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# The territorial dynamics of innovation in China and India

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## Abstract

This article analyses the geography of innovation in China and India. Using a tailor-made panel database for regions in these two countries, we show that both countries exhibit increasingly strong polarization of innovative capacity in a limited number of urban areas. But the factors behind this polarization and the strong contrasts in innovative capacity between the provinces and states within both countries are quite different. In China, the concentration of innovation is fundamentally driven by agglomeration forces, linked to population, industrial specialization and infrastructure endowment. Innovative areas in China, rather than generate knowledge spillovers, seem to produce strong backwash effects. In India, by contrast, innovation is much more dependent on a combination of good local socioeconomic structures and investment in science and technology. Indian innovation hubs also generate positive knowledge spillovers to other regions.

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## 1. Introduction

The world is witnessing a significant change in the geography of innovation. Until recently, research and development (R&D)-led innovation was heavily concentrated in the countries of the so-called Triad. USA and Canada, the European Union (EU) and Japan did most of the investment in R&D and, consequently, generated most of the innovation and, in particular, of the radical innovation (Furman and Hayes, 2004; Dosi et al., 2006). World technology gaps overall are not disappearing, but because the world economy is becoming generally more innovative, any successful developer is required to be more innovative than at points in the past (Kemeny, 2011). Moreover, there is some turbulence in the ranks of developing countries, with a few successful countries moving up world technology ranks, little-by-little. Thus, the privileged position by the countries of the Triad is increasingly being challenged by the emergence of innovation hubs in a few emerging economies The so-called BRICS countries (Brazil, Russia, India, China and South Africa) are perhaps beginning to move closer to the Triad's leadership position. Largely reflecting their efforts, R&D investment has become more globalized (Lundvall et al., 2009; Fu and Soete, 2010) and certain emerging countries in Asia and elsewhere are increasingly basing their economic growth on their capacity to generate new product and process innovations (Mahmood and Singh, 2003; Popkin and Iyengar, 2007).

Throughout most of the 1990s, export growth in China and India was based principally on their cost advantage, and Chinese and Indian firms acted either as 'production platforms' for Western firms or attempted to pursue indigenous innovation strategies (Yeung, 2009). Since the turn of the century—and complementing their cost advantage—Chinese and Indian firms have been moving up the value chain. To do so, they rely on R&D-led innovation and international partnerships (Bruche, 2009; Kuchiki and Tsuji, 2010). Chinese and Indian firms owe their innovation in part to the development and growing maturity of the local innovation systems in those countries (Lundvall et al., 2009).

The rapidly changing roles of China and India in the global innovation picture has attracted considerable attention, from many different explanatory perspectives (Popkin and Iyengar, 2007; Parayil and D'Costa, 2009). Santangelo (2005) and Fu and Soete (2010), for example, have analysed how these countries are catching up on technology. Malerba and Mani (2009) have concentrated on the sectoral dimension of the technological catch-up, while Lundvall et al. (2009) and Kuchiki and Tsuji (2010) have focused, respectively, on the emergence of innovation systems and clusters.

Most such analyses of innovation in China and India emphasise changes in the conditions for the global spread of innovation, or national factors. By contrast, there is little literature on the ways that subnational processes of matching capital, labour and knowledge might affect national innovation output in the two countries. Indeed, beyond a handful of studies,[1] relatively little is known about the geography of innovation across Chinese and Indian provinces and states and virtually nothing about which factors, conditions and interactions determine why some areas in these countries are more innovative than others (e.g. da Motta e Albuquerque, 2003; Sun, 2003; Mitra, 2007; Fu, 2008; Wang and Lin, 2008).

A certain number of studies adapt the 'regional innovation system' approach to developing country contexts (e.g. Asheim and Vang, 2004; Scott and Garofoli, 2007; Chaminade and Vang, 2008; Padilla-Pérez et al., 2009). These studies emphasise the importance of trans-national processes and global–local interactions in shaping regional outcomes—especially the role of multinational enterprises (MNEs) and their links with local firms (Schmitz, 2007; Yeung, 2009), the multiple contributions of diaspora communities (Saxenian, 2006; Filatotchev et al., 2011). They also stress the role of country-specific institutional and policy factors in mediating these global forces (Yeung, 2006) and supporting the upgrade of indigenous human capital and local SMEs (Chaminade and Vang, 2008). However, the great majority of this literature relies on detailed case-studies. They tend to focus on the most successful and interesting city-regions. We therefore lack more systematic, large-scale quantitative evidence, especially cross-country and panel data studies (Padilla-Perez et al., 2009), which could help corroborate whether the insights from case-study analyses are broadly applicable,

1 Liu and Sun (2009), using invention patent data, provide a systematic overview of the evolution of the patenting activity of Chinese provinces between 1985 and 2005 and compare it to that of US states. The paper unveils a number of differences between the geography of innovation in China and in USA, but falls short of analysing the factors which determine the geographical differences between the two countries. It also suggests that the regional innovation policy of the Chinese government should follow a so-called 'basic law of the spatial distribution' of innovative activities, meaning a greater focus on innovation in coastal areas.

and which could shed insight into whether innovative regions emerge for the same reasons in the two countries.

In order to address these issues, this article presents a systematic, cross-country quantitative analysis of the geography of innovation in China and India, arguing that each country has a distinctive geographical process of bringing together the capital, labour and knowledge that underlie innovation. It deploys new panel data sets to explore this geographical matching process.

In order to do this, we first briefly examine some stylized facts about the geographies of innovation in China and India. We then present a model aimed at identifying the factors behind the innovative capacity of Chinese provinces and Indian states. In Section 4, we introduce the results of the analysis, highlighting the important differences in the geographies of innovation between China and India. The final section presents the main conclusions and some preliminary policy implications.

## 2. Geographies of innovation in China and India: stylized facts

As in most parts of the world, innovation, measured by patent applications, in China and India is unevenly spread geographically. In China, innovative activity is highly concentrated along the eastern seaboard, and especially in the South and in the two largest cities (Sun, 2003; Wang and Lin, 2008). Guangdong, with 46% of total patenting activity[2] is the leading province. Guangdong is followed at some distance by Beijing (14%) and Shanghai (13%). The top three Chinese regions account for 73% of all patents. Most other coastal provinces have shares of patent applications which range between 1% and 3% of the total. The Centre and the West of the country, despite counting with some populous provinces, are far less innovative. Only Sichuan (South West) and Hunan (Centre) have more than 1% of all Chinese patents, while western provinces, such as Tibet and Qinghai, and some central provinces, such as Ningxia, barely generate any patenting activity.

The geography of patenting in India is dominated by the high-tech hubs of the country. Cities such as Bangalore, Chennai, Delhi, Hyderabad, Mumbai and Pune are at the origin of the great majority of patents (Mitra, 2007). At the regional level, da Motta e Albuquerque (2003) finds that from 1981 until 2002, nearly half of all patents were assigned to Indian inventors in two states, Maharashtra and Delhi. Our data echoes this; Maharashtra (capital Mumbai) and Delhi respectively account for 26% and 24% of total patents. Andhra Pradesh, with the great majority of its 13% of Indian patents centred in its capital Hyderabad, comes third. All together, the three top Indian states account for 64% of all patents. Other states around Delhi or in the South, such as Karnataka (8.7%, South, capital Bangalore), Haryana (7%, close to Delhi) and Tamil Nadu (7%, South, capital Chennai) form a second tier of innovative states. In contrast, states in the North East are less innovative. This less innovative group includes Uttar Pradesh and West Bengal, the first and fourth most populous states in India. And there is no recorded patent activity until 2007 for most of the north-eastern border states, including some relatively big states such as Assam (with a population of 31 million, according to the 2011 census).

2 Patenting activity as measured by patents filed under the Patent Cooperation Treaty (PCT).

Figure 1 illustrates the distribution of patenting across space in China and India in 2007, focusing on the 20 regions with the highest patent counts. The EU and USA are included in the figure for comparison.

What stands out in Figure 1 is the clear contrast between the spatial structure of 'mature' and 'emerging' innovation systems. In 'mature' innovation systems, such as those of the EU or USA, despite a high degree of geographical agglomeration, patenting activity is spread across a greater number of regions than in 'emerging' systems, where patenting is heavily concentrated in the top three, in the case of China, or in the top six, in the case of India, regions. Whereas in Europe the 20 most innovative regions account for roughly 50% of the patents, this threshold is reached by a single province in China (Guangdong) and by three Indian states (Maharashtra, Delhi and Andhra Pradesh). However, there are also significant differences between the level of concentration of innovative activities in the two 'mature' and the two 'emerging' innovation systems considered. In the 'mature' systems and as mentioned by earlier research (Dosi et al., 2006; Crescenzi et al., 2007), patenting is more territorially concentrated in USA than in the EU.[3] In the 'emerging' systems, the six highest-patenting regions in China account for a bigger share of innovative activity than those in India, although the pattern reverses after that with a long tail of Indian regions.

Over time the trend both in China and India has been towards a rapid increase in patenting, accompanied by a rise in the geographical concentration of innovative activity (Sun, 2003). In 1994, patenting in India was far more concentrated than in China. However, the situation reversed right after 2000 when innovation became more agglomerated in Chinese provinces than in Indian states. Since then the trend has been towards an ever greater concentration of innovation in a few coastal provinces (Liu and Sun, 2009) accompanied by significant structural changes in local-level systems of innovation conditions (Sun and Liu, 2010). These changes emphasize the cumulative nature of the agglomeration process. Such polarization is further reinforced by an emerging trend towards territorial competition among Chinese local authorities for the attraction of external resources from both the 'central' government and international investors (Chien and Gordon, 2008).

What are the reasons behind the rapid expansion of patenting in both China and India and behind the territorial agglomeration of patenting activity? Both India and, in particular, China have invested heavily in innovation 'inputs'. Both countries have witnessed rapidly rising literacy rates and higher education enrolment: in 2007 China had 25 million university students and India 13 million, in comparison to 12 million in USA (Dahlman, 2010). Moreover, the rise in university placements in these two countries has been absolutely phenomenal. Since 1999, China has seen an annual growth in student numbers of 20% or more (Schaaper, 2009). Similarly, during the 1990s Indian universities significantly increased their output of engineering graduates—from 44,000 per year in 1992 to 184,000 in 2000. This compares with 352,000 per year in

3 As far as the EU–US comparison is concerned, the magnitude of this gap is partially attenuated when OECD TL2 (larger) Regions are considered for the EU. However, OECD TL2 regions correspond to US States while TL3 to Economic Areas. The evidence on the spatial concentration of innovative activity remains qualitatively unchanged, irrespective of the spatial scale.

