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China's Regional Inequality in Innovation Capability, 1995–2006

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Abstract

This paper assesses both interregional and intraregional innovation inequality in China from 1995 to 2006. It is revealed that the east–central–west inequality has increased over time, whereas the inter-provincial inequality showed a V-pattern until 2003; Both inequality measures oscillated from 2004 to 2006. Using a decomposition framework recently developed by one of the authors, we determined that the major factors driving innovation inequality are population, economic development level, R&D, location and openness. The aggravated innovation inequality reflects the growth of China's innovation centers in the eastern region and their admission into the global innovation networks. The fact that R&D is a major factor driving the inequality suggests that, considered in the present study, the efficiency of R&D investment improved in certian regions during the period (1995–2006). Finally, geographic location and openness affect innovation inequality primarily through the coupled evolution of innovation capability and economic development, resulting in first-mover advantages to provinces of the eastern region.

Key words: China, inequality decomposition, innovation, regional disparity
JEL codes: O3, O31, O38, R12

I. Introduction

Innovation has become an increasingly important determinant of economic growth (Barsberg, 1987; Fargerberg, 1994). Recognizing the importance of innovation, the Chinese Government

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has been instrumental in directing the country towards becoming a knowledge economy. Recent policy initiatives include the National High-technology Research and Development Plan (863 Plan), the National Basic Sciences Initiative (973 Plan) and the Torch program that specifically aims at facilitating commercialization of scientific research outcomes. Furthermore, the government has set up 53 national high-technology parks to attract foreign high-technology firms and to encourage the development of domestic high-technology companies. These policy initiatives have undoubtedly promoted innovation activities in China. According to Fan and Watanabe (2006), technological progress accounted for more than 40 percent of the economic growth in China during the period from 1981 to 2000. Recent studies by the OECD and the World Bank (OECD, 2008, 2009; Zhang *et al*., 2009) also highlight the improvement in China's innovation capability and its contribution to national economic growth.

Since the market reform in the 1980s, China has achieved remarkable economic development, with an impressive average GDP growth rate of 9 percent. However, against this outstanding national achievement is the increasing inequality in economic development at regional (the eastern, the central and the western regions) and provincial levels. The rich provinces (measured by GDP per capita) have grown faster than poor provinces. For instance, from 1978 to 1997, whereas rich provinces, such as Jiangsu, Zejiang, Fujian, Guangdong and Hainan, grew at an annual rate of 10.4 percent, the average rate of growth for poor provinces, such as Heilongjiang, Qinghai and Tibet, was only around 6 percent during the same period (Bao *et al*., 2002).

Consequently, a considerable literature has emerged on regional income inequality in China (see Wan, 2008). Overall, China's economic inequality at the provincial level declined during the early 1980s, but has increased since the mid-1980s (Chen and Fleisher, 1996; Tsui, 1996; Bao *et al*., 2002; Wan *et al*., 2007). Such research also identifies several variables that affect economic inequality, including factor endowments (e.g. location, labor and infrastructure) and policy related factors (e.g. booming capital investment in coastal provinces, decentralization, agglomerations, improved factor mobility, openness and capital input).

In stark contrast with the well-researched economic inequality, only a few studies have assessed the regional inequality in innovation capability in China (Hu and Xiong, 2000). Given the predominant role of innovation in economic growth and the rapidly rising regional inequality in China, two issues deserve special research attention. First, it is interesting to examine innovation inequality in China. Such research has been undertaken in terms of patent application (Sun, 2000; Liu and White, 2001a; Li, 2009). Second, more importantly, it is crucial to analyze sources or contributing factors of innovation inequality. Although there are studies focusing on determinants of innovation capabilities in China and elsewhere (Guerrero and Sero, 1997), no previous attempt has been made to quantify contributions of various determinants to the inequality of innovation. The typical regression model in the current literature (e.g. Gurrero and Sero, 1997; Sun, 2000; Liu and White, 2001a; Li, 2009) can only be used to gauge the impacts of independent variables on the level of innovation, not the inequality of innovation. The latter requires a regression-based inequality decomposition (see Wan, 2004).

The present paper represents a first attempt to measure and analyze factor contributions to China's regional inequality in innovation capability from 1995 to 2006. We specifically address the following research questions:

1 What was the status of China's regional inequality in innovation capability and how did it change from 1995 to 2006?

2 How much did the relevant factors contribute to the level of innovation capability and how much did they contribute to the regional inequality in innovation capability?

3 What insights and policy implications can we offer from the quantitative analysis?

The paper is structured as follows. In Section II, we review the limited literature on innovation inequality in China and provide a preliminary data analysis. This is followed in Section III by measurement of innovation inequality in China. Section IV presents a regression analysis as well as a decomposition of innovation inequality. Section V discusses the findings of our analysis. Section VI concludes.

II. Literature Review and Preliminary Data Analysis

Utilizing patent data, Li (2009), Liu and White (2001a) and Sun (2000, 2003) are among the few studies to explore innovation inequality in China. Estimating a stochastic frontier model to explain the increasing disparity in innovation performance (indicated by patent data from 1998 to 2003) between China's regions, Li (2009) shows that government support, the constitution of the R&D performers and the regional industry-specific innovation environment are significant determinants of innovation efficiency. Li emphasizes that the innovation efficiency between regions becomes more disparate when innovation modes are transformed from being university and research institute dominant to being firm dominant.

Using a primary index, a top-five index, a top-ten index and the coefficient of variation to indicate spatial pattern of innovation, Sun (2000) finds that patents in China were highly clustered in the east–coastal region and the inland provinces, although the degree of spatial concentration declined from 1985 to 1995. When other indicators of innovation, such as new product sales and R&D spending are used, the spatial concentration is found to be on the rise in the 1990s (Sun, 2003).

