The Geography of Patenting In India: Patterns and Determinants

Pradhan, Jaya Prakash

Centre for Studies in Economics and Planning, Central University of Gujarat

12 October 2013

CONTENTS

THE GEOGRAPHY OF PATENTING IN INDIA: PATTERNS AND DETERMINANTS

Jaya Prakash Pradhan*

Abstract: This study examines the regional profiles of patenting activities in India. The number of most dynamic sub-national spaces in patent applications is found to be limited to just two to three regions or countries. Regionally, West India, North India and South India mostly dominated the patenting activities during 1990–2010. The patent performance is highly concentrated among individual countries: the two leading states, namely Maharashtra and Delhi accounted for more than half of total patent applications filed in India in the study period. Empirical analysis further emphasized that states patenting activities are shaped by the size of local markets, availability of skilled labour force, knowledge institutions and urban centres.

Key words: Patent, Region, India.
JEL classification: O30, P25, N75.

1. Introduction

The literature on innovation is increasingly recognizing innovation as a localised interactive learning process involving local resources, supporting institutions, networking and inter-firm collaborations (Asheim, 2001; Doloreux and Parto, 2004; Pradhan, 2011). That is, a nation's competitive and innovative advantages in specific segments of global markets can be related to the rise of a few selected local regions within its physical boundary. The industrial districts and 'innovative milieu' approaches refer to geographically defined productive systems where economic success of these systems lies in fostering local innovation by ease of information flows, facilitating network linkages, and supporting social relations (Lawson, 1997). The success of Silicon Valley, for example, is related to the innovation milieu made possible by the creative synergies based on social networks among Valley's engineers, managers, and entrepreneurs and their drive for cooperative technological developments (Castells and Hall, 1994).

Location signifies a fundamental dimension of global competition, argued Porter (1998), as innovation and competitive success remain regionally concentrated. Geographical concentrations of interdependent businesses and institutions in a particular activity make local factors like knowledge, relationships, and motivation most crucial for building sustainable advantages. Lundvall and Borrás (1997) suggested that innovation is increasingly getting localized and produced through regional networks of innovating firms, local clusters and research institutions. In the literature on regional innovation systems, the geographical proximity allows firms and organizations of a given region to benefits from interactive learning and innovation through the exchange of tacit and explicit knowledge (Asheim and Isaksen, 1997; Cooke 2001; Asheim and Isaksen, 2002). Therefore, localities, cities and

* Associate Professor, Centre for Studies in Economics and Planning, Central University of Gujarat, Gandhinagar-382 030, Gujarat, India.
Acknowledgement: This study has been prepared for the VIII Annual Conference of the Forum for Global Knowledge Sharing on *Emerging Technologies and Development*, IIT Bombay, October 25–27, 2013. The author is thankful to Prof. N. S. Siddharthan and Prof. K. Narayanan for the invitation and Prof. Keshab Das for useful discussion on the topic.

regions are increasingly becoming chosen level for studies on technological developments and competitiveness of nations.

Yet the recent literature on technological developments of emerging economies is continued to be focused on the national level or sectoral level analyses. This is specifically true for India where most of the studies related to industrial R&D or patent are confined to various sectors or examination of firms' behaviours in selected sectors (Pradhan, 2011). Although, there is a growing literature on industrial clusters that gives a closer look at the role of space (Das, 2005), there has not been adequate focus on disparities in regional technological competencies.

The present study attempts to contribute to the extant technological literature on India by studying the inter-state disparities in patenting activities and examining the role of regional factors that enable a few Indian states to succeed in more patenting than others. Patent statistics are often used as a proxy for innovation activities given their easy availability with technological and geographical information on the invention (Griliches, 1990; Kortum, 1997; Desrochers, 1998). Patent statistics also suffers from a number of limitations notably by the fact that not all invention is patentable. In the Indian case we could get region-wise data only for patent applications, not patent granted, thus, underlying another limitation of the present study. Nevertheless, the patent application represents a firm's belief in the economic value of a new technology that it has developed by spending resources. Therefore, patent literature treat patent applications as a good measure of innovative output (e.g. Griliches, 1990).

The ensuing analysis in this study proceeds as follows: Section 2 presents theoretical knowledge dealing with the process of regional technological capability formation. It formulates the empirical framework with hypotheses for examining the geography of patenting in India. Section 3 examines the trends and patterns of domestic patent applications originating from Indian states from 1990 and tries to understand the broad changes in patenting over space. Issues related to the estimation and data sources are presented in Section 4. Results from econometric analysis of the spatial distribution of patent applications are summarized and discussed in Section 5. The basic objective in this section is to explore why some states do more patenting than others. Section 5 concludes the study with a few policy remarks.

2. The Empirical Framework: Review of Literature and Hypotheses

The R&D-based models of economic growth predict that the flow of new knowledge is directly related to the existing stock of knowledge and the number of scientists and engineers engaged in R&D (Romer, 1990; Jones, 1995; Abdih and Joutz, 2006). Hence, provinces possessing greater stock of knowledge and devoting higher amount of labour into research are likely to be major sources of new knowledge generation. Researchers in these regions are expected to capture an intertemporal spillover of ideas from being proximate to a greater stock of existing knowledge i.e. past ideas facilitate the formation of new ideas. Audretsch and Feldman (1996) based on the innovation database of the United States Small Business Administration provided evidence that the U.S. innovative activity tends to get cluster at the state level more in industries where knowledge-spillovers are the most prevalent.

The literature on the regional innovation system emphasizes that most innovative regions are those that host a pool of qualified human capital and a number of research institutions (e.g. Chaminade, 2011). Skilled regions i.e. regions having a good human capital base are likely to facilitate exchange of ideas among firms and workers to increase potential for technological learning, innovation and economic growth (Jovanovic and Nyarko, 1995). Human capital is an essential prerequisite for innovation even in endogeneous growth model (Romer, 1990) and it enhances the capacity to absorb and adapt available technological knowledge. Faggian and McCann (2009) find that human capital inflows are relatively an important factor for regional innovation performance of the regions of Great Britain in high technology industries than the innovation performance of all industries. For Sweden, Andersson, Quigley and Wilhelmsson (2005) found that human capital stimulate regional patent output.

Recent research put forth the idea that local science and technology (S&T) institutions like universities, training institutes, colleges and R&D laboratories can be a driving force for regional innovation and development. These knowledge institutions contribute to innovation in the region through their research, technology transfers, consulting, conferences, and entrepreneurship development programmes (Arbo and Benneworth, 2007; OECD, 2007; European Commission, 2011). Increasingly academic-industry partnerships are taking the forms of special programme on entrepreneurship and knowledge management, industry funded research programmes, joint R&D programmes, sharing of facilities, etc. Further, students can play as a medium of knowledge exchange between researchers at these institutes and local businesses. For a sample of European regions, Caniëls (1996) has observed that geographic proximity to higher educational institutes is an important determinant of regional innovativeness. Therefore, regions hosting greater number of such institutes are postulated to offer more dynamic institutional environment for innovation than regions not possessing them.