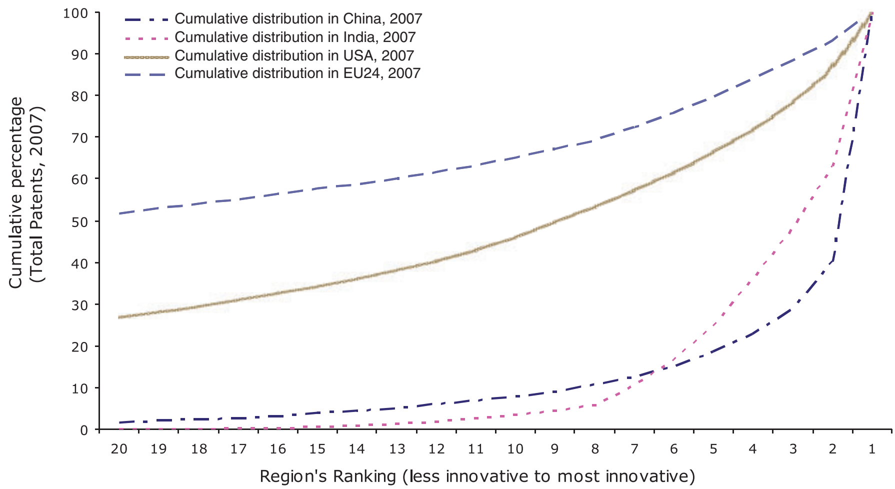


**Figure 1.** Spatial distribution of patenting: Top 20 most innovative regions, 2007 (China, India, EU and USA).
*Source*: OECD, 2010.
*Note*: China: 31 provinces, India: 24 states, USA: 179 BEA Economic Areas, EU24 (Cyprus, Lithuania and Malta not included): 841 OECD TL3 regions.

China and just 76,000 per year in USA (Mitra, 2007). China has also exploited global knowledge by moving students abroad to study in larger numbers than India—and Indian returnees have had significant impacts on the country's Information and Communication Technologies (ICT) sector (Saxenian, 2006). With 926 R&D researchers per million people, China now has the second-highest total number of researchers world-wide (Schaaper, 2009).

Expenditure in R&D has been at the forefront of the innovative effort in China. China's overall R&D spending as a share of GDP almost trebled between 1995 and 2006. China lagged behind India for most of the 1990s in overall R&D expenditure, but overtook its neighbour at the end of the decade and has continued to widen the gap ever since. By contrast, India's expenditure in R&D relative to GDP remained stable during the same period. Moreover, India's headline figure conceals a large R&D rise in pharmaceuticals, ICT, electronics and auto parts (Dahlman, 2010). Both figures also hide important differences in institutional capacity to invest. The Indian government's science and technology spending exhibits a much greater year-on-year volatility than that of China.

How have these investments influenced innovation outputs? Despite an increase in relative investment in science and technology projects in the 1970s and 1980s, China and India exhibited low patent counts in these decades, with a jump in patenting activity finally appearing in the mid-1990s. Figure 2 shows this jump in national 'innovation performance' as measured by patent applications per million people. Both countries have raised their innovation rates, as measured by patents, particularly in the last decade, but China much more so than India.

Indian patenting has increased steadily since the 1990s, while Chinese patenting accelerated from 2005 onwards. Schaaper (2009) reports a 'huge surge in patent applications' at the Chinese patent office and large increases in international patenting by Chinese inventors and firms.

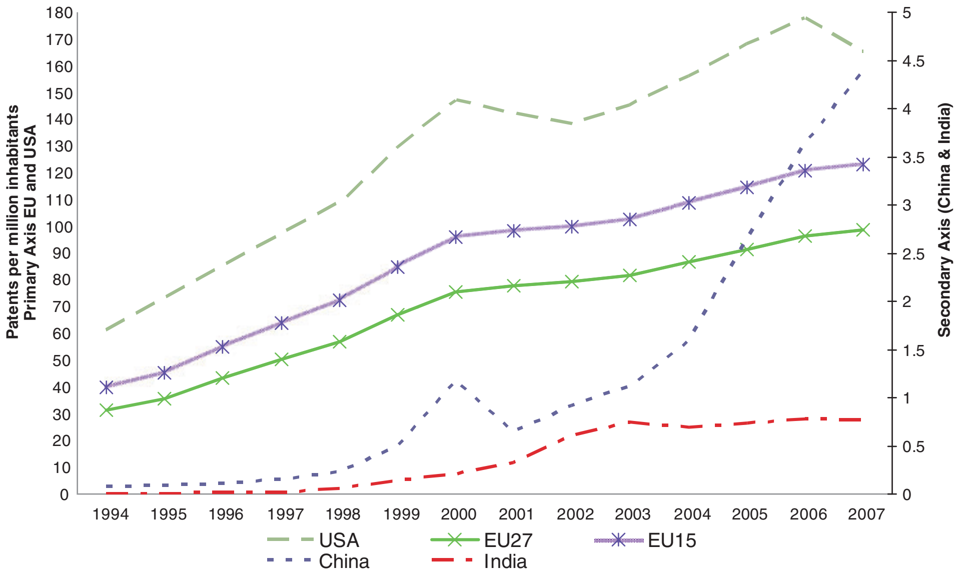


**Figure 2.** Evolution of patent intensity over time in China, India, EU and the USA, 1994–2007.
*Source*: OECD, PatStat.

Both India and China still have some way to go before reaching US or EU levels of patenting activity (Mahmood and Singh, 2003; Schaaper, 2009), as well as those of other 'Asian Tiger' economies (Tseng, 2009). China and India also lag behind some neighbouring countries. Tseng (2009) compares Chinese and Indian patenting in ICT to that in other Asian economies. During the period 1976–2006, the largest number of patent granted in ICT was in South Korea (22,612 in total), followed by Taiwan (19,907), Singapore (1333) and Hong Kong (622). As an average for the period, China and India record only 440 and 81 ICT patents granted in total respectively.

Social and institutional factors account for a great deal of the differences observed in recent innovation trends between both countries. Historically, neither China, nor India have been strangers to the use of innovation and technology-led development policies in order to pursue national prestige or increase their international geopolitical standing. Their space flight and atomic weapons programmes are clear examples of this type of top–down science and technology policies, more aimed at achieving immediate symbolic returns than at enhancing the broad performance of their national innovation systems (Leadbeater and Wilsdon, 2007).

Nonetheless, there is a drive to move away from heavily dominated statist models of public policy and towards market-led reforms (Jian et al., 1996; Fan, 2008; Fleischer et al., 2010; Sun and Liu, 2010). China's earlier move to 'globalise' its economy and revamp its innovation system has borne fruit and is one of the reasons behind the growing gap in innovation between China and India. China's greater emphasis on trade, FDI or the licensing of foreign technology, among others, has produced significant returns in innovation outputs (Dahlman, 2010). India's reform and pace of change, despite taking off after 1991, has been dragged down by a large bureaucracy and less malleable institutions.

## 3. Model and data

### 3.1. The structure of the model

In order to explain these trends and the differences in innovation geographies between China and India, we draw on the three major theoretical strands on the causes of innovation and its geography to build a modified regional knowledge production function (Crescenzi et al., 2007; O'hUallachain and Leslie, 2007) inspired by the 'traditional' framework of Griliches (1979, 1986) and Jaffe (1986). In this production function, regional innovation is proxied by regional patent intensity and explained by a series of factors. First, following endogenous growth models, innovation may be a consequence of the returns of investment in human capital and innovation inputs, such as R&D spending, which lead to higher patenting rates. China and India partly adopted this sort of approach and continue to invest heavily in 'innovation inputs', such as R&D and higher education (Kuijs and Wang, 2006). The economic geography approach to the genesis of innovation holds that differences in innovative performance across territories will emerge from agglomeration economies, because concentrations of firms and skilled workers will increase the creation and diffusion of knowledge, or what are known as localized 'spillovers' or 'learning' (e.g. Acs et al., 2002; Carlino et al., 2007). Finally, the literature on regional innovation systems has emphasized regional-level factors, which include universities and public agencies, networks (e.g. public-private partnerships) and local institutions (Cooke, 2002). How these factors combine in space makes 'the geographic configuration of economic agents (...) fundamentally important in shaping the innovative capabilities of firms and industries' (Asheim and Gertler, 2005, 309–310).

We further extend this traditional framework by accounting for the role of territorial characteristics and spatial processes (Audretsch and Feldman, 1996; Crescenzi et al., 2007; O'hUallachain and Leslie, 2007; Ponds et al., 2010). In this way, we are able to consider both systems of innovation conditions and other internal and external factors (Crescenzi and Rodríguez-Pose, 2012).

The model takes the following form:

$$y_{i,t} = \alpha_i + \tau_t + \beta R\&D_{i,t} + \gamma WR\&D_{i,t} + \delta SF_{i,t} + \zeta WSF_{i,t} + \vartheta x_{i,t} + \varepsilon_{i,t} \qquad (3.1)$$

where:

$y$ represents Regional Patent intensity;
R&D is the share of R&D/S&T Expenditure in regional GDP;
$SF$ is the Social Filter Index;
WR&D and WSF are spatial lags of R&D/S&T and SF respectively with appropriate spatial weights;
$x$ is a set of structural features/determinants of innovation of region $i$;
$\varepsilon$ is an idiosyncratic error;and where $i$ represents the region and $t$ time.

The choice of empirical variables included in the model is set out in Table 1.

### 3.2. Variables included in the model

#### 3.2.1. Dependent variable

Our dependent variable is *patent intensity*. Patent intensity is measured by the number of regional patents per capita and is used as a proxy for the innovative performance of the local economy.

**Table 1.** Empirical variables included in the model

| Variable | Internal factors | External factors |
|---|---|---|
| R&D | Local investment in S&T/R&D | Investment in S&T/R&D in neighbouring areas |
| Social filter | Structural characteristics that would make a region more 'innovation prone', including: • Human capital • Sectoral composition • Use of resources (unemployment) • Demographics | Same characteristics in neighbouring areas |
| Specialization | Krugman index | |
| Relative wealth | GDP per capita | |
| Agglomeration economies | Population density | |
| Infrastructure endowment | Kilometres (km) of motorways/railways | |
| Mobility of people | Migration rate | |
| Fixed effects | Region/province-specific fixed effect + time trends | |

Two panel datasets for Chinese provinces and Indian states are assembled. Data for China cover 30 provinces from 1995 through 2007.[4] Data for India cover 19 states between 1995 and 2004.[5] In the following section, we describe the variables included in the model in detail (see Appendix A, Tables A1 and A2, for technical specifications and data sources: Table A1 for China and Table A2 for India).

The use of patent intensity as our measure of regional innovation in China and India is not without controversy. Not all industries tend to patent with the same intensity and, in an emerging country context, the number of firms or organizations in a position to file patents is rather limited. However, there are no reliable substitute measures and other readily available innovation metrics for India and China tend to follow spatial patterns similar to patents. For instance, multinational firms' location patterns closely match those of patents: between 60% and 80% of all MNEs are concentrated in the Beijing–Shanghai–Guangdong axis, in the case of China, and in Bangalore/Pune/National Capital Region, in India (Bruche, 2009). We also use patent data from Patent Cooperation Treaty (PCT) patent applications,[6] avoiding some much-discussed issues with domestic patent coverage and quality, especially in China (Li and Pai, 2010). "A PCT filing can be seen as a 'worldwide patent application' and is much less biased than

4 For China data are available for the Provincial-level administrative subdivisions: 22 Provinces, 4 Autonomous Regions, 4 Municipalities. Two Special Administrative Regions (Hong Kong and Macau) and One Autonomous Region (Tibet) have been excluded from the analysis due to the lack of data for the selected variables.

5 For India data are available for 18 States and 3 Union Territories. Bihar and Rajasthan are included in descriptive statistics but not in the regression analysis due to the limited number of observations available over time.