Sun (2003) classifies the provinces into two groups and applies a logistic regression to model the cluster membership resulting from the classification. Provinces in Cluster 1 spend more on in-house R&D, and those in Cluster 2 spend more on imported technologies. The four independent variables for the logistic regression are GDP per capita, size of science and technology staff, ratio of international trade to GDP, and a coast–inland dummy variable. However, the model does not work well as none of the independent variables are significant. Also using patent numbers from 1985 to 1995 and a regression model, Liu and White (2001a) suggest that economic activity and innovation inputs (i.e. R&D funding and personnel) lead to differences in innovation performance of regions.

Innovation capability can be measured using different indexes, such as those tracking R&D inputs, patent counts, paper citations and new product announcements (Hu and Xiong, 2000). In the present paper, we follow Audretsch and Feldman (2004) and use patent data as a proxy measure for innovation capability.[1] Hagedoorn and Colldt (2003) find that statistical overlap between various innovativeness indicators is substantial and any of these indicators, including patents, may be used to measure innovation capability. In fact, patents are generally accepted as one of the most appropriate measures for innovation capability (Mansfield, 1986; Barsberg, 1987; Griliches, 1990).

In China, the State Intellectual Property office examines and certifies different types of patents. The invention patents refer to those that are novel and have been developed to the point where they can be used in industry. The utility model patents are creations or improvements relating to the form, construction or fitting of an object, generally having a lower technical requirement than invention patents. The design patents refer to original designs relating to the shape, pattern, color or a combination thereof of objects (China State Intellectual Property Office, website: www. sipo. gov. cn).

Currently, patent data is the most reliable data available at province level for our study period (from 1995–2006). Data for other indicators, such as patent royalty payments and technical journal articles, are not available at provincial level every year. Patents also have an advantage over other indicators because the three kinds of patents indicate different levels of innovation capability. Furthermore, the present paper focuses on decomposing the innovation inequality, a complicated but effective procedure that reveals what caused the inequality; therefore, we use only the most effective indicator, patents.

Relying on the *China Statistical Yearbook on Science and Technology* (National Bureau of Statistics of China, 1995–2007) and the *China Statistical Yearbook* from 1994 to

[1] Patent data have some weaknesses, such as sectoral differences in patenting behavior, and difference in patenting between large and small firms. Furthermore, not all the innovations are patented and the patent counts equalize the economic significance of different new technologies.

2007 (National Bureau of Statistics of China, 1994–2007), we compiled a set of data on innovation and relevant determinants at the regional or provincial level.[2] Table 1 displays number of patents granted in 1995 and 2006, including numbers of inventions, utility model patents and design patents. The table reveals that the eastern region dominated in terms of the number of certified patents, especially Guangdong, Zhejiang, Jiangsu and Shanghai. In

Table 1. Patents in China, 1995 and 2006

Year	1995				2006				R	
By province	Total	Inventions	Utility models	Designs	Total	Inventions	Utility models	Designs	1995	2006
Eastern region										
Beijing	4025	328	3169	528	11 238	3864	5490	1884	11.41	4.39
Tianjin	1034	63	785	186	4159	967	2164	1028	3.53	2.39
Hebei	1580	56	1341	183	4131	407	2699	1025	0.79	0.37
Liaoning	2745	131	2362	252	7399	1063	5277	1059	2.15	1.07
Shanghai	1436	72	1025	339	16 602	2644	6739	7219	3.38	5.65
Jiangsu	2413	72	1884	457	19 352	1631	8849	8872	1.10	1.58
Zhejiang	2131	54	1455	622	30 968	1424	10 503	19 041	1.58	3.84
Fujian	933	17	439	477	6412	310	2578	3524	0.93	1.11
Shandong	2861	84	2222	555	15 937	1092	10 389	4456	1.05	1.06
Guangdong	4611	56	1447	3108	43 516	2441	15 644	25 431	2.20	2.89
Guangxi	665	20	457	188	1442	183	803	456	0.47	0.19
Hainan	108	4	44	60	248	39	103	106	0.48	0.18
Central region										
Shanxi	569	47	480	42	1421	314	890	217	0.60	0.26
Inner Mongolia	415	8	293	114	978	108	543	327	0.59	0.25
Jilin	824	38	723	63	2319	449	1466	404	1.02	0.53
Heilongjiang	1403	44	1248	111	3622	565	2488	569	1.22	0.58
Anhui	574	18	469	87	2235	272	1308	655	0.31	0.23
Jiangxi	509	19	402	88	1536	157	896	483	0.40	0.22
Henan	1145	34	1009	102	5242	450	3260	1532	0.40	0.34
Hubei	1017	55	868	94	4734	855	3031	848	0.57	0.51
Hunan	1515	51	1318	146	5608	581	2540	2487	0.76	0.55
Western region										
Sichuan	2019	79	1486	454	11 728	922	4579	6227	0.57	0.66
Guizhou	274	12	207	55	1337	188	862	287	0.25	0.22
Yunnan	569	35	346	188	1637	355	689	593	0.46	0.23
Shaanxi	1085	52	934	99	2473	602	1443	428	0.99	0.41
Gansu	257	7	215	35	832	145	514	173	0.34	0.20
Qinghai	65	2	61	2	97	30	45	22	0.44	0.11
Ningxia	111	4	98	9	290	64	142	84	0.70	0.30
Xinjiang	312	9	286	17	1187	107	805	275	0.61	0.36
By region										
Eastern China	24 542	957	16 630	6955	161 404	16 065	71 238	74 101	1.60	1.78
Center China	7971	314	6810	847	27 695	3751	16 422	7522	0.60	0.39
Western China	4692	200	3633	859	19 581	2413	9079	8089	0.55	0.42
Total	37 205	1471	27 073	8661	208 680	22 229	96 739	89 712	1	1

Notes: We exclude Tibet from our analysis because data for Tibet are unavailable for earlier years. The total patents granted do not include those for Hong Kong, Macau and Taiwan. The figures for Sichuan include the figures for Chongqing City. The location quotient is calculated for total patents only. The total population used in our calculation does not include the military population, nor the populations of Hong Kong, Macau and Taiwan. R, regional per capita patents relative to national average.

