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REGIONAL INEQUALITY IN TECHNOLOGICAL LEARNING CAPABILITY IN CHINA: INNOVATION SYSTEM PERSPECTIVE

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Abstract

Recognizing the role of innovation in development, this article contributes to the current understanding on inter-regional development divide in China from innovation system perspective. Innovation system perspective postulates that learning capability is at the core of innovation capability that governs development. The present study articulates technological learning capability as distinct from innovation capability. It argues that total number of patent applications could be considered as an appropriate indicator of technological learning capability. Analysis of the trends and patterns in patent applications for the period 1990-2012 observed a declining trend in inter-regional inequality in technological learning capability since 2006 and its convergence across regions. Econometric analysis using negative binomial model, on the drivers of regional technological learning capability, showed the significant influence of interaction among different actors in the innovation system, as expounded by the innovation system perspective. Further, the study provides empirical evidence on the bearing of regional innovation system characteristics and institutional context in which interactions among actors takes place. The study, therefore, underlines the need for strengthening the systems that foster interactive learning capability for addressing regional inequality in technological learning capability, innovation and development.

Keywords: China, technological learning capability, national innovation system, regional inequality

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1. Introduction

The analytics of growth, poverty and inequality has been primary concern of development economists and policy makers. This issue has been one of the most debated with the shifts, reversals, and reaffirmations of views (Shorrocks and Der Hoeven, 2004). Inequality is now at the forefront of public debate with focus on distribution of wealth, about the 1 per cent and the 99 per cent (Piketty, 2014 and Atkinson, 2015). Over the past few years, the rise of China and India in the international economy has gained attention. After a long period of relative stagnation, these two countries, containing nearly two-fifths of the world population, have had their incomes growing at remarkably high rates over the past quarter century or so (Bardhan, 2010). China's progress in addressing absolute poverty has been unparalleled in history. This is evident from an unprecedented decline in the proportion of households under the official poverty line from 53 percent in 1980 to 8 percent in 2001 (Ravallion and Chen 2007). At the same time, a number of studies have highlighted the growing income inequality in China. Increase in household income inequality (Gini coefficient) at the national level from 0.38 in 1988 to 0.49 in 2007 (Li et al., 2013) was higher than in many other countries and the highest in Asia (Asian Development Bank 2007). Along with growing inequality in household income, inequality in income across regions, and between rural and urban areas also is shown to be rising (Knight 2014). Enquiry into the issue of regional inequality by scholars of eminence (Kanbur and Zhang 2005) has shown that fiscal decentralization and trade liberalization contributed to the rise in regional inequality.

China's growth performance during the last three decades has been unparalleled in the history of large developing countries with an impressive average GDP growth rate of over 9 percent. Studies have shown that during 1981-2000 technological progress accounted for more than 40 per cent of Chinese economic growth (Fan and Watanabe, 2006). However, the impressive performance at the national level coincided with growing regional disparities in the levels of economic development (Bao et al., 2002). Economic gaps among regions, as argued by Fagerberg and Verspagen (1996) and Fagerberg et al. (1997) reflect differences in the regions' ability to compete which increasingly depends up on the innovative capacity of the regions concerned. Considering the pivotal role innovation in influencing growth performance, studies have analysed innovation capability across regions in China as conduit for understanding inter-regional development divide (Sun 2000, 2003; Guan and Liu, 2005; Fan and Wan, 2006; Li 2009, among others). However, Innovation System (IS) perspective, currently the most widely used approach in innovation studies (Fagerberg and Sapprasert, 2011), considers learning capability as the core of innovation capability. Drawing insights from this perspective, the present study deviates from the earlier ones with its focus on technological learning capability to understand the inter-regional development divide in China. Viewed through the lens of innovation system perspective, interactive learning capability of different actors in the innovation system is the driving force of innovation process (Lundvall, 1992). Since learning capability is at the core of innovation, which in turn governs development, the nature of developmental outcomes, equal or unequal for example, would be influenced by the learning capabilities at the level of individuals and organizations. Hence, the earlier studies focusing on inter-regional variation in innovation capability, by neglecting technological learning capability, seem to have provided only a partial understanding on the development divide between regions in China.

Innovation system perspective, despite being considered as highly flexible and open, has often been criticized for its ambiguous concepts and unclear boundaries (Li, 2009), which in turn makes it less amenable for theoretically informed empirical studies[12]. Questions have also been raised about the relevance of this perspective in understanding what is going on in large developing countries like China and India characterized by plurality in culture and high level of socio-economic heterogeneity. This is because innovation system perspective emerged mainly from the experience of small number of developed countries like Denmark, Norway and Sweden that are culturally homogenous and socio economically coherent. Recent studies have highlighted the relevance of innovation system perspective in understanding the bearing of innovation on development in developing countries including large economies (Lundval et al., 2009, Arocena and Sutz, 2000, Gu and Lundvall, 2006; Srivinivas and Sutz, 2008). Empirical studies (Furman and Hayes, 2004; Hu and Mathews, 2005) also confirmed the significant bearing of innovation system perspective in understanding the disparity in innovation performance across countries. Though much progress has been made over the years towards providing empirical support for this perspective, much more needs to be accomplished. Hence the significance of the present study stems not only from its contribution towards providing empirical basis for the innovation system perspective but also for highlighting the relevance of technological learning capability in understanding the growing development divide within a large developing country like China.

Against this background, this paper contributes towards the current understanding on regional inequality in China by seeking answers to the following issues; a) what has been the observed trends and patterns in regional inequality in technological learning capability in China, b) what are the drivers of technological learning capability and the role of interaction among different actors in the innovation system? Towards answering these issues, this study conceptualizes technological learning capability and measures it in terms of the number of patent applications as distinct from innovation capability which is often measured by the number of patents granted. It also undertakes an empirical analysis of an extended period (1990-2012) as compared to earlier studies. Further, it makes use of a more appropriate econometric model (negative binomial regression) considering the count data nature of the variable under study to explore the issue at hand. By undertaking an econometric analysis to locate the drivers of interactive learning capability at the regional level, this paper also contributes towards building the much-needed bridge between theory and empirics in innovation system approach.

[1] Given the predominance of qualitative research during the early years of this perspective Patel and Pavitt (1994) called for follow up research quantifying the characteristics, inputs, and outputs of national innovation systems.

The remainder of the paper is organized as follows. Section to presents an overview of policy interventions in China in order to address the issue of inter-regional inequality. Section 3 provides a brief overview of the earlier studies and highlights the points of departure of the present study from its predecessors. Section 4 presents the analytical framework of the study and deals with the measurement issues. Section 5 deals with data base, trends and patterns of inter-regional inequality in technological learning capability followed by the econometric procedure and results of the negative binomial model. Section six highlights the concluding observations.

2. Policy Interventions and inter-regional variation in learning capability

The role of state policy in influencing growth and its developmental implication cannot be over emphasized in China where the state is committed to evolve a socialistic pattern of society despite its increased reliance on market forces. Kanbur and Zhang (2005) argued that regional inequality in China is explained by three key policy variables—the ratio of heavy industry to output, the degree of decentralization, and the degree of openness. Other studies, including the ones by Zhang and Zhang (2003), Wan and Zhou (2005), and Wan et al. (2007), have identified capital input (including domestic and foreign) as the most important determinant of regional inequality. It is evident that the focus of the market based reform measures after 1978 aimed at achieving higher growth and that benefited mostly the coastal areas and therefore contributed to growing inter - regional inequality. It is not unexpected because, as Arthur Lewis noted development must be in egalitarian because it does not start in every part of the economy at the same time (Lewis, 1954). Kuznets (1963) observed that, in the early phases of industrializations, income inequality increases because of the large differences in factor productivity between rural and urban activities. Afterwards, however it eventually declines with the completion of the industrial transformation. With respect to Chinese experience, Gu and Lundvall (2006) observed that getting some concentration of wealth among the few was a first step towards making everybody better off. Local authorities and local entrepreneurs were able to promote simultaneously their political career and their own economic interests by stimulating industrial growth in their region, province, town or village. Most of the extra income created remained under local control and the incentives to reinvest the surplus were strong.

At the same time, growing income inequality in general and inequality across regions in particular has been a major concern for the policy makers. This got manifested in a series of initiatives to address the regional inequality in general and that building an innovation system that facilitates the harnessing of science and technology to address inequality. With the growing regional inequalities, and the concentration of minorities in the backward regions, a number of regional development programs were initiated with significant fiscal, regional and S&T components. These initiatives were also with a view to ease the dissatisfaction of minority peoples and relieve development disparities among ethnic groups, as the backward regions were the ones with higher concentration of minorities. In 1995, the 5th section of the 14th Plenary of the Chinese Communist Party declared that regional inequalities had widened since the reforms. In 1998, the Western Development Program was initiated with a view to boost domestic demand by promoting economic development in the western part of the country. This was followed by the North-east Revival Strategy in 2003, to revive the economy in some old key industrial bases and to ease growing social conflict caused by laid-off workers, and the rise of Central China Program. Needless to say, these programs were also meant for facilitating the development of the minority regions and improve the living standards of minority groups in within the national strategy of evolving a harmonious society.

Given the importance of science, technology and innovation in growth and considering the weakness of the system that evolved during the pre-reform period, R&D system reform began in 1985 that aimed at influencing the relationship between knowledge producers and users and their relationships with the government. The 863 program, named after its date of establishment (March 1986), intended to stimulate the development of advanced technologies in a wide range of fields for achieving greater self-reliance. The National S&T Achievements Dissemination Program initiated in 1990 with a view to, among other things, harnessing S&T achievements into the nation's. About 86% of ethnic minority people live in the western region and most of the rest are in the north-east and central areas: Zheng and Chen (2007) economic and social development in a well-organized and planned manner. It also focuses on creating a favorable environment to mobilize S&T personnel for the implementation of the Program so as to generate benefits in large scale and promote the sustained and coordinated economic and social development. The national program for key basic research projects (also called climbing program), initiated in 1991, aimed at undertaking high-level research on issues that are critical for the development of the country, Subsequently 973 Program, also known as National Basic Research Program, was initiated in 1997 to develop basic research, innovations and technologies aligned with national priorities in economic development and social development. While the program was managed by the Chinese Ministry of Science and Technology, Natural Science Foundation of China also involved in coordinating the research.

Considering the fact that the product structure does matter, the national new products program aimed at guiding and encouraging enterprises and research institutes to accelerate innovative capacity in high technology products. It also aimed at the development of new technology products with the potential for building competitiveness. The Innovation Fund for small technology-based firms (STF) is yet another initiative aimed at supporting and encouraging technology innovation activities of STF, facilitating transformation of scientific research achievement with Chinese characteristics and expediting the industrialization based on high and new technology industries.

Building on to the earlier programs, the National Medium and Long-Term Program for Science and Technology Development 2006-2020 (MLP program) explicitly recognized that China's S&T system that evolved over time was inadequate in meeting the needs of the socialist market economy and for greater economic and S&T development. Hence it aimed at promoting the full-fledged construction of a national innovation system with Chinese characteristics, focusing on S&T resources distribution efficiency and breakthrough in building an enterprise-centered technological innovation system. It also aimed at greater integration between industry, academia, and research with a view to facilitate the emergence of unique Chinese national innovation system and enhance the nation's indigenous innovation capability. MLP also underlined the role of interactive learning, when it called for taking full advantage of the important roles played by universities, research institutes, and national high-tech industrial parks. Ultimately the program aimed at improving the quality of people's life by harnessing scientific and technological progress in social undertakings and related industries. An important aspect of the building national innovation system with Chinese characteristics in the context of inter-regional inequality included regional innovation system planning and associated innovation capacity building to help economic and social development across regions. It especially called for S&T capacity building in the country's central and western regions while earnestly strengthening the construction of grassroots S&T systems at the county (city) levels. From above discussion, though not exhaustive, it is evident that there has been a growing concern with inequality and there has been series of policy interventions to address the issue of regional inequality wherein promoting interactive learning has been high on the agenda.