Innovative activity of regions is also expected to share a positive relationship with the size and growth of regional markets. Schmookler (1966) hypothesized that "the amount of invention is governed by the extent of the market" (pp. 137). He believes that invention is largely an economic activity and as stronger demand increases returns to such activity, patenting can be seen as a function of the size of the market. While analyzing the American economic history and growth, Romer (1996) too reach the same observation that larger markets and larger stocks of resources have enabled the United States to make large investments in basic technologies reflecting new ways of resource utilization. Krugman (1991) argues that regions with growing demand and/or larger local markets are likely to attract increasing number of firms and individuals due to saving on transportation costs and realization of scale economies. This clustering in turn may create a facilitative environment for interactive learning, knowledge spillovers and innovation (Pradhan, 2011). Larger local markets represent larger customer base with a preference for larger variety of goods, which is likely to sustain creation of new products.

Technology intensive industrial structure of regions can influence the creation of knowledge by locally embedded industries. The Pavitt taxonomy of innovation shows that technological processes in different sectors are determined by sector-specific conditions of opportunities and appropriability (Pavitt, 1984). Therefore, patenting may be more important for high-technology sectors like pharmaceuticals and microelectronics than low-technology manufacturing such as textiles and agriculture.

Regional efforts to innovate may also be related to the presence of foreign firms in the host region. Foreign affiliates of multinational enterprises (MNEs) contribute to regional innovation by undertaking R&D investments, delivering competitive effect, creating forward and backward linkages, and generating knowledge spillovers to local firms through demonstration of new technologies and management practices (UNCTAD, 1999, 2001). Cheung and Lin (2004) and Fu (2008) both provided econometric evidence that FDI has played a positive and significant role in the innovation activity of the host Chinese regions.

A voluminous literature posits that larger urban centres/cities are more innovative and productive than smaller ones. For United States, Lim (2003) and Acs, Anselin and Varga (2002) found that the bulk of innovative activity in the United States occurs in the metropolitan areas. Rothwell (2012) found that 93 per cent of the world's patent applications during 2005–09 are filed by residents living in metropolitan areas (i.e. city-regions) which boast just 23 per cent of the world's population. Simmie et al. (2002) provided evidence of European cities that urban centres foster and facilitate creation, diffusion and exchange of knowledge. Bettencourt, Lobo and Strumsky (2007) provided statistical results to the fact that larger metropolitan areas in the United States host disproportionately more inventors than smaller ones and generate more patents per capita. Komninos (2002) discuss about intelligent cities that offer innovation environments based on spatial proximity, learning institutions, and physical-digital innovation ecosystems. Athey et. al. (2007) argued that cities offers a number of advantages to individuals and firms namely, proximity, density, variety and access to urban assets that allow conducive environment for innovation. Therefore, urban areas in regions are taken as a factor conducive for regional innovative activity.

Recent research demonstrates that firms located in clusters score more on innovation due to localized knowledge flows and spillovers emerging from real world business interactions, connections, transactions, and competition (Muro and Katz, 2010). As physical proximity and locally embedded exchanges matter in firms' knowledge creation activities, the inter-regional differences in the incidence of local clusters can have strong influence on the innovative performance of different regions.

The foregoing discussions can be summarized into the following econometric relationship for analyzing patenting activities of our sub-national units, namely Indian states:

$$\begin{aligned} PAT_{kt} = {} & \beta_0 + \beta_1 STKS_{kt-1} + \beta_2 SDP_{kt} + \beta_3 SDPG_{kt} + \beta_4 PSDP_{kt} + \beta_5 SKL_{kt} + \beta_6 INST_{kt} + \beta_7 SFDI_{kt} \\ & + \beta_8 SPL_{kt} + \beta_9 SCON_{kt} + \beta_{10} TWN_{kt} + \varepsilon_{it} \qquad \ldots\ldots\ldots\ldots(A) \end{aligned}$$

Where explanatory variables are as explained in Table-1 and ε_{it} is the random error term.

In the above formulated empirical framework for India, regional innovative output is measured by the number of patent applications originating from sub-national spaces, namely Indian states. A total of eight hypotheses are subsumed in the model A, which can be stated as below:

H1: Patenting level of a region increases with its possession of higher level of the initial stock of knowledge assets.

H2: Higher human capital of a region is likely to favour its patent performance.

H3: The presence of a greater number of higher educational and research institutions enables the host region to achieve a greater filing of patent applications.

H4: Size, sophistication and growth of regional market positively contribute to the region's patenting activities.

H5: A region's industrial specialization in high technology products enhances its patenting opportunities.

H6: Greater the number of foreign firms in a region, higher is its domestic patent application.

H7: A regions' patent applications are positively related to the number or the size of its urban areas.

H8: High spatial density of local firms would foster patenting activities of the host region.

Table-1 Description and Measurement of Variables

Variables	Symbols	Measurements
Dependent Variable		
Regional Patent Application	PAT_{kt}	Number of patent applications originated in *k*th Indian state in the year t.
Independent variables		
Demand conditions		
State Domestic Product (net)	SDP_{kt}	Natural log of gross state domestic product (constant 1999–00 Indian ₹) of *k*th Indian state in year t.
Growth of SDP	$SDPG_{kt}$	Annual percentage change in GSDP (constant 1999–00 Indian ₹) of *k*th Indian state in year t.
Per capita SDP	$PSDP_{kt}$	Natural log of per capita GSDP (constant 1999–00 Indian ₹) of *k*th Indian state in year t.
Factor conditions		
State Technological Knowledge Stock	$STKS_{kt-1}$	Number of cumulative patent applications originating from *k*th Indian state since 1989–90 in year t-1.
State Skills Availability	SKL_{kt}	Natural log of higher education enrolments in *k*th Indian state for *t*th year.
State's Technological Specialization in Manufacturing Sector	SPL_{kt}	Net Value Added (NVA) of high technology manufacturing sectors as a per cent of NVA of total manufacturing sector of *k*th Indian state in year t.
Higher Education Institutions		
State Institutions	$INST_{kt}$	Natural log of number of higher education institutions in *k*th Indian state for *t*th year.
FDI Location		
State's Inward FDI	$SFDI_{kt}$	Cumulative FDI inflows since 1982–83 into *k*th Indian state as a per cent of its GSDP in year t.
Spatial Agglomeration		
Spatial Concentration of Firms	$SCON_{kt}$	Number of manufacturing factories per 1000 sq km of area of *k*th Indian state in year t.
Towns	TWN_{kt}	Natural log of number of towns possessed by *k*th Indian state in year t.

Note: High-technology manufacturing sectors include chemicals, pharmaceuticals, electrical & optical equipment, machinery & equipment and transport equipment; Higher education institutions comprise universities, deemed universities, institutions of national importance, research institutes, colleges for professional education (e.g. engineering, technology, architectural and medical colleges) and colleges for general education.

3. Regional Patterns of Patenting Activity in India

Discussion in the previous section suggests that sub-national spaces may have distinct advantages in innovative activity including patenting if they possess relatively a higher knowledge base, abundance of skilled manpower, large local demand, institutions, size of urban areas and spatial agglomeration of productive units. In a geographically vast country like India, sub-national regions are likely to differ substantially in terms of such determining conditions for innovative activities. Pradhan (2011) provided evidence that relatively a smaller group of Indian regions and states comprise disproportionately larger share of total manufacturing R&D investments in the country. Western and Southern regions together accounted for as much as 65 per cent of manufacturing R&D during 2000─08. The share of top five states (Maharashtra, Andhra Pradesh, Tamil Nadu, Haryana, and Gujarat) was over 63 per cent in the same period. Is this pattern of regional concentration in R&D reflective in regional patenting activity as well? What is the geography of patenting in India and how is it evolving?