[2] We divide China into three regions: the eastern region, the central region and the western region. Although this division is rough, it is the most widely accepted division of regions in the published literature and, currently, there are few good alternatives. More importantly, our model takes each province as a basic unit of analysis. Therefore, in this paper, innovation inequality and its determinants are assessed both at the regional and the provincial level.

sharp contrast, other regions, particularly the western region, fell behind. We also report regional per capita patents relative to the national average, denoted by R. Thus, a region with R > 1 performs better in creating patents than the national average, and vice versa.

Table 1 indicates that, over time, the eastern region increased its R value from 1.60 in 1995 to 1.78 in 2006, demonstrating that the gap between the eastern region and other regions expanded. Looking into individual regions, some provinces/cities (e.g. Beijing, Tianjin, Liaoning, Heilongjiang and Shaanxi) underwent significant drops, while others (such as Shanghai, Zhejiang and Guangdong) experienced substantial gains in R values. In 2006, all provinces in Eastern China, except Hebei, Guangxi, Hainan and Shanxi, possessed R values greater than one. In contrast, provinces in the central and western regions all had R values smaller than one.

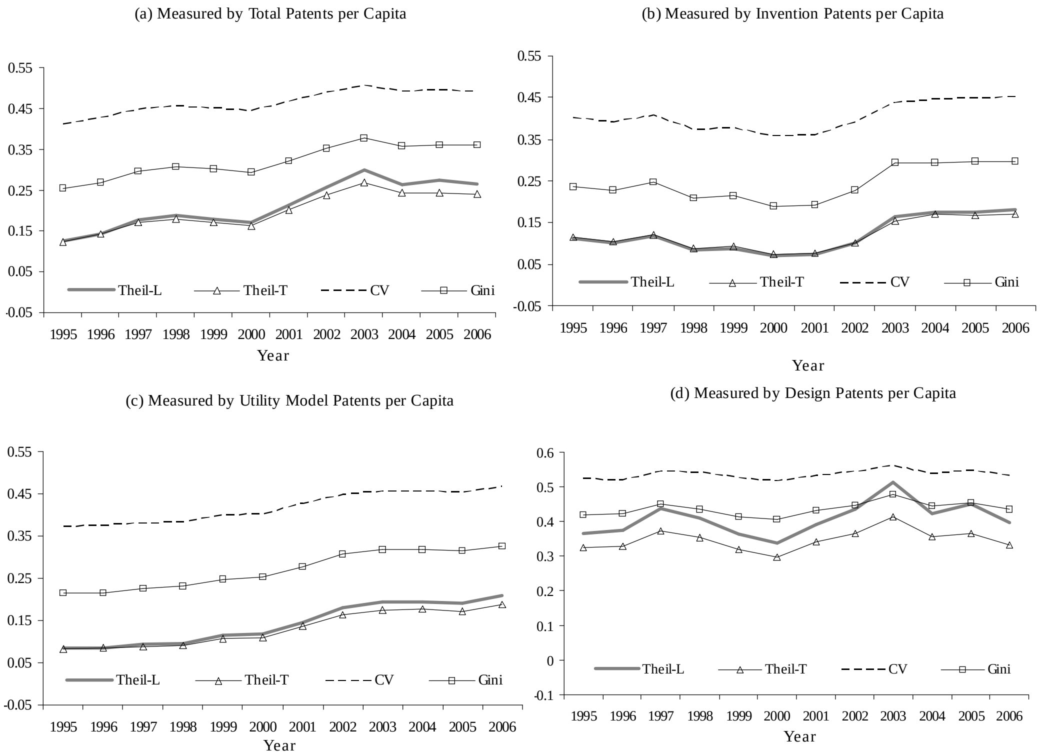
III. Measuring Innovation Inequality

We use the following four indices to formally measure innovation inequality: the coefficient of variation (CV), the Gini coefficient and the two commonly used generalized entropy indices, Theil-L and Theil-T. Figure 1 displays innovation inequality at the regional level for total patent number and its three components. All inequality indexes displayed a similar trend of innovation inequality at the regional level. The innovation inequality measured by total patents increased from 1995 to 2003 (Figure 1a), with a notable drop in 2000, before leveling from 2004 to 2006. The trend differs for innovation inequalities measured using different types of patents. Although the innovation inequality measured by invention patents followed an approximate U-shape, the inequality measured by utility model patents rose continually. Inequality measured by design patents fluctuated around the same level of inequality from 1995 to 2006 and had higher values than the other two inequality measures.

Figure 2 shows innovation inequalities at the provincial level. For invention patents, all indexes showed that the inequality oscillated around the same level, with a dip in 2000 and 2001. For utility model and design patents, the inequality decreased from 1995 to 2000, but increased from 2000 to 2003 (although design patents exhibited a much sharper increase), then decreased or maintained the same level from 2003 to 2006. The trends of inequalities measured by utility model and design patents are shared by the inequality of total patents. This is not surprising as utility model and design patents constitute a greater portion of total patents.[3]

[3] These results seem to be in line with Sun (2000, 2003), who finds a decline in patent concentration from 1985 to 1995 and an increasing concentration afterwards. It should be noted that Sun uses total patent number rather than patent per capita in calculating the inequality indexes.