3. Studies on innovation capability and regional inequality in China

Given the role of innovation in economic growth and development, a number of empirical studies have examined the factors underlying innovation capability. Based on the theoretical insights from the ideas driven growth theory (Romer, 1990), industrial competitive advantage of Porter (1998), and innovation systems approach, Furman et al. (2002) and Furman and Hayes (2004) developed a conceptual framework of the national innovative capacity and examined sources of innovation in 17 OECD countries. Similarly, Hu and Mathews (2005) analysed the national innovative capacity of East-Asian countries. There are a few studies that analysed the regional inequality in innovation capability across provinces in China using Regional Innovation System (RIS) perspective. Most of the existing studies employed patents granted as an indicator of China's regional innovation capability. Studies by Sun (2000, 2003), Liu and White (2001) and Guan and Liu (2005) explored regional variation and concentration in innovative activity at the provincial level and found that patents in China are unevenly distributed and highly clustered in certain provinces. Sun (2003) found that industrial innovation was mostly concentrated in China's eastern-coastal regions and with increasing concentration during 1990 to 1999. These studies found R&D expenditure, R&D personnel engaged in universities and research institutes along with other factors such as openness and urbanization contribute most substantially to the differences in regional innovative capability.

Using standard inequality measures, Fan and Wan (2006) also argue that the regional concentration in patenting has tended to increase during 1995 and 2004. They found that eastern China dominated certified patents and the gap between the eastern regions and others increased. Using a regression based decomposition analysis; they found that GDP, location, urbanization, human capital, and openness are significant factors leading to the disparity in innovation capabilities between regions.

Following Furman et al (2002), Hu and Mathews (2008) examined sources the China's national innovative capacity during 1990 to 2005 and found a positive effect of knowledge stock, private R&D, and ant-trust law on innovative capacity. Li (2009) empirically investigated the disparity in innovation performance between China's provinces during 1998- 2005. Using stochastic frontier approach, he estimated efficiency of innovation system and located the determinants of efficiency. His findings show that government financial support for S&T activities, technology market and industrial structure are significant determinants of innovation performance at the regional level. The regions with developed high-tech industries are found to be efficient in invention patenting. Using negative binomial model, Yoon (2011) explored determinants of regional innovative capacity and found that while knowledge stock, R&D personnel and education have a positive effect on innovation, factors such as firm funding and university R&D were found to be negatively related. In a more recent study, using the methodology of Sun (2000), Fan et al (2012) observed that the east–central–west inequality has increased over time, whereas the provincial inequality showed a V-pattern until 2003 and stabilizing thereafter. In line with the previous studies, they also found innovation inequality is contributed by factors such as population, level of economic development, R&D investment, location and openness.

In sum, these studies have not only confirmed the uneven development of regional innovation capability in China as measured by patent counts but also contributed much towards our understanding on the underlying factors. However, there are a few issues that are common to most of these studies. The first one relates to the kind of data used in the analysis. It may be noted that the use of patent data for analyzing regional innovation capacity is in sync with the earlier studies (Use all which used patents) on the issue at hand. However, we find that different studies have employed different kinds of patent data without justifying their choice of a particular kind of patent data. While Sun (2000) Li (2009) Chen et al. (2009) used the number of patent applications, Lieu and White (2001), Sun (2003) Fan and Wan (2006) Fan et al. (2012) used the number of patents granted. Li (2009) and Yoon (2011) used only institutional patents, both applications and granted. We are inclined to argue that while patents granted could be justifiably used as a measure of innovation capability, number of patent applications cannot be considered as a substitute for it. This is because all the patent applications are not approved for granting patents. In China for example, in 1990 and 2012 out of the total number of patent applications only 53.4 percent and 60.6 percent respectively were granted with much variation across different kinds of patents[3]. In case of invention patents, the success rate was only 20.1 percent in 1990, which increased to 26.3 percent in 2012. When it comes to utility models the success rate increased from 61.6 percent in 1990 to 77 percent in 2012 as compared to 44 and 70 percent respectively in case of design patents. Further, by confining to only institutional patents, individual patents are left out ignoring the individual efforts involved in the innovation process.

The second issue relates to the period of analysis. Most of the previous studies have covered the period only up to 2005. Growing inter-regional variation in development has been a major concern for the Chinese policy makers leading to a

[3] Please see data section for the on the definition of types of patents

number of policy initiatives[4]. The National Medium and Long-Term Program for Science and Technology Development 2006-2020 (MLP) explicitly recognized that China's S&T system that evolved over time was inadequate in meeting the needs of the socialist market economy and for greater economic and S&T development. Hence it aimed at promoting the full-fledged construction of a national innovation system with Chinese characteristics. An important aspect of building national innovation system with Chinese characteristics in the context of inter-regional inequality included regional innovation system planning and associated innovation capacity building to help economic and social development across regions. It especially called for S&T capacity building in the country's central and western regions while strengthening the construction of grassroots S&T systems at the county levels. It also aimed at greater integration between industry, academia, and research with a view to facilitate the emergence of unique Chinese national innovation system and enhance the nation's indigenous innovation capability. MLP underlined the role of interactive learning, when it called for taking full advantage of the important roles played by universities, research institutes, and national high-tech industrial parks. From above discussion, it is evident that MLP (2006-2020) aimed to building innovation system and promote interactive learning as a means of addressing development divide across regions in China.[5] The present study, by extending the analysis to 2012, is hopeful of capturing the effect of these new policy initiatives.

The third issue relates to the conceptual frame adopted. Most of the studies dealt with innovation capability as a conduit for understanding inequality across regions. As will be evident from the analytical framework of the present study (see section 3) innovation system perspective considers innovation as an outcome of technological learning. Therefore, the existing studies, with their focus on innovation, have overlooked the technological learning capability and provided an incomplete understanding on inequality across regions.

4. Analytical framework and conceptual issues

The innovation system perspective considers knowledge as the most fundamental resource in the modern economy, and accordingly, the most important capability is the learning capability- a socially embedded process governed by the institutional context (Lundvall, 1992). Arocena and Sutz (2003) observed that knowledge gap is the main consequence of learning divide, in the sense that weaknesses in the formal and informal learning processes often lead to the low level of innovation capability. Extending these ideas to the issue of inter-country/inter-regional inequality in development, it could be

[4] In 1995, the 5th section of the 14th Plenary of the Chinese Communist Party declared that regional inequalities had widened since the reforms. In 1998, the Western Development Programme was initiated with a view to boost domestic demand by promoting economic development in the western part of the country. The North-east Revival Strategy followed this in 2003. These initiatives were also with a view to ease the dissatisfaction of minority peoples and relieve development disparities among ethnic groups, as the backward regions were the ones with higher concentration of minorities.

[5] For more details please see sydney.edu.au/global-health/international-networks/National_Outline_for_Medium_and_Long_Term_ST_Development1.doc The National Medium and Long-Term Program for Science and Technology Development 2006-2020 (MLP) an outline

inferred that whether a country/region is poor/rich is governed by certain basic capabilities like the learning capabilities of the individuals and organisation in the country/region concerned. Hence, any search for the roots of development divides between and within countries needs to begin by locating the factors and forces that give rise to divides in learning capability. To reflect on regional inequality in learning capability in China we develop an analytical frame based on the National System of Innovation (NSI) developed by Freeman (1987) Lundvall (1992) Nelson (1993) Edquist (1997) among others in general and its derivative Regional Innovation System (RIS) developed by Asheim and Isaksen, (2002) Cooke et al. (1997) Padilla-Perez (2008) among others in particular.

The NIS approach to innovation spells out explicitly the importance of the 'systemic' interactions between the various components of inventions, research, technical change, learning and innovation (Soete et al., 2010). The national systems of innovation also bring to the forefront, the central role of the state as a coordinating agent. An important contribution of the innovation system perspective is towards enhancing our understanding on the link between interactive learning and innovation in contrast to the endogenous growth models that linked technology and economic growth (Lundvall et al., 2009). The interaction as understood in the NSI framework goes beyond the conventional understanding of linkage between industry, academia and the government and encompasses broader user - producer interaction governed by the institutional context (Lundvall, 1992; Lundvall, 1988; Nelson, 1993, 2008).

There are two perspectives within NIS; The first one often referred to as STI (Science Technology and Innovation) mode, in tune with the analyses of national science systems and national technology policies (Nelson, 1993, Mowery and Oxley, 1995), aimed at mapping indicators of national specialization and performance with respect to research and development efforts and interaction among science and technology organizations. The policy issues raised are almost exclusively in the realm of explicit S&T policy focusing on R&D. The second approach, often referred to as DUI (Doing Using and Interacting) mode, (Jensen et al., 2007) takes into account user-producer interactions, social institutions, macroeconomic regulations, financial systems, education and communication infrastructures as far as these have impact on learning and competence building process (Gu and Lundvall, 2006).

It has been argued that regionally identifiable nodes or clusters have emerged with significant bearing on innovation process in the regional economy (Cooke, 2001; Asheim et al., 2007) and learning process and knowledge transfer are highly localised (Maskell and Malmbrerg, 1999). Further, the enduring competitive advantage in a global economy is often extremely locally rooted arising from a concentration of highly specialised skills and knowledge, institutions, related business and customers in a particular region (Porter, 1998). Against these premises, scholars have evolved the concept of Regional Innovation System (RIS) for understanding the innovation process in the regional economies (Ashim and Isaksen, 2002; Asheim et al., 2007; Isaksen, 2003; Cook et al., 1997). Such a perspective appears especially relevant in the context of the current enquiry that deals with inter-regional variation in learning capability in a large developing country like

China characterised by significant variation in culture and social-economic context wherein learning takes place. Perez et al. (2009) argue that across the different interpretations, RIS approaches, stress the systemic dimensions or propensities of the innovation process, being the dynamic interaction between the different components of the system that is individuals, organisations and institutions and their interactions. Thus viewed, the socially embedded and institutionally governed interactive learning (Johnson, 1992: Lundvall, 1992) is central to the process of innovation in all the perspectives on NIS and RIS.

From the above discussion, it is evident that the central pillar of our analytical frame is the nature and extent of interactive learning among different actors in the innovation system. For any agent involved in innovations, there could be two sources of interactive learning- internal and external sources (Lundvall, 1988; Cohen and Levinthal, 1990). The internal interactions refer to intra-firm interactions; for example, between different departments within a firm. The external interactions could be with actors outside the firm. This may be with actors within the country (intra-country interactions) and/or with those outside the country (inter-country interactions). The intra-country interactions refer to interactions among actors within the region/country like users, suppliers, competitors, research institutes, universities, consultants, government agencies and others. In the current context wherein innovation systems are becoming increasingly global, learning is not confined to interaction among the actors within the country. Interactions with actors outside the country (inter-country) include but not limited to FDI, trade in goods, trade in technology/services. In addition, interactions with universities and other actors like customers from outside the country are increasingly becoming important. In the present study, we focus mainly on the above two types of interactions (intra-country and inter-country) while ignoring intra-firm interactions on account of the limits set by data availability.

Given the regional focus of the present study, the second pillar of our analytical frame is the characteristics of the regional innovation system having their bearing on the generation of technological learning capability. Essentially we underscore the influence of learning environment in the regional economy. Since learning being an evolutionary, path dependent and cumulative process, the extent of current learning would be governed by past learning. This is in sync with the literature on idea-driven growth models (Jones, 1995; Romer, 1990) wherein it is argued that the rate at which new knowledge is produced depends on the R&D resources (human and financial capital) devoted to the knowledge generation process and the historical stock of knowledge (previously generated ideas). Finally, we also emphasise the role of institutions. The present study with its focus on regional variation, the role of regional governments through subsidies and incentives for patenting, as argued by earlier studies (Li, 2012; Hu and Jefferson, 2009; Dang and Motohashi, 2015), deserve special attention.