6 "The Patent Cooperation Treaty (PCT) was concluded in 1970 (...) and makes it possible to seek patent protection for an invention simultaneously in each of a large number of countries by filing an 'international' patent application." World Intellectual Property Organisation (WIPO).

national applications. (...) Further, the PCT reflects the technological activities of emerging countries quite well (Brazil, Russia, China, India, etc.).'' (OECD, 2009, 66)

Two important caveats remain. First, patents measure *invention* and tend to be biased towards particular sectors of the economy where inventions are protected via patenting (rather than via trademarks or secrecy, for example) (OECD, 2009). Fagerberg and Shrolec (2009) argue that since minor innovations/adaptations will not be patentable—most innovative activity in emerging countries will not be counted. This is an important issue in the case of China and India, although as both countries rapidly approach the technological frontier in a number of sectors, this objection may be becoming less pertinent than before.

Second, patent counts include both domestic and foreign firms, meaning that they may not fully capture *domestic* innovation capacity (Li and Pai, 2010; Wadhwa, 2010). In the case of MNEs, patents may be filed in any office around the world, regardless of where the invention actually takes place, making it hard to assign patents to specific territories. Duan and Kong (2008), in a study of Chinese patents 1988–2007, observe that most 'Chinese' applications to the USPTO are owned by foreign firms. In India the picture is more complex. da Motta e Albuquerque (2003) finds that between 1981 and 2001, a third of Indian patent applications to the USPTO had foreign assignees, higher than Brazil, South Africa or Mexico. However, Mani (2004) examines Indian-based inventors during the 1990s, reporting that 85% of the patents granted were awarded to public research institutes, as well as some to local firms and individuals—as opposed to 'foreign affiliates located in India'.

### *3.2.2. Independent variables*

As indicated in model (1), the independent variables cover 'internal' conditions, spillover-related factors, and a set of other structural conditions potentially affecting the geography of innovation in the two countries (GDP per capita, transport infrastructure, agglomeration, migration flows).

The internal conditions include R&D expenditure and the social filter. *R&D expenditure* is measured by the percentage of regional GDP devoted to S&T (China) or R&D (India). This indicator has been frequently used in the literature as a measure of 'the allocation of resources to research and other information-generating activities in response to perceived profit opportunities' (Grossman and Helpman, 1991, 6), as well as a proxy for the local capability to 'absorb' innovation produced elsewhere (Cohen and Levinthal, 1990; Maurseth and Verspagen, 2002).

*The social filter* aims at capturing the structural preconditions for the successful development of regional innovation systems. As underlined by the innovation systems approach, the capacity of any given region to generate and use knowledge depends on a complex set of local factors. The most common of these factors encompass regional social and business networks; social stratification and levels of 'modernity' versus 'tradition'. While such factors can be relatively easily identified in case-studies, they must be captured in a more parsimonious way for cross-sectional analysis by a combination 'of innovative and conservative... elements that favour or deter the development of successful regional innovation systems' across a wide variety of places (Rodríguez-Pose, 1999, 82). The social filter variable used in this article is therefore made up of a set of variables available for both China and India in a consistent and comparable fashion, focusing on three main aspects of an 'innovation prone' social

structure: educational achievement (Lundvall, 1992; Malecki, 1997); the productive use of human resources (Gordon, 2001) and demographic structure and dynamism (Rodríguez-Pose, 1999). The combination of proxies for all these different dimensions into one single composite indicator (the Social Filter Index) develops a quantitative 'profile' of an innovation prone regional environment, making it possible to compare the social filter conditions of different regions across countries (Crescenzi and Rodríguez-Pose, 2011).

The first domain is human capital attainment, expressed by the shares of adult population who have completed tertiary education. We expect the stock of human capital, an innovation input, to be positively related to the rate of innovation. The second domain, the structure of productive resources, is measured by the percentage of the labour force employed in agriculture and the rate of unemployment. Both should have a negative association with innovation. Over the past two decades, India and China have been experiencing both large scale rural–urban migration and industrialization, factors linked to improved innovative performance and a declining salience of agricultural activity (Gajwani et al., 2006; Dahlman, 2010). Higher long-term unemployment rates indicate weak local labour demand, and also suggest poor quality human capital (as opposed to education-based *quantity* measures) (Gordon, 2001). For the third domain, we use the percentage of population aged between 15 and 24 for the flow of labour entering the labour force, potentially 'refreshing' the existing stock of knowledge and skills (Crescenzi et al., 2007).

We fit the social filter both as a set of individual variables, and as a 'social filter index' constructed through Principal Component Analysis (PCA). The PCA output is shown in Tables B1 and B2. The first principal component alone accounts for 45% and 36% of the total variance of the original variables considered for China and India respectively. The scores are computed from the standardized value of the original variables by using the coefficients listed under 'Comp1' in Table B2, generating the social filter index.

Both R&D expenditures and the social filter can have effects beyond the borders of regions. Therefore, in addition to describing the 'internal' characteristics of each territory, the model also includes variables representing the characteristics of neighbouring regions that may influence the innovative performance in the region of interest.

The potential of R&D expenditure to spill over beyond regional borders is depicted by the variable *WR&D*. This spatially lagged R&D variable captures extra-regional innovation, by measuring the 'aggregate' impact of innovative activities pursued in neighbouring regions, as they could exert a positive impact on local innovative performance, via inter-regional knowledge exchange channels and complementarities. Conversely, centripetal forces driving the location of innovative activities towards pre-existing 'hot-spots' may lead to the generation of negative externalities: proximity to innovative areas may 'drain' resources from nearby areas.

Following Rodríguez-Pose and Crescenzi (2008), the extra-regional innovative activity is proxied by the average of R&D/S&T intensity in neighbouring regions and is calculated as:

$$WR\&D_i = \sum_{j=1}^{n} R\&D_j w_{ij} \quad \text{with i} \neq \text{j} \tag{3.2}$$

where $R\&D$ is our proxy for regional innovative inputs of the $j$-th region and $w_{ij}$ is a generic 'spatial' weight. In order to test for the spatial scope of the processes discussed above, alternative definitions for the 'spatial weights' have been adopted in our analysis: highly localized spatial processes have been proxied by means of first-order contiguity weights ($w^{FC}$), while long-distance flows have been captured with inverse-distance weights ($w^{ID}$):[7]

$$w_{ij}^{FC} = \begin{cases} 1 \text{ if j directly shares a border or a vertex with i} \\ 0 \text{ otherwise} \end{cases} \tag{3.3}$$

$$w_{ij}^{ID} = \begin{cases} 0 \quad \text{if } i = j \\ \dfrac{\frac{1}{d_{ij}}}{\sum_j \frac{1}{d_{ij}}} \text{if } i \neq j \end{cases} \tag{3.4}$$

where $d_{ij}$ is the linear straight-line distance between region $i$ and $j$ and $w$ the corresponding weight.

The same principle as for WR&D is applied to the social filter. A variable $WSF$ is created in order to capture potential extra-regional social filter spillovers. The measure of extra-regional social filter conditions is calculated following the same principle presented in Equation (3.2). For each region $i$:

$$WSF_i = \sum_{j=1}^{n} SF_j w_{ij} \quad \text{with } i \neq j \tag{3.5}$$

where $SF$ is our social filter index and $w$ is as above.

Finally, our third group of independent variables includes a vector of additional key drivers of innovation. These include economic specialization; levels of GDP per capita; infrastructure endowments; agglomeration levels and inward migration.

The degree of *specialization* is measured, following Midelfart-Knarvik et al. (2002), by the Krugman Index, which is calculated according as follows:

(a) for each region, the share of industry k in that region's total employment: $v_i^k(t)$;
(b) the share of the same industry in the employment of all other regions: $\overline{v}_i^k(t)$ and
(c) the absolute values of the difference between these shares, added over all industries:

$$K_i(t) = \sum_k abs(v_i^k(t) - \overline{v}_i^k(t)) \text{ with } v_i^k(t) = \sum_{j \neq i} x_i^k(t) / \sum_k \sum_{j \neq i} x_i^k(t) \tag{3.6}$$

The index takes the value zero if region $i$ has an industrial structure identical to the rest of the country, and takes the maximum value of two if it has no industries in common with the rest of the country.

The initial level of *GDP per capita* is introduced in the model in order to account for the region's initial wealth as proxy for the distance from the technological frontier (Fagerberg, 1994). The significance and magnitude of the coefficient associated to this variable allows us to test for the existence of technological catch-up.

7 Alternative definitions for the spatial weights matrix are possible: distance weights matrices (defining the elements as the inverse of the distances) and other binary matrices (rook and queen contiguity matrices).

Transport infrastructure may affect innovative performance through a variety of mechanisms. In order to capture the direct impact of transport infrastructure on regional growth, the model includes a specific proxy for the *stock of transport infrastructure*, measured by the total motorways or railways in the region, in kilometres, standardized by the regional population (Canning and Pedroni, 2004). See Table A1 for further detail.

Another independent variable included in the model is *agglomeration*. As indicated by the new economic geography approach, the geographical concentration of economic activity has an independent impact on innovation (Duranton and Puga, 2003; Charlot and Duranton, 2004) and thus needs to be controlled for in order to single out the impact of other 'knowledge' assets such us R&D intensity and Social Filter conditions. We use population density as our proxy of agglomeration.

The regional rate of *migration* (i.e. net inflow of people from other regions)[8] is also included in the model in order to measure the capacity of the region to benefit from external human capital and knowledge by attracting new workers, increasing the size of its labour pool and its 'diversity' in terms of skills and cultural background (Ottaviano and Peri, 2005).

Finally, in the case of China we include the share of state-owned (SOEs) industrial firms as a percentage of all industrial firms. State ownership may affect firms' propensity to innovate and the technological opportunities available to them, as well as the likelihood of forming partnerships with MNEs (Gu et al., 2007; Li et al., 2007; Motohashi and Yun, 2007). SOEs are likely to have politically-motivated locations, and possibly to be less innovation-oriented than privately-owned firms.

## 4. Results of the empirical analysis

Using these variables, we estimate model (1) as a two-way fixed effects panel data regression.[9] In order to minimise any potential spatial autocorrelation, we introduce the 'spatially lagged' variables WR&D and WSF which allows us to take into consideration the interactions between neighbouring regions, minimizing any effect on the residuals.[10] The analysis also uses robust standard errors clustered by state (India) or province (China). We deal with potential endogeneity of the right-hand side variables by fitting these as one-period lags. Finally, because of different accounting units, we express all explanatory variables as a percentage of the respective GDP or population. This is an exploratory analysis aimed at uncovering the territorial dynamics of innovation in the two countries rather than identifying causal relationships—consequently, in what

8 For China, both the net and gross internal rate of migration are available. For India, only the gross inflow of people into each state is available due to the lack of data on outflows. However in the case of China the correlation between net and gross migration rate is 0.95 and regression results are qualitatively identical if net migration is replaced by gross migration in order to match the variable definition of the dataset for India more precisely.

9 The Hausman test indicates that fixed effects is the preferred estimation, rejecting the random-effects specification. In addition the F-Test confirms that the region-specific effects are statistically significant.

10 The absence of spatial correlation is confirmed by conducting Moran's I test for each year. The results of these tests are not significant for the majority of years.

follows, we focus mainly on the sign and significance of coefficients, rather than the size of specific point estimates.[11]

The results are shown in Tables 2–5. Tables 2 and 4 give the main results for China and India respectively. In each case, models (1) through (3) explore the more traditional components deemed to affect innovation by regressing patenting rates on R&D/S&T expenditure and various spatial lags of science spending. Models (4) through (7) introduce the social filter and its spatially weighted variants. Models (8) through (12 for China, or 11 in the case of India) bring in the wider structural factors, as well as any country-specific variables. Tables 3 and 5 decompose the social filter index into its constituent elements respectively for China and India.

