Firm ownership, industrial structure and regional innovation performance in China's provinces

Abstract

This paper uses panel data between 2000 and 2010 to explore how firm ownership and regional industrial structures contribute to regional innovation performance in Chinese provinces. Specifically, we explore how the extent of specialization and diversification in regional industrial structures at the province level foster both MAR and Jacobs spillovers, as well as how foreign and state ownership influence regional innovation. We find: (i) China's regional innovation systems benefit from Jacobs but not MAR externalities, with the former spurring higher quality innovation in the form of increased invention patenting; (ii) state owned enterprises and foreign invested enterprises advance local innovation, with the latter again fostering higher quality innovation; (iii) a convergence towards the combination of low specialization and high diversity in provincial industry is taking place between China's more developed inland coastal provinces and less developed inland provinces. Implications and suggestions for policy-making and future research are discussed.

Keywords: industrial structure, regional innovation performance, R&D, specialization, diversity, China

1. Introduction

Knowledge creation activities in regions are often geographically bounded due to the scope of knowledge spillovers and the tacit nature of knowledge transfer (Zucker et al., 2007; Döring and Schnellenbach, 2006). This geographic agglomeration of innovative activities differs between regions within national innovation systems (NIS), giving innovation systems a local character and highlighting the importance of the regional innovation system (RIS) (Jaffe, Trajtenberg, & Henderson, 1993; Cooke, Uranga, & Etxebarria, 1997). The importance of the RIS has in turn sparked considerable debate on whether and how specialized or diversified regional industrial structures impact on regional innovation capabilities (Buerger & Cantner, 2011; Desrochers & Leppala, 2010; Farahmand, Akbari, & Abootalebi, 2012; Lee, Peng, & Song, 2013; Glaeser, Kallal, Scheinkman, & Shleifer, 1992; Beaudry & Schiffauerova, 2009). Spillovers, in their MAR and Jacobs forms, may be important to regional innovation, but as yet there is limited research on this question for China's RIS, something we address here.

Industrial enterprises are, of course, highly heterogeneous. Such things as ownership structures, firm-size, technological level, firm-age, and the like, also matter for innovation. A lot of the literature to date has focused primarily on the role of inward FDI and foreign invested enterprises (FIEs) and their contribution to local innovation, including via spillovers (Ito et al., 2012; Fosfuri et al., 2001; Fu, 2008). Extant research has also focused on the role of specific industrial sectors as engines of RISs (Senker, 1996; Bell and Albu, 1999).Yet the role of domestic industrial enterprises, which are often owned by a variety of investors, including the state in the Chinese case, may also play a significant role in facilitating local knowledge absorption and creation (Li, 2011). Although ownership concentration in listed firms and the extent to which this impacts economic returns and performance, for example, has been studied (Fahlenbrach & Stulz, 2009; Florackis, Kostakis, & Ozkan, 2009; Rose, 2005), arguably our understanding of firm ownership affects regional innovation is still somewhat limited.

This paper attempts to link up the two aforementioned strands of debate regarding geographic agglomeration, spillovers and firm ownership. We do so using a large, high quality, panel data which operationalizes the most accepted and widely used measures of regional industrial specialization and diversity, as well as several accepted measures of innovative output (invention, utility and design patent) that also capture qualitative aspects of innovation. As China is a developing country with a highly unbalanced economic structure, our goal is to also provide further insights into China's RIS with a view to helping policy-making and pointing directions for future research. China and other emerging economies with unbalanced economic structures are acutely aware of the potential 'middle income trap' and the great need to improve innovation in order to avoid becoming stuck in it (World Bank, 2013).

The paper is organized as follows. The next section builds our hypotheses, following which we explain data and methodology. Results are then reported followed by discussion and concluding comments. Our discussion also draws from our results to investigate the influences of industrial structure and ownership in the three most innovative regions in China (Beijing, Shanghai and Guangdong) and two typical less developed (and less innovative) central regions (Hubei and Hunan, core members of the 'Central Rise' policy to develop inland-regions).

2. Ownership and MAR/Jacobs externalities

2.1 Foreign investment and regional innovation

How and to what extent domestic host economy and domestic enterprises benefit from the presence of FIEs (via their FDI) has attracted considerable scholarly attention. Many developing countries have tried hard to attract FDI to help address their lack of domestic capital and their comparatively weak technological bases (Ito et al., 2012; Sasidharan & Kathuria, 2011). First, FDI brings capital and new technology into the domestic market, which directly fuels domestic innovation and growth (Buckley, Wang, & Clegg, 2007). Second, the new products and services brought by FIEs also provides opportunities for domestic firms to improve their technological levels via learning and imitation (Potterie & Lichtenberg, 2001; Serapio & Dalton, 1999). Third, labor transfers from FIEs to local owned enterprises (LOEs) may enable the transfer of tacit knowledge as employees in FIEs are usually highly trained (Breschi & Lissoni, 2001). Finally, local firms can learn from FIEs through the creation of vertical linkages as suppliers to or customers of FIEs, as well as through competition with FIEs in both local and global markets (Fritsch and Franke, 2004; Liu et al., 2009). Generally, domestic enterprises can also indirectly reap benefits from FDI through several channels. There are numerous benefits, therefore, associated with inward foreign investment and the presence of foreign MNEs.

H1: The presence of FIEs is positively related to a regions' innovation capability.

State-owned and state-holding industrial enterprises (SOEs) are arguably other important players that may, under certain conditions, also influence innovation in China (Li, 2009). SOEs are usually believed to be bureaucratic organizations carrying heavy social burdens that are comparatively inefficient (Lin et al., 1998; Raiser, 1997). China, however, has undergone a process of rapid economic transition to a market based economy. Most SOEs have been significantly restructured, upgraded and improved during the last three decades (Raiser, 1997; Jing and Tylecote, 2005). During this process, Chinese SOEs have been able to maintain important relationships with central and local governments (Elfring & De Man, 1998), which have sometimes also provided them with special access to market and financial resources, which also help with the costs of innovating (Ramasamy, Yeung, & Laforet, 2012). SOEs are also much more likely to benefit from quasi monopoly market positions (Jefferson, Hu, Guan, & Yu, 2003) as the majority of Chinese SOEs are clustered in certain key sectors (e.g., oil and gas, telecommunications) that afford them such market power.