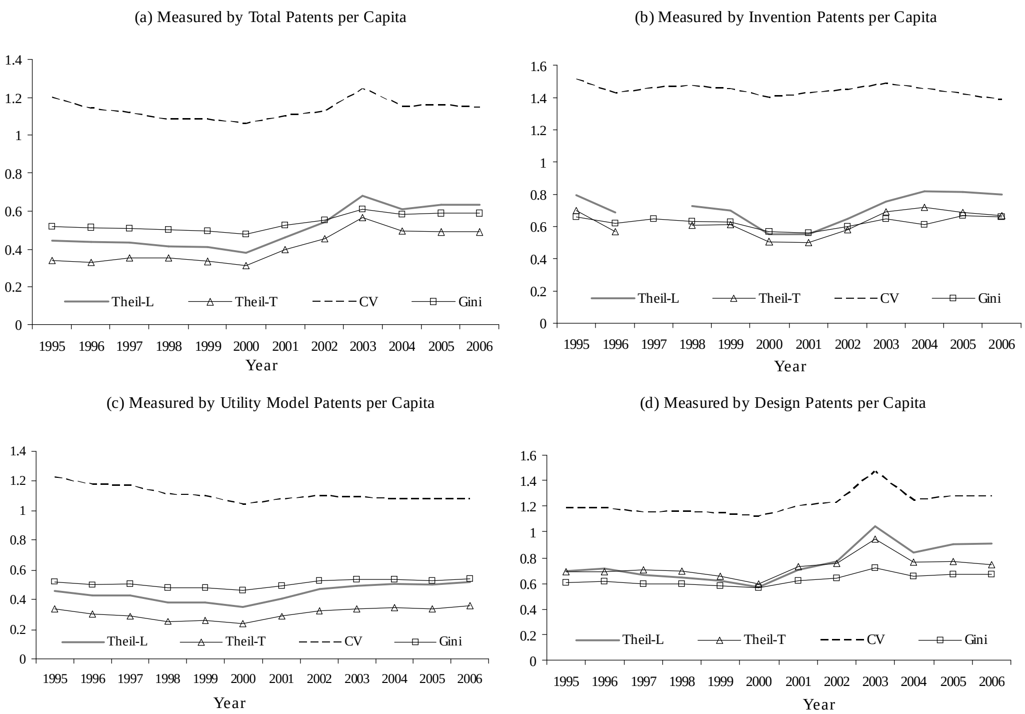
Figure 1. Innovation Inequality at Regional Level



Note: CV, coefficient of variation.

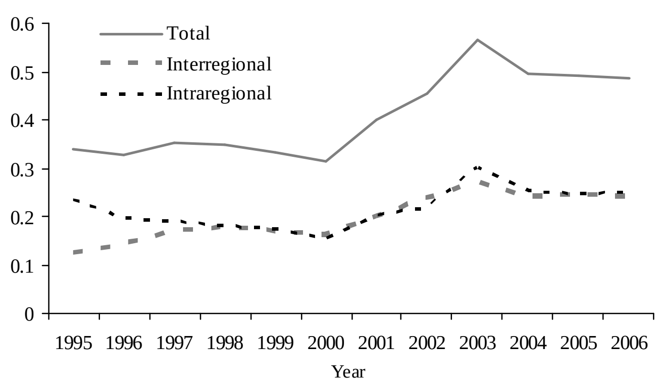
As a prelude to the regression-based decomposition in the next section, we examine the composition of total regional inequality in innovation capability by decomposing the Theil-T index. The decomposition breaks down total inequality into two components: one caused by the differences between the regions (interregional or between-group component) and the other caused by the difference within the regions (within-group or intraregional component). Applying this to our data, the results reveal that both components contributed significantly to the total inequality in innovation capability (Figure 3). Interregional innovation inequality increased over time until 2003 (with a dip around 2000) then declined afterwards. Intraregional innovation inequality first declined from 1995 to 2000, rose sharply until 2003, then declined and maintained the same level from 2003 to 2006. The overall increased interregional innovation inequality from 1995 to 2003 corresponded to the widening gap in economic growth between the east region and the central and western regions in the 1990s and the early 2000s. The declining interregional innovation inequality after 2003, in contrast, may be associated with the catching-up of the central and western regions in economic development through programs such as the West China Development Program.

Figure 2. Innovation Inequality at Provincial Level



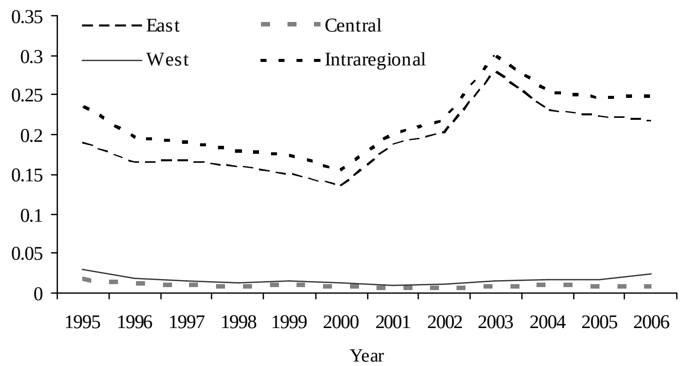
Note: CV, coefficient of variation.