The model generally performs better for Chinese data, as we have a longer time period and more observations (because of a larger number of spatial units for a longer time series). Results for India tend to be more volatile.

### 4.1. China

The estimations for China are given in Table 2. Regressions (1) to (3) explore the 'linear' elements of the innovation process. The results indicate that regional R&D spending is not significantly connected to local patenting, and that spatially weighted science and technology spending is negative and insignificant. This echoes other findings for the European Union, where R&D spending tends to be centralized at nation state level generating a detachment between local innovative efforts and localized output (Crescenzi et al., 2007). The fact that R&D spillovers are also not significant (contrary to large part of the existing evidence on the EU) is also possibly a sign of a disconnect between the more dynamic innovation hubs in China and a national R&D policy which may still aim to counterbalance the concentration of innovative activities by funding R&D activities in more remote or less accessible regions for either strategic (i.e. keeping some military industry away from the coast) or development reasons.

The introduction of the social filter in regressions (4) through (8) leads to an interesting twist in the story. The social filter index is positively and significantly (at the 5% level) associated with innovation rates. However, the introduction of agglomeration indicators removes this significance. As in the case of the R&D spillovers, the spatial lags of the social filter (using first order contiguity weights) are negative, becoming negative and significant when structural factors are controlled for.

Models (9) to (12) include a wider set of structural factors. The introduction of agglomeration measures dominates the analysis. Both the Krugman index and population density have a positive and significant connection to innovation at the 1% level. Railway density has a large point estimate but is only marginally significant in the full models, perhaps because China has shown a preference until recently for

11 For China the results presented in the tables are based on a fully balanced panel dataset with data for all provinces and years covered by the analysis. For India data limitations are more significant and make it impossible to produce an equally balanced panel dataset. While the results presented in the tables are based exclusively on the data available from the original sources a number of tests have been implemented in order to test the robustness of the results to different sample sizes. In order to increase the number of available observations and test the robustness of our results we used linear interpolation (i.e. new data points are constructed only within the range of a discrete set of known data points) of missing values for patent intensity only. This procedure increased the number of available observation with qualitatively unchanged results, confirming the robustness of our results.

**Table 2.** China, social filter index, 1995–2007

| Variables | (1) Patents per capita | (2) Patents per capita | (3) Patents per capita | (4) Patents per capita | (5) Patents per capita | (6) Patents per capita | (7) Patents per capita | (8) Patents per capita | (9) Patents per capita | (10) Patents per capita | (11) Patents per capita | (12) Patents per capita |
|---|---|---|---|---|---|---|---|---|---|---|---|---|
| Regional R&D/S&T expenditure | 0.0410 | 0.0696 | 0.0349 | 0.0274 | 0.00673 | 0.0249 | 0.0269 | −0.00805 | −0.0533 | −0.0963 | 0.492* | −0.0961 |
| | *(0.131)* | *(0.131)* | *(0.133)* | *(0.123)* | *(0.123)* | *(0.123)* | *(0.124)* | *(0.0898)* | *(0.0601)* | *(0.0701)* | *(0.267)* | *(0.0707)* |
| Spatially weighted S&T (inverse dist) | | −4.13e−09 | | −4.64e−09 | | −4.08e−09 | −4.91e−09 | −7.93e−10 | −1.63e−08 | −7.98e−09 | −7.45e−09 | −7.84e−09 |
| | | *(3.64e−09)* | | *(3.36e−09)* | | *(3.44e−09)* | *(3.42e−09)* | *(3.01e−09)* | *(3.85e−09)**** | *(2.56e−09)**** | *(2.28e−09)**** | *(2.59e−09)**** |
| Spatially weighted S&T (first order contiguity) | | | 2.37e−10 | | −4.81e−10 | | | | | | | |
| | | | *(1.13e−09)* | | *(1.06e−09)* | | | | | | | |
| Social filter | | | | 0.00316 | 0.00322 | 0.00315 | 0.00310 | 0.00104 | 2.76e−06 | −0.000552 | −0.000377 | −0.000537 |
| | | | | *(0.00123)*** | *(0.00124)**** | *(0.00124)*** | *(0.00123)*** | *(0.000878)* | *(0.000520)* | *(0.000564)* | *(0.000506)* | *(0.000548)* |
| Spatially weighted social filter (inverse dist) | | | | | | −0.00374 | | | | | | |
| | | | | | | *(0.00366)* | | | | | | |
| Spatially weighted social filter (first order contiguity) | | | | | | | 0.000738 | −0.00197 | −0.00141 | −0.00210 | −0.00110 | −0.00217 |
| | | | | | | | *(0.00100)* | *(0.000985)*** | *(0.000761)** | *(0.000742)**** | *(0.00100)* | *(0.000766)**** |
| Krugman index | | | | | | | | 0.0300 | | 0.0204 | 0.0213 | 0.0205 |
| | | | | | | | | *(0.00566)**** | | *(0.00408)**** | *(0.00427)**** | *(0.00419)**** |
| Railway density | | | | | | | | 0.183 | | 0.134 | 0.141 | 0.134 |
| | | | | | | | | *(0.0725)*** | | *(0.0604)*** | *(0.0496)**** | *(0.0615)*** |
| Population density | | | | | | | | | 0.000148 | 0.000176 | 0.000294 | 0.000175 |
| | | | | | | | | | *(5.52e−05)**** | *(4.91e−05)**** | *(5.86e−05)**** | *(5.19e−05)**** |
| Net migration | | | | | | | | | −1.81e−05 | 2.83e−05 | 4.57e−05 | 2.79e−05 |
| | | | | | | | | | *(2.24e−05)* | *(1.04e−05)**** | *(1.06e−05)**** | *(1.07e−05)**** |
| GDP per capita | | | | | | | | | 8.27e−07 | | | |
| | | | | | | | | | *(2.63e−07)**** | | | |
| Int. term exp. S&T* pop. density | | | | | | | | | | | −0.00111 | |
| | | | | | | | | | | | *(0.000536)*** | |

(continued)

**Table 2.** Continued

| Variables | (1) Patents per capita | (2) Patents per capita | (3) Patents per capita | (4) Patents per capita | (5) Patents per capita | (6) Patents per capita | (7) Patents per capita | (8) Patents per capita | (9) Patents per capita | (10) Patents per capita | (11) Patents per capita | (12) Patents per capita |
|---|---|---|---|---|---|---|---|---|---|---|---|---|
| State-owned industrial firms (% industrial firms) | | | | | | | | | | | | −0.000940 |
| | | | | | | | | | | | | *(0.00239)* |
| Constant | −0.000546 | 1.50e−05 | −0.000495 | 0.00215 | 0.00145 | 0.000353 | 0.00267 | −0.0332 | −0.0493 | −0.0798 | −0.121 | −0.0794 |
| | *(0.00245)* | *(0.00246)* | *(0.00245)* | *(0.00241)* | *(0.00235)* | *(0.00288)* | *(0.00272)* | *(0.00590)****** | *(0.0185)****** | *(0.0167)****** | *(0.0215)****** | *(0.0173)****** |
| Year dummies | X | X | X | X | X | X | X | X | X | X | X | X |
| Observations | 390 | 390 | 390 | 390 | 390 | 390 | 390 | 390 | 390 | 390 | 390 | 390 |
| *R*-squared | 0.092 | 0.099 | 0.092 | 0.144 | 0.136 | 0.146 | 0.145 | 0.312 | 0.400 | 0.400 | 0.570 | 0.401 |
| Number of id | 30 | 30 | 30 | 30 | 30 | 30 | 30 | 30 | 30 | 30 | 30 | 30 |

Robust standard errors in parentheses.
***$p<0.01$, **$p<0.05$, *$p<0.1$.

**Table 3.** China, individual components of the social filter, 1995–2007

| Variables | (1) Patents per capita | (2) Patents per capita | (3) Patents per capita | (4) Patents per capita | (5) Patents per capita | (6) Patents per capita | (7) Patents per capita | (8) Patents per capita | (9) Patents per capita |
|---|---|---|---|---|---|---|---|---|---|
| Regional R&D/S&T expenditure | −0.0605 | −0.0749 | −0.0602 | −0.0636 | −0.0957 | −0.0556 | −0.109 | 0.512 | −0.108 |
| | *(0.101)* | *(0.104)* | *(0.101)* | *(0.101)* | *(0.0833)* | *(0.0663)* | *(0.0744)* | *(0.271)** | *(0.0743)* |
| Spatially weighted S&T (inverse dist) | −1.06e−08 | | −1.10e−08 | −1.13e−08 | −5.93e−09 | −1.64e−08 | −9.34e−09 | −9.58e−09 | −9.24e−09 |
| | *(3.71e−09)**** | | *(3.95e−09)**** | *(3.83e−09)**** | *(2.74e−09)*** | *(3.90e−09)**** | *(2.47e−09)**** | *(2.29e−09)**** | *(2.50e−09)**** |
| Spatially weighted S&T (first order contiguity) | | −2.23e−09 | | | | | | | |
| | | *(1.11e−09)*** | | | | | | | |
| Young population (15–24) | 0.0972 | 0.0996 | 0.0968 | 0.0973 | 0.0890 | −0.00276 | 0.0205 | 0.00340 | 0.0202 |
| | *(0.0278)**** | *(0.0292)**** | *(0.0279)**** | *(0.0278)**** | *(0.0239)**** | *(0.0218)* | *(0.0226)* | *(0.0175)* | *(0.0235)* |
| Human capital accumulation (pop. tert. educ) | 0.124 | 0.124 | 0.125 | 0.122 | 0.0414 | −9.44e−05 | 0.0135 | 0.0439 | 0.0142 |
| | *(0.0467)**** | *(0.0487)*** | *(0.0469)**** | *(0.0464)**** | *(0.0339)* | *(0.0346)* | *(0.0292)* | *(0.0284)* | *(0.0290)* |
| Unemployment rate (urban) | 0.00731 | −0.0282 | 0.0120 | 0.0160 | 0.0636 | 0.00847 | 0.0807 | 0.0783 | 0.0789 |
| | *(0.0439)* | *(0.0396)* | *(0.0493)* | *(0.0456)* | *(0.0490)* | *(0.0252)* | *(0.0374)*** | *(0.0324)*** | *(0.0351)*** |
| Agricultural employment (%) | −0.00681 | −0.00774 | −0.00696 | −0.00676 | −0.00555 | −0.000451 | −0.000844 | 0.000796 | −0.000749 |
| | *(0.00346)*** | *(0.00383)*** | *(0.00340)*** | *(0.00342)*** | *(0.00274)*** | *(0.00216)* | *(0.00190)* | *(0.00251)* | *(0.00197)* |
| Spatially weighted social filter (inverse dist) | | | 0.00186 | | | | | | |
| | | | *(0.00293)* | | | | | | |
| Spatially weighted social filter (first order contiguity) | | | | 0.00141 | −0.000656 | −0.00136 | −0.00140 | −0.000409 | −0.00146 |
| | | | | *(0.000761)** | *(0.000760)* | *(0.000762)** | *(0.000689)*** | *(0.00103)* | *(0.000687)*** |
| Krugman index | | | | | 0.0270 | | 0.0212 | 0.0206 | 0.0213 |
| | | | | | (0.00446)*** | | (0.00438)*** | (0.00411)*** | (0.00446)*** |
| Railway density | | | | | 0.112 | | 0.104 | 0.108 | 0.105 |
| | | | | | *(0.0537)*** | | *(0.0560)** | *(0.0451)*** | *(0.0579)** |
| Population density | | | | | | 0.000149 | 0.000157 | 0.000288 | 0.000156 |
| | | | | | | *(6.34e−05)*** | *(5.63e−05)**** | *(5.86e−05)**** | *(5.94e−05)**** |