Although studies have considered the relationship between state ownership and innovation (Li, 2009), the specific effects of SOEs on regional innovation and the systems of regional innovation have not yet garnered much attention. This is of interest because of the considerable heterogeneity in regional ownership structures and concentration. Some studies argue that SOEs are less innovative because they are excessively wed to the directions of state policy and also have low overall levels of efficiency (Lin et al., 1998; Raiser, 1997). SOEs also generally face less domestic market competition than other types of local enterprises making them reluctant to conduct R&D activities as they face less competitive pressure to do so (Raiser, 1997; Gao, 2004). On the other hand, some point out that, to the contrary, SOEs are now facing increasing challenges from FIEs and local private SMEs and as a result they in fact have strong incentives to invest in R&D (Girma et al., 2009; Li, 2011). Moreover, Chinese policy-makers are endeavoring to move from being a 'world manufacturing factory' to becoming a 'global innovation centre' (Williams, Graham, Jakobs, & Lyytinen, 2011). SOEs are hoping to play an essential role in implementing this strategy and their investment in R&D and S&T projects (also with universities and research institutions) have increased dramatically. Annual R&D expenditures in China's largest state owned business groups, for example, grew by over 40% per annum between 1997 and 2008, far faster than other ownership classes (Big Business Group Yearbook, 2008). So SOEs may, after all, be conducive to local innovation in and the development of RISs.

H2a: The presence of SOEs is positively related to a region's innovation capability.

This being said, there is now also a general widespread concern about the quality of Chinese innovation (OECD, 2008; World Bank, 2013). While a scramble to register patents may be ongoing, an important consideration may also be the types of patents being registered and the actual extent of creative innovative activity embodied in these patents is also a concern. In particular, it has been suggested the innovative outputs of Chinese enterprise may not be comparable to their foreign counterparts, so leading to the '*middle income trap*' problem, in which China remains unable to compete in low value added labor-intensive sectors, but also unable to move to the cutting edge technological frontier (World Bank, 2013). As noted recently by the OECD, the capabilities for making productive use of the large accumulated investments in R&D, human resources for science and technology and related infrastructure, have developed much more slowly in the China's indigenous state sector businesses (OECD, 2008). Thus considerable question marks have been raised about the qualitative nature of the innovation being undertaken in the state sector.

> H2b: The qualitative nature of SOE related innovation outputs is inferior to that of FIEs.

2.2 Industrial externalities and local innovation

A branch of theory explaining the dynamics of regional innovation relates to industrial structure and the types of externalities that are created through the propensity for agglomerations or clusters which foster the right type of environment for innovation. Indeed, the overall institutional and environmental conditions in which innovation takes place are considered vital for China's long term innovative performance to improve (World Bank, 2013). Dynamic externalities are considered to strongly influence long-run industrial growth in the recent literature on endogenous growth (Beaudry and Schiffauerova, 2009). There are two broad types of externalities of regional industrial development, Marshall-Arrow-Romer (MAR) externalities associated with specialization and Jacobs externalities associated with diversification. The MAR model claims that the concentration of an industry in a region promotes knowledge spillovers between firms and facilitates innovation in that particular industry within that region (Beaudry and Schiffauerova, 2009). Jacobs (1969), by contrast, believed in diversity as the major engine for fruitful innovations, because *"the greater the sheer number of and variety of division of labour, the greater the economy's inherent capacity for adding still more kinds of goods and services"* (Jacobs, 1969, p. 59). Here the most important sources of knowledge spillovers are external to the industry within which the firm operates (Beaudry and Schiffauerova, 2009).

Studies supporting the MAR model emphasize knowledge transfer within the same or similar industries. Tacit or codified knowledge with lower transmission costs flows between actors within the same sector (Saxenian, 1994). This knowledge exchange is embedded within the labor mobility of skilled workers (Edler, Fier, & Grimpe, 2011), collaborative R&D activities (Gross, 2013; Liao and Yu, 2013) or even via enhanced communications (Storper and Venables, 2004). Second, industrial localization may lead to a less competitive, more monopolistic environment (Glaeser et al., 1992). These scholars believe that an insular environment protects innovation and that powerful companies within a local cluster can rearrange R&D resources more efficiently and pursue frontier technology more easily (Frenken, Oort, & Verburg, 2005; Mukkala, 2004). This argument has been supported by various cases in both developed countries and emerging market (Venables, 1996; Jaffe et al., 1993; Sun and Liu, 2010).

H3: Industrial specialization is positively related to a region’s innovation capability.

Supporters of the Jacobs model focus mainly on the interactive effect of communication between different industries, especially complementary sectors. Emerging technology fields benefit from a more diverse economy since they promote greater skill exchange between sectors (Harrison, Kelley, & Gant, 1996). Further opportunities to imitate, share and recombine ideas and practices across industries are believed to be embedded within a more diverse regional economy (Beaudry and Schiffauerova, 2009).

H4a: Industrial diversity is positively related to a region's innovation capability

Both specialization and diversification may both have advantages, depending upon ones viewpoint. At a conceptual level the question of which spillovers may be more powerful remains unresolved. As such it becomes an empirical question as to which type of externality exerts the more positive influence. In general, the majority of empirical studies do find positive empirical evidence for both Jacobs and MAR spillovers, with many studies finding their simultaneous presence (Beaudry and Schiffauerova, 2009). A recent meta-analysis of existing studies, however, found that the positive effects of inter-industry type Jacobs' spillovers were stronger than intra-industry type MAR spillovers (de Groot et al. 2009).

H4b: Industrial diversity in a region is more strongly associated with improved innovation capability than industrial specialization.

3. Data and methodology

We use multivariate regression analysis using panel data (2000-2010) of China's 30 provinces to further explore the hypotheses. Province level business ownership data is taken from the *China Statistic Yearbook* (National Bureau of Statistics of China (NBS)). The *China Statistic Yearbook on High Technology Industry* (NBS and National Development and Reform Commission (NDRC) and Ministry of Science and Technology (MOST)) is also used and data for calculating dynamic externalities via regional industrial specialization and diversity is collected from the *China Statistic Yearbook of Industrial and Economy* (NBS).[1]

3.1 Variable measurement

[1] Data collected from the NBS includes enterprises with gross output value exceeding 5 million RMB.