Conceptual issues

Interactive learning, as expounded in the Innovation System literature has a wider connotation. Given the issue at hand, we shall limit ourselves to technological learning capability. Going by our analytical framework, innovation capability cannot be considered as equal to technological learning capability though it is an upshot of it. While the innovation system perspective considers technological learning capability as central to innovation capability, its measurement has not received the attention of scholars that it deserves. The available wisdom considers R&D as an input measure of innovative activity and patents granted as a measure of outcome (Patel and Pavitt, 1995). R&D activities, by their very nature, lead to technological learning. Since all the R&D efforts do not necessarily lead to patents[6], patents granted captures only a part of the technological learning that results from R&D. Therefore, it could be inferred that the number of patents granted involves an underestimation of technological learning as it ignores the technological learning acquired by those patent applications that failed to obtain patents[7]. From the innovation system perspective, which distinguishes between STI-mode of innovation and DUI mode of innovation, technological learning through R&D is only a subset of the total learning capability. Much learning and capability building takes place through non-R&D based interactions. Thus viewed, neither patents granted nor R&D expenditure could be considered as a comprehensive indicator of technological learning. Patent applications, by definition, captures a broader set of technological learning than what is evidenced by patents granted. Further, they could also represent more comprehensively the learning outcomes of R&D and technological learning that results from non-R&D related activities – we mean DUI mode of learning. Based on these considerations, we measure technological learning capability by the number of patent applications. Though this measure is not a perfect one, it represents technological learning better than patents granted or R&D expenditure.

Finally, since the present study is based on innovation system framework in general and regional innovation system in particular, there is the need for clarity on the concept of region adopted here. Following previous studies, we consider provincial-level regions as the unit of analysis because comparable data needed for the analysis is available and thus making an empirical comparison between regions possible and reliable.

5. Empirical Analysis

Database

Data for the present study have been gathered at the provincial level from the online official statistics published in *China Statistical Yearbook*, *China Statistical Yearbook on Science and Technology*, and *Annual Report of Patent Statistics*. *China Science and Technology Statistics Data Book* is an annual on-line publication provided by the Ministry of Science and Technology of China (MOST). This includes data on almost all important aspects related to science, technology and innovation in China. *Statistical Yearbook*, published by the Chinese National Bureau of Statistics, is a database

[6]Griliches pointed out that not all inventions are patented, and the inventions that are patented differ greatly in ‘quality’, in the magnitude of inventive output associated with them (1990, p. 1669)

[7] This article, for example, not accepted for publication by a particular journal cannot be taken to imply that the authors have not learned anything during the process of its preparation

on all the socio-economic aspects of China. The State Intellectual Property Office (SIPO) of the PRC brings out data on China's domestic patent statistics annually.

In china, there are three types of patents - invention patents, utility models and designs. Invention patents, with a term of 20 years, represent the most important and technologically sophisticated inventions involving significant technological improvement in products or processes. Invention patent applications, therefore, are subjected to detailed search and examination which takes approximately 3 to 5 years. Utility model patents are less technologically innovative than invention patents and are granted for technical solutions that relate to shapes or structures and have a term of 10 years from the date of filing. Utility model applications usually are subjected only to novelty assessment and formality examination, which is usually completed within 12 months. Design patents involve for only minor modifications and aesthetic design improvements with a term of 10 years. They provide exclusive use of the aesthetic features of a product and therefore its appearance as opposed to how the product functions. Usually, the scrutiny of applications is completed within a period of one year or less. Needless to say, these three categories of patents involve different degree of technological learning and vary in terms of their economic value.

For the empirical analysis, we merge Chongqing, which became a centrally administered municipality in 1997, with Sichuan because data on Chongqing independent of Sichuan is not available for the period before 1997. For econometric analysis, we dropped Tibet and the period prior to 2000 on accounts of the non-availability on some of the variables. Thus the estimation of the econometric model relates to 29 provinces for the period 2000-2012 while the analysis using descriptive statistics relates to 30 provinces (Tibet included) for the period 1990-2012. Before undertaking econometric analysis of drivers of learning capability across provinces, we shall briefly present the trends and patterns in inter-regional technological learning capability using descriptive statistics.

Technological learning capability across regions: trends and patterns

Fig 1 shows the trends in the total number patent applications along with its constituents. It is evident that during 1990-2012 there has been a massive increase in the total number of patents as well its constituents. To be more specific, the total number of patents applied increased from 0. 36 million in 1990 to 18.8 million in 2012 recording an annual compound growth rate of 18.9 percent (Table 1) [8]. This tends to suggest a significant increase in the technological learning capability that coincided with near double-digit growth rate in GDP recoded by China during the period under consideration. It is further evident that there has been acceleration in the rate of technological learning capability overtime. Total number of patent applications during the second period (2000-2012) was high as 25.1% when compared to only 10.4% during the first period (1990-2000). Further, the observed rate of growth in the invention patents (Table 1), involving

[8] We have also estimated growth rates following structural break analysis proposed by Bai and Perron (2003). The analysis showed a break in 1999. We have found two break points in case of utility models and design patents. Results of this analysis are available on request.

higher level technological learning, during the second period was highest (30.1%) as compared to utility models (22.35) as design patents (25.3).

Fig 1: Trend in the total number of patent applications and its constituents

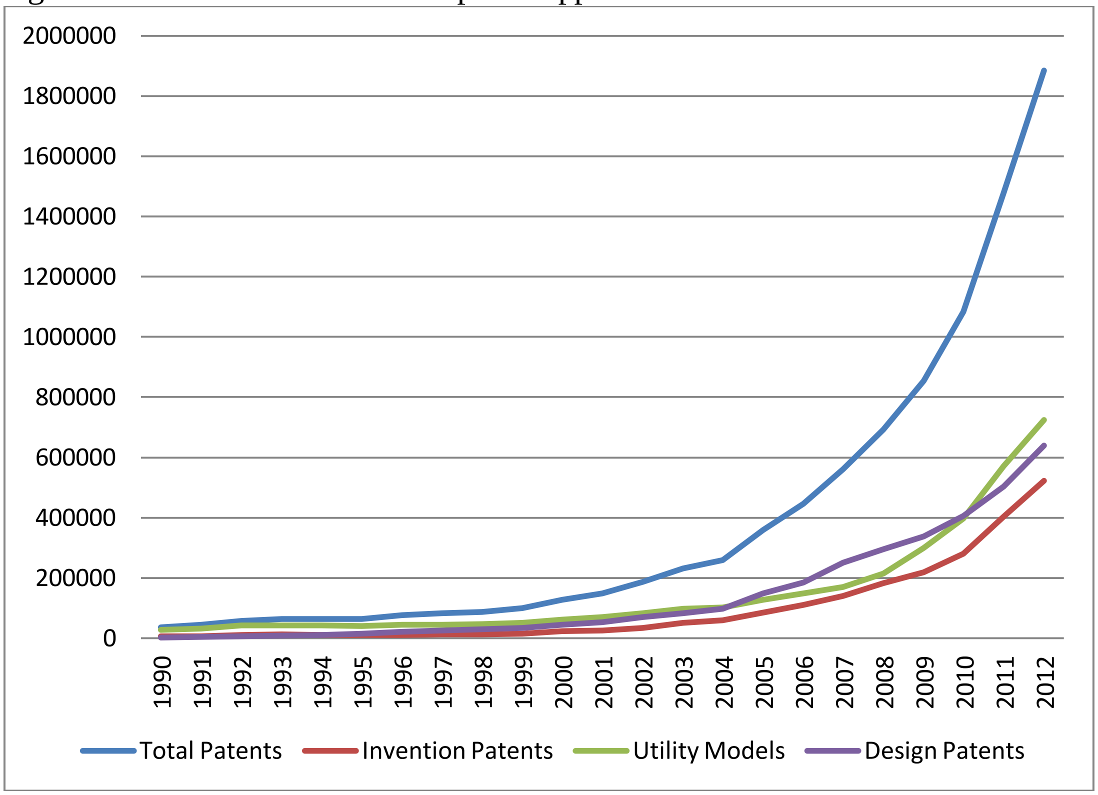


Table 1: Compound Annual Growth Rate of Patent Applications (%)			
	1990-1999	2000-2012	1990-2012
Total Patent Applications	10.41	25.11	18.89
Invention Patents	8.11	30.08	22.63
Utility Patents	5.34	22.38	14.22
Design Patents	30.47	25.36	26.24

Figure 2 shows the trend in the share of different kind's patents in the total patent applications. The figure shows a major change in the composition of total patent applications over time. During the early years utility patents, presumably with relatively less technical content and involving less technological learning, accounted for the largest share. However, their share in patent applications declined from 75 percent in 1990 to only 34 percent in 2012. At the same, the share of invention patents presumably involving higher technological learning, increased from 16% in 1990 to 27.7% in 2012.

Fig 2: Trend in the share of invention patents, utility models and design patens in the total number of patent applications (%)

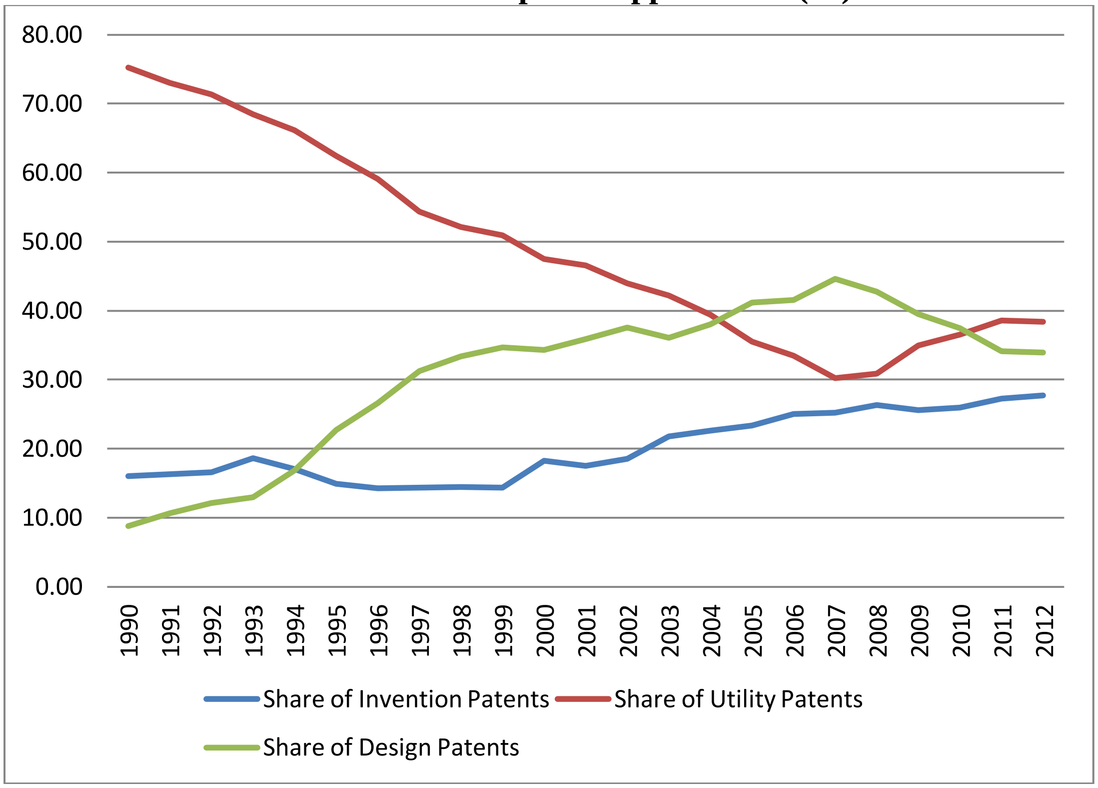


Table 2 presents regional distribution of patent applications by dividing the provinces into three broad regional categories; Eastern, Central and Western.[9] Following, Fan et al, (2012), Yoon (2011) and Fan and Wan (2006) we measure regional per capita patents relative to the national average, denoted by R as an indicator of inter-regional variation in patent applications. A region with R > 1 performs better in patent applications than the national average, and vice versa. It is evident from the table that as we move from 1990 to 2006 the value of R in eastern region increased (from 1.42 to 1.67) and that of central region and western region declined (from 0.66 to 0.37 and 0.54 to 0.34 respectively). As indicated by Fan et al (2012) it suggests that the inter-regional inequality in patent applications increased during 1990-2006. Table 2 also shows that, going by the estimated values of R, there has been a trend reversal since 2006. In contrast to the trend during pre 2006 period, the value of R declined in eastern region where as that of central and western region increased indicating a declining inter-regional variation in patent applications.

