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ORIGINAL PAPER

Chinese innovation-driving factors: regional structure, innovation effect, and economic development—empirical research based on panel data

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Abstract The implementation of innovation-driven strategy is of great significance. Analysis of the driving factors of innovation performance from quantitative and systematic perspectives is needed for policy making. By drawing upon the LMDI model, this study identifies the driving factors and their corresponding contributions in the innovation performance of 30 Chinese provincial-level regions during the period 2000–2012. The innovation performance is decomposed into the regional economic structure effect, R&D intensity effect, innovation efficiency effect, and economic development effect according to the driving mechanism. The results indicate that the third effect in this list, innovation efficiency, contributes the most to innovation performance at 54.28%, followed by the regional R&D intensity at 27.49%, and China's economic development at 19.92%. The effect of the regional economic structure is negative, at −1.69%. This study further analyzes four major economic areas of China and identifies the channels through which each area conducts their innovation activities. The empirical findings provide information for policy measures to implement innovation-driven strategies.

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1 Introduction

With the advent of the “Third Industrial Revolution”, technological innovation has reached a high-water mark. On the international stage, the USA has launched its technological innovation plan (TIP) and “the American innovation strategy”; France put forward the industrial innovation plan “create tomorrow’s products”; Germany introduced its “2020—innovation partnership” and “standard innovation plan”; both the UK and Singapore have launched an “innovation voucher program (IVS)”; Japan has proposed a “digital Japanese innovation plan (ICT)”; South Korea has put forward a “creative economic” plan. These examples show that in many countries, technological innovation is becoming considered a national core strength. Domestically, China’s economy has grown rapidly for more than 30 years, becoming the world’s second largest economy, but unfortunately the growth mainly relies on high consumption of raw materials and energy. Many industries, especially manufacturing, have a serious lack of core technology, lack of innovation, and unhealthy reliance upon external technology. Therefore, it is urgent for China to speed up technology innovation, realizing endogenous growth. China has put forward its innovation-driven development strategy, and stressed that “scientific and technological innovation plays a strategic supporting role in improving society’s productive forces and overall national strength, and must be placed in the core of national development.” The strategy aims to “promote the efficient allocation and comprehensive integration of innovation resources and focus on innovation development.” As one of the largest developing countries in the world, there is increasing variation in terms of innovation development conditions between regions, which may affect the overall innovation performance. Kelley et al. (2012) divided economic development phases into three categories: the factor-driven stage (per capita GDP below \$5000), efficiency-driven stage (per capita GDP \$5000–\$10,000), and innovation-driven stage (per capita GDP above \$10,000). The “Global Competitiveness Report 2014–2015”, issued by the World Economic Forum, points out that China is in the efficiency-driven stage. Table 1 illustrates the general information of economic development in 31 administrative provincial-level regions[1] in mainland China. Most regions are efficiency-driven, and the innovation-driven regions are mainly located in the east of China, examples being the regions of Beijing, Tianjin, and Shanghai, Jiangsu and Zhejiang. The unbalanced regional development hinders the implementation of China’s innovation-driven strategy. Considering this background, the impact of regional disparity on innovation activities is a problem worthy of discussion. Using the Logarithmic Mean Divisia Index (LMDI) decomposition model (Ang et al. 1998), this paper studies the drivers of innovation and identifies the channels through which four geographical areas of China conduct their innovation activities.

As Oxman (1992) pointed out, “Measurement is the first step that leads to control and eventually to improvement”. Relevant studies on measurement-oriented innovation activities are burgeoning in the literature. Wang and Huang (2007) evaluated the relative efficiency of R&D activities across countries using the data envelopment analysis (DEA) method within the production framework. Chen and Guan (2012)

[1] For convenience, we will refer to the administrative provincial-level regions as regions in what follows.