(continued)

**Table 3.** Continued

| Variables | (1) Patents per capita | (2) Patents per capita | (3) Patents per capita | (4) Patents per capita | (5) Patents per capita | (6) Patents per capita | (7) Patents per capita | (8) Patents per capita | (9) Patents per capita |
|---|---|---|---|---|---|---|---|---|---|
| Net migration | | | | | | −1.70e−05 | 1.93e−05 | 3.62e−05 | 1.90e−05 |
| | | | | | | *(2.44e−05)* | *(1.29e−05)* | *(1.04e−05)****** | *(1.37e−05)* |
| GDP per capita | | | | | | 8.23e−07 | | | |
| | | | | | | *(2.88e−07)****** | | | |
| Int. term exp. S&T* pop. density | | | | | | | | −0.00113 | |
| | | | | | | | | *(0.000537)**** | |
| Stateowned industrial firms (% industrial firms) | | | | | | | | | −0.000676 |
| | | | | | | | | | *(0.00237)* |
| Constant | −0.0130 | −0.0137 | −0.0121 | −0.0122 | −0.0418 | −0.0489 | −0.0784 | −0.121 | −0.0782 |
| | *(0.00370)****** | *(0.00408)****** | *(0.00397)****** | *(0.00377)****** | *(0.00645)****** | *(0.0193)**** | *(0.0164)****** | *(0.0219)****** | *(0.0168)****** |
| Year dummies | X | X | X | X | X | X | X | X | X |
| Observations | 390 | 390 | 390 | 390 | 390 | 390 | 390 | 390 | 389 |
| *R*-squared | 0.260 | 0.241 | 0.260 | 0.262 | 0.374 | 0.400 | 0.409 | 0.583 | 0.409 |
| Number of id | 30 | 30 | 30 | 30 | 30 | 30 | 30 | 30 | 30 |

Robust standard errors in parentheses.
***$p<0.01$, **$p<0.05$, *$p<0.1$.

**Table 4.** India, social filter index, 1995–2004

| Variables | (1) Patents per capita | (2) Patents per capita | (3) Patents per capita | (4) Patents per capita | (5) Patents per capita | (6) Patents per capita | (7) Patents per capita | (8) Patents per capita | (9) Patents per capita | (10) Patents per capita | (11) Patents per capita |
|---|---|---|---|---|---|---|---|---|---|---|---|
| Regional R&D expenditure | 1.734 | 1.832 | 1.787 | 1.638 | 1.657 | 1.641 | 1.505 | 1.456 | 1.314 | 1.545 | 0.194 |
| | *(0.968)** | *(1.064)** | *(0.952)** | *(1.067)* | *(0.963)** | *(0.875)** | *(0.806)** | *(0.885)* | *(0.774)** | *(0.810)** | *(0.321)* |
| Spatially weighted R&D (inverse dist) | | 2.14e–09 | | 1.43e–09 | | | | | | | |
| | | *(4.41e–09)* | | *(4.36e–09)* | | | | | | | |
| Spatially weighted R&D (first order contiguity) | | | 2.37e–09 | | 2.20e–09 | 2.04e–09 | 1.71e–09 | 1.75e–09 | 1.04e–09 | 1.24e–09 | 1.06e–09 |
| | | | *(1.03e–09)*** | | *(1.05e–09)*** | *(9.16e–10)*** | *(8.81e–10)** | *(9.07e–10)** | *(8.96e–10)* | *(9.54e–10)* | *(8.19e–10)* |
| Social filter | | | | 0.000189 | 0.000148 | 0.000246 | 0.000261 | 0.000255 | 0.000253 | 0.000210 | 0.000194 |
| | | | | *(8.87e–05)*** | *(8.90e–05)* | *(0.000106)*** | *(0.000113)*** | *(0.000115)*** | *(0.000108)*** | *(0.000110)** | *(9.07e–05)*** |
| Spatially weighted social filter (inverse dist) | | | | | | 0.00231 | | | | | |
| | | | | | | *(0.00158)* | | | | | |
| Spatially weighted social filter (first order contiguity) | | | | | | | 0.00113 | 0.00111 | 0.000848 | 0.000694 | 0.000357 |
| | | | | | | | *(0.000580)** | *(0.000605)** | *(0.000517)* | *(0.000472)* | *(0.000304)* |
| Krugman index | | | | | | | | −0.000574 | | −8.15e–05 | −0.000985 |
| | | | | | | | | *(0.00153)* | | *(0.00133)* | *(0.000951)* |
| Road density | | | | | | | | −3.94e–06 | | −4.53e–05 | −3.69e–05 |
| | | | | | | | | *(8.34e–06)* | | *(2.12e–05)*** | *(1.75e–05)*** |
| Population density | | | | | | | | | −3.56e–06 | 1.41e–06 | −7.68e–08 |
| | | | | | | | | | *(2.87e–06)* | *(1.26e–06)* | *(1.07e–06)* |
| GDP per capita | | | | | | | | | −6.04e–08 | | |
| | | | | | | | | | *(3.80e–08)* | | |
| Gross migration (inter-state) | | | | | | | | | 1.75e–05 | 1.74e–05 | 1.30e–05 |
| | | | | | | | | | *(6.53e–06)**** | *(7.55e–06)*** | *(6.07e–06)*** |
| Int. term exp. S&T* pop. density | | | | | | | | | | | 0.000999 |
| | | | | | | | | | | | *(0.000276)**** |
| Constant | −0.00204 | −0.00385 | −0.00443 | −0.00313 | −0.00417 | −0.00441 | −0.00354 | −0.00311 | 0.000568 | −0.00622 | −0.00288 |
| | *(0.00110)** | *(0.00432)* | *(0.00190)*** | *(0.00428)* | *(0.00194)*** | *(0.00192)*** | *(0.00156)*** | *(0.00211)* | *(0.00438)* | *(0.00348)** | *(0.00211)* |
| Year dummies | X | X | X | X | X | X | X | X | X | X | X |
| DelhiTrend | X | X | X | X | X | X | X | X | X | X | X |
| Observations | 92 | 92 | 92 | 92 | 92 | 92 | 92 | 92 | 92 | 92 | 92 |
| *R*-squared | 0.903 | 0.904 | 0.911 | 0.906 | 0.912 | 0.919 | 0.923 | 0.923 | 0.935 | 0.938 | 0.964 |
| Number of id | 19 | 19 | 19 | 19 | 19 | 19 | 19 | 19 | 19 | 19 | 19 |

Robust standard errors in parentheses.
***$p<0.01$, **$p<0.05$, *$p<0.1$.

**Table 5.** India, individual components of the social filter, 1995–2004

| Variables | (1) Patents per capita | (2) Patents per capita | (3) Patents per capita | (4) Patents per capita | (5) Patents per capita | (6) Patents per capita | (7) Patents per capita | (8) Patents per capita |
|---|---|---|---|---|---|---|---|---|
| Regional R&D expenditure | 1.649 | 1.599 | 1.583 | 1.445 | 1.379 | 1.255 | 1.426 | 0.0956 |
| | *(1.101)* | *(1.020)* | *(0.929)** | *(0.842)** | *(0.937)* | *(0.778)* | *(0.844)** | *(0.315)* |
| Spatially weighted R&D (inverse dist) | 1.86e−09 | | | | | | | |
| | *(4.90e−09)* | | | | | | | |
| Spatially weighted R&D (first order contiguity) | | 2.81e−09 | 2.58e−09 | 2.15e−09 | 2.20e−09 | 2.05e−09 | 2.25e−09 | 1.96e−09 |
| | | *(1.32e−09)*** | *(1.11e−09)*** | *(1.22e−09)** | *(1.29e−09)** | *(1.15e−09)** | *(1.15e−09)** | *(9.56e−10)*** |
| Young population (15–24) | 0.0200 | 0.0246 | 0.0236 | 0.0221 | 0.0223 | 0.0333 | 0.0329 | 0.0355 |
| | *(0.0162)* | *(0.0152)* | *(0.0151)* | *(0.0137)* | *(0.0143)* | *(0.0205)* | *(0.0219)* | *(0.0165)*** |
| Human capital accumulation (pop. tert. educ) | 2.44e−06 | −3.54e−06 | −2.32e−06 | −2.22e−06 | −2.33e−06 | −5.78e−06 | −7.12e−06 | −5.23e−06 |
| | *(1.10e−05)* | *(1.05e−05)* | *(9.55e−06)* | *(1.04e−05)* | *(1.08e−05)* | *(9.94e−06)* | *(9.92e−06)* | *(8.28e−06)* |
| Agricultural employment (%) | −0.000288 | −0.000145 | −0.000365 | −0.000448 | −0.000444 | −0.000304 | −0.000205 | −0.000144 |
| | *(0.000144)** | *(0.000148)* | *(0.000209)** | *(0.000235)** | *(0.000244)** | *(0.000223)* | *(0.000226)* | *(0.000161)* |
| Unemployment rate (urban) | −0.00705 | −0.00157 | −0.00312 | −0.00735 | −0.00710 | −0.00337 | −0.000809 | −0.00166 |
| | *(0.00998)* | *(0.00957)* | *(0.00954)* | *(0.0102)* | *(0.0104)* | *(0.00908)* | *(0.00943)* | *(0.00785)* |
| Spatially weighted social filter (inverse dist) | | | 0.00221 | | | | | |
| | | | *(0.00165)* | | | | | |
| Spatially weighted social filter (first order contiguity) | | | | 0.00113 | 0.00113 | 0.000783 | 0.000572 | 0.000218 |
| | | | | *(0.000631)** | *(0.000659)** | *(0.000555)* | *(0.000494)* | *(0.000313)* |
| Krugman index | | | | | −0.000504 | | −3.14e−05 | −0.000920 |
| | | | | | *(0.00155)* | | *(0.00136)* | *(0.000988)* |
| Road density | | | | | 2.23e−06 | | −4.22e−05 | −3.35e−05 |
| | | | | | *(1.03e−05)* | | *(1.74e−05)*** | *(1.21e−05)**** |
| Population density | | | | | | −1.14e−06 | 1.97e−06 | 5.11e−07 |
| | | | | | | *(3.07e−06)* | *(1.03e−06)** | *(7.63e−07)* |
| GDP per capita | | | | | | −3.28e−08 | | |
| | | | | | | *(3.87e−08)* | | |

(continued)

**Table 5.** Continued

| Variables | (1) Patents per capita | (2) Patents per capita | (3) Patents per capita | (4) Patents per capita | (5) Patents per capita | (6) Patents per capita | (7) Patents per capita | (8) Patents per capita |
|---|---|---|---|---|---|---|---|---|
| Gross migration (inter-state) | | | | | | 1.78e−05 | 2.00e−05 | 1.56e−05 |
| | | | | | | *(5.84e−06)****** | *(5.97e−06)****** | *(4.43e−06)****** |
| Int.term exp. S&T* pop. Density | | | | | | | | 0.00100 |
| | | | | | | | | *(0.000259)****** |
| Constant | −0.00722 | −0.00880 | −0.00882 | −0.00738 | −0.00705 | −0.00890 | −0.0132 | −0.0105 |
| | *(0.00450)* | *(0.00343)**** | *(0.00337)**** | *(0.00281)**** | *(0.00316)**** | *(0.00657)* | *(0.00520)**** | *(0.00408)**** |
| Year dummies | X | X | X | X | X | X | X | X |
| DelhiTrend | X | X | X | X | X | X | X | X |
| Observations | 92 | 92 | 92 | 92 | 92 | 92 | 92 | 92 |
| $R$-squared | 0.907 | 0.915 | 0.921 | 0.925 | 0.925 | 0.939 | 0.943 | 0.969 |
| Number of id | 19 | 19 | 19 | 19 | 19 | 19 | 19 | 19 |

Robust standard errors in parentheses.
***$p<0.01$, **$p<0.05$, *$p<0.1$.

building roads. Net migration is positive and significant at the 1% level, but point estimates are much smaller than for agglomeration measures. To further explore agglomeration processes, we interact science and technology spending with population density. The interaction term is negative and significant at 5%, but renders local R&D spending positive and significant.