Figure 3. Decomposition of Interprovincial Innovation Inequality



To highlight the specific changes at the regional level, we further decompose the intraregional innovation inequality of the Theil-T index into contributions by the three regions, the eastern region, the central region and the western region (Figure 4). The provincial units of the regions can be found in Table 1. The decomposition shows that the

Figure 4. Decomposition of Intraregional Innovation Inequality



innovation inequality in the eastern region was significantly higher than in the central and the western regions. Although both the central and the western regions maintained very low inequality with little change, the eastern region contributed the most to the total intraregional innovation inequality. The eastern region includes 12 coastal provinces that vary greatly in terms of factors critical to innovation activities, which will be detailed in the next section. In contrast, provinces in the central and western regions bear more similarities with each other. The analysis of income inequality also indicates that the eastern region contributed the most to the intraregional inequality (Fan and Sun, 2008).

IV. Decomposing Innovation Inequality

To implement the regression-based inequality decomposition, we first need to model innovation as a knowledge production function. A conventional functional form is:

$$Y_i = aRD_i^b HK_i^g e_i , \tag{1}$$

where Y stands for the output of innovation activity, RD represents R&D inputs and HK represents human capital inputs. The subscript i represents the unit of observation, such as regions, industries or enterprises (Audretsch and Feldman, 2004). To incorporate the spatial dimension, Jaffe (1989) modifies the above traditional model and uses:

$$Y_{si} = aIRD^{b1} * UR_{si}^{b2} * (UR_{si} * GC_{si}^{b3}) * e_{si} , \tag{2}$$

where IRD is private corporate expenditure on R&D, UR is the research expenditure at universities and GC measures the geographic coincidence of university and corporate research. The subscript si represents a state (s) and an industry (i). Equation (2) is also used by Acs *et al*. (1992) and Feldman (1994) in modeling innovation.

In studying China's patent distribution, Sun (2000) uses the same model specification to investigate the contribution of the level of regional development, R&D, openness (import, export and presence of foreign enterprises) and agglomeration (urbanization) to patent production, but finds that R&D and agglomeration are not significant factors. However, Sun did not intend to quantify the impacts of various input factors on the spatial inequality of innovations. The regression model is only suitable for explaining the level of innovation capability, not its spatial variation. In what follows, we will first estimate a regression model and then use the estimated model to conduct an inequality decomposition.

1. Regression Analysis: Innovation Capability

Using the published consumer price indexes and the provincial price index of Brandt and Holz (2006), we deflated all observations in value terms. To deal with the delay between innovation inputs and output, we follow Gurrero and Sero (1997) by lagging independent variables by 1 year in our empirical model. This also helps alleviate the possible simultaneity problem.

We follow the "general-to-specific" modeling strategy in this paper (i.e. we start with as many explanatory variables as possible subject to data availability). To explain the per capita number of patents (*Y*), education and R&D funding ought to be considered. Therefore, we include average years of schooling of labor force (*Edu*) and per capita public R&D funding (*RD*) as independent variables. Following Sun (2000), we use rate of urbanization (*Urban*) to capture possible agglomeration effects. Because most inventions occur in the non-farming sectors, it is necessary to control for structure of economic activities. For this purpose, we take share of agricultural GDP (*Stru*) as an independent variable. We also include per capita GDP (*GDP*), the trade/GDP ratio (*Opent*) and the foreign direct investment/GDP ratio (*Openf*). *GDP* represents level of development and *Opent* and *Opentf* may either stimulate or crowd out domestic innovative capability. We incorporate location variables by defining *D1* and *D2* as the dummy variables for the eastern region and the central region, respectively. To allow for nonlinearity, we also include the squares of education and R&D in the model. Difference in the impacts of education on inventions across regional belts are considered by adding *D1*Edu* and *D2*Edu*. Finally, year dummies are used to denote reform and other time-dependent forces underlying innovation. To minimize missing variable bias, several extra variables are considered, including total population (*Pop*), consumer price index (*CPI*) and per capita value of high-technology product (*HT*). Population size may bring about economies of scale or economies of specialization in innovative activities. *CPI* signals macroeconomic environment and *HT* may reflect non-public R&D inputs.

Following earlier studies of innovation, we use a double-log form similar to Equations (1) and (2) to fit the Chinese data. The log–log specification involves taking

Table 2. Regressional Model Estimation Results

	Coefficent	Standard error	*t*	*P* > |*t*|
*RD**	–0.2884	0.1160	–2.49	0.013
*RD2**	0.0750	0.0144	5.22	0.000
Edu	0.7755	0.2312	3.35	0.001
Edu2	–0.0488	0.0172	–2.84	0.005
Openf	–0.0329	0.0070	–4.70	0.000
Opent	0.0066	0.0008	8.33	0.000
Urban	–0.0064	0.0025	–2.54	0.011
Stru	0.0064	0.0038	1.68	0.094
*GDP**	0.9948	0.0941	10.57	0.000
*HT**	0.0134	0.0130	1.03	0.304
CPI	1.0895	0.2356	4.63	0.000
*D1*Edu*	–0.0548	0.0658	–0.83	0.405
*D2*Edu*	0.2089	0.0621	3.36	0.001
D1	0.4136	0.5036	0.82	0.412
D2	–1.7024	0.4607	–3.70	0.000
*Pop**	0.0234	0.0403	0.58	0.562
year_1996	–0.4159	0.0808	–5.15	0.000
year_1997	–0.5212	0.0926	–5.63	0.000
year_1998	–0.3946	0.0993	–3.97	0.000
year_1999	0.1269	0.1044	1.22	0.225
year_2000	0.0144	0.1053	0.14	0.891
year_2001	–0.2331	0.1089	–2.14	0.033
year_2002	–0.3349	0.1151	–2.91	0.004
year_2003	–0.2766	0.1159	–2.39	0.018
year_2004	–0.4832	0.1238	–3.90	0.000
year_2005	–0.7957	0.1415	–5.62	0.000
year_2006	–0.6688	0.1357	–4.93	0.000
Constant	–4.5262	0.8833	–5.12	0.000
Number of observations	348			
F(27, 320)	183.42			
Adjusted R^2	0.9342			