[9] We have followed Fan et al, (2012) and Yoon (2011) to divide the regions broadly into three categories. Here it is important to note that it is the most widely accepted division of regions in the published literature despite its limitations.

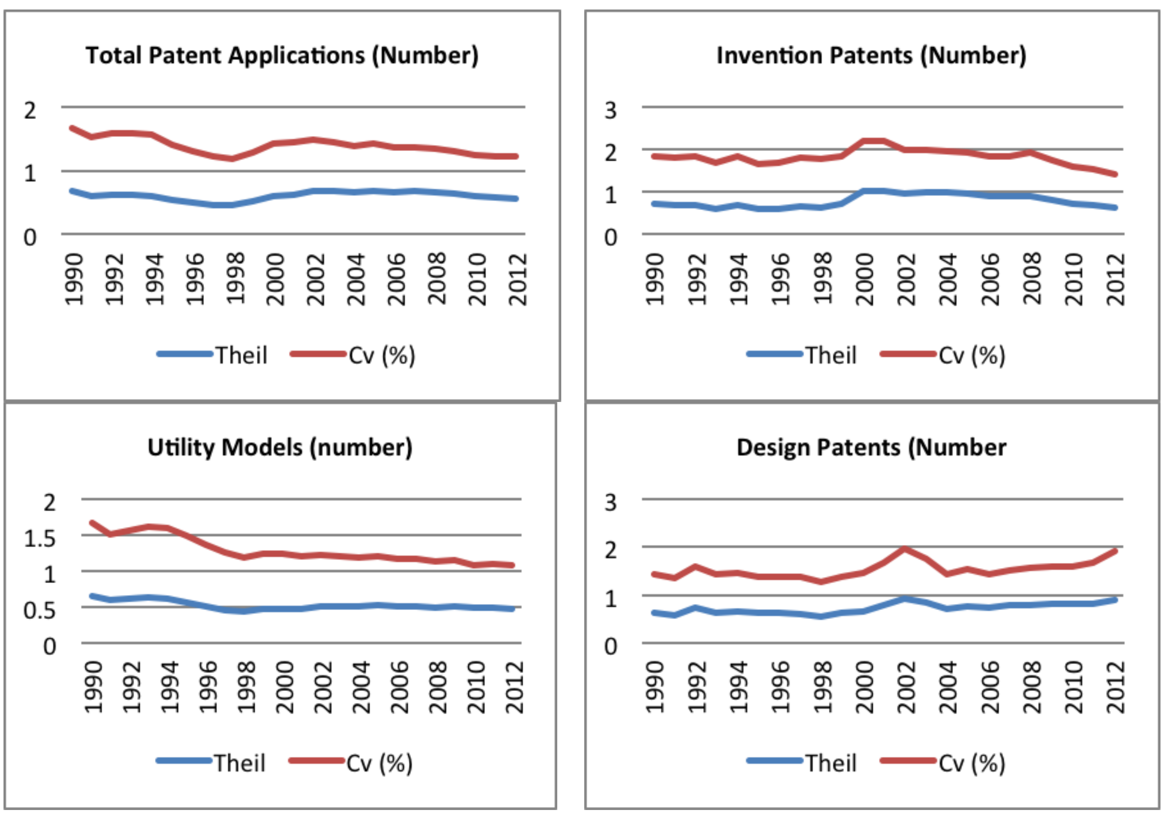
Table 2: Regional Distribution of Patents								
	Patents Applied				R			
	1990	**2000**	**2006**	**2012**	**1990**	**2000**	**2006**	**2012**
Eastern	**22124**	**91613**	**349258**	**1418753**	**1.42**	**1.58**	**1.67**	**1.57**
Bejing	4284	10344	26555	92305	12.64	7.45	4.83	3.19
Tianjin	975	2789	13299	41009	3.53	2.74	3.6	2.07
Hebei	1477	3848	7220	23241	0.77	0.57	0.3	0.23
Liaoning	3153	7151	17052	41152	2.55	1.68	1.16	0.67
Shanghai	1526	11337	36042	82682	3.66	6.93	5.34	2.48
Jiangsu	2706	8211	53267	472656	1.28	1.1	2.02	4.27
Zhejiang	2243	10316	52980	249373	1.72	2.17	3.04	3.25
Fujian	540	4211	10351	42773	0.57	1.21	0.84	0.82
Shandong	2553	10019	38284	128614	0.96	1.09	1.2	0.95
Guangdong	1948	21123	90886	229514	0.98	2.4	2.8	1.55
Guangxi	650	1762	2784	13610	0.49	0.36	0.17	0.21
Hainan	69	502	538	1824	0.33	0.63	0.19	0.15
Central	**8867**	**23080**	**60096**	**279112**	**0.66**	**0.48**	**0.37**	**0.42**
Shanxi	640	1475	2824	16786	0.71	0.45	0.24	0.33
Inner Mongolia	347	1138	1946	4732	0.51	0.47	0.23	0.14
Jilin	1017	2501	4578	9171	1.31	0.92	0.49	0.24
Heilongjiang	1230	3106	6535	30610	1.11	0.8	0.5	0.57
Anhui	471	1877	4679	74888	0.27	0.3	0.22	0.89
Jiangxi	601	1557	3171	12458	0.51	0.37	0.21	0.2
Henan	1133	3823	11538	43442	0.42	0.4	0.36	0.33
Hubei	1238	3486	14576	51316	0.73	0.61	0.74	0.63
Hunan	2190	4117	10249	35709	1.14	0.62	0.47	0.38
Western	**4594**	**13453**	**35768**	**187534**	**0.54**	**0.44**	**0.34**	**0.43**
Sichuan	2091	6276	19580	105236	0.62	0.55	0.52	0.68
Guizhou	267	986	2674	11296	0.26	0.26	0.21	0.23
Yunnan	461	1710	3085	9260	0.4	0.4	0.2	0.14
Shaanxi	993	2080	5717	43608	0.96	0.56	0.45	0.83
Gansu	307	798	1460	8261	0.44	0.31	0.17	0.23
Qinghai	111	174	325	844	0.79	0.33	0.17	0.11
Ningxia	114	341	671	1985	0.78	0.61	0.32	0.22
Xinjiang	250	1088	2256	7044	0.52	0.58	0.32	0.23
Total	**35590**	**128174**	**445211**	**1885569**	**1**	**1**	**1**	**1**

Notes: R denotes relative per capita patents to national average.

To reflect further on the evolving interregional inequality in technological learning, we estimated the Theil index and Coefficient of Variation for the total number of patent applications along with its constituents across provinces. This analysis is in line with analysis of sigma convergence across regions and countries undertaken by Barro and Sala-i-Martin (1992). These estimates are presented in fig.3. It is evident from the figure that the trend in CV and Theil are in sync with each other. With respect of total number of patents applications, we observe three phases. An initial declining phase (1990-98) wherein the Theil index declined from 0.66 to 0.44 percent. This was followed by the second phase of increasing (1998-2005) trend in inequality with Theil index increasing from 0.44 in 1998 to 0.69 in 2005. The third phase (2006-2012) is characterized a declining trend in inequality with the value of Theil declining from 0.69 in 2005 to 0.58 in 2012, which was lower than that in 1990. The overall trend that we have observed is in tune with the observation by Sun (2000), that the spatial concentration of patents declined during 1985-95. Similarly our observation regarding the second phase is in sync with that of Guan and Lieu (2005) and Fan and Wan (2006) wherein they observed an increasing inequality since 1997.

When it comes to invention patents, inequality increased to peak in 2001. Since then, inequality declined steadily such that the level in 2012 is lower than what was observed in 1990. In case of utility model, inequality, after recording a fluctuating trend up to 1993, showed a declining trend thereafter. With respect to design patents, though they may be less significant in terms of learning outcomes, the estimated value of Theil index indicated an upward trend up to 2002 followed by a declining trend and the recent years indicating an upward trend. From the above discussion it may be inferred that there has been a declining trend in interregional in equality in technological learning capability which became more pronounced after 2006. As far as our understanding goes, the observation that interregional inequality declined during the recent past is yet to be reported in the literature.

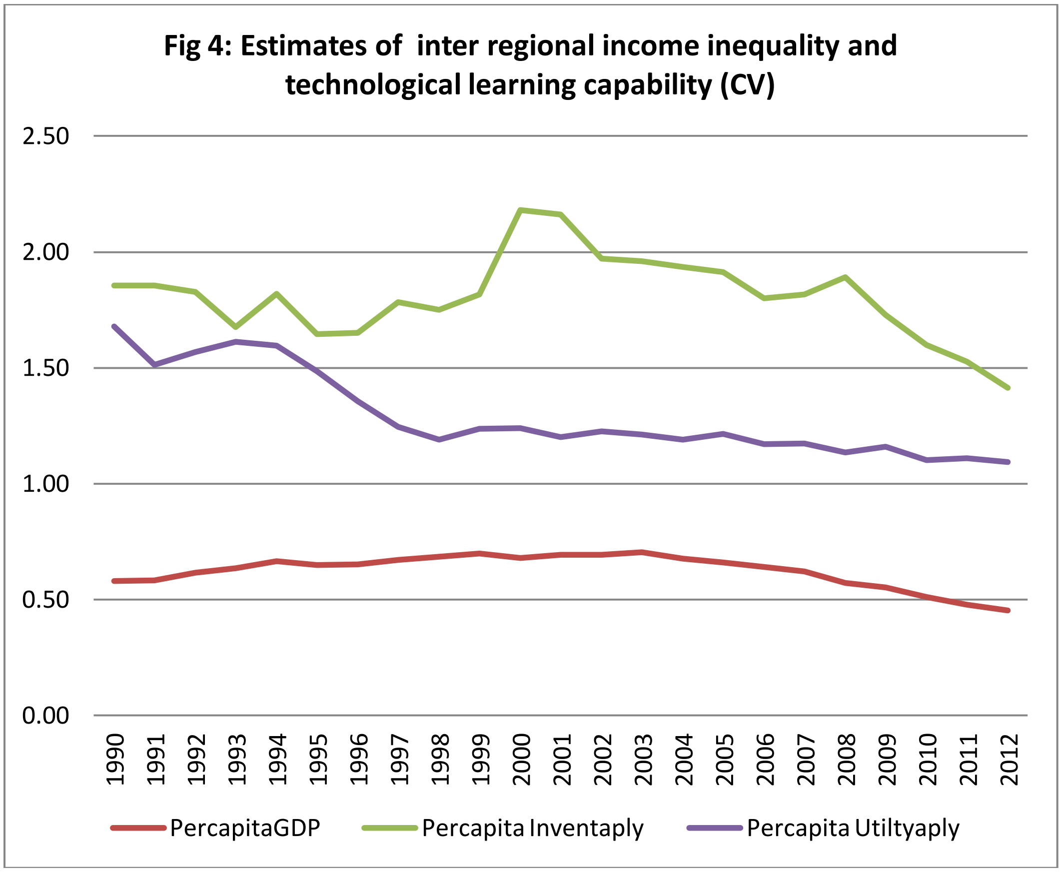
Fig. 3: Inter-regional Inequality in Per-capita Patent Applications



Having observed a declining trend in the inter-regional inequality in the technological learning capability, the pertinent question is to explore it's bearing on income inequality across regions. This however is an issue that requires a detailed exploration, which is beyond the scope of this paper. To set the ground for future enquiries, we have estimated inter-regional inequality in per capita GDP during 1990-

2012 across the regions. Since we observed perfect trend synchronization in the estimated values of Theil and coefficient of variation we report only the estimates of CV.

Figure 4 clearly indicates that there is broad trend synchronization between inequality in invention patents (the major source of learning capability) and income inequality. The observed trend therefore, reinforces the role of technological learning in overall economic performance and its role in governing inter-regional income inequality.



Yet another measure of convergence proposed by Barro and Sala-i-Martin (1992) is the β convergence. In the present context, β convergence involves an analysis of the empirical relationship between the initial level of learning capability as manifested by patent applications and its subsequent growth rate. A positive association between the two shows high growth in advanced regions and therefore divergence in technological capability and vice versa. The results of the estimated beta coefficients presented in table 3 indicates regional convergence with respect to technological learning capability in terms of total number of patent applications, utility models and design patents.