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Empirical papers favor patent count data as a legitimate source of reliable quality data capturing innovation output and local knowledge creation (Jaffe et al., 1993; Acs et al., 2002; von Wartburg et al., 2005; Cheung and Lin, 2004). Existing literature adopts patent count number in several ways, for example: by the amount of patent applications; number of granted patents; or patent forward citations as indicator for innovation output. Directly using patent applications and grants, however, suffers from several shortcomings. First, patent applications numbers in the yearbooks exaggerate the local innovation output as not every patent application will be approved. Second, due to the varying approval time required for patents according to the specific type, using numbers of granted patents in each year might create time lag biases. To overcome these problems, we use the granted patent count in the application year to measure regional innovation performance, collected manually from the SIPO website. Regional innovation capability is often measured by regional patent applications as intermediate innovative outputs (Fu, 2008; Liu and White, 1997; Usai, 2011; Wang and Zhou, 2013). Patent application count accurately represents innovation capability of individual regions as the same patent application standards and procedures are applied across regions (Huang et al., 2012; Li, 2011; Usai, 2011). Following Paci and Usai (1999), Fu (2008) and Huang et al. (2012), we use the number of total domestic patent applications per 10,000 inhabitants as the primary dependent variable, which reduces the heterogeneity of territorial units.

Further, to explore differences in the qualitative nature of innovative activity we also further decompose our total patent count measure to invention, design and utility sub-categories (see, for example, Table 4~~Table 4~~). Patents registered in SIPO can be classified into these three categories. The consensus of existing literature regards invention and utility model patents to encompass more novel knowledge or knowledge with greater economic potential than external design patents (Albuquerque, 2000; Motohashi, 2008; Li, 2012). By

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running separate regressions for each type of patent we can further ascertain insights into the qualitative impact of industrial structure and ownership on innovation (Table 4~~Table 4~~).

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3.2 Explanatory variables: capturing MAR and Jacobs externalities and FIEs and SOEs

There are no agreed upon proxies for MAR and Jacobs' externalities and it is generally agreed use of different proxies can be problematic for reaching a consensus regarding the impact of these externalities in the empirical literature (Beaudry and Schiffauerova, 2009). Nonetheless, we develop what we believe are comprehensive and accurate proxies of diversity and specialization that overcomes some of the empirical challenges. The first of these involves the level of aggregation at which industrial specialization and diversification are measured (ranging from 1 to the far finer 6 digit breakdown). It has been found that 'the probability to detect Jacobs externalities increases with the level of detail of industry classification' (it does not, however, have such tendency for MAR externalities) (Beaudry and Schiffauerova, 2009: 323). Our data adopts that level most commonly used in other studies, namely the 2-digit classification (Chinese Industrial Classification GB/T 4754 — 2002).

The second of these involves the measures of specialization and diversification. We also use the most commonly used proxies in other studies. To proxy conditions for possible MAR externalities we take local industrial specialization as a measure of the local concentration of an industry at the beginning of the sample period. The formula we use is:

$$S_{ij} = (\frac{y_{ij}}{y_{i.}}) / (\frac{y_{.j}}{y_{..}}) \qquad (1)$$

where y_{ij} is gross industrial output value in industry j in region i, $y_{i.}$ is the total industrial output in region i, $y_{.j}$ is the national industrial output in industry j, and $y_{..}$ is the total national industrial output. Hence, S_{ij} measures industry j's share of output in region i

relative to that in the entire country. A higher measure of S_{ij} indicates that region i is more specialized in industry j (Gao, 2004). Due to the availability of data at hand, we calculated industrial specialization indicators for 27 industries [2] (for details, see Table 4a and Table 5a in appendix).

According to Beaudry and Schiffauerova (2009), 35 of 67 studies use a 'share' measure as their measure of specialisation, where: 'Share represents indicators based on the relative sizes of the industry, where the proportion a particular industry within the same or other industries in the country, region, and so on, are calculated' (Beaudry and Schiffauerova, 2009: 322). By comparison, the second most popular measure (employment related) was used in 17 studies.

For Jacobs' externatlities we employed the concept of diversity to mirror the extent to which local industrial structure was diversified. Let $\varphi_{ij} = (y_{ij} / y_{i.})$ be industry j's share of industry in region i. Then a Hirschman-Herfindahl index can be used as a measure of local industrial diversity.

$$D_{ij} = \sum_{k \neq j} \varphi_{ik}^2 \tag{2}$$

The bigger of D_{ij}, the less level of diversity of local industrial structure in the region. This definition follows (Henderson, 1997; Gao, 2004). In order to make the measure of diversity has positive monotonicity, we minus D_{ij} from 1. That is

$$d_{ij} = 1 - \sum_{k \neq j} \varphi_{ik}^2 \tag{3}$$

Therefore, the higher of d_{ij}, the more diversified of local industrial structure. Since diversity is a regional level indicator, we adopted the average of specializations of all local industries to display overall specialization of industrial structure at regional level.

[2] The number of local industries changed from 2000 to 2008 due to the modification of industrial catalog made by NBS.

$$RS_i = \sum_{j=1}^{n} S_{ij} / n \qquad (4)$$

where n is the amount of local industries.

It has been found that 38 of 67 studies measuring Jacobs externalities also used HHI to measure diversification, making it by far the most commonly used measure (Beaudry and Schiffauerova, 2009: 323). By comparison, the second most popular measure (employment in innovative and non-innovative firms) was used in only 10 studies.

Finally, to test the relationship between FIEs and regional innovation capability, we employ the proportion of total industrial output value contributed by local FIEs in a region to measure the presence of enterprises with foreign ownership, following Buckley et al. (2002) and Tian (2006). To test the relationship between SOEs and regional innovation capability, we employ the proportion of total industrial output value contributed by local SOEs in a region to measure the presence of SOEs, following (Gao, 2004).

3.3 Control variables

We also control for a number of factors that might influence regional innovative activity. The definitions, operationalization and data source for each variable are summarized in Table 1~~Table 1~~. Regions with higher levels of R&D expenditures are more likely to innovate, as R&D investment (capital) creates new products and production process (Griliches, 1992; Jaffe et al., 1993; Usai, 2011; Wang, 2010). We therefore control for regional R&D intensity (*RDI*), which is the ratio of regional R&D expenditure over GDP.