Note: * Log transformation is done on variable.

logarithms of both the dependent and independent variables, with the exception of ratio, year and dummy variables. The OLS estimation result of this model is tabulated in Table 2.[4]

One may argue that one or more of the independent variables could be endogenous, although the time-variant variables have already been lagged by 1 year to capture the lag between innovation inputs and innovation output. Consequently, we re-estimate the model using the generalized method of moment (GMM) technique of Blundell and Bond (1998) that allows for serial correlation within individuals and allows for endogeneity. We can then apply the Hausman test with the null hypothesis that the GMM and OLS estimation results are not systematically different (Hausman, 1978). The Hausman test result indicates

[4] There are several estimation methods for panel data models. One popular approach is to use OLS with fixed effects. An alternative is to take the first difference and then apply OLS. The latter would remove regional dummy variables from the model. Because we need the coefficient estimates for dummy variables for inequality decomposition, OLS with fixed effects is preferred here.

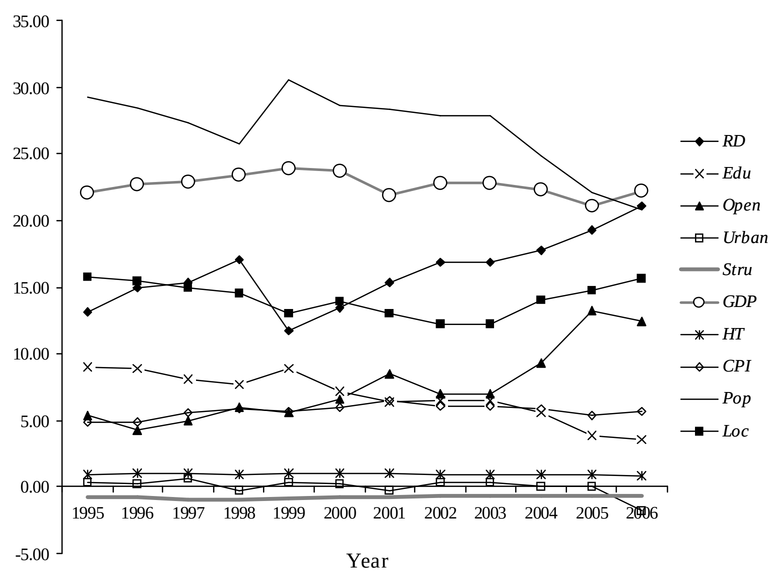
absence of significant endogeneity bias in our log–log model. Therefore, we will base our decomposition on the log–log model.

2. Regression-based Inequality Decomposition

We now conduct the decomposition exercise to quantify contributions of relevant factors to the inequality of innovation capability in China. It is known that different measures of inequality often produce different results, which may carry over to inequality decomposition. In this section, we present the decomposition using the Gini index because it is the most widely acknowledged index for inequality analysis. Decompositions based on Theil-L and Theil-T produced similar results.

Following Wan *et al*. (2007), we combine all regional dummy variable terms, naming them *Loc*, to represent location, and *D1*Edu* is merged with *Edu* and *Edu2* to form *HC* (human capital). *Opent* and *Openf* are combined to represent globalization, denoted by *Open*. All other variables retain their original definitions. To briefly explain the technique developed by Wan (2004), the residual represents the contribution made by variables not included in our model. All remaining inequalities are explainable by variables included in the model (see Wan *et al*., 2007). The decomposition results (i.e. percentage contributions by various factors to innovation inequality from 1995 to 2006) are shown in Figure 5. They

Figure 5. Percentage Contribution of Various Factors to Regional Innovation Inequality



Notes: *RD*, per capita public R&D funding; *Edu*, average years of schooling of labor force; *Urban*, rate of urbanization; *Open*, globalization; *Stru*, share of agricultural GDP; *HT*, per capita value of high-technology product; *Pop*, total population; *CPI*, consumer price index; *Loc*, location.

indicate that variations in population, level of economic development, R&D investment and location are the four factors contributing most to regional innovation inequality in China.

V. Discussion

Our findings, when placed in the context of China's regional income inequality, evolving national innovation system, geographic locations of regions, and its integration with the global economy, can offer the following insights for policy-makers. First, the innovation inequality implies the rise of China's own innovation centers in the eastern region and their admission into the global innovation networks; it also highlights a coupled evolution between innovation capability and economic development that may either help or trap policy-makers. Second, our results suggest that regions in China have improved in terms of the efficiency of R&D investment during the period (1995–2006), possibly due to the change of the structural composition of R&D (i.e. moving from government-supported R&D to market-driven R&D). Third, geographic location and openness affect innovation inequality primarily through the coupled evolution of innovation capability and economic development, resulting in first-mover advantages to eastern region provinces in further improving innovation capability.

1. Aggravated Innovation Inequality

The distribution of patents per capita and the four inequality indices demonstrate the increased spatial concentration of innovation activities in China's eastern region, especially in provinces/cities such as Shanghai, Beijing, Zhejiang, Guangzhou and Tianjin. In reverse to the decline of innovation inequality from 1985 to 1995 (Sun, 2000), we found that innovation inequality actually increased at both regional and provincial levels from 1995 to 2003. Until 2003, regional (east–central–west) inequality increased over time and interprovincial inequality exhibited a V-pattern, then both oscillated around the same level from 2004 to 2006 (Figures 1–4).