Table 3: Convergence results: Estimates of β coefficients				
	Total Patents	**Invention Patents**	**Utility Models**	**Design Patents**
β coefficient	-1.508* (-1.98)	0.800 (0.87)	-1.428** (-2.05)	-4.894*** (-3.7)
Constant	29.177 (5.75)***	19.465*** (4.24)	25.325*** (5.7)	51.314*** (9.3)
Observations	30	29	30	29
R^2	0.122	0.027	0.13	0.336

Note: Figures in the parenthesis indicate t values
*** indicates statistical significance at 1 percent level, ** indicates statistical significance at 5 percent level and *indicates statistical significance at 10 percent level

As already mentioned, invention patents involve higher technological learning efforts. Therefore, the differential trend observed in case of invention patents indicates the longer time span required for less developed regions to catch up. While the approach adopted by Barro and Sala-i-Martin in their analysis of income is based on neo-classical growth model, our analysis of convergence in technological learning capability has to be seen in terms of the changing nature of interaction between different actors in the innovation system and the role of institutions therein. It is to this issue that we turn now.

Determinants of technological learning capability: econometric analysis

Drawing from our analytical framework, we shall now discuss the econometric procedure for analysing the determinants of technological learning capability. In the model that we estimate the dependent variable is the number of patent applications. The count nature of our data does not follow the properties and conditions of OLS estimation. Hausman et al. (1984) have used count regression model in order to estimate the relationship between R&D and patents. In order to take advantage of count characteristics, two kinds of count regressions have been used in the literature, Poisson and negative binomial models. One important assumption for the asymptotical efficiency of the Poisson estimator is its assumption that the conditional mean (E (Y|X)) is equal to the conditional variance (Var (Y|X)). In empirical analysis, most often, the violation takes the form of the conditional variance being much larger than the conditional mean, leading to the situation of over-dispersion. A consequence of this is that the standard errors will be underestimated resulting in inflated statistical significance. One solution to the over-dispersion bias is to adopt a parametric specification that allows for the conditional variance to be different from the conditional mean. One such estimator is the Negative Binomial estimator, which assumes that the conditional mean is the product of a deterministic term and an error term that follows the gamma distribution. Given the nature of our panel data with huge variation in patent applications across the provinces, the negative binomial fixed effect models are the most appropriate regression model (see Table.4). This model allows the discrete nature of the patent counts with skewed distribution, solves the problem of overdispersion, and controls for unobserved regional specific effects (Baltagi, 2008).[10]

[10] For details on the count data regression models, see Cameron and Trivedi (2013)

The negative binomial model could be specified as

$$\lambda_{it} = \exp\,(x_{it}\beta + \varepsilon_i) \quad \ldots\ldots.\ 1$$

Where β denotes vector of coefficients related with $x_{it}$and ε_i denotes unobserved region specific effects. Drawing from equation (1) the expected number of patent applications received by a region per year could be shown as

$$E(y_{it}/x_{it}) = Var(y_{it}/x_{it}) = \lambda_{it} = \exp\,(x_{it}\beta + \varepsilon_i)\ldots\ldots..\ 2$$

Here $E(y_{it}/x_{it})$ and $Var(y_{it}/x_{it})$ shows the conditional mean and variance of patent counts given x_{it} . The number of patent applications by a specific region is independent of one another and average patents per year shows the characteristics of the given province, which depends on the vector of the regressors x_{it}. However, as already argued, the negative binomial model rejects the assumption of the Poisson model that the conditional mean is equal to the conditional variance. In order to model the overdispersion, the negative binomial model uses the different specification of parameter λ_{it} as shown in equation (1) by inserting ε_i into the Poisson specification of parameter $\lambda_{it} = \exp\,(x_{it}\beta + \varepsilon_i)$. Based on the equation (1), the negative binomial distribution has conditional mean λ_{it} and variance $\lambda_{it} + \theta^{-1}\,\lambda_{it}^2$ θ, where θ is the parameter of the gamma distribution. The negative binomial model can be estimated using the maximum likelihood techniques, shown in the following equation

$$L(\beta, \lambda_{it}) = \sum_{i=1}\sum_{i=1}[-\,\lambda_{it} + y_{it}(x_{it}\beta + \varepsilon_i) - ln y_{it}] \quad \ldots\ldots\ldots..\ 3$$

We shall begin with describing how different variables in the model have been constructed within limits set by data availability. For the reasons already discussed, the number of patents applied measures technological learning capability in the present study. Hence dependent variable in the estimated model, represented by PATAPLY, is the number of patent applications.

Hypotheses and variable construction

Following our analytical framework it is hypothesised that there are three sets of factors governing technological learning capability across regions; interaction among actors within the country (intra-country interactions), interaction with actors outside the country (inter-country interactions), and regional innovation system specific factors.

Intra-country interactions

Technology market (LNTECHMKT)

Innovation system scholars, in general, underlined the crucial role of interaction between knowledge users and producers in technological learning and innovation. Gu and Lundval (2006) considered the absence of this type of interaction as one of the major weaknesses of Chinese innovation system under the centrally planned regime. To the extent that the technology market facilitates interaction between producers and users of knowledge, establishment of a market for technology may be considered as a major step towards fostering interactive learning process. The purpose of setting up such technology markets was to find additional resources from the business sector for research institutes that were previously funded by the government. However, this, in turn, has had the effect of bringing together business and research leading to greater interaction and technological learning along with the expected policy outcome of mobilising more resources from business for research. To represent the effect of interactive learning between the users and producers of technological knowledge within the country, following Li (2009) and Yoon (2011), we have considered the contract value in the regional technology market. Here it needs to be noted that the sale of technological knowledge produced within a region need not be confined to the same region. Further, the sale of technological knowledge is not confined to universities and research institutes alone. Firms could be both buyers and sellers. It was shown that in 2005 universities and research institutes received only 23 percent of the contract value and that of firms was found to be as high as 59 percent (Li, 2009). In the estimated model the contract value of technological transactions is represented by the variable LNTECHMKT, which is measured as the logarithm of the value of technology transactions in a specific region wherein the knowledge has been generated.

Interactions among universities Research Institutes and firms (LNFIRMFUNDUNI)

Technology market captures the interactive learning by sharing the research outcomes through transactions in technology market. However, much learning takes place in the process of technology generation and before it is ready for sale through the market. Moreover, all the R&D efforts need not necessarily result in the generation of saleable technology notwithstanding the learning that takes place through the interaction of different actors concerned. There are a growing number of studies that highlight the role of interactive learning between firms, universities and research institutes in the generation of new knowledge/innovations. (Cohen et al., 2002; Eun et al., 2006; Eom and Lee, 2010, Lee et al., 2009) Therefore the present study considers interactions among universities, research institutes and firms as another form of intra-country interaction leading to technological learning capability. Such interactive learning in this study is captured through Science & Technology (S&T) funds raised by universities and research institutes from firms. This is represented by the variable LNFIRMFUNDUNI, which is measured by the logarithm of the financial resources, raised by the universities and research institutes from the firms.

Inter-country interactions: FDI and Trade

In a globalised world, interactive learning effort by actors in an innovation system is not confined to other actors within the economy. They also interact with actors outside the country. It is often argued that the developing countries have the latecomer advantage on account of the opportunity to learn from actors outside. Thus technological knowledge from advanced economies is one of the most important avenues for the actors within the innovation systems of transition economies like China. Learning from external actors could take place through various mechanisms, which has been much discussed in the literature (Gerschenkron, 1962). Most important channels include foreign direct investment (Cantwell, 1989; Fu, 2008; Liu and Wang, 2003), international trade (Soete, 1987) and technology licensing (Evenson and Joseph, 1999). Following previous studies (Sun, 2003; Fan and Wan, 2006; Li, 2009 and Yoon, 2011) such interactions are captured through trade (exports and imports) and foreign Direct Investment (FDI). In this study, the influence of FDI is captured by the variable LNFDI measured in terms of the logarithm of the value of FDI into the region concerned. Since China has emerged as a major source of outward direct investment, and a major participant in global innovation network, these are also important sources of learning. In the absence of regional level data on such variables, we have not considered them in the present analysis.

Studies have highlighted the important role played by international trade both exports and imports in developing countries. Viewed from the innovation system perspective both exports and imports facilitate interaction among domestic and foreign actors. Such interactions apart from promoting DUI mode of innovation could also be instrumental in promoting more STI-mode of innovation. While exports and imports could be considered as means of interactive learning, their influence on technological learning could be different depending on the structure of trade as well as its direction. In the present study, therefore we separately consider both exports and imports wherein the former is measured as logarithm of exports (LNEXPORTS) and latter as logarithm of imports (LNIMPORTS)

Factors specific to the regional innovation system

Thus far we have considered factors that represent interactive learning among actors within and outside the country. Since the present study is concerned with the inter-regional variation in technological learning capability, we also take into account certain region-specific factors or the broad characteristics of the regional innovation system. The characteristics of the regional innovation systems are captured in the present study by two variables; namely regional GDP and extent of regional R&D effort.

GDP at the provincial level (LNGDPPERCAPITA)

In our analytical framework, drawing from innovation system perspective and Romer, (1990), it has been argued that the extent of knowledge generation through interactive learning depends upon the available stock of knowledge. Issues, however, arise in its measurement because of the absence credible data on stock of knowledge and the knowledge that became redundant. Furman et al. (2002) considered GDP as a measure of accumulated knowledge. Though we are inclined to believe that this is a less precise measure, in the absence of any other proxy, following Furman et al. (2002) we consider per capita GDP at the regional level as a measure of accumulated knowledge possessed by the region concerned. In this study, this is represented by LNPERCAPITAGDP measured as the logarithm of per capita GDP of the region concerned.

R&D effort (RDGDP)

The role of research and development in generating innovation, which we consider an offshoot of technological learning, is expected to play a major role in the generation of technological learning. Cross-country studies on the differential performance of innovation have assigned key role for R&D (Furman et al. 2002; Furman and Hayes, 2004; Hu and Mathews, 2005). As a key characteristic of regional innovation system, we consider R&D as having a major role in generating technological learning capability in the region concerned. Earlier studies on regional innovation capability in China have highlighted the positive influence of R&D effort in regional innovation capability (Sun, 2003; Hu and Mathews, 2008, Yoon, 2011). Following earlier studies, we measure R&D effort at the provincial level as R&D as a proportion of regional GDP.

Institutional factors (SUBSIDYDUMMY)

As already indicated, State, through its various policies and programs do influence the interactive learning behaviour of various actors in the innovation system. Studies argue that the provincial governments in China have played an active role in promoting innovative activities by introducing various subsidies and incentives (Li 2012; Lei et al., 2012; Dang and Motohashi, 2015). Li (2012) pointed out that the monetary incentives provided by the provincial governments through the subsidy programs have been implemented with varying intensity. Though the subsidy program was started in 1999, by 2007 all the provincial governments offered financial support for filing patent applications. The empirical evidence indicates that introduction of subsidy programs have indeed played a significant role in increasing patent applications in China (Li 2012; Lei et al., 2012; Dang and Motohashi, 2015). Dang and Motohashi (2015) observed that there exists considerable variation in the nature and extent of subsidies across regions. However, earlier studies (Li, 2012) have taken only incidence of the subsidy and not their nature and intensity. In this paper, the bearing of financial support on patent applications has been incorporated by considering the different forms subsidies offered. These include; a) filing fee subsidy, b) examination fee subsidy and c) grant contingent. Based on Dang and Motohashi (2015) we capture the regional variability in subsidy by introducing a dummy variable (subsidy dummy) which takes value 1 if a province provides all the three types of subsidies (Dang and Motohashi, 2015) and the amount offered is high at least in two and 0 otherwise.