The availability of human capital (*HRC*) particularly the skilled labor force, is another important influence on regional innovation as regional human capital represents the capability to absorb and recognize external knowledge (Fu, 2008; Mankiw et al., 1992; Wang, 2010). We thus control for (*HRC*), which is calculated as the ratio of residents with tertiary degrees divided by regional total inhabitants. Moreover, regional scale can have an effect on

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innovative output as increasing returns to scale yield externalities (Feldman and Audretsch, 1999). To account for such impacts, we use the natural logarithm of the number of total employees (*EMP*) in a region as a proxy for the economic size of the regions.

We also expect that R&D activities thrive in regions with high rates of economic and industrial growth (Rodríguez-Pose and Crescenzi, 2008). These regions attract more foreign and domestic investment for innovation and grow faster (Fu et al., 2011). We use regional GDP growth rate (*GDP*) as a proxy to control for the effect of regional economic growth potential across regions and sectors (Cheung and Lin, 2004).

As knowledge spillovers take time to be absorbed and affect a region's innovation capability, we use a *one year lag* for all independent variables in our regression estimations. The underlying assumption is that patents are a result of a lengthy innovative process. Another advantage of lagging all independent variables by a year is that this procedure can remove possible endogeneity (Fu, 2008; Usai, 2011).

Table 1 Definition and descriptions of variables

Variable name	Acronym	Operationalization
1. Regional patent count	PAT_{it}	Natural logarithm of patent applications/10000 inhabitants of region *i* in year *t-1*
2. Research intensity	$RDI_{i,t-1}$	Natural logarithm of R&D expenditure/GDP of region *i* in year *t-1*
3. Human capital	$HRC_{i,t-1}$	Natural logarithm of the proportion of local residents with a tertiary degree of region *i* in year *t-1*
4. GDP growth rate	$GDP_{i,t-1}$	Natural logarithm of GDP growth rate of region *i* in year *t-1*
5. Employment	$EMP_{i,t-1}$	Natural logarithm of number of employees of region *i* in year *t-1*
6. Foreign invested enterprises	$FIE_{i,t-1}$	Natural logarithm of the proportion of the output of FIEs against total output of region *i* in year *t-1*1
7. State owned enterprises	$SOE_{i,t-1}$	Natural logarithm of the proportion of the output of SOEs against total output of region *i* in year *t-1*1
8.Specialization	$SPE_{i,t-1}$	Natural logarithm of Formula (4) in year *t-1*
9.Diversity	$DIV_{i,t-1}$	Natural logarithm of Formula (3) in year *t-1*

Sources: China Statistical Yearbook on Science and Technology, China Industry Economy Statistical Yearbook, and Chinese Statistiacl Yearbook in various years.

3.4 Descriptive statistics

Following prior studies (Cheung and Lin, 2004; Fu, 2008), the Lagrange Multiplier and Hausman tests are adopted to determine the choice between a random- and fixed-effects models. The results of the Hausman test are significant, indicating that it is appropriate to adopt a fixed-effects model for our estimations.

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The mean, standard deviation, and correlations of all variables show most of the independent variable correlation coefficients are smaller than 0.40. The highest correlation value of 0.58 is between regional human capital and R&D intensity and we further compute Variance Inflation Factors (VIF) to ensure the results will not be affected by multicollinearity. VIF values for each independent variable are shown (bottom line of Table 2~~Table 2~~). The largest VIF values is 2.65 that is much smaller than the threshold of 10 (Belsley, 1980). We include the average value of VIF for each estimation, all of which are smaller than 2.1. Multicollinearity is therefore not a serious concern.

Table 2 Descriptive statistics and correlation matrix

Variable	1	2	3	4	5	6	7	8	9
1. PAT_{it}	1.00								
2. $RDI_{i,t-1}$	0.73*	1.00							
3. $HRC_{i,t-1}$	0.71*	0.58*	1.00						
4. $GDP_{i,t-1}$	0.45*	0.31*	0.25*	1.00					
5. $EMP_{i,t-1}$	0.09	0.12	-0.30*	-0.01	1.00				
6. $FIE_{i,t-1}$	0.71*	0.48*	0.42*	0.36*	0.12	1.00			
7. $SOE_{i,t-1}$	0.02	0.25*	0.30*	0.00	-0.40*	-0.38*	1.00		
8. $SPE_{i,t-1}$	-0.07	-0.09	-0.05	-0.15	-0.04	-0.01	0.00	1.00	
9. $DIV_{i,t-1}$	0.14*	0.07	0.14	0.27*	0.04	-0.03	0.06	0.08	1.00
Mean	6.05	1.14	7.36	12.38	2200.32	26.69	48.15	1.04	0.98
S.D.	0.23	0.97	5.07	2.35	1504.17	23.83	17.40	0.41	0.21
VIF		2.65	2.64	2.44	2.37	1.77	1.16	1.12	1.07

Note: The panel consists of 30 regions for 10 years (2001-2010).

4. Results

Table 3~~Table 3~~ provides the regression results of all models using domestic patent applications per 10,000 inhabitants as the dependent variable (with fixed effects). All estimates are

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corrected for heteroskedasticity using Huber-White robust standard errors clustered by regions. The F tests are all significant.

Table 3 Panel regression using all patent applications as dependent variable

	Model 1	Model 2	Model 3	Model4
$RDI_{i,t-1}$	0.927***	0.556*	0.796**	0.469
	(0.288)	(0.288)	(0.301)	(0.312)
$HRC_{i,t-1}$	0.983***	0.804***	0.887***	0.707***
	(0.255)	(0.222)	(0.216)	(0.191)
$GDP_{i,t-1}$	0.608**	0.353*	0.705**	0.418*
	(0.240)	(0.188)	(0.257)	(0.218)
$EMP_{i,t-1}$	0.182***	0.283***	0.174**	0.246***
	(0.064)	(0.071)	(0.064)	(0.066)
$SOE_{i,t-1}$		0.998***		1.055***
		(0.325)		(0.324)
$FIE_{i,t-1}$		0.469***		0.424**
		(0.145)		(0.179)
$SPE_{i,t-1}$			0.068***	0.027
			(0.014)	(0.025)
$DIV_{i,t-1}$			0.471*	0.548**
			(0.262)	(0.266)
Constant	-3.794***	-8.754***	-3.787***	-8.538***
	(0.904)	(1.685)	(0.842)	(1.588)
R^2	0.5616	0.6122	0.5863	0.6301
F test	50.10***	44.30***	31.89***	32.65***
Observation	300	300	300	300
VIF	1.63	2.11	1.47	1.90

Notes: Regional patent applications per 10,000 inhabitants. T-statistics are reported in parentheses, * p<0.1, ** p<0.05, *** p<0.01. Robust standard errors clustered by regions reported in parentheses.