This aggravated inequality in innovation implies an increase in China's innovation clusters due to the economies of scale or economies of specialization in innovation activities. Geographic agglomeration of innovation activities tends to occur in large urban areas and knowledge spillovers are geographically bounded (Nelson and Winter, 1982; Jaffe *et al*., 1993; Feldman, 1994). Most published studies on clustering of innovation activities focus on industrialized countries (Feldman, 1994; Guerrero and Sero, 1997); for instance, innovation and new products clustered in states such as New Jersey, Massachusetts, California and

New York in the USA (Feldman and Florida, 1994). However, emerging economies have started to appear in the landscape of global innovation networks. Transmission of knowledge and geographical agglomeration of innovation activities, enabled by direct and frequent face-to-face contact (Dosi, 1988), low transaction costs (Scott, 1998) and economies of scale and scope (Krugman, 1991), are more likely to be found in large provincial capitals of Chinese provinces with large population sizes. Shanghai, Beijing and Zhejiang in China, as well as Bangalore and Hyderabad in India are such examples from the emerging countries and have been increasingly recognized as essential members of global innovation networks (Ernst,2006).

Our findings also indicate the coupled evolution of innovation capability and economic development, even for an emerging country like China. During the period of analysis, regional innovation inequality shared a similar trend with China's income inequality (Bao *et al*., 2002; Wan *et al*., 2007; Fan and Sun, 2008). In addition, while innovation capability is frequently cited as a significant factor in explaining regional and international economic variation (Fargerberg, 1994), our decomposition result shows that the level of economic development (GDP per capita) has been the most important factor contributing to China's regional disparity in innovation capability, accounting for approximately 20–25 percent of the inequality, demonstrating a high correlation between innovation capability and economic development.

Policy-makers need to take advantage of and avoid pitfalls of this coupled evolution between innovation capability and economic development. In the past two decades, to promote sustained economic development, some Chinese provinces with higher levels of economic development have accumulated enough resources and deliberately upgraded their industrial structures to be knowledge-intensive, leading to clusters of innovation activities in their large urban areas. In contrast, the lagging provinces, especially those in China's west, are extremely limited in terms of resources to further economic development or improve innovation capability. The central and regional governments need to pay special attention to the needs of these provinces.

2. R&D Investment, Human Capital and National Innovation System

Needless to say, the output of a knowledge economy, here indicated by patent numbers, is closely associated with inputs such as R&D investment and human capital. Our results show that, from 1995 to 2006, R&D investment increased its contribution and became the second most important factor affecting China's regional disparity in innovation capability, accounting for 20 percent of the inequality, next only to economic development level. Our finding, based on the data from 1995 to 2006, indicates the opposite of the finding of Sun (2000), who, based on data from 1985 to 1995, states that R&D is not a significant factor for innovation in China due to the inefficiency of R&D investment sponsored by the government. This inconsistency may be due to the different methodologies and data used. Placing results from the regression and decomposition analysis in the context of the changing national innovation systems in China, we are in line with others (Gu and Lundvall, 2006; Li, 2009) in stating that the change of the structural composition of R&D (i.e. from government-supported R&D to market-driven R&D) led to not only the geographic concentration of innovation outcomes between regions, but also the increased efficiency of R&D investment in China's national and regional innovation systems.

The most prominent change in China's national innovation system has been the transition from having mainly government-sponsored R&D for public research institutes and universities to having market-driven R&D for businesses, especially large and medium enterprises (Liu and White, 2001b; Gu and Lundvall, 2006). In fact, enterprises have invested heavily in innovation activities, reflected by their significantly increasing share of science and technology funding from 1991 to 2001 and R&D expenditure from 1995 to 2001 (Fan and Watanabe, 2006). Industrial enterprises now own the majority of utility model and design patents. However, due to data limitations, we did not study how the spatial disparity in enterprises and their R&D investment affect inequality of innovation capability. We suggest that this independent variable be added in future research.

It is worth mentioning that human capital is found to be not as significant as other factors mentioned above in driving the inequality in China's innovation capability and its contribution declined gradually over the period considered in the present study. Human capital is considered an important input of knowledge production (Audretsch and Feldman, 2004) and a crucial element of a regional innovation system (Asheim and Vang, 2006). However, the results of the present paper indicate that the inequality in average labor talent (measured by years of education) has a limited impact on inequality in patents creation. As patents were created by a very small portion of the highly skilled labor force, we recognize this as one of the limitations of this empirical study. Therefore, we suggest that in future research, if data is available, highly skilled labor force numbers should be used rather than average labor talent as an indicator for specialized human capital.

3. Geographic Locations, Openness and Innovation Inequality

Our results highlight that geographic location (the region that a province belongs to) and openness (trade and foreign direct investment) contribute significantly to innovation inequality, accounting for 15 and 10 percent of the inequality, respectively. We argue that geographic location and openness affect innovation inequality primarily through the coupled evolution between innovation capability and economic development, and that provinces in the eastern region possess first-mover advantages. Although some provinces, such as

Guangxi and Hainan, remain backward in innovation capability, most provinces in the eastern region rank highly in terms of innovation capability, as well as in level of economic development (Bao *et al*., 2002; Fan and Sun, 2008).

Geographic location and openness have been recognized as important factors contributing to China's regional gap in economic development (Bao *et al*., 2002), which started to increase in the middle of the 1980s before dramatically widening in 1992 after the initiation of the radical opening policy to attract foreign investment and trade. Economic growth has been led by the provinces in the eastern region, whose economies took off from 1992. Although more or less the same preferential policies were in place for foreign investors in provinces across China, an overwhelming proportion of foreign investors were drawn to the coastal regions due to location and transportation advantages. In the 1990s, most foreign investors in coastal regions were engaged in processing trade, and imported raw materials and parts, processed and assembled them, and then exported the final products to the world market (Bao *et al*., 2002).

