = 4$).

The ordered logistic regression is based on the assumption of proportional odds or parallel regressions. More precisely, the changes in regressors x_i are assumed to produce the very same increase in the odds that the response variable crosses any threshold τ_y (Agresti, 2013). Given that the dependent variable takes four possible outcomes ω_y ($Y_i = 1, 2, 3, 4$), there are three implied thresholds to be considered ($\tau_y = \omega_y - 1$). As an example, one standard-deviation increase in the concentration indicator H_i is expected to reduce about 92% the probability that the response variable y_i^* moves, let say, from the lowest class ($Y_i = 1$) to the three-class block above ($Y_i > 1$) as much as from the lowest two-class block ($Y_i = 1, 2$) to the highest two-class block ($Y_i = 3, 4$). The validity of this assumption can be verified performing a Brant test, the results of which are reported in Table 6. As the test statistics are non-significant for individual regressors and overall, there is no room for rejecting the null hypothesis

Table 6 Brant test of the proportional odds assumption.

	χ^2	df
All	7.46	8
O_i	3.73	2
L_i	0.32	2
H_i	0.04	2
T_i	1.57	2

p-value: $^{*} < 0.1$;$^{**} < 0.05$;$^{***} < 0.01$

of proportional odds and the effects produced can be taken as symmetric over the three thresholds.[8]

The regression output has returned for now just a quantification of the changes in the odds that the latent variable y_i^* crosses these thresholds τ_y. Nothing has been said instead about the odds that the dependent variable y_i falls into alternative classes as predicted by regressors x_i. This probability can be obtained computing the marginal effects at given values of regressors for each one of the possible dependent outcomes ω_y (or classes of $Y_i = 1, 2, 3, 4$). Those reported in Table 7 are then the odds that Chinese prefectural cities are grouped into a given class of embeddedness ($Y_i = \omega_y$) conditional on the four local patterns of innovation (x_i), more formally, $\partial Pr(y_i = \omega_y)/\partial x_i$ at some representative values of x_i.[9]

Let start start from the indicator of concentration $H_i = 4$ for which the regression has been said to produce the most robust prediction. The odds that an observation falls into the class $Y_i = 1$ are 32% if the 25^{th}-percentile value of H_i is taken, and they increase up to 96% at the 75^{th}-percentile value of H_i. On the opposite, the odds to fall into the class $Y_i = 2$ reduce from 47% to 3% moving from the 25^{th}-percentile to the 75^{th}-percentile of H_i, and the same happens for the classes $Y_i = 3$ (from 15% to 0%) and $Y_i = 4$ (from 5% to 0%). The array of estimated odds is obviously bound to the original distribution of observations in the sample, so that observations here are more likely to fall into the class $Y_i = 1$ unconditional as well as conditional on regressors. Nonetheless, substantial changes in the odds are produced by taking alternative points within the distribution of H_i (and supposing that the other regressors are held their values unchanged).

In sum, an increase of the concentration of innovative activities across applicants H_i is associated to an increase in the odds that a city is grouped into the class $Y_i = 1$ and a decrease in those it is grouped into a different class

[8] As an alternative, the likelihood ratio test between pairs of classes can be performed to produce an overall test statistic. In this case, the statistic for the full specification is $\chi^2(8) = 16.82$, which results to be significant (p-value = 0.032). It turns to be non-significant however where the observations grouped into the class $Y_i = 4$ are excluded, $\chi^2(4) = 4.14$ (p-value = 0.387), that is also much closer to the $\chi^2(4) = 3.35$ (p-value = 0.501) from the Brant test. The likelihood ratio test appears therefore to be more sensitive to a small group of observations in this case, reason why the Brant test has been preferred.

[9] For probabilities computation, when the representative values of one regressor are observed, the remainder of regressors are taken the mean value.

Table 7 Predicted probabilities at the most representative values of regressors.