Models 1, 2, 3 and 4 report the results using a one-year lag between all independent variables and regional innovation capability in terms of patenting per 10,000 inhabitants (Table 3~~Table 3~~). As the base model for estimating, the first model includes control variables, the second and third model include the effects of different industrial ownerships and industrial structures associated with spillovers, respectively. All explanatory variables are introduced in model 4.

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In hypothesis 1 and 2a, we hypothesized that FIEs and SOEs are two contributors to regional innovation. Model 4 shows that the effect of SOEs is positive with a significance at

0.01 level (β=1.055, p<0.01, model 4) and the effect of FIEs is also statistically positive on regional patenting per 10,000 inhabitants (β=0.424, p<0.01, model 4). Meanwhile, in hypothesis 3 and 4a, we hypothesized that industrial specialization and diversity have positive externalities on regional innovativeness. Table 3~~Table 3~~ illustrates that industrial specialization is positively related to regional innovativeness but the effect is not statistically significant (β=0.027, p>0.1, model 4). By contrast, the effect of industrial diversity is positive on regional patenting and also statistically significant (β=0.548, p<0.01, model 4). Therefore, hypothesis 4a is supported but 3 is not.

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As noted, considering that invention and utility model patents are generally considered to embody more novel knowledge than external design patents, we further examine these measures of innovativeness as our dependent variable (again using patents per 10,000 inhabitants) (Table 4~~Table 4~~) to explore hypotheses 2b and 4b, which consider the qualitative nature of regional innovation. Models 14, 15 and 16 in Table 4~~Table 4~~ illustrate that the effect of SOE concentration on all three types of regional patenting is positive and statistically significant. The effect of SOEs on external design patenting, however, is much larger than on invention and utility models patenting. This indicates that SOEs have a comparative focus on innovation that embodies less novel knowledge. The effect of local FIEs on all three types of patenting is also statistically positive but the effect is comparatively far stronger for invention and design patents rather than utility models. This partially supports hypothesis 2b.

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Turning again to MAR and Jacobs spillovers and their qualitative nature, we find a statistically significant positive effect for specialization (i.e. MAR spillovers) on utility models (β=0.043, p<0.05, model 15) but not on invention and external design patents. The effect of industrial diversity (i.e. Jacobs spillovers), by contrast, is statistically positive on both invention (β=0.527, p<0.4, model 14) and utility models patenting (β=0.505, p<0.1, model 15). This result is in line with some prior studies that show specialization is conducive to incremental innovations while diversity is a facilitator for more radical innovations (Frenkin et al. 2005). These results therefore also support the view of the earlier finding that diversification, possibly via the creation of Jacobs type externalities, is a more important driver of Chinese regional innovation than specialization (and MAR type externalities).

Table 4. Panel regression using three types of patent applications as dependent variable

	Model 5 (invention)	Model 6 (utility)	Model 7 (design)	Model 8 (invention)	Model 9 (utility)	Model 10 (design)	Model 11 (invention)	Model 12 (utility)	Model 13 (design)	Model 14 (invention)	Model 15 (utility)	Model 16 (design)
$RDI_{i,t-1}$	1.294***	0.940***	0.582	0.914***	0.678**	0.076	1.162***	0.815***	0.488	0.832**	0.603**	0.017
	(0.297)	(0.244)	(0.376)	(0.311)	(0.253)	(0.349)	(0.311)	(0.252)	(0.404)	(0.344)	(0.274)	(0.375)
$HRC_{i,t-1}$	1.049***	0.914***	1.014***	0.871***	0.784***	0.762**	0.955***	0.822***	0.959***	0.632**	0.699***	0.696**
	(0.262)	(0.220)	(0.341)	(0.235)	(0.205)	(0.286)	(0.225)	(0.197)	(0.299)	(0.260)	(0.192)	(0.253)
$GDP_{i,t-1}$	0.819***	0.344*	0.889**	0.564**	0.161	0.534**	0.922***	0.439**	0.977**	0.632**	0.253	0.565*
	(0.261)	(0.198)	(0.341)	(0.231)	(0.168)	(0.250)	(0.275)	(0.213)	(0.364)	(0.260)	(0.196)	(0.282)
$EMP_{i,t-1}$	0.244***	0.277***	-0.044	0.336***	0.355***	0.108	0.241***	0.271***	-0.030	0.301***	0.330***	0.080
	(0.074)	(0.057)	(0.090)	(0.070)	(0.065)	(0.102)	(0.075)	(0.060)	(0.089)	(0.069)	(0.064)	(0.097)
$SOE_{i,t-1}$				0.839**	0.808***	1.575***				0.893**	0.856***	1.615***
				(0.365)	(0.280)	(0.460)				(0.371)	(0.273)	(0.466)
$FIE_{i,t-1}$				0.502***	0.318**	0.615***				0.454**	0.249*	0.596**
				(0.169)	(0.128)	(0.178)				(0.200)	(0.143)	(0.239)
$SPE_{i,t-1}$							0.073***	0.067***	0.068***	0.029	0.043**	0.011
							(0.014)	(0.012)	(0.024)	(0.024)	(0.019)	(0.042)
$DIV_{i,t-1}$							0.458*	0.446*	0.245	0.527*	0.505*	0.362
							(0.268)	(0.247)	(0.372)	(0.301)	(0.259)	(0.325)
Constant	-6.213***	-4.588***	-4.241***	-10.595***	-8.484***	-11.824***	-6.252***	-4.595***	-4.457***	-10.394***	-8.333***	-11.66***
	(1.026)	(0.784)	(1.148)	(1.767)	(1.536)	(2.210)	(0.969)	(0.761)	(1.113)	(1.642)	(1.414)	(2.170)
R^2	0.6549	0.5899	0.3568	0.6926	0.6226	0.4348	0.6749	0.6170	0.3682	0.7058	0.6444	0.4402
F test	64.34***	45.33***	17.75***	40.72***	32.47***	17.33***	38.73***	27.17***	12.84***	29.75***	23.12***	14.31***
Observation	300	300	300	300	300	300	300	300	300	300	300	300

Notes: Regional patent applications per 10,000 inhabitants. T-statistics are reported in parentheses, * p<0.1, ** p<0.05, *** p<0.01. Robust standard errors clustered by regions reported in parentheses.