Table 1 Per capita GDP and economic development stages of regions in 2013

Area	Region	Per capita GDP (dollar)	Stage	Area	Region	Per capita GDP (dollar)	Stage
East	Beijing	14,853.62	Innovation-D	West	Inner Mongolia	10,855.47	Innovation-D
	Tianjin	15,727.12	Innovation-D		Guangxi	4908.45	Factor-D
	Hebei	6217.59	Efficiency-D		Chongqing	6865.30	Efficiency-D
	Shanghai	14,410.36	Innovation-D		Sichuan	5218.47	Efficiency-D
	Jiangsu	12,005.24	Innovation-D		Guizhou	3683.31	Factor-D
	Zhejiang	11,008.16	Innovation-D		Yunnan	4028.67	Factor-D
	Fujian	9288.50	Efficiency-D		Tibet	4170.37	Factor-D
	Shandong	9051.32	Efficiency-D		Shaanxi	6867.38	Efficiency-D
	Guangdong	9408.70	Efficiency-D		Gansu	3910.83	Factor-D
	Hainan	5663.63	Efficiency-D		Qinghai	5856.04	Efficiency-D
Central	Shanxi	5592.90	Efficiency-D		Ningxia	6318.52	Efficiency-D
	Anhui	5086.50	Efficiency-D		Xinjiang	5948.92	Efficiency-D
	Jiangxi	5108.21	Efficiency-D	Northeast	Liaoning	9936.70	Efficiency-D
	Henan	5503.36	Efficiency-D		Jilin	7602.01	Efficiency-D
	Hubei	6853.07	Efficiency-D		Heilongjiang	6041.96	Efficiency- D
	Hunan	5899.30	Efficiency-D				

Factor-D refers to Factor-driven stage; Efficiency-D refers to Efficiency-driven stage; Innovation-D refers to Innovation-driven stage divided the innovation process into two sub-processes, technological development and technological commercialization, and evaluated China's regional innovation systems. Considering that communication of tacit and asymmetric knowledge is hindered by regional boundaries, and that social culture and specific governance rules in China vary from one region to another, the regional innovation system (RIS) gives insight into analyzing innovation activities from the perspective of the administrative regions. Using a discrete time hazard model, Li and Tellis (2016) found that the time for new products to take off varies dramatically across provinces in China. Wang et al. (2016) studied the relationships between the regional innovation environmental components and innovation efficiency. Bai (2013) estimated the regional innovation efficiency in China and investigated major factors affecting efficiency scores using the stochastic frontier methods. Li (2009) investigated the underlying factors of the increasing disparity in innovation performance across the Chinese regions. Buesa et al. (2010) studied the determinants of regional innovation in Europe, and identified five important aspects: the national environment, the regional environment, innovating firms, universities, and the R&D done by public administration. Yang and Yang (2015) constructed an integrated analysis framework to investigate the intertemporal change of China's eco-innovation gains as well as the regional differences. This kind of analysis points to significant disparities in innovation activities across regions. These differences suggest that regional factors might have an impact on innovation. Also in the present paper, we take the cross-region difference into consideration.

Existing research on innovation mainly focuses on the selection of an evaluation method for regional innovation ability, the establishment of an index system, and the factors influencing regional innovation ability. These selections allow us to have an overall understanding of the regional innovation ability, and to understand how the government, enterprises, universities, and foreign merchants involved in R&D affect innovation performance. As noted above, despite the extensive literature on innovation, there have been few attempts to work on the relative importance of different factors synchronously, especially from the perspective of regional disparity. In this context, this paper decomposes innovation performance into the regional economic structure, regional R&D intensity, regional innovation efficiency, and national economic development. By applying the LMDI model, this paper investigates the driving factors of innovation performance from both systematic and dynamic perspectives.

Since the final effects of innovation activities are embodied in the improvement of innovation, this paper selects the change in innovation output as the proxy for innovation performance (Yang and Yang 2015). Considering the fact that factors influencing innovation performance are multifaceted, ranging from economic to political circumstances, the LMDI method is applied in this paper due to its adaptability (Achour and Belloumi 2016). By using the LMDI model, this paper differs from previous studies mainly in two aspects. First, drawing upon insights from regional innovation system research, it proposes the comprehensive analytical framework of innovation activities from the perspective of regional disparity. Second, by decomposing the innovation performance into four components, we can identify the intertemporal change of China's innovation output, and the relative importance of different components. Additionally, this paper breaks down China into four geographical areas and empirically examines the promoting or inhibiting factors for the innovation performance of each area, so as to broaden the understanding of the geographical distribution and the development status of China's innovation. The results can provide information for policy makers to identify pathways through which each area realizes innovation. To the best of our knowledge, this paper is pioneering work that modifies the LMDI model for studying the differential impact of driving factors on innovation performance in a transitional economy. The remaining parts of this paper are organized as follows. Section 2, based on the extant research, depicts our modeling methodology, and calibrates the LMDI decomposition model for this dynamic innovation perspective. Section 3 shows an empirical analysis based on provincial-level panel datasets from China's innovation history. In Sect. 4, we analyze the innovation-driven factors of the East, Middle, West and Northeast areas of China. The conclusions and policy implications are summarized in Sect. 5.