Regressor	Value	Outcomes of the dependent variable $Y_i = 1$	$Y_i = 3$	$Y_i = 3$	$Y_i = 4$
O_i	p25	0.8113***	0.1610***	0.0219**	0.0055*
		(0.0533)	(0.0430)	(0.0100)	(0.0033)
	p50	0.8150***	0.1579***	0.0214**	0.0054*
		(0.0507)	(0.0430)	(0.0096)	(0.0032)
	p75	0.8184***	0.1552***	0.0210**	0.0053
		(0.0542)	(0.0458)	(0.0099)	(0.0033)
L_i	p50	0.8233***	0.1511***	0.0203**	0.0051*
		(0.0490)	(0.0415)	(0.0092)	(0.0031)
	mean	0.7536***	0.2093***	0.0294**	0.0075
		(0.0708)	(0.0594)	(0.0136)	(0.0046)
H_i	p25	0.3215***	0.4737***	0.1560***	0.0486**
		(0.0543)	(0.0585)	(0.0397)	(0.0222)
	p50	0.7092***	0.2431***	0.0378***	0.0098*
		(0.0555)	(0.0477)	(0.0141)	(0.0053)
	p75	0.9597***	0.0354*	0.0040	0.0010
		(0.0224)	(0.0193)	(0.0028)	(0.0008)
T_i	p25	0.8361***	0.1405***	0.0186**	0.0047
		(0.0543)	(0.0461)	(0.0092)	(0.0030)
	p50	0.8210***	0.1530***	0.0206**	0.0052*
		(0.0509)	(0.0432)	(0.0094)	(0.0031)
	p75	0.7994***	0.1708***	0.0236**	0.0060**
		(0.0541)	(0.0457)	(0.0106)	(0.0036)

p-value: $^* < 0.1$;$^{**} < 0.05$;$^{***} < 0.01$
standard errors in brackets

$Y_i > 1$. What happens in the case of the localization of knowledge creation and diffusion L_i is right the opposite, as it results to be positively correlated to the dependent variable y_i. The odds that a city is grouped into the class $Y_i = 1$ are higher indeed where a lower value $L_i = 0$ (median) is taken, while the odds that a city is grouped into one of the upper classes $Y_i = 1$ increase at a higher value $L_i = 0.013$ (mean). Also an increase of technology cycle time T_i, despite it is statistically non-significant, is associated to a decrease in the odds that a city is grouped into the class $Y_i = 1$ and an increase it is in the upper classes. An effect of technology cycle time T_i has been then detected, although it cannot be generalized outside this specific empirical exercise.

Differently, no change in the odds associated to each class of the dependent variable y_i results to be conditional upon an increase of the originality of innovative activities O_i. In this case, therefore, statistical non-significance appears to entail more serious problems, such as a wrong specification of its linkage with embeddedness, so that the original hypothesis (H1) of a positive relation existing between the gains in embeddedness and the originality of local innovative activities must be taken as not verified. On the other hand, the hypotheses that embeddedness is (H2) positively linked with the localization of its knowledge base and (H3) negatively linked with the concentration of innovative activities are fully verified. Finally, the hypothesis (H4) that embeddedness is non-negatively related to technology cycle time is verified here but evidence cannot be taken as a general result.

5 Conclusions

Innovative activities have grown very fast in China since the mid-1990s, intertwining with the geography of national economic development. Along this process, the structural traits of innovative activities have emerged as varying over time and, for what concerns the most here, cities. Those traits include embeddedness, that is, the depth innovative activities are anchored to their local environment and are expected to gain in mature innovation systems (Cooke et al., 1998). Previous research relying upon patent statistics shows internationally relevant activities to be far from reaching high levels of embeddedness in several Chinese prefectural cities where they are performed (Prodi et al., 2018). In the present paper, the accomplishments on this front have been supposed to be associated to corresponding patterns of innovation, especially those identified for cross-country comparison of the role technological catching up in economic development (Lee, 2013).

The core of the paper has been accordingly to present an empirical exercise based on data rearranged from the OECD Patent Databases to investigate the correlation between the measure of embeddedness proposed in Prodi et al. (2018) and the indicators of the originality of innovation, the localization of its knowledge base, the concentration of innovation across innovators, and the cycle time of technologies selected in Lee (2013). Four research hypotheses were posted, two of which are fully verified: embeddedness increases with an increase of the localization of knowledge creation and diffusion (H2), and it decreases with an increase of the concentration of local innovative activities across patent applicants (H3). Although not generalizable, there is evidence supporting also that embeddedness does not decreases with an increase of technology cycle time (H4), while the specification of the supposed positive linkage between the embeddedness and originality of local innovation (H1) results to be more problematic.

These results clearly suggest that the empirical settings suffer some limitations. First, there is a sort of misalignment potentially contributing to weaken the evidence. The methodology proposed in Prodi et al. (2018) is indeed purposely penalizing those cities with a poor patenting history at the EPO, taking the period average of values after and not before computing the locational indicators on which embeddedness is measured. This strategy is possible because null values are simply summed as zeros in counting, but the case is unfortunately much different for the innovation-pattern indicators that are built on more sophisticated algorithms. Since period-pooled data has to be preferred, explanatory variables here are somehow relatively overestimating some aspects of the local innovative activities compared to the dependent variable that, on the opposite, features to relatively underestimate another one.