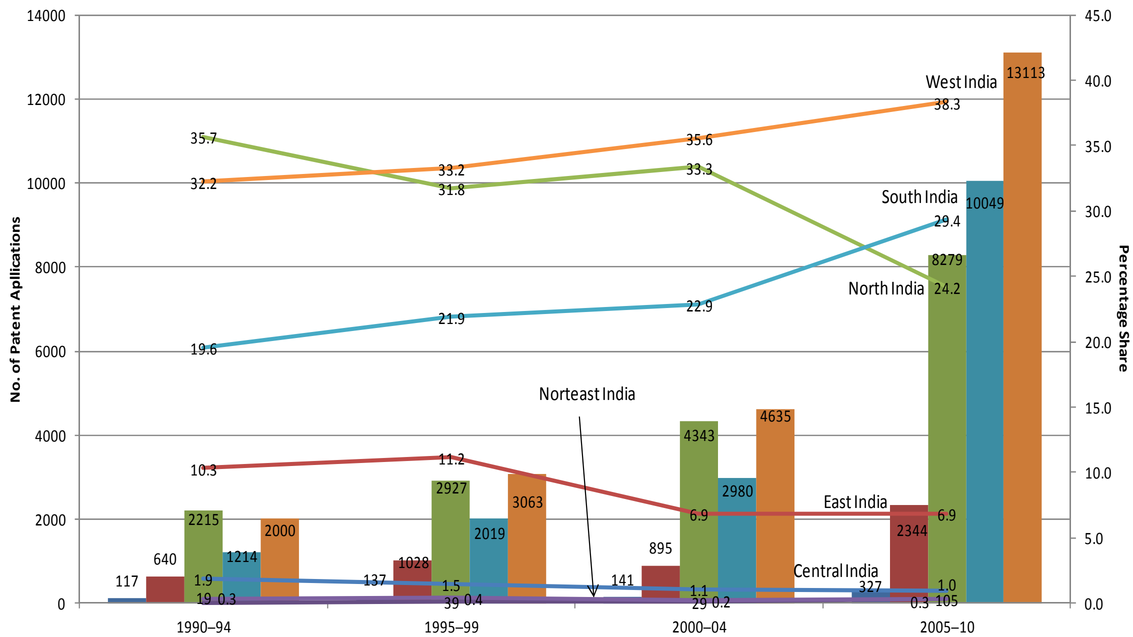
Figure-1 and Table-2 summarize results from a region-wise analysis of trends in the domestic patent applications originating from Indian states for four different periods starting since 1990─94. The number of patent applications from India stood at 9213 during 1995─99 up by 48.5 per cent from 6205 recorded in the first half of the 1990s. The implementation of the Patents Amendment Bill (2005) with retrospective effect from January 1, 2005 to introduce product patents and patentability of software appeared to have created a new environment for intellectual properties. The number of patent applications rose sharply to 34217 in the period 2005─10, which is 2.6 times their number during 2000─04. Between 1995─99 and 2005─10, number of patent applications accelerated the most in South India (398 per cent), followed by West India (328 per cent) and North India (183 per cent).

The patenting activities in India were largely concentrated in two Indian regions, namely North India and West India during the early 1990s. Nearly 68 per cent of patent applications in India originated from these two regions in the period 1990─94. The share of South India and East India stood at 19.6 per cent and 10.3 per cent respectively in the same period. However, Central India and Northeast India remained by far the minor actors in patenting activities at the national level. Thus in general patenting activities in the early 1990s exhibited considerable disparities among regions.

The phase from 1995 to 2010 saw distinct changes in the geography of patenting activities in India. West India continued to surge ahead to emerge as the largest contributor to national patenting with 38 per cent share in the period 2005─10. North India was unable to sustain its share in the national patent applications which dipped to 24 per cent during 2005─10 from 32 per cent achieved in the early 1990s. The 2000s period saw rapid growth in the number of patent applications filed by South India which achieved a share of 29 per cent to become the second important region for patenting efforts. The combined share of West India and South Indian in the number of patent applications stood at 68 per cent in the period 2005─10. This regional pattern of patenting mirrors the similar findings on R&D by Pradhan (2011). Overall, technological activities in terms of R&D or patenting both reveal a more concentrated distribution over space.

The magnitude of spatial concentration gets more intense at the level of states. In the period 1990─94, the most dominating state in filing of patent applications was Delhi, followed by Maharashtra with shares of 30 per cent and 28 per cent respectively. In the former, however, the high share may represents the greater clustering of research institutions and may also involves cases of companies that have R&D facilities elsewhere though filing patent applications from the company's registered office in Delhi. These top two states jointly accounted for as high as 58 per cent share of patent applications in the early 1990s. As many as 21 Indian states including union territories have a share ranging below 1 per cent.

Figure-1: Patent Applications by Regions in India, 1990─94 to 2005─10



Note: Vertically plotted bars represent number of patent applications originating from different regions while line graph shows regional share in national patent applications.

Source: Based on Table-2.

During the subsequent periods, Delhi and Maharashtra continued to comprise the top two states contributing to patent applications in India. While Maharashtra consistently improved its patenting activities to attain a share of 33 per cent during 2005─10, Delhi experienced a fall in its share to 17 per cent. As a group both these states accounted for half of patent applications in this period.

Among Indian states, the relative position of Tamil Nadu turns out to be the third largest or the fourth largest in filing of patent applications over different periods. From being the fourth largest patent contributing state during 1991─94, West Bengal has suffered a decline in its share to be at the sixth position in the 2000s. Karnataka stands out as an important case as it succeeds in more than doubling its share in domestic patent applications between 1991─94 and 2005─10 to emerge as the third largest patent contributing state recently. The position of Kerala another southern state changed from sixth during 1991─94 to ninth during 2005─10. Gujarat had occupied seventh position in the early 1990s as well as in the late 2010s. The number of states including union territories that had a share below 1 per cent now stands at 20 during 2005─10. So there are marked spatial concentration and heterogeneity among states with respect to performance of filing patent applications.

Comparing patenting activities of states with dissimilar local economies by absolute number of patents or share therein has an apparent limitation. This simple way of inter-state patent filing comparison, however, ignore the size of sub-national economy. Larger state economies represented by GSDP are likely to have more patenting activities than smaller state economies. Patent intensity that attempt to measure resident patent behavior of spaces after taking into their economic size is a more reasonable method of benchmarking patent performance of states.