2 Modeling

2.1 Methodology

Index decomposition methods include the Laspeyres index method, Logarithmic Mean Divisia Index (LMDI) method, Paasche method, the Arithmetic Mean Divisia Index (AMDI) method, Theil index method (Ang 2005; Li and Wang 2008). Ang et al. (1998) found that the residual error of Laspeyres decomposition and Paasche decomposition is big and that of the simple Divisia index method is small, but the LMDI residual error is 0. The residual indicates that target variable cannot be explained entirely by the model, meaning a decline in the persuasiveness of the quantitative driving effect. As a result, the LMDI method, whose residual is zero, is favored by researchers (Lei et al. 2012). Besides, LMDI is a good way to decompose the research object (an overall index) into several indices with economic meanings. It is useful to separate out the effect of various factors, and this method has been adopted in the United States, Canada, and other countries. Lei et al. (2012) contrasted 10 kinds of decomposition methods for the Chinese industrial wastewater emission factor from 2001 to 2009, and concluded that the LMDI method was superior to other methods. There has been a flourishing interest in LMDI to address various kinds of real-world problems, including environmental protection, energy consumption in transportation sector, and economic development (Achour and Belloumi 2016; Ang 2015; Hatzigeorgiou et al. 2008; Sun et al. 2013). Based on the analysis above, this paper adopts the LMDI method to construct an innovation performance decomposition model.

2.2 Model building

The first step in developing our model is to determine a measure of innovation output for index decomposition. Several alternative indicators of innovation output have been used in the previous empirical literature, such as new product sales income, patent counts, patent counts per capita, and scientific publications (Buesa et al. 2006; Cowan and Zinovyeva 2013). Although controversial, the number of patents has also served as a measure for innovation output in a vast amount of research (Acs et al. 2002;

Bronzini and Piselli 2016; Fritsch and Franke 2004; Guan and Chen 2010; Guan et al. 2009). Some researchers have pointed out that patents cannot entirely explain the actual innovation quality, as in a comment by Griliches (1990), "not all inventions are patentable, not all inventions are patented, and the inventions that are patented differ greatly in quality". Despite such objections, the correlation between patent activity and innovation is close ($r = 0.934$) (Feldman and Florida 1994). Compared to alternative measurements, patents can guarantee the originality and are more likely to correspond to market value (Bronzini and Piselli 2016; Buesa et al. 2010). In the light of these considerations, we believe that patent activity is the most appropriate proxy for innovation output for the time being. Data available in the China Statistical Yearbook includes both patent applications and patent grants. As the time lag of the patent grants is uncertain, the patent applications can be closely related to contemporaneous or lagged R&D activities (Li 2015). Also, due to some man-made factors in government agencies, a large uncertainty exists (Branstetter and Sakakibara 2000; Griliches 1979, 1990; Hong et al. 2015; McCarthy et al. 2010). Following the literature, we take the number of patent applications as a proxy of innovation output. For simplicity, we refer to "the number of patent applications per ten thousand people" as "patent count" in what follows. According to the Kaya identity, the innovation output can be divided into four factors, as seen in Eq. (1)

$$\frac{O}{P} = \sum_i \frac{Y_i}{Y} \cdot \frac{RD_i}{Y_i} \cdot \frac{O_i}{RD_i} \cdot \frac{Y}{P} \tag{1}$$

Here, P is the population; O_i is the patent applications of region i; O is the national patent applications; Y_i is the GDP of region i; Y is the national GDP; and RD_i is the expenses for internal R&D activities of region i.

We use the following definitions. The regional economic structure $\left(S_i = \frac{Y_i}{Y}\right)$ is the share of a regional GDP relative to the national GDP. R&D intensity $\left(R_i = \frac{RD_i}{Y_i}\right)$ is the R&D expenditure relative to regional GDP in region i. Innovation efficiency[2] $\left(E_i = \frac{O_i}{RD_i}\right)$ is the patent count per unit of R&D expenditure in region i. Economic development $\left(F = \frac{Y}{P}\right)$ is a measure based on per capita GDP. Therefore, the national patent count $I = \frac{O}{P}$ can be expressed as follows:

$$I = \sum_i S_i \cdot R_i \cdot E_i \cdot F \tag{2}$$

Equation (2) says that the national patent count is influenced by regional economic structure, R&D intensity, innovation efficiency, and the overall economic development.

[2] As is common practice, innovation efficiency is defined as the ratio between the composite indicator scores for one or more input dimensions and one or more output dimensions. To be specific, more innovation outputs at the given inputs or less innovation inputs for the same amount of innovation outputs means higher innovation efficiency. This paper defines the ratio between patent applications and R&D expenses as the innovation efficiency.