Finally, model (12) includes a control for the share of state-owned firms. As predicted, we find a negative coefficient—potentially indicating that a strong presence of state-owned enterprises may drag down regional innovation—although the coefficient is not significant.

The decomposition of the social filter into its constituent variables is presented in Table 3. The results of this analysis corroborate those of Table 2, highlighting the robustness of the exercise. Reflecting a weak association between the social filter index and innovation in China, none of the indicators making up the social filter index has a robust connection to innovation. While in the earlier regressions [Regressions (1) to (4)] the presence of a young population or the levels of human capital are positively and significantly associated with regional innovation and agricultural employment has a negative connection with it, the introduction of the indicators depicting levels of agglomeration, industrial specialization and infrastructure endowment in the analysis in regressions (5) to (9) renders these connections insignificant. By contrast, the relatively strong associations between spatially weighted S&T variable, on the one hand, and between agglomeration, industrial specialization and transport infrastructure density, on the other, remain largely untouched.

Overall, the results suggest that the geography of innovation in China is akin to what could have been predicted under a 'new' economic geography framework. It is a traditional agglomeration story: richer regions with an intense agglomeration of activities, good infrastructure endowments, and a greater degree of industrial specialization not only have higher patenting rates, but also absorb innovative potential from neighbouring areas. When agglomeration effects are taken into account, the R&D spillovers become negative and significant, generating what is known as the 'Krugman shadow effect' (McCann and Ortega-Argilés, 2011), that is the agglomeration of innovation in core areas leads to ever greater concentration of innovation by promoting further outflows of knowledge from neighbouring regions. This drawing of resources from surrounding areas is a sign of the presence of what can be considered as a less mature innovation system.

It might appear paradoxical that China has a geography of innovation led by agglomeration forces, which are generally considered to be a strong feature of a market-driven economy. The territorial distribution of Chinese innovation is characterized by the overwhelming concentration of innovative activity in Guangdong province. This mega-agglomeration of export-oriented industry is the country's main innovation hub, but the Guangdong agglomeration is in many ways the result of a national strategy designed to turn China into the workshop of the world. However, this top–down strategy was subsequently allowed to interact with 'market' forces in a powerful way. Other innovative areas have also benefited from policy intervention by the Chinese government. As Wang (2010) notes, the particular importance of Special Economic Zones (SEZs) in 1978, which acted to spatially concentrate FDI flows—and thus technology transfer—have played an important role in developing clusters of high-tech innovative activity in Southern and coastal regions such as Guangdong, Fujian, Hainan, Hunchun and the Pudong Development Zone (Shanghai). Inland regions, on

the other hand, were allowed far less 'integration with the outside world' (Jian et al., 1996). These trends have been reinforced by the increasing 'territorial competition' among Chinese provinces whereby politically stronger and economically wealthier local authorities have actively promoted the concentration of innovative activities 'at the expense' of neighbouring (competing) areas (Chien and Gordon, 2008). In addition, internal restrictions on labour and capital mobility have played an important role in the development of the Chinese spatial economy (Duflo, 2010) and, as a consequence, on its geography of innovation. Although restrictions on capital mobility have been progressively eased over time, enduring restrictions on labour movement in combinations with high levels of informal rural–urban migration have contributed to concentrate human and physical capital in urban areas, accelerating the prominence of urban centres as innovation hubs. Hence, in this first big phase of Chinese innovation development, the paradox is that we are seeing an unusually 'pure' case of market-driven agglomeration effects and the mutually supportive relationship of urbanization, localization and innovation, which owes much to a planned economy.

### 4.2. India

India appears to have a radically different geography of innovation from China (Table 4). R&D expenditures, in regressions (1) to (3), suggest a more conventional relationship between R&D inputs and innovation outputs. Unlike China, we find that regional R&D spending is important for regional innovation, with point estimates which are very large, although only significant at the 10% level. Moreover, R&D spending as a determinant of regional innovative capacity maintains its importance as social conditions and structural factors are introduced in the analysis. Unlike China, spillovers from R&D are positive and significant at the 5% level, although the levels of significance drop once net migration is included in the model.

In India, the social filter is positive and significant at the 5% level in most specifications, indicating that specific socioeconomic local level structures play an important role in the genesis and reception of innovation (regressions 4–8). Agglomeration, industrial specialization and transport infrastructure indicators have a weaker effect in India than in China (regression 9–11). Population density has no independent influence on the distribution of innovative activity in India and the coefficient for the Krugman Index is insignificant. Road density and net migration are both, by contrast, significant at the 5% level, with the latter being the most salient. As noted above, interacting R&D with population density leads to a positive association with innovation, although in the opposite direction to the Chinese case. This suggests marginal returns to concentrating R&D, which are not present in China.

The individual components of the social filter index do not matter, but their joint effect is powerful, Table 5. With many individual components of the social filter, for example, regional R&D spending appears to be insignificant, implying that factors such as high levels of education, the demographic structure of the population, the level of agricultural employment or the unemployment rate, taken individually, do not have an important influence on state-level innovation in India. It is their combination that functions as a genuine filter, suggesting a synergy that contributes to local innovation and enhances returns to R&D investment. Moreover, the interaction of R&D with population density remains positive and significant, underscoring the importance of scale to Indian R&D output.

All in all, the territorial configuration of innovation in India is more dispersed than in China, both quantitatively and qualitatively. The pattern of innovation across Indian states is shaped by a combination of regional R&D investment and social conditions. R&D investment generates knowledge spillovers which travel across state boundaries. Reflecting these forces, spillovers associated with local socioeconomic conditions are more limited, probably because knowledge can more easily be absorbed from one local milieu to another. In both China and India, the interaction of R&D and population density is highly significant; unlike China, in India the coefficient is positive and renders R&D spending alone insignificant, once again reflecting that the Indian territorial innovation process is an urban one in a country with unevenly developed social and institutional capacities across different dense areas. Paradoxically, though, the greater geographical diffusion of knowledge in India than in China stems from the fact that there are many dense areas with adequate social filter conditions.

This spatial configuration of innovation analysed above makes sense when seen in terms of the historical development of India. As in China, India historically placed significant restrictions on factor movement (Dahlman, 2010). India's policy stance since the 1950s focused on directing capital, with heavy tariffs on foreign trade and a 'license Raj' limiting internal firm entry, exit and size (Fernandes and Sharma, 2011). Additionally, only a few foreign firms were allowed to set up in the country (Bound, 2007). India's firm entry/exit restrictions were, however, progressively reduced in the 1980s; then a balance of payments crisis in 1991 led to the abolition of both tariffs and internal and international entry limits. The cumulative effect of these policies has been, on the one hand, to create 'artificial clusters' of economic activity, some of which have proved enduring (Fernandes and Sharma, 2011). On the other hand, the dismantling of the 'license Raj' 'resulted in a sizeable reallocation of industrial production' (Aghion et al., 2008, 1409) across states in response to different investment climate conditions. As a consequence, Indian clusters may also reflect the organic clustering of MNEs and the role of regionally-specific transnational networks, which are market-led processes, as well as differences in the quality of education and infrastructure, that expose the more decentralized nature of India and the development of its entrepreneurial capacities and networks (D'Costa, 2003; Taeube, 2004).

## 5. The territorial innovation processes of India and China: conclusion

Both China and India have experienced significant transformations in national innovation outputs in recent years. They have gone from being innovation backwaters towards a possible future role as key hubs in the global geography of innovation. The aim of this article has been to address how these transformations are expressed territorially, and how the territorial process of matching innovation inputs and interactions affects innovation performance in the two countries.

The analysis presented above must be considered exploratory, due to the problems with subnational data gathering in emerging economies, the frequent questions about the reliability of subnational Chinese and Indian data, and the caveats about using patent density as a valid measure of innovation. Nevertheless, it approaches this complex subject with theoretical rigour and generates results that are more general than case-studies of particular regions.

With these caveats in mind, we conclude that the geography of innovation in these two emerging economies takes different forms and has different processes of matching capital, labour and knowledge. Innovation in China seems to be driven by a density/R&D nexus, thus concentrating innovation in a few super-centres. The traditional top–down nature of Chinese development and the national emphasis on R&D have created these major centres; but a counterpart is that the social and entrepreneurial conditions for innovation are not available in as many places in China as in India, and places interact less in China than in India. The Chinese system seems to have worked well for the rapid development of the Chinese innovation system. However, as China is now diversifying its economy and progressively moving up the world division of labour and technology hierarchy, it needs to develop its urban system in order to attenuate congestion costs and spread development (Demurger et al., 2002). Development can be diffused in a hierarchical way without spreading much innovation; but leaving just a few centres as innovative regions (i.e. Guangdong, Beijing and Shanghai) could also create the equivalent of congestion costs and monopoly effects and biases in innovation (Yusuf and Nabeshima, 2010). There is therefore a legitimate question as to how China will not just disperse production and urbanization, but also innovation.

India has its own version of this challenge, but it is shaped by different forces. As the territorial effects of the 'license Raj' have eroded, factors related to the specific socioeconomic and institutional conditions of Indian states, such as the differences in social filter, networks, policies and practices are making themselves increasingly felt on the Indian innovation landscape. This means that we are probably just beginning to see what the longer-term territoriality of innovation will be in India. The geography of innovation in India may evolve towards an even greater cleavage between innovative and globalized regions and the rest, with possibly an emergence of some 'middle-sized' highly innovative centres, alongside the mega-urban areas (such as Delhi and Mumbai) that will blend innovation-localization and the effects of urbanization and global gateway roles (Wilson and Purushothaman, 2003; Florida et al., 2008). Whether this happens will depend on factors like the inertia linked to current urbanization patterns and to a path dependency from the past effects of the 'license Raj'. How specific local factors—social filter, local and regional institutions and the like—adapt to the shifting circumstances linked to globalization and trade liberalization will determine which specific regions and states in India move up in the world technology ladder. These processes will be shaped by the more democratic, but also bureaucratic, Indian political system and the ways that local politics/policies will increasingly reflect the basics of spatial-social filter differences.