5. Discussion and conclusions

Our results suggest provincial industrial structures may influence the RIS in China, particularly via Jacobs' spillovers and, in turn, Chinese innovation. Foreign investment and presence of SOEs also has an impact, with the former seemingly more important than the latter. What therefore is the regional balance (or imbalance) and overall nature of provincial industrial structures, including specialization, diversification and ownership, in China? Are levels of specialization and diversification highly heterogeneous and how have these been evolving? Are certain regions, as a result, more or less likely to benefit from these spillovers than others?

To further explore these questions we now additionally consider some cross-sectional snapshots from our provincial data-set that describe and compare the three most innovative regions in China (Beijing, Shanghai and Guangdong) with two typical less developed (and less innovative) central regions. We use Hubei and Hunan, core members of the *'Central Rise'* policy to develop inland-regions implemented since 2006. Beijing and Shanghai are China's political and financial centers, respectively. Guangdong pioneered the *'Open door'* reforms implemented from 1980s (see these regions on a map of China in figure 1).

They are highly innovative regions compares the amount of each type of patents filed in each region in this period. Beijing and Shanghai's innovation growth have clearly been driven by invention patents (

Table 5~~Table 5~~) while in Guangdong, although the absolute volume of each type of patent is larger than the other two coastal regions, it is dominated by external design.

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For the two central regions, utility models are more common than invention and design.

Table 5 Increase rate and change of share of the three types of patent from 2000 to 2010

Region	Increase rate (%)			Change of share (%)		
	Invention	Utility	Design	Invention	Utility	Design
Beijing	922	355	167	23	-12	-11
Shanghai	432	815	472	-8	11	-3
Guangdong	2180	750	321	21	5	-26
Hubei	846	560	743	6	-8	2
Hunan	669	354	572	8	-33	25

Source: Compiled by authors using collected data from SIPO website.

5.1 MAR and Jacobs externalities and regional Chinese innovation

How have levels of industrial specialization and diversification been evolving and are certain regions more likely to benefit from spillovers than others? Table 6~~Table 6~~ shows each of these regions, with the exception of Hubei, became more specialized between 2000 and 2008. As a whole the big three regions were specialized in technology intensive industries while the two central regions, by contrast, were specialized in labor or capital intensive industries. The impact of specialization on regional innovation, however, has earlier been shown to be limited (Table 3~~Table 3~~). More interesting then is the question of diversification and the potential for regional Jacobs' spillovers.

Figures 2 and 3 graphically illustrate regional trends in diversity and specialization. The circles represent the two central regions (Hubei and Hunan) and diamonds Beijing, Shanghai and Guangdong. We set the level of specialization of 1.0 and the diversity of 0.85 as criteria so as to divide four segments within a matrix. Each segment captures different types of comparative industrial structure: low

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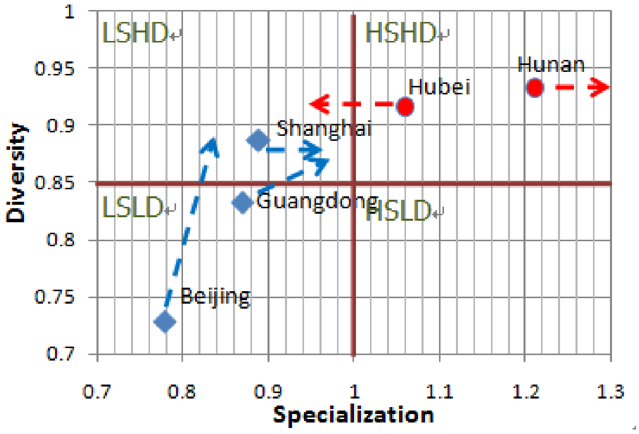
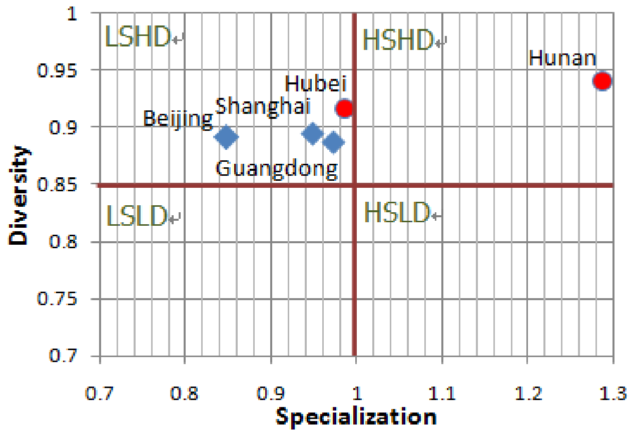
specialization and low diversification (LSLD), low specialization and high diversification (LSHD), high specialization and low diversification (HSLD), high specialization and high diversification (HSHD). These segments illustrate the relative degree of specialization and diversity.



Source: Compiled by authors using the aforementioned estimation data.
Figure 2 Matrix of specialization and diversity of the five regions in 2000



Source: Compiled by authors using the aforementioned estimation data.
Figure 3 Matrix of specialization and diversity of the five regions in 2008

The figures show (also see Table 6~~Table 6~~) Beijing and Guangdong, in keeping with their status as innovative regions, appear to have become considerably more

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diversified (increasing by 0.16 and 0.06 respectively) in terms of their industrial mix over this period. This potentially may have helped them reap additional Jacobs type spillover benefits, those we have also found to be associated with qualitatively superior innovation (i.e. invention and utility model patents). It is interesting to also note, however, that both Hubei and Hunan could potentially have, at least initially, also have benefitted from these to an even to a greater extent than their developed region counterparts (Table 6~~Table 6~~). While the levels of diversification in these central regions remained static, they are nonetheless high and exceed the levels seen in the coastal regions. This suggests that the impacts of these spillovers are likely only one of the elements determining innovation, and arguably minor. While considerable increases in diversification were witnessed in the coastal developed regions, it is arguably the far higher levels of FIE (and SOE) activities, with the potential for high value innovation, that have made the major impact on innovation.