The change of the innovation output from year $T-1$ to year T can be expressed as follows.

$$\Delta I = I^{T} - I^{T-1} = \Delta I_S + \Delta I_R + \Delta I_E + \Delta I_F \tag{3}$$

The meaning of Eq. (3) is that any change in patent count can be decomposed into four effects: ΔI_S is the contribution of regional economic structure to innovation performance; ΔI_R is the contribution of R&D intensity to innovation performance; ΔI_E is the contribution of innovation efficiency to innovation performance; and ΔI_F is the contribution of economic development to innovation performance. The R&D intensity factor and innovation efficiency factor are collectively referred to as the innovation effect. If the contribution of the factor effect is positive, the innovation output increases, and vice versa. Detailed explanations of each factor follow.

1. Regional economic structure refers to how the economic development differ in various regions, since developed regions and underdeveloped regions coexist. Due to regional comparative advantages (Ricardo et al. 1819), the developed regions exert an incentive effect on the backward regions. Too much difference, however, is bad for the stable, harmonious development of a national economy.
2. The R&D intensity factor refers to the effect of the R&D expenditure of the region i GDP on innovation performance. Generally, the innovation input of high quality can optimize innovation fundamentals and improve innovative potential (Furman et al. 2002; Griffith et al. 2004), so R&D input contributes positively to the innovation output.
3. Innovation efficiency refers to the patent count per unit of R&D input in a region. Theoretically, when a region's innovation efficiency rises, the efficiency of R&D expenditure improves (Wang 2007). While other factors remain unchanged, the innovation output will increase.
4. Overall economic development is the ability of a country or an area to create or obtain wealth in a certain period. Per capita GDP reflects the economic performance of a country, in our case, China. The economic development effect is that the economic development and patent count change in the same direction. It is widely believed that innovation is intertwined with economy in a mutually beneficial way. On one hand, innovation can boost the economic development; on the other hand, the improvement of a country or region's economy will provide a better environment for innovation (Brown et al. 2009; Porter 2008).

According to the LMDI method, each factor can be expressed as follows.

$$\Delta I_S = \sum_i W_i \cdot \left(\ln S_i^T - \ln S_i^{T-1}\right) \tag{4}$$

$$\Delta I_R = \sum_i W_i \cdot (\ln R_i^T - \ln R_i^{T-1}) \tag{5}$$

$$\Delta I_E = \sum_i W_i \cdot \left(\ln E_i^T - \ln E_i^{T-1}\right) \tag{6}$$

$$\Delta I_F = \sum_i \cdot W_i \cdot (\ln F^T - \ln F^{T-1}) \tag{7}$$

where W_i is the weight of region i, determined by the logarithmic mean function as follows.

$$W_i = \begin{cases} \frac{I_i^T - I_i^{T-1}}{\ln I_i^T - \ln I_i^{T-1}} & I_i^T \neq I_i^{T-1} \\ I_i^T & I_i^T = I_i^{T-1} \\ 0 & I_i^T = I_i^{T-1} = 0 \end{cases} \tag{8}$$

$$\begin{aligned} &\Delta I_S + \Delta I_R + \Delta I_E + \Delta I_F \\ &= \sum_i \frac{I_i^T - I_i^{T-1}}{\ln I_i^T - \ln I_i^{T-1}} \cdot \left(\ln S_i^T R_i^T E_i^T F^T - \ln S_i^{T-1} R_i^{T-1} E_i^{T-1} F^T - 1\right) \\ &= \sum_i \frac{I_i^T - I_i^{T-1}}{\ln I_i^T - \ln I_i^{T-1}} \cdot \left(\ln I_i^T - \ln I_i^{T-1}\right) \\ &= \sum_i I_i^T - \sum_i I_i^{T-1} \\ &= I^T - I^{T-1} \\ &= I \end{aligned} \tag{9}$$

So LMDI is a complete decomposition, that is, the decomposition residual is zero. In other words, the innovation performance can be completely explained by a combination of the regional economic structure effect ΔI_S, R&D intensity effect ΔI_R, innovation effect ΔI_E, and economic development effect ΔI_F.

The ratio of the effect of the various factors to the total effect of innovation performance, is called the contribution ratio of the various factors.

$$s = \frac{\Delta I_S}{\Delta I}, \quad r = \frac{\Delta I_R}{\Delta I}, \quad e = \frac{\Delta I_e}{\Delta I}, \quad f = \frac{\Delta I_F}{\Delta I} \tag{10}$$

3 An empirical study of innovation in China

3.1 Data

To estimate the LMDI model, the empirical analysis now presented is based on statistical data about the innovation-driven activities in 30 provincial-level regions in mainland China (excluding Tibet due to incomplete data). The data source is based on the *China Statistical Yearbook* and *China Statistical Yearbook on Science and Technology* published by China's National Bureau of Statistics and Ministry of Science and Technology. To eliminate the influence of price changes in the nominal variables, the GDP and R&D expenditures are adjusted for inflation with GDP deflator taking 2000 as the base year. Considering the existence of time lags when analyzing the transformation of innovation inputs into innovation outputs, this paper selects a 1-year