The geography of innovation in emerging countries is shaped by a basic list of forces that are similar to those shaping geography of innovation in developed areas, but such factors operate in different ways from one context to another. For example, even between the USA and Europe, the geographical foundations of innovation have significant differences, which have shaped their patterns of interregional inequality in different ways (Crescenzi et al., 2007). The generic policy recipes for fostering innovation consist of investing more in R&D, facilitating the attraction of foreign direct investment or improving human capital or infrastructure. Such policies have impacts, both in promoting innovation and in determining its territorial pattern and the pattern of incomes, that are shaped by country- and place-specific territorial processes that we have analysed in this article. This implies that policies aimed at improving the

innovative capacity of China and India, or any country for that matter, need to consist of more than the generic recipe and go beyond any 'golden rule' for the spatial distribution of of innovative activities (Liu and Sun, 2009).

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## References

Acs, Z. J., Anselin, L., Varga, A. (2002) Patents and innovation counts as measures of regional production of new knowledge. *Research Policy*, 31: 1069–1085.

Aghion, P., Burgess, R., Redding, S., Zilibotti, F. (2008) The unequal effects of liberalization: evidence from dismantling the license raj in India. *American Economic Review*, 98: 1397–1412.

Asheim, B. T., Gertler, M. (2005) The geography of innovation: regional innovation systems. In J. Fagerberg, D. Mowery, R. Nelson (eds) *The Oxford Handbook of Innovation*, pp. 291–317. Oxford: Oxford University Press.

Asheim, B., Vang, J. (2004) What can Regional Systems of Innovation and Learning Regions offer Developing Regions? Paper presented at the Globelics Conference.

Audretsch, D., Feldman, M. (1996) Innovation in cities: science-based diversity, specialisation and local competition R&D spillovers. *European Economic Review*, 43: 409–429.

Bound, K. (2007) *India: The Uneven Innovator*. London: Demos.

Bruche, G. (2009) *A New Geography of Innovation - China and India Rising*. New York: Vale Columbia Center, Columbia University.

Carlino, G., Chatterjee, S., Hunt, R. (2007) Urban density and the rate of invention. *Journal of Urban Economics*, 61: 389–419.

Chaminade, C., Vang, J. (2008) Globalisation of knowledge production and regional innovation policy: supporting specialized hubs in the Bangalore software industry. *Research Policy*, 37: 1684–1696.

Charlot, S., Duranton, G. (2004) Communication externalities in cities. *Journal of Urban Economics*, 56: 581–613.

Chien, S., Gordon, I. (2008) Territorial competition in China and the West. *Regional Studies*, 42: 31–49.

Cohen, W. M., Levinthal, D. A. (1990) Absorptive capacity: a new perspective on learning and innovation. *Administrative Science Quarterly*, 35: 128–152.

Cooke, P. (2002) Regional innovation systems: general findings and some new evidence from biotechnology clusters. *Journal of Technology Transfer*, 27: 133–145.

Crescenzi, R., Rodríguez-Pose, A. (2011) *Innovation and Regional Growth in the European Union*. Berlin: Springer.

Crescenzi, R., Rodríguez-Pose, A. (2012) An 'integrated' framework for the comparative analysis of the territorial innovation dynamics of developed and emerging countries. *Journal of Economic Surveys*, 26: 517–533.
Crescenzi, R., Rodríguez-Pose, A., Storper, M. (2007) The territorial dynamics of innovation: a Europe–United States comparative analysis. *Journal of Economic Geography*, 7: 673–709.
da Motta e Albuquerque, E. (2003) *Immature Systems of Innovation: Introductory Notes About a Comparison Between South Africa, India, Mexico and Brazil Based on Science and Technology Statistics*. Cedeplar: Universidade Federal de Minas Gerais.
Dahlman, C. (2010) Innovation strategies of three of the BRICS: Brazil, India and China- what can we learn from three different approaches. In X. Fu, L. Soete (eds) *The Rise of Technological Power in the South*. Basingstoke: Palgrave MacMillan.
D'Costa, A. P. (2003) Uneven and combined development: understanding India's software exports. *World Development*, 13: 211–226.
Demurger, S., Sachs, J., Woo, W. T., Bao, S., Chang, G., Mellinger, A. (2002) Geography, economic policy and regional development in China. *Asian Economic Papers*, 1: 146–197.
Dosi, G., Llerena, P., Sylos Labini, M. (2006) The relationships between science, technologies and their industrial exploitation: an illustration through the myths and realities of the so-called 'European Paradox'. *Research Policy*, 35: 1450–1464.
Duan, Y., Kong, Y. (2008) The Role of R&D Offshoring in Explaining the Patent Growth of China and India at USPTO. Paper presented at the 2008 IEEE International Conference on Management of Innovation and Technology, Bangkok.
Duflo, E. (2010) Transportation Infrastructure and Urban Growth in China. Presentation to International Growth Centre Conference on Cities and Growth, London, 16 December.
Duranton, G., Puga, D. (2003) *Micro-Foundations of Urban Agglomeration Economies*. Cambridge, MA: NBER.
Fagerberg, J. (1994) Technology and International Differences in Growth Rates. *Journal of Economic Literature*, 32(3): 1147–1175.
Fagerberg, J., Shrolec, M. (2009) Innovation systems, technology and development: unpacking the relationships. In B.-A. Lundvall, K. J. Joseph, C. Chaminade, J. Vang (eds) *Handbook of Innovation Systems and Developing Countries: Building Domestic Capabilities in a Global Setting*. Cheltenham: Edward Elgar.
Fan, P. (2008) *Innovation Capacity and Economic Development China and India*. Helsinki: UNU World Institute for Development Economics Research.
Fernandes, A. M., Sharma, G. (2011) *Together We Stand? Agglomeration in Indian Manufacturing*, Mimeo.
Filatotchev, I., Liu, X., Lu, J., Wright, M. (2011) Knowledge spillovers through human mobility across national borders: evidence from Zhongguancun Science Park in China. *Research Policy*, 40: 453–462.
Fleischer, B., Li, H., Zhao, M. Q. (2010) Human capital, economic growth, and regional inequality in China. *Journal of Development Economics*, 92: 215–231.
Florida, R., Gulden, T., Mellander, C. (2008) The rise of the mega-region. C*ambridge Journal of Regions, Economy and Society*, 1: 459–476.
Fu, X. (2008) Foreign direct investment, absorptive capacity and regional innovation capabilities: evidence from China. *Oxford Development Studies*, 36: 89–110.
Fu, X., Soete, L. (eds) (2010) *The Rise of Technological Power in the South*. Basingstoke: Palgrave MacMillan.
Furman, J. L., Hayes, R. (2004) Catching up or standing still?: National innovative productivity among "follower" countries, 1978–1999. *Research Policy*, 33: 1329–1354.
Gajwani, K., Kanbur, R., Zhang, X. (2006) *Comparing the Evolution of Spatial Inequality in China and India: A Fifty-Year Perspective*, Washington, DC: IFPRI.
Gordon, I. (2001) Unemployment and spatial labour markets: strong adjustment and persistent concentration. In R. Martin, P. Morrison (eds) *Geographies of Labour Market Inequality*. London: Routledge.
Griliches, Z. (1979) Issues in assessing the contribution of R&D to productivity growth. *Bell Journal of Economics*, 10: 92–116.
Griliches, Z. (1986) Productivity, R&D, and basic research at the firm level in the 1970s. *American Economic Review*, 76: 141–154.

Grossman, G. M., Helpman, E. (1991) Quality ladders in the theory of growth. *The Review of Economic Studies*, 58: 43–61.
Gu, Q., Zhou, N., Xiao, P. (eds) (2007) *An Approach to Establish the Policy Supporting System for Private Enterprises' Technological Innovation in China*. Beijing: China Private Economy Innovation International Forum.
Jaffe, A. (1986) Technological opportunity and spillovers of R&D: evidence from firms' patents, profits and market value. *American Economic Review*, 76: 984–1001.
Jian, T., Sachs, J., Warner, A. (1996) Trends in regional inequality in China. *China Economic Review*, 7: 1–21.
Kemeny, T. (2011) Are technology gaps growing or shrinking in the age of globalization? *Journal of Economic Geography*, 11: 1–35.
Kuchiki, A., Tsuji, M. (eds) (2010) *From Agglomeration to Innovation: Upgrading Industrial Clusters in Emerging Economies*. Basingstoke: Palgrave Macmillan.
Kuijs, L., Wang, T. (2006) China's pattern of growth: moving to sustainability and reducing inequality. *China and World Economy*, 14: 1–14.
Leadbeater, C., Wilsdon, J. (2007) *The Atlas of Ideas: How Asian Innovation Can Benefit Us All*. London: Demos.
Li, X., Pai, Y. (2010) The changing geography of innovation activities: what do patent indicators imply? In X. Fu, L. Soete (eds) *The Rise of Technological Power in the South*. Basingstoke: Palgrave MacMillan.
Li, Y., Liu, Y., Ren, F. (2007) Product innovation and process innovation in SOEs: evidence from the Chinese transition. *The Journal of Technology Transfer*, 32: 63–85.
Liu, F., Sun, Y. (2009) A comparison of the spatial distribution of innovative activities in China and the US. *Technological Forecasting and Social Change*, 76: 797–805.
Lundvall, B.-A. (ed.) (1992) *National Systems of Innovation. Towards a Theory of Innovation and Interactive Learning*. London: Pinter.
Lundvall, B.-A., Joseph, K. J., Chaminade, C., Vang, J. (eds) (2009) *Handbook of Innovation Systems and Developing Countries: Building Domestic Capabilities in a Global Setting*. Cheltenham: Edward Elgar.
Mahmood, I., Singh, J. (2003) Technological dynamism in Asia. *Research Policy*, 32: 1031–1054.
Malecki, E. (1997) *Technology and Economic Development: The Dynamics of Local, Regional and National Competitiveness*. Cambridge: Addison-Wesley, Longman.
Malerba, F., Mani, S. (eds) (2009) *Sectoral Systems of Innovation and Production in Developing Countries: Actors, Structure and Evolution*. Cheltenham: Edward Elgar.
Mani, S. (2004) Institutional support for investment in domestic technologies: an analysis of the role of government in India. *Technological Forecasting and Social Change*, 71: 855–863.
Maurseth, P. B., Verspagen, B. (2002) Knowledge spillovers in Europe: a patent citations analysis. *Scandinavian Journal of Economics*, 104: 531–545.
McCann, P., Ortega-Argilés, R. (2011) *Smart specialisation, regional growth and applications to EU cohesion policy*. *Working Papers 2011/14*. Institut d'Economia de Barcelona (IEB).
Midelfart, K. H., Overman, H. G., Redding, S., Venables, A. J. (2002) The location of European industry. *European Economy*, 2: 216–273.
Mitra, R. (2007) *India's Emergence as a Global R&D Center - an Overview of the Indian R&D System and Potential*. Ostersund: Swedish Institute for Growth Policy Studies.
Motohashi, K., Yun, X. (2007) China's innovation system reform and growing industry and science linkages. *Research Policy*, 36: 1251–1260.
O'hUallachain, B., Leslie, T. F. (2007) Rethinking the regional knowledge production function. *Journal of Economic Geography*, 7: 737–752.
OECD, (2009) *OECD Patent Statistics Manual*. Paris: OECD.
Ottaviano, G., Peri, G. (2005) Cities and cultures. *Journal of Urban Economics*, 58: 304–337.
Padilla-Perez, R., Vang, J., Chaminade, C. (2009) Regional innovation systems in developing countries: integrating micro and meso-level capabilities. In B.-A. Lundvall, J. Vang, K. J. Joseph, C. Chaminade (eds) *Handbook of Innovation Systems and Developing Countries*. Cheltenham: Edward Elgar.
Parayil, G., D'Costa, A. (2009) *The New Asian Innovation Dynamics: China and India in Perspective*. Basingstoke: Palgrave Macmillan.