The coupled evolution of economic development and innovation capability provided a head start for provinces in the eastern region to upgrade their industrial infrastructure and attract R&D-intensive investment (including foreign direct investment) and international trade activities. For instance, in the 1990s, Shanghai worked hard to attract high-technology industries and invested heavily in human capital to attract knowledge-intensive activities, especially from foreign direct investment (Asheim and Vang, 2006). In the 1980s, Guangdong transformed itself from an economic backward province to one of the economic leaders in the country by developing export-oriented processing, mainly through attracting oversea investment from Hong Kong, Macau and Taiwan (HKMT), taking full advantage of its geographic and cultural proximity. When advantages in export-oriented processing industries gradually diminished in the 1990s, Guangdong focused on upgrading its industrial structure and emphasized high-technology sectors as new economic growth engines, relying on domestic companies and non-HKMT foreign firms that were more R&D intensive (Huang and Sharif, 2009).

With their accumulated resources from earlier economic development, we argue that provinces in the eastern region have first-mover advantages (Lieberman and Montgomery, 1988, 1998) vis-à-vis provinces in the central and western regions to improve innovation capability. Although since 2000 the central government has utilized policy support, such as the West China Development Program (WCDP), to stimulate economic development in the lagging regions, their long-term effectiveness for economic growth and innovation capability are unclear. For instance, some have argued that WCDP focuses on energy exploitation of the western region to facilitate the development of the coastal area. In our view, with their latecomer status and very limited resources, it remains an extremely challenging task for provinces in the central and western regions to catch up with the eastern region in either economic development or innovation capability unless some drastic measures are taken by the central government.

Our regression model also indicates that openness contributes significantly to innovation inequality, implying the spillover effects of international trade and benefits of foreign direct investment on innovation capability. However, policy-makers should be aware of the possible negative effects of openness on local innovation capability due to competition for local R&D resources, little diffusion to host countries, and the adverse effects of mergers and acquisitions (UNCTAD, 2005). We also suggest that it might be helpful to add foreign R&D investment as an independent variable for future research if data is available. The inflow of foreign R&D may have aggravated the innovation inequality in China, as such investment is very selective and is directed at only a few locations. For instance, 60 percent of the foreign R&D laboratories in China are located in Beijing, 18 percent in Shanghai and 6 percent in Shenzhen (Yuan, 2005).

Finally, high-technology parks, economic structure (share of agricultural GDP) and urbanization have relatively stable and small impacts on the inequality. The low contribution of high-technology development (per capita revenue from high-technology parks) indicates that high-technology parks, initiated by the national government, although stimulating high-technology development, have limited impact on changing the existing regional inequality in innovation capability. A negative contribution of the economic structure variable indicates that China's certified patents are generated mainly by industrial/service sectors, which are mostly located in urban area. Although China is advanced in agriculture research and technology, most innovations in the agricultural sector are created by public research institutes in Beijing and those provinces that do not have a high share of agricultural GDP.

Although due to data availability we did not use an independent variable in our decomposition analysis to reflect private ownership at the provincial level, we should be aware of the impact of the incentive structure on innovation capability and inequality. In China, in contrast to the centralized, planning-oriented incentive structure, the market economy system has facilitated the growth of creativity and commercialization of research results from public research institutes and universities (Gu, 1999; Liu and White, 2001b).

VI. Conclusion

Using several indexes, the present paper has assessed both interregional and intraregional innovation inequality in China from 1995 to 2006. It is revealed that, until 2003, the east–central–west regional inequality increased over time, whereas the interprovincial inequality exhibited a V-pattern; both oscillated from 2004 to 2006.

The methodology framework used in the present paper is a regression-based inequality decomposition recently developed by one of the authors that has also been adopted for inequality analysis in other fields, such as development economics. This method allows us to quantify contributions of various determinants to the inequality of innovation, whereas the typical regression model can only be used to measure the impact of independent variables on the level of innovation, not the inequality of innovation. Other research on regional innovation inequality can benefit from this methodological contribution.

Our analysis identifies and quantifies the following major factors driving innovation inequality: population, economic development level, R&D investment, location and openness. The insights and policy implications of the present paper are summarized as follows.

First, the aggravated innovation inequality implies the growth of China's innovation centers in the eastern region and their admission into the global innovation networks; it also highlights a coupled evolution between innovation capability and economic development that may either help or trap policy-makers. Therefore, the lagging regions have fallen further behind the advanced regions in terms of technology development. As innovation capability plays a vital role for growth, national policy-makers, as well as regional and local policy-makers, should be aware that the increasing inequality in innovation capability may seriously affect lagging regions' ability to catch up (in terms of economic development), especially in knowledge-intensive sectors.

Second, our results suggest that the efficiency of R&D investment in regions in China improved during the period (1995–2006), possibly due to the change of the structural composition of R&D; that is, from government-supported R&D to market-driven R&D. A more equalized R&D investment, further encouragement of enterprises' involvement in innovation and nurturing domestic high-technology companies in the inland provinces may be effective in helping the lagging regions.

Third, geographic location and openness affect innovation inequality primarily through the coupled evolution of innovation capability and economic development, resulting in first-mover advantages to the eastern region provinces in further improving innovation capability. Although policies geared specifically toward the central and western regions to support economic development or innovation capability and further opening up of China's inland will help to overcome the geographic disadvantages of these regions, catching-up in either economic development or innovation capability remain extremely challenging tasks for inland provinces.

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