Table 2 Definitions and sources of variables

Variable	Definition	Data source
Y_i	GDP of region i	China Statistical Yearbook: 2001–2013
Y	GDP of 30 provincial-level regions	China Statistical Yearbook: 2001–2013
RD_i	Expenses for internal R&D activities of region i	China Statistical Yearbook on Science and Technology: 2001–2013
O_i	Number of patent applications of region i	China Statistical Yearbook on Science and Technology: 2001–2014
P	Total number of people of 30 provincial-level regions	China Statistical Yearbook: 2001–2013

The data for a given year are reported in the Statistics Yearbook of the subsequent year

lag for the R&D process to check the robustness of the empirical study. That is, the GDP, population, and expenditure for R&D for 2000–2012 is thus matched with patent applications for 2001–2013. Therefore, the analysis considers two specifications, one considers no time lag for patent applications and the other uses a 1-year lag for patent applications. All of the variables are measured at the provincial level, the definitions and sources of which are provided in Table 2. The data are available from the authors upon request.

As shown in Fig.1a, the national innovation performance has experienced rapid development during the entire study period. The number of China's patent applications has continued to grow since 2000, from 1.017 per 10,000 people in 2000 to 16.31 items per 10,000 people in 2013. Although the increase actually decreased in 2004 and 2006 (see Fig. 1b), the increase remained positive and quickly resumed rising after each of these anomalies. The underlying reason for the improvement mainly lies in the fact that since the end of the twentieth century, the Chinese central government has gradually realized that the development of scientific technology and innovation ability are related to the sustainable development of the economy. A series of important strategies have been proposed, such as the Knowledge Innovation Project, Technology Innovation Strategy, and Innovation-oriented National Construction, and a series of policies and regulations have been implemented to encourage technological innovation in enterprises. These policy instruments drive the fundamental transformation of China's innovation system, improving innovation ability.

3.2 LMDI decomposition results

The data sources used here quantify China's innovation performance at the national level, but determining the underlying sources of China's innovation gains is another important topic worthy of attention. To this end, this paper adopts the LMDI decomposition method based on the additive decomposition principle, to decompose the

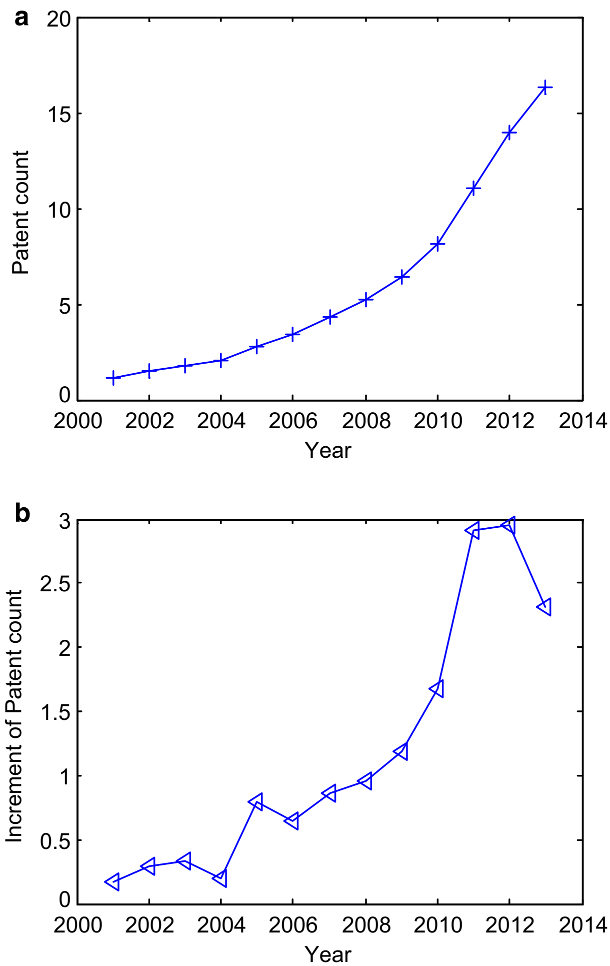

Fig. 1 **a** Growth curve of patent count; **b** growth curve of the increase in patent count. *Note*: "Patent count" is the number of patent applications per 10,000 people

patent count in China year by year from 2000 to 2012. The decomposition results using the chosen four factors (regional economic structure, R&D intensity, innovation efficiency, economic development) are shown in Table 3. It is evident that the results are robust and consistent in both time-lag cases. For ease of illustration, this paper focuses on the interpretation of the first case, where the number of contemporary patent applications is the variable being decomposed.