Table-2: State-wise Patent Applications, 1990–94 to 2005–10

Region/State	Patent Applications in Number			
	1990–94	**1995–99**	**2000–04**	**2005–10**
Central India	117 (1.9)	137 (1.5)	141 (1.1)	327 (1.0)
Chhattisgarh	13 (0.2)	15 (0.2)	16 (0.1)	52 (0.2)
Madhya Pradesh	104 (1.7)	122 (1.3)	125 (1.0)	275 (0.8)
East India	640 (10.3)	1028 (11.2)	895 (6.9)	2344 (6.9)
Bihar	35 (0.6)	59 (0.6)	42 (0.3)	140 (0.4)
Jharkhand	54 (0.9)	92 (1.0)	111 (0.9)	472 (1.4)
Orissa	47 (0.8)	55 (0.6)	31 (0.2)	100 (0.3)
West Bengal	504 (8.1)	822 (8.9)	711 (5.5)	1632 (4.8)
North India	2215 (35.7)	2927 (31.8)	4343 (33.3)	8279 (24.2)
Chandigarh	16 (0.3)	16 (0.2)	33 (0.3)	135 (0.4)
Delhi	1865 (30.1)	2525 (27.4)	3510 (27.0)	5904 (17.3)
Haryana	79 (1.3)	79 (0.9)	182 (1.4)	639 (1.9)
Himachal Pradesh	1 (0.0)	14 (0.2)	22 (0.2)	53 (0.2)
Jammu & Kashmir	4 (0.1)	6 (0.1)	7 (0.1)	19 (0.1)
Punjab	45 (0.7)	72 (0.8)	111 (0.9)	311 (0.9)
Uttar Pradesh	199 (3.2)	209 (2.3)	461 (3.5)	1076 (3.1)
Uttarakhand	6 (0.1)	6 (0.1)	17 (0.1)	142 (0.4)
Northeast India	19 (0.3)	39 (0.4)	29 (0.2)	105 (0.3)
Arunachal Pradesh	0 (0.0)	0 (0.0)	0 (0.0)	1 (0.0)
Assam	15 (0.2)	33 (0.4)	26 (0.2)	90 (0.3)
Manipur	0 (0.0)	0 (0.0)	0 (0.0)	1 (0.0)
Meghalaya	2 (0.0)	3 (0.0)	1 (0.0)	5 (0.0)
Mizoram	0 (0.0)	0 (0.0)	0 (0.0)	2 (0.0)
Nagaland	0 (0.0)	0 (0.0)	0 (0.0)	3 (0.0)
Sikkim	0 (0.0)	0 (0.0)	0 (0.0)	1 (0.0)
Tripura	2 (0.0)	3 (0.0)	2 (0.0)	2 (0.0)
South India	1214 (19.6)	2019 (21.9)	2980 (22.9)	10049 (29.4)
Andhra Pradesh	112 (1.8)	436 (4.7)	744 (5.7)	2483 (7.3)
Karnataka	294 (4.7)	457 (5.0)	679 (5.2)	3704 (10.8)
Kerala	264 (4.3)	356 (3.9)	382 (2.9)	699 (2.0)
Pondicherry	8 (0.1)	15 (0.2)	6 (0.0)	22 (0.1)
Tamil Nadu	536 (8.6)	755 (8.2)	1169 (9.0)	3141 (9.2)
West India	2000 (32.2)	3063 (33.2)	4635 (35.6)	13113 (38.3)
Daman & Diu	0 (0.0)	0 (0.0)	5 (0.0)	1 (0.0)
Goa	12 (0.2)	13 (0.1)	15 (0.1)	16 (0.0)
Gujarat	231 (3.7)	336 (3.6)	798 (6.1)	1627 (4.8)
Maharashtra	1712 (27.6)	2624 (28.5)	3744 (28.7)	11249 (32.9)
Rajasthan	45 (0.7)	90 (1.0)	73 (0.6)	220 (0.6)
Grand Total	6205 (100)	9213 (100)	13023 (100)	34217 (100)

Note: Patent applications of an erstwhile state during 1990–2001 were divided between the new states created from it by using the average share of these new states in their combined patent applications during 2002–05; parenthesis contain percentage share.

Source: Authour's computation based on *Annual Report*, Controller General of Patents, Designs & Trade Marks, various years.

Patent intensity values for Indian regions and states are summarized in Table-3 for the three periods, 1995─99, 2000─04, and 2005─10. For India as a whole, patent intensity has grown by 4.4 per cent to 142 between the first two periods and by 46 per cent between the last two periods to 207. This suggest that patent culture in India underwent a massive jump in the latter half of the 2010s, which may be a result of implementation of new patent regime and facilitative business environment after economic liberalization policies.

Among regions, the patent intensity was highest at 184 for North India during 1995─99, followed by West India with 166, South India with 117 and East India with 102. The bottom two regions are Central India and Notheast India with patent intensity of 32 and 19 respectively. As many as four regions, namely South India, East India, Central India and Notheast India may be termed as under-performers as their patent intensities fall below the national patent intensity of 136 in this period.

The period 2000─04 witnessed North India maintaining its lead position with a patent intensity of 201 but West India with 196 observed to be significantly closing the intensity gap. South India demonstrated improved patent intensity to 126 which is catching up with the level of national patent intensity. In this period, East India, Central India and Notheast India reported significant decline in their patent intensity from previous levels achieved during the late 1990s. These bottom three regions appeared to have failed in improving their patenting climate relative to other regions in India.

The inter-regional patent intensity during 2005─10 reveals interesting results. West India and South India are found to have made large upwards leaps. With a patent intensity of 295, West India emerged as the highest patent performer state. South India experienced a significant acceleration in its patent intensity to become 232, which is 84 per cent higher than 126 achieved in the previous period. The patent intensity performance of North India was 219, which is above the national patent intensity level. In spite of lagging behind the national average patent intensity, East India, Central India and Notheast India have seen large expansion in their patent intensities during this period.

Delhi turns out to be the most patent intensive state in India for all periods. It has patent intensity of 1182 in the period 1995─99, which is 4.5 times that of Maharashtra ─ the second best performing state. As mentioned earlier this marked gap in the patent intensity of top state and other states are a result of heavy concentration of national research and technology institutions located in Delhi. Being the national capital, Delhi can be treated as an outlier from rest of Indian states in terms of patent intensity. The top 10 states, based on patent intensities during 1995─99 include Delhi, Maharashtra, West Bengal, Tamil Nadu, Pondicherry, Kerala, Karnataka, Chandigarh, Andhra Pradesh and Gujarat. In this list as many as five southern states are present indicating a vibrant patenting culture existing in South India. It also includes large state economies as well as small economies representing union territories.

Delhi, Maharashtra and Tamil Nadu continued to be the top three states on patent intensity scores all through the 2000─04 period. However, Gujarat an industrial hub of India demonstrated a significant improvement to come out as the fourth patent intensive state. Its patent intensity increased massively by 90 per cent between 1995─99 and 2000─04 to reach 135. This reflects that the industrial culture of Gujarat is getting translated into patent culture in the liberalized phase. During this period other states that figured in the list of top 10 states include Chandigarh, Karnataka, Andhra Pradesh, Kerala, West Bengal and Jharkhand.

Table-3 Patent Intensity of Indian States, 1990─94 to 2005─10

Region/State	No. of patent applications per ₹ 1000 billion current GSDP		
	1995─99	**2000─04**	**2005─10**
Central India	32	26	35
Chhattisgarh	13	11	18
Madhya Pradesh	39	31	43
East India	102	63	92
Bihar	32	15	27
Jharkhand	69	66	158
Orissa	32	14	23
West Bengal	158	95	127
North India	184	201	219
Chandigarh	104	128	244
Delhi	1182	1151	921
Haryana	38	61	109
Himachal Pradesh	28	28	37
Jammu & Kashmir	10	8	13
Punjab	27	31	55
Uttar Pradesh	29	50	72
Uttarakhand	12	22	97
Northeast India	19	10	21
Arunachal Pradesh	0	0	6
Assam	24	14	30
Manipur	0	0	4
Meghalaya	23	5	14
Mizoram		0	13
Nagaland	0	0	9
Sikkim	0	0	10
Tripura	17	7	4
South India	117	126	232
Andhra Pradesh	82	103	185
Karnataka	121	127	385
Kerala	134	100	95
Pondicherry	137	30	57
Tamil Nadu	141	165	251
West India	166	196	295
Goa	50	46	24
Gujarat	71	135	134
Maharashtra	261	287	468
Rajasthan	27	17	29
Grand Total	136	142	207

Source: Authour's computation based on (i) *Annual Report*, Controller General of Patents, Designs & Trade Marks, various years; (ii) *Statements on State Domestic Product*, Central Statistical Organization, various years.