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Table 6 Specialization and diversity of local industrial structure in the five regions

Region	Specialization		Diversity	
	2000	2008	2000	2008
Beijing	0.78	0.85	0.73	0.89
Shanghai	0.89	0.95	0.89	0.90
Guangdong	0.87	0.97	0.83	0.89
Hubei	1.06	0.99	0.92	0.92
Hunan	1.21	1.29	0.93	0.94

Source: Compiled by authors using data collected from China Industry and Economy Statistic Yearbook.

The arrows in Figure 2 indicate the direction of regional movement between 2000 and 2008. They show Hunan remained stable in the area of HSHD while Hubei shifted from HSHD to LSHD. Beijing and Guangdong were located in LSLD initially in 2000. Beijing had considerably lower levels of specialization and diversification than Shanghai and Guangdong. However, during a decade of restructuring, both

Guangdong and Beijing edged into LSHD, and became more similar to Shanghai. Beijing's transformation has been considerable: specialization and diversity increased 0.07 and 0.16, respectively.

The figures suggest that the degree of specialization and diversification therefore appear to be undergoing a convergence process. We further observe that LSHD has become the most common structure, with Beijing, Guangdong and Hubei moving into this quadrant during the sample period (and Shanghai is also there but has taken a small step towards greater specialization). Convergence towards a particular portfolio of industrial specialization and diversity at the regional level may be taking place in China (Huallacháin and Lee, 2011).

As regards specialization, our overall results showed it to have no effect on innovation as measured by total (all kinds) of patents. At the level of different patent types, however, some did show increased patenting activity (i.e. utility models). Clearly, the inland regions appear to have higher levels of specialization (although these were also universally increasing in the coastal regions), so may potentially benefit from these. However, it is worth keeping in mind that the big three coastal regions were far more concentrated in technology intensive industries, such as electronics *and telecommunications Equipment*, *instruments and meters* and *general Machinery*'. By contrast, Hubei and Hunan were more specialized in areas such as t*obacco processing* and *mining*. Generally, the share of gross output of 'high technology enterprises' (HTEs) of the big three regions was around 20% during the sample period. It was much lower in Hubei and Hunan and the contribution to local innovation output made by local hi-tech industries was not significant in these two provinces (Prevezer et al., 2012). The coastal regions, by contrast, had become the R&D center of China. For example, the gross output and amount of patent applications of *electronics and telecommunications equipment* in Guangdong accounted for 36% and 71% respectively of total the total patent applications in the whole China (Prevezer, Li, & Panzarasa, 2012). HTEs have clustered in coastal regions in China (Hu et al., 2005; Zhou & Xin, 2003). As they are more likely to produce more innovative novel knowledge the share of inventions and utility models of the big-three regions indicates the potential linkage between HTEs and high quality R&D outputs. By contrast, although levels of specialization may be generally higher and have also in some cases increased (i.e. Hunan), because the industries in which these inland provinces are specializing in have limited innovative potentiality, the impacts of increased specialization have been limited.

To summarize, in general there has been a convergence process in play in provincial industrial structures. By 2008, for example, there were close similarities in levels of industrial diversification, according to our findings the more important source of spillovers (i.e. of the Jacobs type). This suggests other, more important factors, are driving the wide disparities in innovation performance across regions.

5.2 Ownership: provincial disparities in FIEs and SOEs

MAR and Jacobs spillovers, as mentioned, are of course only one of many factors affecting regional innovation. The developed regions of China also benefit enormously from foreign investment and a proliferation of large central SOE groups. There is considerable regional heterogeneity within China's RIS regarding the contribution of SOEs and FIEs (Table 7~~Table 7~~). How different levels of SOEs and FIEs affect the innovative capacity of a region is therefore also an important question. Our earlier findings show that while SOEs do drive patenting activity, FIEs are arguably a still more important source. To what extent does the presence of FIEs and SOEs drive regional innovation performance in China?

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Comparisons of the five regions point to considerable geographical differences and heterogeneity in the contributions of FIEs and SOEs. Table 7~~Table 7~~ shows the deflated absolute value and shares of gross industrial output of SOEs, FIEs and collective-owned enterprises (COEs), limited liability enterprises (LLEs) and private enterprises (POEs). [3]

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Table 7 Gross industrial output value and proportion of local industrial enterprises in the five regions

Region	2000				2010			
	SOE	FIE	COE	LLE	SOE	FIE	POE	Others
Beijing	1742.7[a]	1150.3	175.3	164.0	4853.3	3667.3	543.6	123.7
	(0.54[b])	(0.36)	(0.05)	(0.05)	(0.53)	(0.40)	(0.06)	(0.01)
Shanghai	3205.1	3431.2	394.8	464.8	7490.3	12321.1	2331.5	1014
	(0.43)	(0.46)	(0.05)	(0.06)	(0.32)	(0.53)	(0.10)	(0.04)
Guangdong	3126.1	7274.4	1202.5	809.6	8812.8	30468	10844.1	7321.3
	(0.25)	(0.59)	(0.10)	(0.07)	(0.15)	(0.53)	(0.19)	(0.13)
Hubei	1929.0	336.3	564.5	545.8	5769.2	2909.4	3859.6	1935.1
	(0.57)	(0.10)	(0.17)	(0.16)	(0.40)	(0.20)	(0.27)	(0.13)
Hunan	1077.5	97.1	241.7	238.3	3590.9	938.4	5492.7	2701.5
	(0.65)	(0.06)	(0.15)	(0.14)	(0.28)	(0.07)	(0.43)	(0.21)

Note: [a] The unit of the output is 100 million RMB. [b] Figure in the parenthesis is the share of output in respective to the total output of a region.
Source: Compiled by the authors using data collected from the National Bureau of Statistics, P.R.China, various years.

The gross industrial output values of SOEs and FIEs in the big-three regions accounts for a very large proportion of the local industrial output (for instance, 90% in Beijing in 2000 increasing to 93% in 2010). In contrast, the contribution of SOEs and FIEs in the central regions was lower, decreasing from 67% to 60% and 71% to 35% in Hubei and Hunan, respectively. The position of SOEs and FIEs was by no means as important in these inland, less developed regions. FIEs in Shanghai and Guangdong were the biggest players, contributing over half of local industrial output in both periods. Beijing, by contrast, was more dependent on local SOEs, which accounted

[3] We deflated output values in 2010 to 2000 prices using deflators provided by *World Bank* dataset For details, refer to http://data.worldbank.org/country/china.

for 54% and 53% of local industrial output in 2000 and 2010, respectively. This clearly may also go some way to explaining the differing levels of invention, utility and design patents registered between the regions (**Error! Reference source not found.**~~Figure 2~~).