To reflect the annual change trend of each effect intuitively, a line chart is shown in Fig. 2. The patent count increases by an average of 1.0834 items (per 10,000 people) from 2000 to 2012. Among the four factors, the innovation efficiency component acts as a positive determinant of China's innovation performance, and its increase effect is 0.5880 items. Both R&D intensity and economic development also play a

Table 3 Decomposition results of China's innovation performance (2000–2012)

	Total effect	Regional economic structure	R&D intensity	Innovation efficiency	Economic development
Patent count					
2000–2001	0.1628	0.0038	0.0753	0.0710	0.0127
2001–2002	0.2942	0.0422	0.0793	0.1402	0.0325
2002–2003	0.3314	0.0065	0.0799	0.1835	0.0615
2003–2004	0.2029	−0.0092	0.1099	−0.0485	0.1507
2004–2005	0.7930	−0.0085	0.1507	0.4927	0.1581
2005–2006	0.6405	0.0041	0.1854	0.3535	0.0975
2006–2007	0.8675	−0.0134	0.1610	0.5645	0.1554
2007–2008	0.9638	−0.0523	0.3164	0.3596	0.3401
2008–2009	1.1859	−0.0073	0.7654	0.4053	0.0225
2009–2010	1.6829	−0.0288	0.1832	0.9801	0.5484
2010–2011	2.9112	−0.0827	0.4268	1.7299	0.8372
2011–2012	2.9641	−0.0744	1.0406	1.8246	0.1733
Mean	1.0834	−0.0183	0.2978	0.5880	0.2158
$(Patent\ count)_{t+1}$					
2000–2001	0.2974	0.0049	0.0935	0.1836	0.0154
2001–2002	0.3351	0.0522	0.1002	0.1422	0.0405
2002–2003	0.2036	0.0086	0.094	0.0288	0.0722
2003–2004	0.7708	−0.0096	0.1459	0.4459	0.1886
2004–2005	0.6744	−0.0083	0.2019	0.2738	0.207
2005–2006	0.8720	0.0066	0.2365	0.5072	0.1217
2006–2007	0.9769	−0.0162	0.1981	0.6013	0.1937
2007–2008	1.1937	−0.0615	0.3983	0.437	0.4199
2008–2009	1.6906	0.0013	0.9587	0.7024	0.0282
2009–2010	2.9083	−0.027	0.2335	1.9781	0.7237
2010–2011	2.9882	−0.0987	0.5361	1.4478	1.103
2011–2012	2.3308	−0.0806	1.2751	0.9248	0.2115
Mean	1.2702	−0.0190	0.3727	0.6394	0.2771

positive role, having increase effects of 0.2978 items and 0.2158 items, respectively, but regional economic structure has a negative effect, an increase effect of −0.0183 items. Figure 2 shows that R&D intensity effect positively drives innovation performance; with the exception that the 2004 innovation efficiency effect is negative. The economic development effect is positive. The regional economic structure effect is positive from 2000 to 2003, but turns negative after 2003.

The ratio of the driving factor effect to the total effect is used to quantify the contribution of each factor to the innovation output change, as shown in Table 4. By the average contribution rate of various factors on the innovation performance, we can

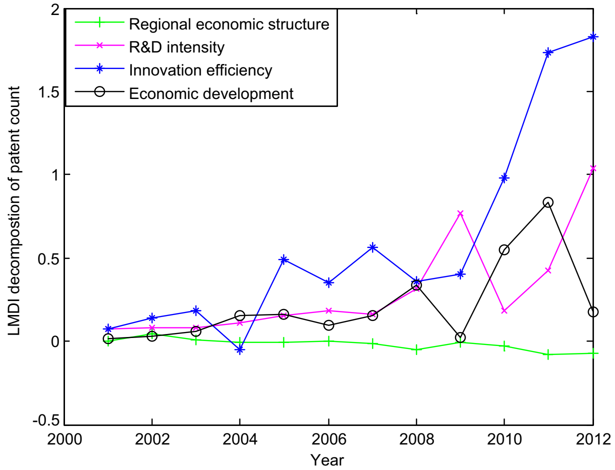

Fig. 2 The contributions of the four factors to innovation output variance

Table 4 Contribution ratios of the four factors (%) (2000–2012)