Table 4: Variable Construction		
Variable Code	Definition	Construction
PATAPLY	Total Number of Patent Applications	Total number of patents applied
INVENTAPLY	Invention patents applied	Total number of invention patents applied
UTILITYAPLY	Utility patents applied	Total number of utility patents applied
DESIGNAPLY	Design Patent applied	Total number of design patents applications
LNFIRMFUNDUNI	Firm-university interactions	Logarithmic value of firms funding university R&D
LNTECHMKT	Technology transactions	Logarithmic value of total technology transactions in the market
LNFDI	Foreign direct investment	Logarithmic value of foreign direct investment
LNEXPORTS	Exports	Logarithmic value of exports
LNIMPORTS	Imports	Logarithmic value of imports
RDGDP	R&D expenditure	R&D expenditure as a proportion of GDP
LNGDPPERCAPITA	Per-capita income	Logarithmic value of per capita income
SUBSIDYDYMMY		Value is 1 if a province provides all the three types of subsidies and the amount offered is high at least in two and 0 otherwise

Results of the econometric analysis:

Drawing from the econometric procedure and hypotheses, the estimated negative binomial model may be stated as follows.

$$Y_{it} = \exp[\beta_0 + \beta_1 \text{lnfirmfunduni}_{it} + \beta_2 \text{lntechmkt}_{it} + \beta_4 \text{lnfdi}_{it} + \beta_5 \text{lnexports}_{it} + \beta_6 \text{lnimports}_{it} + \beta_7 \text{rdgdp}_{it} + \beta_8 \text{lngdppercapita}_{it} + \beta_9 \text{SUBSIDYDUMMY} + e_{it} + u_{it} \quad (5)$$

High variability in the mean and standard deviation of patent data is evident from table 5, and that justifies our selection of negative binomial regression. Further, we have tested over-dispersion parameter á. The significance of this test in all the cases indicates negative binomial model is appropriate for the dataset. The negative binomial model allows each province's Poisson parameter to have its own random distributions. The two different models, fixed effects and random effects models could be estimated.

Table 5: Summary statistics					
Variable	Observations	Mean	Standard Deviation	Minimum	Maximum
PATAPLY	420	20039.34	43395.77	10	472656
INVENTAPLY	420	5124.202	10801.47	2	110091
UTILITYAPLY	420	7413.257	13604.79	3	108599
DESIGNAPLY	420	7501.883	21289.54	3	255474
LNFIRMFUNDUNI	420	15.46	1.32	11.33	18.15
LNTECHMKT	420	-1.63	1.72	-7.44	3.17
LNFDI	420	-2.50	1.77	-6.67	0.87
LNEXPORTS	420	-0.73	1.83	-5.01	3.63
LNIMPORTS	420	-1.02	2.04	-6.89	3.30
RDGDP	420	.0104	.01003	0	.0594
LNGDPPERCAPITA	420	-4.20	0.76	-5.97	-2.42
SUBSIDYDUMMY	420	0.5	0.50	0	1

We have estimated two models separately for total patent applications, invention patents, utility models and design patents which are considered as indicators of technological learning capability. The first model (model 1) estimates the effect of intra-country and inter-country interactions and the second model (model 2) incorporates regional innovation system characteristics as well. We have estimated both fixed effects and random effects models. However, the use of Hausman test is found unsuitable to choose the appropriate model since the condition of positive semi-definiteness of variance-covariance matrix is found to be invalid in this model, resulting in negative $\chi 2$ values in some cases. Therefore, we report fixed effect estimates, which are consistent even if the individual effects are correlated with the explanatory variables. The significance of Wald test in all the models shows that variables considered in the model for the analysis are adequate and results are appropriate for statistical inference.

Estimates of the negative binomial model (Model 1 and Model 2) for all indicators of technological learning capability (total patent applications, invention patent applications, utility models and design patents) are presented in table 6. The positive and statistically significant value of the estimated coefficient for technology market (Model 1) suggests that the establishment of technology market in China has had a positive influence in terms of building technological learning capability regardless of the way we measure it. Here it may be noted that earlier studies (Li, 2009 and Yoon, 2011) also have reported similar results. Thus viewed the establishment of technology market has not only enabled knowledge producing entities to get access to more financial resources but also in creating an environment that promotes interactive learning capabilities. Model 1 also confirms the positive influence of university-industry interaction in facilitating technological learning that has been well documented in the literature (Nelson, 1986; Cohen and Levinthal 1989; Cohen et al. 1998; Cohen, Nelson, and Walsh 2002). The estimated value of the coefficients further indicates that the bearing of industry-university interaction is the highest in case of invention patents as compared to utility models and design patents having less technological content. Thus, model 1 reaffirms the role of STI-mode of interactions in technological learning capability. When it comes to inter-country interactions, mostly taking place in DUI mode, we find a positive bearing of exports in technological learning capability in all indicators except for utility models. When it comes to imports, estimated coefficients reveal its positive and significant influence in case of total patent applications as well as in design patents. This tends to suggest that trade facilitates greater interaction between users and producers abroad leading to both STI learning and DUI learning thereby contributing to technological learning capability in general. Moreover, in the current context wherein exporters have to comply with numerous quality standards, exporting activity appears to enable them to increase their learning and knowledge while complying with these standards. This observation also is in line with the findings of earlier studies (Sun, 2003; Fan and Wan, 2006; Hu and Mathews, 2008) which indicated the positive role of trade in promoting innovation capability. However, when it comes to FDI, the negative and statistically significant value of the estimated coefficient is in contrast to the generally held view that inward foreign direct investment acts as a source of learning for developing countries through various means including spillovers.

The negative and statistically significant value of the estimated coefficient of FDI in both the models (1 and 2) tends to suggest that the actors in the innovation system consider FDI and domestic technological learning capability as substitutes. A similar finding has also been reported by earlier studies (Yoon, 2011; Fan et al., 2012). Yoon (2011) has highlighted the possibility of FDI crowding out domestic firms in the competitive market leading to over-reliance on foreign technology. In the light of vast empirical literature on the spillover effects of FDI in generating technological capability, our finding of FDI having a negative effect on technological learning capability is hard to accept. Another strand of literature argues that the effects of FDI depend on the absorptive capacity of the firm or region concerned (Saggi, 2002; Fu, 2008). Hence, we have tried to examine whether the effect of FDI is conditional upon the regions. Following Fan and Wan (2006) Fan et al. (2012), we categorised the provinces into three broad geographical regions, east, central and west. We then introduced interaction variable LNFDI with regions in the model 2 by making the western region as the base category. The positive and significant coefficient value of FDI in the eastern region indicates that FDI has positive effect on technological learning capability as compared to the western region in case of total patents, invention patents and utility models. It is well known that eastern region in China is more industrialised with the highest number of industrial clusters than the other regions (Fu, 2008). Thus viewed, FDI tends to contribute towards technological learning capability if the region concerned has the absorptive capacity.

Model 2 incorporates the regional innovation system variables in addition to the intra-country and inter-country interactions incorporated in model 1. As in case of Model 1, Model 2 also has been estimated for all four indicators of technological learning. Estimated values of the coefficients in model 2, in general, establishes our hypotheses regarding the influence of regional innovation system specific factors and the role of institutions along with intra-country and inter-country interactions in the determination of technological learning capability.

Among the regional innovation system related factors, the estimated coefficients of regional per capita income is positive and statistically significant regardless of how we define technological learning capability. This finding lends empirical support to the key hypothesis of the present study drawn from innovation system perspective and Romer (1990) that since learning is cumulative and path dependent, the flow of knowledge in an economy is driven by its existing stock of knowledge. This finding is also in sync with an earlier cross-country study by Furman and Hayes (2004). The estimated coefficient of regional R&D effort, yet another variable representing regional innovation system characteristics is positive and statistically significant in case of all the indicators of technological learning capability. This empirical evidence is in conformity with the existing literature (Furman et al., 2002; Sun, 2003; Hu and Mathews, 2005, 2008 and Yoon, 2011) that underlined the role of R&D in learning and innovation.

Two findings from the full model (Model 2) deserve further discussion. The positive contribution of exports observed in case of model 1 has been reaffirmed even after controlling for regional innovation system related factors. But when it comes to imports, as against our hypothesis, we observe a negative and statistically significant influence on invention patents and utility models. To the extent that we have considered aggregate exports and imports without considering their direction, it is difficult to draw any definite inference. Nonetheless, the negative sign of the coefficient of imports with respect to invention patents and invention patents tends to suggest that actors in the innovation system engaged in more knowledge-intensive activities consider foreign knowledge as substitute for local knowledge. Hence, heightened import competition might be adversely affecting technological learning activities in more knowledge-intensive activities. The estimated coefficient of university-industry interactions is found positive and significant in case of invention patents and utility models.

From model 2 it is evident that regardless of the way we measure technological learning capability, the estimated coefficient of subsidy dummy is positive and statistically significant. This finding corroborates broadly with the argument by Li (2012) where he argued that the explosive growth in patents in China is contributed by patent subsidy programs implemented by different provincial government. There is also a line of argument saying that non-innovation related motives for acquiring patents may have played an important role in the patenting surge (Hu and Lijing, 2017). We have already noted the various initiatives undertaken under the MLP 2006-2020 which also would have contributed towards technological learning and patent applications. In the light of these observations, we further analysed the bearing of patent subsidy on patent applications by estimating structural break in patent applications following Bi and Parron (2003). The results (see appendix Table A1) indicated that in 20 out of 29 provinces there was a trend break in patent applications even before the introduction of patent subsidy programs and the number provinces with structural breaks declined to 12 during 1999 to 2006 (after the introduction of subsidy and before the MLP). Similarly, 25 out of total provinces showed a trend break after 2007, indicating the combined outcome of subsidy programs and the MLP. These findings call for more detailed analysis to arrive at a definitive conclusion the role of patent subsidy on technological learning.

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Table 6: Fixed Effects Regression Model of Negative Binomial Regression								
Dependent Variable	Total Patent Applications		Invention Patents		Utility Patents		Design Patents	
	Model 1	Model 2	Model 1	Model 2	Model 1	Model 2	Model 1	Model 2
	Coefficients (Z-Values)	Coefficients (Z-Values)	Coefficients (Z-Values)	Coefficients (Z-Values)	Coefficients (Z-Values)	Coefficients (Z-Values)	Coefficients (Z-Values)	Coefficients (Z-Values)
LNFIRMFUNDUNI	0.63*** (13.82)	.009 (0.16)	0.88*** (19.14)	.214*** (3.75)	0.62*** (13.62)	.119** (2.09)	0.39*** (6.77)	-.142* (-1.94)
LNTECHMKT	0.29*** (8.48)	.110*** (3.67)	0.41*** (11.12)	.132*** (4.28)	0.25*** (7)	.063** (2.06)	0.12*** (2.69)	.088** (2.18)
LNFDI	-0.17*** (-4.54)	-.223*** (-7.12)	-0.24*** (-5.65)	-.255*** (-7.77)	-0.11*** (-2.63)	-.207*** (-6.06)	-0.24*** (-4.85)	-.172*** (-3.79)
LNFDI*ESTERN		.213*** (4.76)		.320*** (6.98)		.202*** (4.06)		.036 (0.62)
LNEXPORTS	0.21*** (2.91)	.207*** (4.27)	0.34*** (4.31)	.214*** (4.28)	0.08 (1.09)	.122** (2.32)	0.30*** (3.2)	.287*** (4.07)
LNIMPORTS	0.12* (1.81)	-.0757 (-1.51)	-0.03 (-0.49)	-.142*** (-2.78)	0.07 (0.99)	-.176*** (-3.43)	0.18** (2.2)	-.0416 (-0.58)
RDGDP		11.762*** (4.35)		15.731*** (5.76)		8.352*** (2.70)		13.89*** (3.45)
LNGDPPERCAPITA		1.096*** (16.08)		1.251*** (19.81)		1.062*** (15.61)		.908*** (11.18)***
SUBSIDYDUMMY		.1452*** (3.10)		.112** (2.45)		.096* (1.72)		.273*** (3.82)
Constant	-7.68*** (-10.18)	6.708*** (5.96)	-12.04*** (-15.62)	4.002*** (3.70)	-7.61*** (-10.08)	4.519*** (4.17)	-4.98*** (-5.22)	7.432*** (5.35)
Observations	420	420	420	420	420	420	420	420
Number of groups	29	29	29	29	29	29	29	29
Wald chi2	1734.18 (0.00)	2952.03 (0.00)	2263.5 (0.00)	4725.64 (0.00)	927.48 (0.00)	1637.66 (0.00)	532.47 (0.00)	1154.61 (0.00)
Log likelihood	-3559.56	-3392.072	-3076.44	-2838.22	-3240.52	-3110.71	-3142.42	-3042.201