The rankings of Delhi and Maharashtra remained the same during the 2005─10 period. However, Karnataka, which had a sixth position in patent intensity scores in the late 1990s, has seen consistently improved performance to be the third largest patent intensive state. Next important states are Tamil Nadu, Chandigarh, Andhra Pradesh, and Jharkhand. While all the above mentioned states barring Delhi increased their patent intensities, Gujarat slides to eighth position as its patent intensity largely remained the same over the previous period. The ninth and tenth ranking went respectively to West Bengal and Haryana.

4. Estimation Issues, Methods and Data Sources

As the dependent variable y_i is a count variable assuming non-negative integer values, $y_i \in \{0, 1, 2, \ldots\}$, the method of ordinary least squares (OLS) is not an appropriate choice. As the count data is not continuous, assuming errors to follow normal distribution may not be tenable and predicted values of the dependent variables from OLS may goes below zero. As a result a number of alternative estimators like Poission and Negative Binomial (NB) models are suggested for dealing with count data (Hausman, Hall and Griliche, 1984; Hilbe, 2007; Cameron and Trivedi, 1998).

Under the Poisson regression model, the dependent variable is assumed to be characterized by a Poisson distribution and its conditional mean is modeled as $E(y_i|\boldsymbol{x_i}) = \lambda_i = \exp(\alpha+\boldsymbol{x_i}'\beta)$, where $\boldsymbol{x_i}$ is a vector of covariates. This distribution has the equidispersion property i.e. $E(y_i|\boldsymbol{x_i}) = \lambda_i = \text{Var}\ (y_i|\boldsymbol{x_i})$. Maximization of the log likelihood function $lnL = \sum_{i=1}^{N}[y_i(\alpha + x_i'\beta) - \lambda_i - ln\Gamma 1 + yi]$ results in the derivation of estimates for the parameters of the model (Green, 2005, 2008). As the observed data mostly display pronounced deviation from the assumption of equidispersion, researchers generally use the NB model as appropriate alternative to the Poisson model.

The NB model allows different variance from mean for the dependent variable y_i. The NB model can be interpreted as a continuous (gamma) mixture of Poissons (Green, 2008). y_i is modeled as a Poisson variable with a mean $h_i\lambda_i$ where h_i itself is assumed to be a random variable that has a gamma distribution (the mixing distribution). As a result the observed count variable will have a NB distribution. Specifically, $E(y_i|\boldsymbol{x_i}, \varepsilon_i) = \exp(\alpha+\boldsymbol{x_i}'\beta+\varepsilon_i) = h_i\lambda_i$ where $hi = \exp(\varepsilon_i)$ is assumed to have a one parameter gamma distribution, $G(\theta, \theta)$ with mean 1 and variance $1/\theta = \kappa$. The unconditional probability density function for the NB distribution is provided by $Prob(y_i|\boldsymbol{x_i}) = [\Gamma(\theta + y_i) r_i^{\theta}(1 - r_i)^{y_i}]/[\Gamma(1 + y_i)\,\Gamma(\theta)]$ where $r_i = \theta/(\theta + \lambda_i)$. Estimates of the parameters of the NB model (α, β, θ) can be obtained by the application of the maximum likelihood estimation (Hausman, Hall and Griliche, 1984).

Theoretically, the NB as well as its alternatives like the zero-inflated Poisson (ZIP) model and the zero-inflated NB (ZINB) model are all suitable for modeling overdispersed count variables with excessive zeros (Drukker, 2007). Zero-inflated models are characterized by two different processes, a binary choice model (e.g. a logit model) for the zero counts and a count model for nonzero counts (Long, 1997). However, Allison (2012) based on both the log-likelihood and BIC statistics found that the conventional NB model fits much better than the ZIP model. The choice between the NB and the ZINB can be decided by Vuong's (1989) likelihood ratio test. While a ZINB model could fit better than a NB model, likelihood ratio test conducted by Allison (2012) reveals that the difference in their fit is usually negligible.

In view of the above discussion, the present study has decided to use the NB model as the preferred method of estimation since the dependent variable, namely state-wise number of patent applications exhibit overdispersion property[1]. As the occurrence of zero count in our sample for the number of patent applications is about 16 per cent, ZINB is also adopted as alternative method of estimation.

[1] The unconditional mean of the number of patent application data is 126 and its standard deviation is 291.

Panel data approaches like fixed effects or random effects to the NB and ZINB models are desirable for our unbalanced panel dataset as they have the ability to control for time-invariant unobserved heterogeneity among individual states. However, available commands for fitting random-effects and conditional fixed-effects overdispersion models in statistical package like STATA are as laid down in Hausman, Hall and Griliche (HHG) (1984) and where these effects are applied to the distribution of the dispersion parameter, not $\boldsymbol{x_i}'\beta$ (STATA, 2013).

Allison and Waterman (2002) have shown that HHG NB model is not a true fixed effects method as it allows for individual-specific variation in the dispersion parameter rather than in the conditional mean. They, based on a simulation study, suggested that the application of an unconditional NB estimation with dummy variables to represent fixed effects as a good alternative method. There was no evidence of any incidental parameters bias in this method of estimation and also it has better sampling properties than the fixed-effects Poission estimator. Following the suggestion by Allison and Waterman (2002), the empirical analysis in the present study proceeded with the estimation of the conventional NB and ZINB regressions and their unconditional fixed effects versions.

Data Source

The present study is based primarily on information compiled from different secondary sources. The annual data on patent applications according to the state of origin were collected from various issues of *Annual Report*, the Controller General of Patents, Designs & Trade Marks. States' real Gross State Domestic Product (GSDP), growth of real GSDP, and real per capita GSDP were derived from the nominal and real series collected from various *Statements on State Domestic Product* released by the Central Statistical Organization (CSO).

State level higher education enrolments and number of higher education institutions were collected from various issues of the *Selected Educational Statistics* published by the Department of Higher Education under the Ministry of Human Resource Development (MHRD) and various annual reports of the MHRD, Government of India. For estimating state level technological specialization of manufacturing sector, net value added for total manufacturing and high technology industries were calculated from 3 digit industry data obtained from various reports of *Annual Survey of Industries* (*ASI*), CSO. High-technology manufacturing segment is defined to include chemicals, pharmaceuticals, electrical & optical equipment, machinery & equipment and transport equipment. The number of manufacturing factories per state is also collected from the *ASI*.