	Regional economic structure	R&D intensity	Innovation efficiency	Economic development
Patent count				
2000–2001	2.3342	46.2531	43.6118	7.8010
2001–2002	14.3440	26.9545	47.6547	11.0469
2002–2003	1.9614	24.1098	55.3712	18.5576
2003–2004	−4.5343	54.1646	−23.9034	74.2730
2004–2005	−1.0719	19.0038	62.1311	19.9369
2005–2006	0.6401	28.9461	55.1913	15.2225
2006–2007	−1.5447	18.5591	65.0720	17.9135
2007–2008	−5.4264	32.8284	37.3106	35.2874
2008–2009	−0.6156	64.5417	34.1766	1.8973
2009–2010	−1.7113	10.8860	58.2388	32.5866
2010–2011	−2.8408	14.6606	59.4222	28.7579
2011–2012	−2.5100	35.1068	61.5566	5.8466
Mean	−1.6923	27.4911	54.2792	19.9220

see the regional economic structure effect, innovation effect (R&D intensity effect and innovation efficiency effect), and economic development effect on China's innovation performance during the 13 years from 2000 to 2012. For China's innovation-driven strategy, the innovation effect is the best enhancer, imbalanced regional development negatively influences innovation, and the national economic development stimulates innovation to some extent.

Table 5 CV_W of China (2000–2012)

Year	2000	2001	2002	2003	2004	2005	2006
CV_W	0.937	0.945	0.982	1.006	1.015	1.050	1.061
Year	2007	2008	2009	2010	2011	2012	
CV_W	1.052	1.035	1.027	1.005	0.970	0.948	

3.2.1 The effect of regional economic structure

It is normal that economic disparities exist between different regions. Regional economic disparity has a dual effect: the demonstration effect will promote the innovation activities in that advanced places are models for the less-advanced, but if the gaps are too big then they may affect the development of the whole country (Cai et al. 2002). In the current study, the effect of regional economic structure is positive from 2000 to 2003, but turns negative after 2003. From an overall perspective, the imbalanced economic structure has a negative effect on innovation output. By reference to Williamson (1965), we measure economic disparity among regions as a variation coefficient weighted by population (CV_W) from 2000 to 2012. CV_W is an important indicator to measure regional economic disparity. The bigger the value, the greater the regional economic disparity. Table 5 shows that the CV_W of China increases starting in 2000, but then decreases after reaching a peak in 2006. The reason for this is likely related to China joining the WTO in 2001 and becoming further integrated into the world economic system. Then, China widely participated in international activities, sharing the benefits of globalization (Ianchovichina and Martin 2004). However, the benefit was not evenly distributed across the country, which further expanded the regional economic gap (Wan et al. 2006, 2007). The gap was decreasing until 2006. But consider the GDP of provinces in 2012: Guangdong, Jiangsu, and Shandong exceeded 5000 billion (Chinese RMB yuan) and Guangdong had a GDP of 5706.79 billion, while in contrast Ningxia, Qinghai, and Tibet were under 250 billion. Although the growth trend of regional economic disparity has been eased, on the whole, the regional development remains imbalanced, which is harmful to the coordinated development of the national economy and has a negative effect on innovation. On average, the regional disparity negatively influences the growth of the innovation output, showing that it is necessary to continue to regulate and control regional economic structure.

3.2.2 The effect of regional R&D intensity

R&D intensity contributes 27.49% of the growth of patent count during this period. As China's economic power continues to grow, its overall economy performance is improved, and technological innovation funding increases year by year (Wei 2013). Since 2000, the Chinese government's support for science and technology activity has increased each year, and the national R&D expenditures increased from 89.57 billion to 1029.84 billion, the R&D personnel rising from 92.21 to 324.7 per 10,000 person-years. As the government and enterprises pay more attention to innovation input, the innovation output rises significantly (Furman et al. 2002; Li 2009). The number of patent applications in 2012 was 1,885,569 items, which is 14.7 times that of 2000 (128,174 items). Note, however, that Chiu et al. (2012) found that although R&D expenditure does play a certain role in promoting innovation performance, its effect is not as big as commonly believed. As shown in Table 4, although R&D intensity is a positive driver for innovation output, its contribution is not big, having a minimum as low as 10.89%, which reminds us that increasing R&D input is not enough, by itself, to significantly enhance innovation performance.

3.2.3 The effect of regional innovation efficiency

Innovation efficiency (the patent applications per 100 million yuan R&D expenditures) has been increasing since 2000. The increase is 11.88 items per 100 million between 2000 and 2001 and reached 79.60 items per 100 million between 2011 and 2012. This shows that China's innovation efficiency has been improving in the last 10 years and that innovation efficiency promotes innovation output. During the study period, although the innovation efficiency effect did fluctuate, its general trend was upward. It is noteworthy that innovation efficiency decreased between 2003 and 2004, and the contribution ratio was quite low at −23.90%. The most likely reason for this anomaly is that the "SARS" disease outbreak in 2003 influenced innovation activities.