Second, the analysis is limited to Chinese prefectural cities. Though China is a paradigmatic case for the aims of this paper, it does not allow a full-scale investigation of the linkages between the embeddedness and local patterns of innovation. Despite patent data have been rearranged at a prefectural level to substantially increase the number of observations, and the analysis was focusing on the period that the data set was populated the most, the highest among the classes of embeddedness considered ($Y_i = 4$) remains very small in size. It has been shown above how these few observations increase the noise in the analysis, but there is no way to predict how the evidence could have been molded by an appropriately populated alternative outcome of the dependent variable.

Despite these limitations, the analysis has been able to unveil some traits of the evolution of innovative activities in China. The insights produced into the linkages between the embeddedness and the local patterns of innovation contribute indeed the literature with some new hints. First, the diffusion of innovative activities along economic development is shown to exhibit place-specific features. These traits appear to be related more to the nature than the cumulation of local development paths. The embeddedness of innovative activities can therefore contribute to better understanding the political economy of industrial upgrading and technological catching up and, especially, China's developmental model. Second, among the patterns considered, a shorter technology cycle time is confirmed to be characteristic of technological catching up. Where higher grades of embeddedness are reached, that is, the maturity of local innovation systems is appreciable, innovative activities may develop indeed the capabilities to step into more complex knowledge paths. Again, this step does not exclusively depend on cumulative dynamics, with the possibility that success in technological catching up can turn into a trap itself where a local innovative system fails to appropriately develop complementary characteristics. Third, despite the limitations of the empirical exercise, the findings here suggest that the methodology to measure the embeddedness of innovative activities recently proposed in Prodi et al. (2018) is quite robust to a number of theoretically consistent assumptions so that it is worth of further development, potentially leading to enrich the state of the art of patent statistics.

It remains however to explain the positive linkage between the embeddedness and the originality of innovative activities failing empirical verification (H1), which no doubt deserves additional investigation in future research. A possible direction of this research can be already advanced here referring to the very same arguments that the measurement of embeddedness is built on. Indigenous innovative activities are said indeed likely to be displaced by foreign or, more simply, external innovative activities where the developmental path critically relies on exogenous seeding. Accordingly, an increase of embeddedness entails indigenous innovative activities to grow more than those non-indigenous, which could be eventually counter-displaced. A positive linkage between the embeddedness and the originality of innovative activities is therefore a very strong hypothesis in this picture, given that it implicitly supposes the quality of new indigenous activities to be at least the same of those non-indigenous. Rather, emerging innovative activities could be expected to embody more-incremental and, then, less-original results, especially where they strive for clinging to exogenous seeds, such as the local operations of the MNE or newly offshored tasks in the GVC. Evidence of a positive linkage is then more likely to emerge limited to the evolution of the indigenous component or, alternatively, taking account of the dynamics by which indigenous innovative activities gain relevance against those non-indigenous. In both cases, the point is a more complex specification of the linkage.

As a matter of facts, the analysis presented here is in a pure descriptive fashion and relies on an extreme stylization. In particular, the channels through which technological capabilities can be transferred from external to indigenous innovators, such as, FDI, import of capital goods, import and re-export of intermediate goods within GVC, licensing and imitation, human-capital mobility (De Marchi et al., 2018; Fagerberg et al., 2018; Lee et al., 2018), are not considered. The empirical exercise has been purposefully modeled as the simplest as possible in order to offer some straightforward insights. And the findings are deemed robust enough to support delivering that local innovation systems, i.e., relevant agglomerations of indigenous innovative activities, can emerge in emerging countries and strengthen featuring both shared and distinctive characteristics. Those shared are (1.1) an increase in the number of local companies and entities that are capable to engage in internationally-relevant innovation so that innovative activities become less concentrated and (1.2) an increase in the capability to set local technological trajectories along which developmental change cumulate over time. The pair of these characteristics can be considered as first-level conditions for local innovation systems to develop in emerging economies. Distinctive or second-level characteristics are instead (2.1) the capability to enter more or less complex paths of knowledge creation and (2.2) a focus on more or less radical changes, the pair of which appear to be more tightly related to local strategies, that is, what role local innovation systems aim to achieve in the global scenario.

Compliance with Ethical Standards

Conflict of Interest: The authors declare that they have no conflict of interest.

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