State-wise FDI stock was estimated by accumulating FDI inflows data since 1982─83. The FDI inflows data from 1982─83 to 2003─04 are on approval terms and from 2004─05 onwards inflows are on actual basis. FDI data up to 2003─04 came from foreign collaborations dataset maintained by the Institute for Studies in Industrial Development and from 2004─05 information obtained from *SIA Newsletter*, (Annual Issue), various years have been used. It needs to be noted that the data related to the sub-period since 2004─05 is FDI actual inflows data classified as per RBI (Reserve Bank of India) regions. State-wise number of towns was collected from *Census of India* 1991 and 2001.

5. Empirical Results and Interpretation

The empirical estimation of the patent function specified in Model A has been conducted for the 1995–2010 period. Multicollinearity analysis reveals the existence of a high degree of linear correlation among explanatory variables with SDP_{kt}, SKL_{kt}, and TWN_{kt} respectively experiencing 21.14, 17.85 and 13.95 values of the variance inflating factor (VIF). The condition number for the correlation matrix is computed to be 286.4 suggesting a severe collinearity problem.

For minimizing adverse effects of the multicollinearity, we ran different auxiliary (fixed effect panel) regressions fitting each of the independent variable on selected regional factors with which each had strong correlation (i.e., variables having at least 0.5 magnitude of correlation coefficient) in a sequential process. The auxiliary regression that contributed maximum reduction in the condition number was first estimated and residual from this regression is used in the place of original variable.

Multicollinearity tests were again conducted on the matrix of independent variables containing the residual of the first replaced variable. Different auxiliary regressions were fitted and the one that contributes maximum reduction in the remaining condition number was estimated and residual thereof is used to replace the concerned original variable. In this way, three auxiliary regressions are thus estimated and residuals have been used in place of three original variables[2].

Appendix Table-A1 summarizes univariate descriptive statistics for different variables used in the analysis. Findings from the NB and ZINB regressions and their unconditional fixed effects versions are reported in Table-4. The significant values of Wald Chi-square statistics for all the estimated models suggest that all of the estimated coefficients in a regression are not simultaneously equal to zero. Each of the estimated model as a whole, thus, is able to meaningfully explain inter-state disparities in patenting activities. The likelihood-ratio test of alpha (i.e. over-dispersion parameter) is equal to zero produces very high values for Chi-square, which confirmed that our data is not Poisson and the NB model is appropriate. The Vuong test is found to strongly favours ZINB against the standard NB regression but it moderately supports fixed-effects ZINB against the standard NB regression.

5.1. The Count Coefficients

The count coefficients predict the number of patent applications for those states that reported non-zero counts. $STKS_{kt-1}$ representing the states' existing stock of technological knowledge has a significant and positive impact across estimations. This supports the hypothesis that the available knowledge stock of a region directly facilitates its current innovative outputs through knowledge spillovers. Thus, the high patent performing states in India are those that already have build a strong knowledge base in the past.

[2] Auxiliary regressions are: (i) *SDP* on *SKL*, *INST*, and *TWN*; (ii) *PSDP* on *SPL* and *SCON*; (iii) *SKL* on *SDP*, *INST*, and *TWN*.

Table-4 NB and ZINB Estimation of Patent Applications by Indian States

Dependent Variable: *Number of Patent Applications (PAT)*				
Independent Variables	*NB*	*Fixed-effects NB*	*ZINB*	*Fixed-effects ZINB*
Count Coefficient (Z-value)				
$STKS_{kt-1}$	0.000237	0.000043	0.000272	0.000040
	(5.79)***	(2.18)**	(5.45)***	(1.98)**
SDP_{kt}	1.942359	2.528814	1.934459	2.434224
	(4.09)***	(3.75)***	(4.50)***	(3.44)***
$SDPG_{kt}$	0.000163	-0.009513	0.000393	-0.008344
	(0.02)	(1.69)*	(0.04)	(1.37)
$PSDP_{kt}$	-1.116395	-1.432815	-1.129708	-1.258597
	(2.70)***	(1.71)*	(2.98)***	(1.44)
SKL_{kt}	1.048658	1.473992	1.007159	1.399240
	(4.02)***	(3.79)***	(4.24)***	(3.16)***
$INST_{kt}$	0.344327	0.699788	0.351768	0.675871
	(6.51)***	(5.04)***	(7.06)***	(4.86)***
SPL_{kt}	0.011298	-0.005004	0.008160	-0.004424
	(4.63)***	(1.46)	(3.05)***	(1.36)
$SFDI_{kt}$	-0.007552	-0.005229	-0.004435	-0.003821
	(1.98)**	(1.27)	(1.21)	(0.73)
$SCON_{kt}$	0.002517	-0.000037	0.002033	0.000057
	(12.81)***	(0.07)	(10.67)***	(0.08)
TWN_{kt}	1.200541	0.698855	0.990091	0.673809
	(12.67)***	(2.36)**	(11.02)***	(1.79)*
Constant	-5.099163	-3.640831	-3.945474	-3.364256
	(12.13)***	(1.45)	(8.74)***	(1.14)
Excess Zero Logit Coefficient (Z-value)				
$STKS_{kt-1}$			-0.353960	-0.007500
			(3.41)***	(1.88)*
SDP_{kt}			-4.016242	1.300333
			(1.55)	(0.53)
$PSDP_{kt}$			5.920513	2.984036
			(1.80)*	(1.49)
SKL_{kt}			-3.611626	-1.715987
			(1.44)	(1.31)
Constant			1.683843	-2.733640
			(3.03)***	(4.20)***
Log pseudolikelihood	-1899.7711	-1656.0738	-1879.064	-1640.572
Wald chi2(10)	1113.05		924.38	
Wald chi2(37)		8149.30		8732.24
Prob > chi2	0.0000	0.0000	0.0000	0.0000
Likelihood-ratio test of alpha=0				
chibar2(01)	17000	4095.33		
Prob>=chibar2	0.000	0.000		
Vuong test of zinb vs. standard negative binomial				
Z			2.90	1.37
Pr>z			0.0019	0.0851
N	447	447	447	447

Note: Robust Z statistics in parenthesis; * p<0.1; ** p<0.05; *** p<0.01

Among the three market characteristics, SDP_{kt} turns out with a positive and significant coefficient throughout. This may confirm the proposition that local market size plays an important role in shaping the magnitude of patenting activities of a region. States with large size of local market may offer adequate demand to profit seeking enterprises to undertake more R&D for beating market competition. However, growth of local market appears to be less relevant for the observed pattern of inter-state patent applications. $SDPG_{kt}$ mostly had an insignificant coefficient, especially for estimations related to the zero-inflated models. $PSDP_{kt}$ comes up with a negative sign throughout and achieves statistical significance in the NB, fixed-effects NB, and ZINB regressions. Thus, Indian states with high per capita income are lagging in filing patent applications than those having low per capita income.

Across estimations, SKL_{kt} has a positive coefficient that is statistically different from zero. This underlines the importance of skilled human resources for states to moves into higher patent activities. Thus, policies that are aimed at increasing the size of enrolments of students in higher education may contribute to the technological development of their home states.

$INST_{kt}$ turns up with a positive and significant effect over all the estimations. States that have built up more number of knowledge institutions like universities, institutes of technologies, engineering and medical colleges, etc., they have distinct advantages in patenting activities. As argued earlier, firms' proximity and access to these institutions facilitates local innovation through partnering firms in joint R&D programme, undertaking industry funded research or undertaking knowledge sharing through conferences, workshops, and publication. Efforts for increasing number of knowledge institutions can be important in improving a state's innovation and patent capabilities.