Although SOEs in Hubei were also the largest contributors to industrial output, their share had declined from 57% to 40%, while the contribution of FIEs increased 10%. Moreover, the industrial structure of Hunan was significantly reshaped during this period by small-scale private enterprises, not SOEs. FIEs accounted for less than 10% of Hunan's industrial output during the sample period. The industrial structures of Beijing and Hubei were therefore most driven by large SOEs, in Shanghai and Guangdong FIEs were most important, and Hunan was becoming dominated by private enterprises. From the perspective of the number of local industrial enterprises we can draw very similar conclusions: namely that FIEs clustered in Beijing, Shanghai and Guangdong whereas POEs grew rapidly in Hubei and Hunan during the period. Evidence using the number of employees shows similar patterns.

SOEs and FIEs are the main contributors to regional economies. The proportion of these enterprises exceeds half of local gross industrial output value. For Beijing, Shanghai and Guangdong, the role played by SOEs and FIEs was stable and important. Meanwhile, FIEs in Shanghai and Guangdong were more active than in other regions. POEs become the main contributor for local economy in Hunan in 2010. Considering that POEs usually do not have significant R&D expenditures and R&D personnel, their innovation strategies are more likely to focus on shorter term profitability, and their innovation outputs are also lower quality than SOEs and FIEs. This is why the share of utility model patents declined 33% while the share of external design patents increased 25% during 2000 to 2010.

All in all, i~~I~~n the debate on MAR and Jacobs externalities there has been considerable uncertainty on the impacts of each (Beaudry & Schiffauerova, 2009). As Beaudry and Schiffauerova (2009: 319) note: ‘the question as to which of the Marshall– Arrow–Romer (MAR) or Jacobs externalities is the most beneficial to growth or innovation is rather complex’. This is in part because it ‘depends on the way it is measured, where it is measured, on which industries, at which level of aggregation’ (Beaudry and Schiffauerova, 2009: 319).

To the best of our knowledge few studies have considered their potential impact on regional innovation in China. Here we find evidence to support the idea that China’s provinces may benefit from higher levels of industrial diversification. We also found that provinces with higher levels of foreign and state ownership performed better at innovation. Specifically, FIEs led to significantly more increase in invention patents, whereas SOEs contributed seemingly to lower value added innovations, albeit actively.

It is difficult to precisely understand the relationship between industrial structure and regional innovation performance and the contribution of MAR and Jacobs externalities. This is in part because of the uncertainty about how to measure diversification and specialization, what scale of geographical unit of analysis to use and what dependent variables are most appropriate to measure innovation. Future studies can no doubt consider alternative levels of industrial disaggregation (i.e. 3, 4, 5 or even 6 digit levels), different units of geographical analysis (i.e. probably smaller) and different dependent variable measurements to see if similar results are found. Our first attempt at this question for China, as noted, has tried to adopt an empirical stance that is closely informed by previous studies and thus one that creates results that may be broadly comparable. Future research might also try and undertake more detailed case work to identify the microeconomic foundations of the intra and inter-industrial knowledge spillovers at work in the different regions of China. As Desrochers and Leppala (2011) note, these still remain something of an unopened 'black box', particularly in the case of a large and diverse emerging market like China.

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Appendices

Figure 1 Administrative divisions of People's Republic of China (PRC)

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Table 3 The top three specialized industries in the five regions in 2000 and 2008

Region	2000		2008		
	Production.	SPE.		Production.	SPE.
Beijing					
Electronic and Telecommunication Equipment	1199.03	2.90	Electronic and Telecommunication Equipment	2378.29	2.58
Oil and Refinement	115.44	1.68	Instrument & Meter	208.48	2.01
Beverage Production	77.16	1.43	Electricity & Heat	1242.39	1.94
Shanghai					
Transportation Equipment	813.09	1.75	Electronic and Telecommunication Equipment	5158.73	2.49
Ferrous metal	450.27	1.53	General Machinery	2183.02	1.89
Chemical Fibers	159.66	1.43	Transportation Equipment	2552.21	1.61
Guangdong					
Instrument & Meter	321.92	2.28	Electronic and Telecommunication Equipment	14956.36	3.07
Electronic and Telecommunication Equipment	3490.78	2.06	Instrument & Meter	1316.22	2.41
Electrical Machinery Equipment	1368.12	1.67	Electrical Machinery Equipment	6964.17	2.07
Hubei					
Transportation Equipment	451.77	2.24	Transportation Equipment	2397.03	2.64
Food Process	164.88	1.46	Nonmetal Minerals Mining & Dressing	114.36	2.28
Pharmaceutical Production	114.16	1.40	Tobacco Processing	257.6	2.10
Hunan					
Tobacco Processing	59.65	3.91	Tobacco Processing	412.86	4.00
Nonferrous Metal	86.05	2.83	Nonmetal Minerals Mining & Dressing	123.56	2.92
Oil and Refinement	56.79	1.91	Nonferrous Metal	177.82	2.90

Note: The unit for the production is 100 million RMB as 1990's price. SPE.=specialization
Source: Compiled by authors from China Industry and Economy Statistic Yearbook

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Table 4a The number and share of the three types patents in 2000 and 2010

Region	2000			2010		
	Invention (%)	Utility (%)	Design (%)	Invention (%)	Utility (%)	Design (%)
Beijing	3176	3778	1683	32471	17188	4490
	(37)	(44)	(19)	(60)	(32)	(8)
Shanghai	4406	2263	2373	23446	20699	13585
	(49)	25	(26)	(41)	(36)	(23)
Guangdong	1705	5025	11792	38789	42708	49622
	(9)	(27)	(64)	(30)	(32)	(38)
Hubei	699	1529	491	6613	10090	4137
	(26)	(56)	(18)	(32)	(48)	(20)
Hunan	707	1713	603	5434	7782	4053
	(23)	(57)	(20)	(31)	(24)	(45)

Note: Figures in the parentheses show the total as a percentage of the full regional sample.
Source: Compiled by authors by using data collected from the website of SIPO.