Pedroni, P., Canning, D. (2004) *The Effect of Infrastructure on Long-run Economic Growth*. Department of Economics Working Papers 2004-04, Department of Economics, Williams College.

Ponds, R., van Oort, F., Frenken, K. (2010) Innovation, spillovers and university-industry collaboration: an extended knowledge production function approach. *Journal of Economic Geography*, 10: 231–255.

Popkin, J. M., Iyengar, P. (2007) *IT and the East: How China and India are Altering the Future of Technology and Innovation*. Boston, MA: Harvard Business School Press.

Rodríguez-Pose, A. (1999) Innovation prone and innovation averse societies: economic performance in Europe. *Growth and Change*, 30: 75–105.

Rodríguez-Pose, A., Crescenzi, R. (2008) R&D, spillovers, innovation systems and the genesis of regional growth in Europe. *Regional Studies*, 42: 51–67.

Santangelo, G. (ed.) (2005) *Technological Change and Economic Catch-Up: The Role of Science and Multinationals*. Cheltenham: Edward Elgar.

Saxenian, A.-L. (2006) *The New Argonauts: Regional Advantage in a Global Economy*. Cambridge, MA: Harvard University Press.

Schaaper, M. (2009) *Measuring China's Innovation System: National Specificities and International Comparisons*. Paris: OECD.

Schmitz, H. (2007) Transitions and trajectories in the build-up of innovation capabilities: insights from the global value chain approach. *Asian Journal of Technology Innovation*, 15: 151–160.

Scott, A., Garofoli, G. (eds) (2007) *Development on the Ground: Clusters, Networks and Regions in Emerging Economies*. Oxford: Routledge.

Sun, Y. (2003) Geographic patterns of industrial innovation in China during the 1990s. *Tijdschrift voor Economische en Sociale Geografie*, 94: 376–389.

Sun, Y., Liu, F. (2010) A regional perspective on the structural transformation of China's national innovation system since 1999. *Technological Forecasting and Social Change*, 77: 1311–1321.

Taeube, F. (2004) Transnational networks and the evolution of the indian software industry: the role of culture and ethnicity. In D. Audretsch, D. Fornahl, C. Zellner (eds) *The Role of Labour Mobility and Informal Networks for Knowledge Transfer*, pp. 97–121. Dordrecht: Kluwer.

Tseng, C. (2009) Technological innovation and knowledge network in Asia: evidence from comparison of information and communication technologies among six countries. *Technological Forecasting and Social Change*, 76: 654–663.

Wadhwa, V. (2010) Chinese and Indian Entrepreneurs are Eating America's Lunch. *Foreign Policy*, 28 December.

Wang, C., Lin, G. (2008) The growth and spatial distribution of China's ICT industry: new geography of clustering and innovation. *Issues & Studies*, 44: 145–192.

Wang, J. (2010) *The economic impact of special economic zones: evidence from Chinese municipalities*. Mimeo.

Wilson, D., Purushothaman, R. (2003) Dreaming with BRICs: The Path to 2050. *Global Economics Paper*. 99. NY: Goldman Sachs.

Yeung, H. (2006) Globalising Asian capitalism. an economic geographical perspective. In S. Bagchi-Sen, H. Lawton Smith (eds) *Economic Geography*. London and New York: Routledge.

Yeung, H. (2009) Regional development and the competitive dynamics of global production networks: an East Asian perspective. *Regional Studies*, 43: 325–351.

Yusuf, S., Nabeshima, K. (2010) *Two Dragon Heads Development. Paths for Beijing and Shanghai*. Washington D.C.: World Bank Publications.

# Appendix

## A. Definitions of variables

**Table A1.** Definitions of variables for China

| Variable | Definition | Source(s)** |
|---|---|---|
| Patenting indicator (dependent variable) | | |
| PCT applications per capita (per 1000 persons) | Number of provincial PCT applications (count)/total regional population | OECD.Stat |
| Innovation efforts | | |
| Regional S&T expenditure | Intramural expenditure on Science and Technology (S&T) as a share of total regional GDP*. | China Statistical Yearbook on Science and Technology, 1991–2008 |
| Social filter | | |
| Agricultural employment | Agricultural employment as a share of total provincial employment. | China Statistical Yearbook, 1991–2008 |
| Unemployment rate | Unemployment rate at the provincial level (in urban areas only). | China Statistical Yearbook, 1991–2008 |
| Young population (15–24) | People aged 15–24 years as share of total population in the province. | China Population Census Data |
| Human capital accumulation (tertiary education) | People with college-level or higher degrees as a share of total provincial population (aged 6 years and above). | China Statistical Yearbook, 1991–2008 |
| Structure of the local economy | | |
| GDP per capita | Total regional GDP/total provincial population (units). | China Statistical Yearbook, 1991–2008 |
| Population density | Calculated as average population (units) in year *t*/surface of the province (sq km). | China Statistical Yearbook, 1991–2008 |
| Krugman index | Provincial-level Krugman Index calculated on the basis provincial employment in 15 major sectors defined by the 1990 official statistical classification of industrial sectors. | China Statistical Yearbook, 1991–2008 |
| Railway density | Length of railways in operation (km) in the province/total surface of the province (sq km). | China Statistical Yearbook, 1991–2008 |
| Net migration | Net inter-provincial migration per 1000 persons, calculated as the difference between total migratory inflows minus total migratory outflows. | China Population Census Data |
| State-owned industrial firms (% total industrial firms) | Industrial state-owned enterprises as share of total industrial enterprises. | China Statistical Yearbook, 1991–2008 |

For more information about how China collect R&D/S&T data and the definition of R&D/S&T statistics, please refer to the website: China Science and Technology Statistics (Chinese only) (http://www.sts.org.cn/), which is under the Ministry of Science and Technology, China.
*Data on intramural expenditure for S&T activities cover innovative activities pursued in: (1) independent research and science institutions under government control, (2) higher learning education and (3) large and medium enterprises. In line with UNSECO guidelines, this item includes expenditure for: (1) research and experimental development (R&D), (2) R&D applied services (3) scientific and technological services (STS) and (4) S&T popularization activities. Disaggregated provincial-level R&D data are only available since 1998 and with a limited geographical coverage.
**China statistical Yearbook and Population Census data can be accessed through China Data Online (http://chinadataonline.org/) and National Bureau of Statistics of China website (http://www.stats.gov.cn/). For the years not covered by these websites, we relied on paper-based editions of these publications.

**Table A2.** Definitions of variables for India

| Variable | Definition | Sources** |
|---|---|---|
| Patenting indicator (dependent variable) | | |
| PCT applications per capita (per 1000 persons) | Number of State PCT applications (count)/total regional population. | OECD.Stat |
| Innovation efforts | | |
| Regional R&D expenditure | Combines Central Government Extramural and State total expenditure in R&D as a share of regional GDP*. | Research and development statistics 2004–2005 and 2007–2008; Research and Development in Industry 2000–2001, Ministry of Science and Technology, Govt. of India; Planning Commission, India |
| Social filter | | |
| Unemployment rate | Rate of unemployment at the state level (urban areas) | Planning Commission, Govt. of India. |
| Agricultural employment | Agricultural employment as a share of total employment at the state level. | Census of India 1991, 2001 |
| Human capital accumulation (tertiary education) | People with college, diploma or higher degrees (in urban areas) as a share of total state population (aged 7 years and above). | National Sample Survey |
| Young people | People aged 15–24 years as a share of total state population. | Census of India 1991, 2001 |
| Structure of the local economy | | |
| Population density | Calculated as average population (units) in year *t*/surface of the state (sq km). | Central Statistics Office |
| GDP per capita | Calculated as regional gross domestic product/regional population (units). | Central Statistics Office |
| Krugman index | State-level Krugman Index calculated on the basis State GDP in 13 major sectors. | Central Statistics Office |
| Gross migration | Inter-state migratory in-flows per 1000 persons. | Census of India 1991, 2001 |
| Road density | Calculated as the length of state roads (km)/surface of the state (sq km). | Basic Road Transport Statistics of India, Ministry of Transport and Highways |

*Extramural R&D: 12 major scientific agencies/department. Institutions receiving support from funding agencies classified into five categories: Universities/Colleges and Universities, Institutes of National Importance, National Laboratories and other Institutions under State Governments, Voluntary Agencies, Registered Societies. No data are available for Private R&D expenditure at the State-level.

**The data sources listed in the table have been accessed through Indiastat.com (http://www.indiastat.com/). Additional data have been collected from the Central Statistic Office (http://mospi.gov.in/) including India key economic and survey data. Census data have been collected from the Census of India (http://ww.censusindia.net/). In addition Science and Technology Management Information System (NSTMIS), under the responsibility of the Department of Science and Technology, provides R&D statistic reports (http://www.nstmis-dst.org/index.asp). For some state-level census data not available on line we relied upon paper-based publications.

## B. Principal component analysis results—social filter index

**Table B1.** Principal component analysis: eigenanalysis of the correlation matrix

| Component | Eigenvalue | Difference | Proportion | Cumulative |
|---|---|---|---|---|
| China | | | | |
| Comp1 | 1.78367 | 0.607117 | 0.4459 | 0.4459 |
| Comp2 | 1.17655 | 0.390576 | 0.2941 | 0.7401 |
| Comp3 | 0.785977 | 0.532178 | 0.1965 | 0.9366 |
| Comp4 | 0.2538 | | 0.0634 | 1 |
| India | | | | |
| Comp1 | 1.42679 | 0.397231 | 0.3567 | 0.3567 |
| Comp2 | 1.02956 | 0.140551 | 0.2574 | 0.6141 |
| Comp3 | 0.889012 | 0.234381 | 0.2223 | 0.8363 |
| Comp4 | 0.654631 | | 0.1637 | 1 |

**Table B2.** Principal component analysis: principal components' coefficients

| Variable | Comp1* | Comp2 | Comp3 | Comp4 | Unexplained |
|---|---|---|---|---|---|
| China | | | | | |
| Young population (15–24) | −0.0159 | −0.7543 | 0.6441 | 0.1262 | 0 |
| Population with tertiary educ. | −0.6743 | 0.2201 | 0.1046 | 0.6971 | 0 |
| Unemployment rate (urban) | 0.2586 | 0.6176 | 0.7407 | −0.0559 | 0 |
| Agricultural employment | 0.6915 | −0.0337 | −0.1602 | 0.7036 | 0 |
| India | | | | | |
| Young population (15–24) | 0.5725 | −0.2819 | 0.5164 | −0.571 | 0 |
| Population with tertiary educ. | 0.6567 | 0.1375 | 0.15 | 0.7262 | 0 |
| Agricultural employment | −0.4901 | −0.1991 | 0.786 | 0.3184 | 0 |
| Unemployment rate (urban) | −0.0285 | 0.9284 | 0.3033 | −0.2127 | 0 |

*For the calculation of the social filter index, the score for Comp1 in China has been pre-multiplied by −1 to match the interpretation of the index computed for India (proxy for innovation proneness).