SPL_{kt} capturing the specialization of manufacturing activities in technology-intensive sectors has a predicted positive and significant effect in the NB and ZINB regression. However, it has got a negative coefficient that is statistically not different from zero in the fixed-effects NB and fixed-effects ZINB regression. In view of this mixed performance of SPL_{kt} one may infer that technology-intensive production specialization gives host states greater abilities to increase their technological assets. However, specialization's favourable role in states' patent performance disappears once the effects of state-specific time-invariant variables are controlled through fixed-effects approaches.

$SFDI_{kt}$ included for exploring the role of foreign firms in expanding patent capabilities of host states is found to possess a negative coefficient all through but significant only for the NB regression. Thus, patent promoting role of FDI is at best smaller or insignificant for host Indian states.

$SCON_{kt}$ generally had a positive coefficient and assumed significance only for the NB and ZINB regressions. This suggests that spatial concentration of firms may involve a move up the patenting ladder for Indian states. When controlling for fixed effects, the impact of this variable turns very weak.

Finally, TWN_{kt} possessed a positive impact across estimations, which is statistically significant. So, how much Indian states file patent applications depends on their urban areas. Besides providing access to a strong skill base, institutional support, linkages and technical infrastructure, urban areas have the benefit of demand proximity to technologically benefit the host state economy.

5.2. The Excess Zero Logit Coefficients

The simple logit formulation based on four explanatory variables attempts to predict whether or not a state would be in "certain zero" group. $STKS_{kt-1}$ turns out with a negative sign and statistically significant for both the zero-inflated estimations. As innovative activities are path dependent in nature, states with higher initial stock of regional knowledge are less likely to be in the group of zero patent states. The size and nature of the state economy in terms of GSDP or Per capita GSDP and its endowment of human resources are found to be poor indicators for explaining excess zeros. While SDP_{kt} and SKL_{kt} had insignificant coefficients, the positive and modestly significant coefficient of SDP_{kt} in the ZINB regression loses its significance in the fixed-effects ZINB model.

6. Concluding Remarks

This paper has examined the geography of patenting activities in India and analyzed their determinants. The findings indicate that filing of patent applications has grown considerably after India implemented the new patent regime in 2005 with notable changes in the regional sources of their origin. West India and North India were the two most dominating regions in patenting throughout the period 1990–2004 accounting for over 65 per cent of total patent applications in India. However, South India overtook significantly North India in patent applications during 2005–10 to emerge as the second most dynamic region after West India.

The spatially concentrated feature of patenting in India becomes more pronounced at the state levels. More than half of the number of patent applications originated from just two states, namely Delhi and Maharashtra during the study period. While Gujarat's share in total patent rose marginally between 1990–94 and 2005–10, Karnataka significantly improved its share to be the third largest patent contributing state during 2005–10. In terms of patent intensity, as many as five states from South India are in the list of top 10 states, suggesting that this region possess a vibrant patenting culture.

The NB and ZINB analysis of the role of spatial factors in inter-state disparities in patent applications have shown that the availability of skilled labour force, knowledge institutions, scale of regional demand, urban areas and stock of past innovative output are key factors in strengthening patent efforts of a state. This implies that the states can consider a range of measures as indicated below to improve their technological capabilities and patenting:

- Instituting marketing supports, information provision, and other arrangements aimed at enabling regional firms to reach national markets can induce more patent activities in states with smaller size of local markets. Enlargement of the market focus of firms from local demand to national demand would mitigate the constraint of market size for greater innovation activities.
- Strengthening of regional skills base through increased enrollments at colleges, universities and institutes of technologies would help states to create a favorable environment for innovation and patenting activities. Incentives, better facilities and other measures designed to increase attendance rates and contain high drops out rates for higher education may be useful for Indian states with poor technological activities.
- Increasing the number of knowledge institutions through increased state governments' spending on high education appear to have large social returns in the forms of greater technological activities.

- As urban areas are important centres of innovation, provision of efficient infrastructure and amenities in such areas may complement states' technological efforts. Planned promotion of tier II cities and satellite towns may have favourable links with technological capabilities of states.
- Restructuring manufacturing activities towards technology-intensive products and a high level of spatial agglomeration of firms may help states to make the transition to dynamic hub of technological developments.

Overall this study highlights that when it comes to patenting and technological activities, the challenge is to integrate technology policies of the state with general policies covering education, institutions and urbanization for creating a regional eco-system of innovation. It is the interplay between these policies that determines how states build their technological competencies.

Reference

Abdih, Y. and F. Joutz (2006), 'Relating the Knowledge Production Function to Total Factor Productivity: An Endogenous Growth Puzzle', *IMF Staff Papers*, 53(2), pp. 242–271.

Acs, Z. J., L. Anselin and A. Varga (2002), 'Patents and innovation counts as measures of regional production of new knowledge', *Research Policy*, 31(7), pp.1069–1085.

Allison, P. D. and R. P. Waterman (2002), 'Fixed effects negative binomial regression models', *Socological Methodology,* 32(1), pp. 247–265.

Allison, P.A. (2012), *Logistic Regression Using SAS: Theory & Application*, North Carolina, USA: SAS Press.

Andersson, R., J. M. Quigley and M. Wilhelmsson (2005), 'Agglomeration and the spatial distribution of creativity', *Papers in Regional Science*, 84(3), pp. 445–464.

Arbo, P. and P. Benneworth (2007), Understanding the Regional Contribution of Higher Education Institutions: a Literature Review, *OECD Education Working Paper*, No. 9, Paris: Organisation for Economic Co-Operation and Development.

Asheim, B. (2001), 'Localized Learning, Innovation and Regional Clusters', in Mariussen, A. (ed.), *Cluster policies - Cluster development?*, Nordregio Report 2001:2, pp. 39–58, Nordic Centre for Spatial Development: Stockholm.

Asheim, B. and A. Isaksen (2002), 'Regional innovation system: The integration of local 'sticky' and global 'ubiquitous' knowledge', *Journal of Technology Transfer*, 27(1), pp. 77–86.

Asheim, B. T. and A. Isaksen (1997), 'Location, agglomeration and innovation: Towards regional innovation systems in norway?', *European Planning Studies*, 5(3), 299–330.

Athey, G., C. Glossop, B. Harrison, M. Nathan and C. Webber (2007), *Innovation and the city: How innovation has developed in five city-regions*, London: National Endowment for Science, Technology and the Arts (NESTA).

Audretsch, D. B. and M. P. Feldman (1996), 'R&D spillovers and the geography of innovation and production', *The American Economic Review*, 86(3), pp. 630–640.

Bettencourt, L.M.A., J. Lobo, D. Strumsky (2007), 'Invention in the city: Increasing returns to patenting as a scaling function of metropolitan size', *Research Policy*, 36(1), pp. 107–120.

Cameron, C. and P. Trivedi (1998), *Regression Analysis of Count Data*, New York: Cambridge University Press.