Note: Figures in the parenthesis indicate Z values
*** indicates statistical significance at 1 percent level, ** indicates statistical significance at 5 percent level and *indicates statistical significance at 10 percent level

Conclusion

The inter-regional disparity in development in China has attracted substantial scholarly attention. The available empirical evidence suggests that along with the remarkable economic performance, inter-regional development divide has been on the increase. In contrast to the commonly held view, the present study highlights that there has been a turnaround in China's inter-regional inequality in development along with its key determinants, technological learning capability, which became pronounced since 2006. Considering the key role of innovation in influencing growth performance, earlier studies have focused on inter-regional variation in innovation capability across regions as a source of growing interregional inequality. Innovation system perspective, the most widely used approach in innovation studies at present, postulates technological learning as the core of innovation capability, which governs development. Hence weaknesses in the formal and informal learning processes lead to the low level of innovation capability. Extending these ideas to the issue of inter-regional inequality in development the present study postulated that region is poor/rich is governed by certain basic capabilities like the learning capabilities of the individuals and organisation in the region concerned. To reflect on regional inequality in learning capability in China, we develop an analytical frame based on the National System of Innovation (NSI) perspective and its derivative Regional Innovation System (RIS). Drawing insights from this perspective, we analysed technological learning capability in order to understand inter-regional development divide in China. The study measured technological learning capability in terms of total number of patent applications as distinct from innovation capability often measured through the number of patents granted. Technological learning at the regional level has been hypothesised as governed by both STI and DUI mode of interactions, which were captured in terms of intra-country interactions, inter-country interactions and regional innovations system specific factors. By empirically verifying the role of different types of interactions, the present study contributes towards providing empirical support to innovation system perspective. Apart from this, the present study uses more appropriate econometric tools and covers an extended period of analysis (1990-2012) that will take into account various national level and regional level policies that aimed at promoting the full-fledged construction of national innovation system with the Chinese characteristics especially since 2006.

Analysis of the trends and patterns in inter-regional inequality in technological learning capability revealed the following. An increase in inter-regional inequality was observed up to 2002 in case of invention patents and design patents. When it comes to utility patents, which accounted for the largest share of the patents applied, there has been a declining trend in inter-regional inequality. As a result, the total patent applications recorded a V pattern up to 2005 as observed by earlier studies. Since 2002, we have observed a declining trend in inter-regional inequality in technological learning capability which became pronounced after 2006 in case of total patents, invention patents and utility models. Further, our analysis has also shown that there has been a regional convergence in technological learning capability along with declining trend in the inter-regional inequality in per capita income since 2006.

Econometric analysis of the drivers of technological learning capability provided empirical evidence to support the positive influence of both STI and DUI mode of interactions. The study reaffirms the positive role of intra-country interactions in STI-mode, as indicated by market value of technology transactions and industry funding for university research. Thus viewed, the Chinese policy of harnessing market forces for facilitating technological development has also resulted in strengthening innovation system by promoting interactive learning. The present study also highlights the positive contribution of DUI mode of interaction with actors outside the country indicated by exports and imports, in building technological learning capabilities. This tends to suggest that the export-oriented strategy under globalisation seems to have helped Chinese regions in building technological learning capability through DUI mode of learning. The finding regarding the influence of FDI is broadly in sync with the generally held view that, absorptive capacity of the region concerned is crucial for taking advantage of the FDI inflows. With respect to regional innovation system characteristics, the study highlighted the role of research and development at the regional level in fostering technological learning capabilities and addressing regional developmental divide. Equally important, technological learning being cumulative and path dependent, the past stock of knowledge has an important role in building technological learning capabilities. Finally, the study also highlights the role of institutional interventions as is evident from various national level policies that coincided with the patent subsidy program initiated by most of the regional governments in promoting technological learning capability.

On the whole, in sync with the innovation system perspective, the study provides empirical evidence to support the view that bridging development divide calls addressing learning divide especially by building technological learning capabilities. To be more specific, in addressing inter-regional inequality in China, the focus of Chinese policy makers shall be to further strengthening the institutional architecture for facilitating inter-country and intra-country interactions to build technological learning capabilities among individuals and organisations. However, it is not our claim that the study has dealt comprehensively with all types of interactions that could be instrumental in technological learning. Hence, the focus of future research shall be on other forms of intra-country and inter-country interactions along with intra-firm interactions in building technological learning capability.

References

Arocena, R. and Sutz, J., 2000. Looking at national systems of innovation from the South. Industry and Innovation, 7(1), pp.55-75.

Arocena, R. and Sutz, J., 2003. Inequality and innovation as seen from the South. Technology in Society, 25(2), pp.171-182.

Asheim, B., Coenen, L. and Vang, J., 2007. Face-to-face, buzz, and knowledge bases: sociospatial implications for learning, innovation, and innovation policy. Environment and Planning C: Government and Policy, 25(5), pp.655-670.

Asheim, B.T. and Isaksen, A., 2002. Regional innovation systems: the integration of local 'sticky'and global 'ubiquitous' knowledge. The Journal of Technology Transfer, 27(1), pp.77-86.

Bai, J., & Perron, P. 2003. Computation and analysis of multiple structural change models. *Journal of applied econometrics*, *18*(1), 1-22.

Baltagi, B., 2008. Econometric analysis of panel data. 4th edition, John Wiley & Sons.

Bao, S., Chang, G.H., Sachs, J.D. and Woo, W.T., 2002. Geographic factors and China's regional development under market reforms, 1978–1998. China Economic Review, 13(1), pp.89-111.

Bardhan, P. 2010. Awakening Giants. *Feet of Clay: Assessing the Economic Rise of China and India*.

Barro, R.J. and Sala-i-Martin, X., 1992. Convergence. Journal of political Economy, 100(2), pp.223-251.

Cameron, A.C. and Trivedi, P.K., 2013. Regression analysis of count data. Second edition, Cambridge university press. New York, USA

Cantwell, J., 1989. Technological innovation and multinational corporations. Oxford, Basil Blackwel

Chen, Y., Yang, Z., Shu, F., Hu, Z., Meyer, M. and Bhattacharya, S., 2009. A patent based evaluation of technological innovation capability in eight economic regions in PR China. World Patent Information, 31(2), pp.104-110.

Cohen, W. M., Florida, R., Randazzese, L., & Walsh, J. 1998. Industry and the academy: uneasy partners in the cause of technological advance. *Challenges to research universities*, *171*(200), 59.

Cohen, W.M. and Levinthal, D.A., 1990. Absorptive capacity: A new perspective on learning and innovation. Administrative science quarterly, 35(2), pp.128-152.

Cohen, W.M., Nelson, R.R. and Walsh, J.P., 2002. Links and impacts: the influence of public research on industrial R&D. Management science, 48(1), pp.1-23.

Cooke, P., 2001. Regional innovation systems, clusters, and the knowledge economy. Industrial and corporate change, 10(4), pp.945-974.

Cooke, P., Uranga, M.G. and Etxebarria, G., 1997. Regional innovation systems: Institutional and organisational dimensions. Research Policy, 26(4), pp.475-491.

Dang, J., & Motohashi, K. 2015. Patent statistics: A good indicator for innovation in China? Patent subsidy program impacts on patent quality. *China Economic Review*, *35*, 137-155.

Edquist, C., (ed) 1997. Systems of innovation: technologies, institutions, and organizations. London, Pinter Publishers.

Eom, B.Y. and Lee, K., 2010. Determinants of industry–academy linkages and, their impact on firm performance: The case of Korea as a latecomer in knowledge industrialization. Research Policy, 39(5), pp.625-639.
Eun, J.H., Lee, K. and Wu, G., 2006. Explaining the "University-run enterprises" in China: A theoretical framework for university–industry relationship in developing countries and its application to China. Research Policy, 35(9), pp.1329-1346.
Evenson, R.E. and Joseph, K.J., 1999. Foreign technology licensing in Indian Industry: an econometric analysis of the choice of partners, terms of contract and the effect on licensees' performance. Economic and Political Weekly, 34(27).1801-1809.
Fagerberg, J. and Sapprasert, K., 2011. National innovation systems: the emergence of a new approach. Science and Public Policy, 38(9), pp.669-679.
Fagerberg, J. and Verspagen, B., 1996. Heading for Divergence? Regional Growth in Europe Reconsidered. JCMS: Journal of Common Market Studies, 34(3), pp.431-448.
Fagerberg, J., Verspagen, B. and Caniels, M., 1997. Technology, growth and unemployment across European regions. Regional Studies, 31(5), pp.457-466.
Fan, P. and Wan, G., 2006. China's regional inequality in innovation capability, 1995-2004 (No. 2006/153). Research Paper, UNU-WIDER, United Nations University (UNU).
Fan, P. and Watanabe, C., 2006. Promoting industrial development through technology policy: Lessons from Japan and China. Technology in Society, 28(3), pp.303-320.
Fan, P., Wan, G. and Lu, M., 2012. China's regional inequality in innovation capability, 1995–2006. China & World Economy, 20(3), pp.16-36.
Freeman, C., 1987. Technology policy and economic performance: Lessons from Japan. London: Pinter Publishers.
Fu, X., 2008. Foreign direct investment, absorptive capacity and regional innovation capabilities: evidence from China. Oxford Development Studies, 36(1), pp.89-110.
Furman, J.L. and Hayes, R., 2004. Catching up or standing still?: National innovative productivity among 'follower'countries, 1978–1999. Research Policy, 33(9), pp.1329-1354.
Furman, J.L., Porter, M.E. and Stern, S., 2002. The determinants of national innovative capacity. Research Policy, 31(6), pp.899-933.
Gerschenkron, A., 1962. Economic backwardness in historical perspective: a book of essays. Cambridge, MA: Belknap Press of Harvard University Press.
Griliches, Z., 1990. Patent statistics as economic indicators: a survey (No. w3301). National Bureau of Economic Research. Cambridge MA, USA
Gu, S. and Lundvall, B.Å., 2006. China's Innovation System and the Move Towards Harmonious Growth and Endogenous Innovation, DRUID Working Paper (06-7). Online Retrieved April 10, 2015 from http://www.druid.dk/wp/pdf_files/06-07.pdf.
Guan, J. and Liu, S., 2005. Comparing regional innovative capacities of PR China based on data analysis of the national patents. International Journal of Technology Management, 32(3-4), pp.225-245.

Hagedoorn, J. and Cloodt, M., 2003. Measuring innovative performance: is there an advantage in using multiple indicators?. Research Policy, 32(8), pp.1365-1379.

Hausman, J.A., Hall, B.H. and Griliches, Z., 1984. Econometric models for count data with an application to the patents-R&D relationship. Econometrica, 52(4), 909–938

Ho, C. Y., & Li, D. 2008. Rising regional inequality in China: Policy regimes and structural changes. *Papers in Regional Science*, *87*(2), 245-259.

Hu, A. G., & Jefferson, G. H. 2009. A great wall of patents: What is behind China's recent patent explosion?. *Journal of Development Economics*, *90*(1), 57-68.

Hu, A. G., Zhang, P., & Zhao, L. 2017. China as number one? Evidence from China's most recent patenting surge. *Journal of Development Economics*, *124*, 107-119.

Hu, M.C. and Mathews, J.A., 2005. National innovative capacity in East Asia. Research Policy, 34(9), pp.1322-1349.

Hu, M.C. and Mathews, J.A., 2008. China's national innovative capacity. Research Policy, 37(9), pp.1465-1479.

Isaksen, A., 2003. Lock-in'of regional clusters: the case of offshore engineering in the Oslo region, in Isaksen, A (eds) Cooperation, Networks and Institutions in Regional Innovation Systems", Edward Elgar. Cheltenham and Northampton, MA, 247-273.

Jaffe, A.B., 1989. Real effects of academic research. The American Economic Review, pp.957-970.