Caniëls, M.C.J. (1996), 'Regional Differences in Technology: Theory and Empirics', *MERIT Research Memoranda*, No. 96–005, Maastricht: Maastricht Economic Research Institute on Innovation and Technology.
Castells, M. and Hall, P. (1994), *Technopoles of the World –the Making of Twenty-first-Century Industrial Complexes*, London and New York: Routledge.
Chaminade, C. (2011), 'Exploring the role of regional innovation systems and institutions in global innovation networks', *Circle Working Paper*, No. 2011/15, Centre for Innovation, Research and Competence in the Learning Economy, Lund: Lund University.
Cheung, K., and P. Lin (2004), 'Spillover effects of FDI on innovation in China: Evidence from the provincial data', *China Economic Review*, 15(1), pp. 25–44.
Cooke, P. (2001), 'Regional innovation systems, clusters and the knowledge economy', *Industrial and Corporate Change*, 10(4), pp. 945–974.
Das, K. (ed.) (2005), *Indian Industrial Clusters*, Aldershot, UK: Ashgate.
Desrochers, P. (1998), 'On the Abuse of Patent as Economic Indicators', *The Quaterly Journal of Austrian Economics*, 1(4), pp. 51–74.
Doloreux, D. and S. Parto (2004), 'Regional Innovation Systems: A Critical Synthesis', *INTECH Discussion Paper*, No. 2004/17, The United Nations University, Institute for New Technologies: Maastricht.
Drukker, D. M. (2007), 'My raw count data contains evidence of both overdispersion and excess zeros', *STATA FAQ*. Available at: http://www.stata.com/support/faqs/statistics/overdispersion-and-excess-zeros/.
European Commission (2011), *Connecting Universities to Regional Growth: A Practical Guide*, Brussels: DG for Regional Policy.
Faggian, A. and P. McCann (2009), 'Human capital, graduate migration and innovation in British regions', *Cambridge Journal of Economics*, 33(2), pp.317–333.
Fu, X. (2008), 'Foreign Direct Investment, Absorptive Capacity and Regional Innovation Capabilities: Evidence from China', *Oxford Development Studies*, 36(1), pp. 89–110.
Green, W. (2005), 'Functional Form and Heterogeneity in Models for Count Data', *Foundations and Trends in Econometrics*, 1(2), pp. 113–218.
Green, W. (2008), 'Functional forms for the negative binomial model for count data', *Economics Letters*, 99(3), pp. 585–590.
Griliches, Z. (1990), 'Patent Statistics as Economic. Indicators: A Survey', *Journal of* Economic *Literature*, 28(4), pp. 1661–1707.
Hausman, J., B. H. Hall, and Z. Griliches (1984), 'Econometric Models for Count Data with an Application to the Patents-R&D Relationship', *Econometrica*, 52(4), 909–938.
Hilbe, J. M. (2007), *Negative Binomial Regression*, Cambridge, UK: Cambridge University Press.
Jones, C. (1995), 'R&D-Based Models of Economic Growth', *Journal of Political Economy*, 103(4), pp. 759–84.
Jovanovic, B. and Y. Nyarko (1995), 'The transfer of human capital', *Journal of Economic Dynamics and Control*, 19(5–7), pp. 1033–1064.
Komninos, N. (2002), *Intelligent Cities: Innovation, knowledge systems and digital spaces*, London and New York: Taylor and Francis.
Kortum, S. (1997), 'Research, Patenting, and Technological Change', *Econometrica*, 65(6), pp. 1389–1419.
Krugman, P. (1991), 'Increasing Returns and Economic Geography', *Journal of Political Economy*, 99(3), pp.483–499.
Lawson, C. (1997), 'Territorial Clustering and High Technology Innovation: From Industrial Districts to Innovative Milieux', *ESRC Centre for Business Research Working Paper*, No. 54, Cambridge: University of Cambridge.

Lim, U. (2003), 'The Spatial Distribution of Innovative Activity in U.S. Metropolitan Areas: Evidence from Patent Data', *The Journal of Regional Analysis and Policy*, 33(2), pp. 97-126.

Long, J. S. (1997), *Regression Models for Categorical and Limited Dependent Variables,* Thousand Oaks, CA: Sage Publications.

Lundvall, B-Å and S. Borrás (1997), *The Globalising Learning Economy: Implications for Innovation Policy.* Brussels: Commission of the EU.

Muro, M. And B. Katz (2010), 'The New 'Cluster Moment': How Regional Innovation Clusters can Foster the Next Economy', Brookings Institution Paper, Washington, DC: Metropolitan Policy Program at Brookings.

OECD (2007), *Higher Education and Regions: Globally Competitive, Locally Engaged*, Paris: Organisation for Economic Co-Operation and Development.

Pavitt, K. (1984), 'Sectoral patterns of technical change: towards a taxonomy and a theory', *Research Policy*, 13(6), pp. 343–373.

Porter, M. E. (1998), 'Clusters and the new economics of competition', *Harvard Business Review*, 76(6), pp.77–90.

Pradhan, J. P. (2011), 'Regional heterogeneity and firms' R&D in India', *Innovation and Development*, 1(2), pp. 259–282.

Romer, P. M. (1990), 'Endogenous Technological Change', *Journal of Political Economy*, 98(5), pp. S71–S102.

Romer, P.M. (1996), 'Why, indeed, in America? Theory, History, and the Origins of Modern Economic Growth', *American Economic Review*, 86(2), pp.202–206.

Rothwell, J. (2012), 'Global Innovation: The Metropolitan Edition', *The New Republic*, March 16.

Schmookler, J. (1966), *Invention and Economic Growth*, Cambridge: Harvard University Press.

Simmie, J., J. Sennett, P. Wood and D. Hart (2002), 'Innovation in Europe: A tale of networks, knowledge and trade in five cities', *Regional Studies*, 36(1), pp. 47–64.

STATA (2013), 'xtnbreg — Fixed-effects, random-effects, & population-averaged negative binomial models', *STATA Manuals*, No. 13, pp. 1–13, College Station, Texas: STATA Press.

UNCTAD (1999), *World Investment Report 1999: Foreign Direct Investment and the Challenge of Development*, New York and Geneva: United Nations.

UNCTAD (2001), *World Investment Report 2001: Promoting Linkages*, New York and Geneva: United Nations.

Vuong, Q. H. (1989), 'Likelihood ratio tests for model selection and non-nested hypotheses', *Econometrica*, 57(2), pp. 307–333.

Appendix

Table A1: Univariate Descriptive Statistics for Variables

Variable	Mean	Std. Dev.	Min	Max
PAT_{kt}	126.13	290.70	0.00	2443.00
$PATI_{kt}$	103.92	216.99	0.00	1758.00
SDP_{kt}	26.57	1.41	23.43	29.20
$SDPG_{kt}$	7.74	6.20	-13.92	35.80
$PSDP_{kt}$	9.94	0.54	8.40	11.45
$STKS_{kt-1}$	879.06	2109.58	0.00	16886.00
SKL_{kt}	11.98	1.44	8.11	14.61
SPL_{kt}	30.68	22.10	-18.49	91.94
$INST_{kt}$	5.51	1.62	0.61	8.25
$SFDI_{kt}$	8.04	16.16	0.00	114.69
$SCON_{kt}$	234.18	585.48	0.62	2859.65
TWN_{kt}	4.38	1.48	0.00	6.72
Regression Residuals				
SDP_{kt}	-4.45e-11	0.19	-0.61	0.73
$PSDP_{kt}$	1.29e-10	0.26	-0.66	0.70
SKL_{kt}	-2.49e-10	0.35	-1.05	1.06