Jensen, M.B., Johnson, B., Lorenz, E. and Lundvall, B.Å., 2007. Forms of knowledge and modes of innovation. Research Policy, 36(5), pp.680-693.

Jian, T., Sachs, J. D., & Warner, A. M. 1996. Trends in regional inequality in China. *China economic review*, *7*(1), 1-21.

Johnson, B., 1992. Institutional learning', in Lundvall, B.-Å. (ed.), National Innovation Systems: Towards a Theory of Innovation and Interactive Learning, London, Pinter Publishers

Jones, C.I., 1995. R & D-based models of economic growth. Journal of political Economy, 103(4) pp.759-784.

Kanbur, R., & Zhang, X. 1999. Which regional inequality: rural-urban or coast-inland? An application to China. *Journal of Comparative Economics*, *27*(4), 686-701.

Kanbur, R., & Zhang, X. 2005. Fifty years of regional inequality in China: a journey through central planning, reform, and openness. *Review of development Economics*, *9*(1), 87-106.

Knight, J. 2014. Inequality in China: an overview. *The World Bank Research Observer*, *29*(1), 1-19.

Knight, J. 2014. Inequality in China: an overview. *The World Bank Research Observer*, 29(4), 1-19.

Lee, K., Joseph, K.J., Abraham, V., Eun, J.H., Wu, G., Wang, Y., Rasiah, R., Govindaraju, C., Intarakumnerd, P., Schiller, D. and Cho, H., 2009. Promoting effective modes of university-industry interactions and their evolution for economic catch up in Asia. Final Research Reports for the IDRC. Ottawa: International Research Development Centre.

Lei, Z., Sun, Z. and Wright, B., 2012. Patent subsidy and patent filing in China. University of California, Berkeley, mimeo.

Li, Shi, Luo Chuliang, and Terry Sicular. 2013. "Overview: Income Inequality and Poverty in China, 2002–2007." In Rising Inequality in China: Challenge to the Harmonious Society, eds. Li Shi, Hiroshi Sato, and Terry Sicular, 24-59. Cambridge and New York: Cambridge University Press

Li, X., 2009. China's regional innovation capacity in transition: An empirical approach. Research Policy, 38(2), pp.338-357.

Liu, X. and Wang, C., 2003. Does foreign direct investment facilitate technological progress?: Evidence from Chinese industries. Research Policy, 32(6), pp.945-953.

Liu, X. and White, S., 2001. An exploration into regional variation in innovative activity in China. International Journal of Technology Management, 21(1-2), pp.114-129.

Lundvall, B.-Å., 1988. Innovation as an interactive process: From user-producer interaction to the National Innovation Systems, in Dosi, G., Freeman, C., Nelson, R.R., Silverberg, G. and Soete, L.,(eds.), Technology and economic theory, London, Pinter Publishers

Lundvall, B.Å., 2007. National innovation systems—analytical concept and development tool. Industry and innovation, 14(1), pp.95-119.

Lundvall, B.-Å., ed. 1992. National Innovation Systems: Towards a Theory of Innovation and Interactive Learning, London, Pinter Publishers

Lundvall, B.Å., Johnson, B., Andersen, E.S. and Dalum, B., 2002. National systems of production, innovation and competence building. Research Policy, 31(2), pp.213-231.

Lundvall, B.A., Joseph, K.J., Chaminade, C. and Vang, J. eds., 2009. Handbook of innovation systems and developing countries: building domestic capabilities in a global setting. Edward Elgar Publishing.

Malerba, F., 1992. Learning by firms and incremental technical change. The economic journal, 102(413), pp.845-859.

Maskell, P. and Malmberg, A., 1999. Localised learning and industrial competitiveness. Cambridge journal of economics, 23(2), pp.167-185.

Mowery, D.C. and Oxley, J.E., 1995. Inward technology transfer and competitiveness: the role of national innovation systems. Cambridge journal of economics, 19(1), pp.67-93.

National Bureau of Statistics of China, 1990–2012, China Statistical Yearbook on Science and Technology, Beijing: China Statistical Press

Nelson, R. R. 1986. Institutions supporting technical advance in industry. *The American Economic Review*, 186-189.

Nelson, R.R. ed., 1993. National innovation systems: a comparative analysis. Oxford university press. Oxford, UK.

Nelson, R.R., 2008. What enables rapid economic progress: What are the needed institutions?. Research Policy, 37(1), pp.1-11.

Padilla-Pérez, R., 2008. A regional approach to study technology transfer through foreign direct investment: the electronics industry in two Mexican regions. Research Policy, 37(5), pp.849-860.

Padilla-Perez, R., Vang, J. and Chaminade, C., 2009. Regional innovation systems in developing countries: integrating micro and meso-level capabilities. In B A

Lundvall et al (eds) Handbook of Innovation Systems and Developing Countries: Building domestic capabilities in a global setting, 140-182, Edward Elgar Publications, UK.

Patel, P. and Pavitt, K., 1994. National innovation systems: why they are important, and how they might be measured and compared. Economics of innovation and new technology, 3(1), pp.77-95.

Patel, P., Pavitt, K., 1995. Patterns of technological activity: their measurement and interpretation. In: Stoneman, P. (Ed.), Handbook of the Economics of Innovation and Technical Change. Blackwell, Oxford

Piketty, T. (2014). Capital in the 21st Century. *Cambridge: Harvard University Press*

Porter, M.E., 1998. Competitive strategy: Techniques for analyzing industries and competitors. 2nd edition, free press.

Ravallion, M., & Chen, S. (2007). China's (uneven) progress against poverty. *Journal of development economics*, *82*(1), 1-42.

Romer, P., 1990. Endogenous Technological Change. Journal of Political Economy, 98(5), pp 71-102.

Saggi, K., 2002. Trade, foreign direct investment, and international technology transfer: A survey. The World Bank Research Observer, 17(2), pp.191-235.

Shorrocks, A., & Van der Hoeven, R. (2004). *Growth, inequality, and poverty: Prospects for pro-poor economic development*. Oxford University Press on Demand.

Soete, L., 1987. The impact of technological innovation on international trade patterns: the evidence reconsidered. Research Policy, 16(2), pp.101-130.

Soete, L., Verspagen, B., Ter Weel, B., 2010. Systems of innovation. In Bronwyn H. Hall and Nathan Rosenberg (eds) Handbook of the Economics of Innovation, 1, 1159-1180, Elsevier.

Srinivas, S. and Sutz, J., 2008. Developing countries and innovation: Searching for a new analytical approach. Technology in Society, 30(2), pp.129-140.

Sun, Y., 2000. Spatial distribution of patents in China. Regional studies, 34(5), pp.441-454.

Sun, Y., 2003. Geographic patterns of industrial innovation in China during the 1990s" Journal of Economic and Social Geography, 94 (3), 376–89.

Yang, C. H., Lee, C. M., & Lin, C. H. A. 2012. Why does regional innovative capability vary so substantially in China? The role of regional innovation systems. *Asian Journal of Technology Innovation*, *20*(2), 239-255.

Yao, S., & Zhang, Z. 2001. On regional inequality and diverging clubs: a case study of contemporary China. *Journal of Comparative Economics*, *29*(3), 466-484.

Yoon, J., 2011. Exploring regional innovation capacities of PR China: Toward the study of knowledge divide. PhD Dissertation submitted to Georgia Institute of Technology, Georgia.

Zhang, X., & Zhang, K. H. 2003. How does globalization affect regional inequality within a developing country? Evidence from China. *Journal of Development Studies*, *39*(4), 47-67.

Table A1: Structural Break Analysis of Total Patent Applications								
	Start Year	1 Break	2nd Break	3rd Break	Growth Rates			
Anhui	2003	1999	2007	2010	(1990-1998) 11.53	(1999-2006) 11.75	(2007-2009) 53.26	(2010-2012) 48.53
Bejing	**2000**	**2001**	**20008**	No Break	(1990-2000) 6.39	(2001-2007) 18.61	(2008-2012) 20.53	
Fujian	2002-2005-2006	1995	2002	2009	(1990-1994) 29.24	(1995-2001) 16.39	(2002-2008) 13.06	(2009-2012) 28.89
Gansu	**2002**	**2005**	**2010**	No Break	(1990-2004) 6.70	(2005-2009) 19.53	(2010-2-12) 36.86	
Guangdong	2000	1995	2001	2006	(1990-1994) 27.34	(1995-2000) 19.33	(2001-2005) 24.23	(2006-12) 16.23
Guangxi	**2001**	**2000**	**2010**	No Break	(1990-99) 7.56	(2000-2009) 8.78	(2009-12) 40.24	
Guizhou	2002	1996	2005	2010	(1990-95) 13.91	(1996-2004) 10.16	(2005-09) 17.90	(2010-12) 36.40
Hainan	2001	1993	1997	2008	(1990-92) 39.33	(1993-96) 19.41	(1997-2007) 6.41	(2008-12) 21.72
Hebei	2005	1993	2001	2009	(1990-92) 23.81	(1993-00) 5.81	(2001-2008) 10.31	(2009-12) 22.74
Heilongjiang	2001	1993	2002	2010	(1990-92) 32.40	(1993-2001) 4.74	(2002-2009) 11.55	(2010-12) 41.34
Henan	2002	1996	2005	2010	(1990-95) 12.29	(1996-2004) 9.84	(2005-2009) 26.34	(2010-12) 20.66
Hubei	2007	2000	2005	2009	(1990-99) 8.35	(2000-2004) 21.32	(2005-2008) 24.45	(2009-12) 21.00
Hunan	2004-2006-2007	2000	2004	2010	(1990-99) 2.96	(2000-03) 14.95	(2004-09) 16.71	(2010-12) 26.77
Inner Mongolia	2002	1994	2003	2010	(1990-93) 19.66	(1994-2002) 7.26	(2003-2009) 10.04	(2010-12) 21.80
Jiangsu	2000	2001	2006	2009	(1990-00) 9.04	(2001-2005) 30.49	(2006-2008) 44.76	(2009-12) 32.11
Jiangxi	2002	1996	2003	2009	(1990-1995) 8.23	(1996-2002) 8.72	(2003-2008) 11.22	(2009-12) 28.80
Jilin	2004	1998	2002	2007	(1990-97) 4.74	(1998-2001) 13.30	(2002-2006) 9.15	(2007-12) 10.57
Liaoning	2006	1999	2003	2009	(1990-98) 5.44	(1999-02) 15.43	(2003-08) 13.17	(2009-12) 16.24
Ningxia		1999	2002	2007	(1990-98) 4.07	(1999-2001) 23.87	(2002-06) 9.08	(2007-12) 14.87
Qinghai	2006	1998	2006	2010	(1990-97) 3.01	(1998-2005) 6.07	(2006-2009) 25.31	(2010-12) 13.78
Shaanxi	2003	2003	2007	2010	(1990-02) 3.94	(2003-06) 21.76	(2007-09) 35.86	(2010-12) 32.97
Shandong	2003	1993	2003	2006	(1990-92) 21.83	(1993-02) 10.79	(2003-05) 29.65	(2006-12) 21.64
Shanghai	1999	1996	2000	2005	(1990-95) 7.54	(1996-99) 21.11	(2000-04) 32.75	(2005-12) 14.10
Shanxi	2003	2000	2006	2009	(1990-99) 5.12	(2000-05) 9.06	(2006-08) 28.65	(2009-12) 30.22
Sichuan	2001	2000	2005	2009	(1990-99) 8.05	(2000-2004) 19.75	(2005-2008) 22.82	(2009-12) 29.89
Tianjin	2000	2002	2005	2010	(1990-01) 7.38	(2002-04) 43.92	(2005-2009) 14.70	(2010-12) 25.20
Xinjiang	2001	1993	2003	2010	(1990-92) 34.75	(1993-02 8.71	(2003-09) 11.74	(2010-12) 28.36
Yunnan	2003-2004	1994	2000	2008	(1990-93) 19.22	(1994-99) 6.70	(2000-07) 13.69	
Zhejiang	2001-2005-2006	1996	2002	2007	(1990-95) 11.59	(1996-01) 18.18	(2002-06) 28.88	(2007-12) 24.53