3.2.4 The effect of national economic development

The economic development also had an important influence on innovation performance during this period. In general, the higher the level of economic development, the more funds are provided for R&D, thus improving innovation ability. China mainly depends on investment and exports to drive its economy (Ianchovichina and Martin 2004), especially since joining the WTO. The contribution of net exports to GDP is rising and the foreign trade dependency rate is rising quickly. The serious global financial crisis triggered by the subprime mortgage crisis in 2008 pushed the world into recession. The contribution of net exports to GDP fell sharply, from 18.0% in 2007 to 8.8% in 2008, bottoming out in 2009 (−37.4%), which affected China's economy. The shrinking external demand, coupled with the rising costs of raw materials, fuel, and labor, resulted in a large number of small and medium-sized export-oriented enterprises closing down. The resulting unemployment had tremendous effects on the national economy and also affected China's innovation rate. The economy slowed down due to the financial crisis, which explains the slight effect of economic development on innovation output in 2008.

4 Innovation differences among four major economic areas

China is vast, and due to the differences of geographical location, economic foundation, regional policy, and S&T inputs (e.g., capital and labor), the regional innovation ability is not balanced. Having analyzed the influences on the national innovation performance, we now consider a smaller scale viewpoint by looking at geographical areas of the country. We divide the 30 provincial-level regions into four administra-

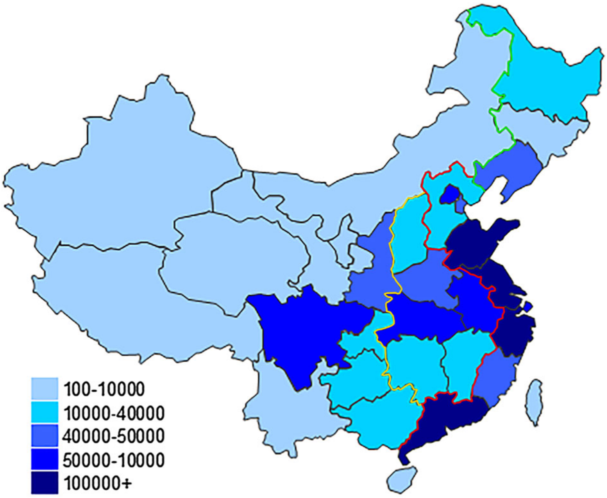

Fig. 3 Spatial distribution of patent applications (2013)

tive areas[3]: East, Central, West, and Northeast. In order to compare the difference of regional innovation drivers, we consider each major economic region as a research object, investigating their innovation-driving factors.

For ease of illustration, the following maps show the patent counts of the provincial-level regions in China. Figure 3 illustrates the spatial distribution of provincial innovation output based on patent applications in 2013. Figure 4 shows the spatial distribution visual description of the increase in patent applications from 2012 to 2013, with darker color indicating a higher value and lighter color indicating a lower value. It can clearly be seen that regions in the eastern area exhibit high performances, especially Shandong, Jiangsu, Zhejiang, and Guangdong, each of which had more than 100,000 patent applications. Jiangsu, ranked first, had 504,500 applications. In contrast, the western regions such as Xinjiang, Qinghai, Gansu, and Inner Mongolia have low patent counts of less than 10,000. There is a big gap in the cross-area innovation output, with the average of the eastern area being 2.13 times that of the nation (73,647), compared to the West's 0.33 times. The gaps between the Central, West, and Northeast areas are small. Overall, the distribution of patent count increases is roughly the same as that of patent applications in 2013.

We further shed some light on the path differences of China's cross-region innovation gains during 2000–2012 by replicating the LMDI decomposition. As shown in Table 6, the innovation performance and the contribution of each driving factor varies across the four areas. The realizing paths of innovation can be identified according to the relative importance of the four components.

[3] The East area includes Beijing, Tianjin, Hebei, Shanghai, Jiangsu, Zhejiang, Fujian, Shandong, Guangdong, and Hainan. The Central area includes Shanxi, Anhui, Jiangxi, Henan, Hubei, and Hunan. The West area includes Inner Mongolia, Guangxi, Chongqing, Sichuan, Guizhou, Yunnan, Shaanxi, Gansu, Qinghai, Ningxia, and Xinjiang. The Northeast area includes Liaoning, Jilin, and Heilongjiang (Source: China Statistical Yearbook).

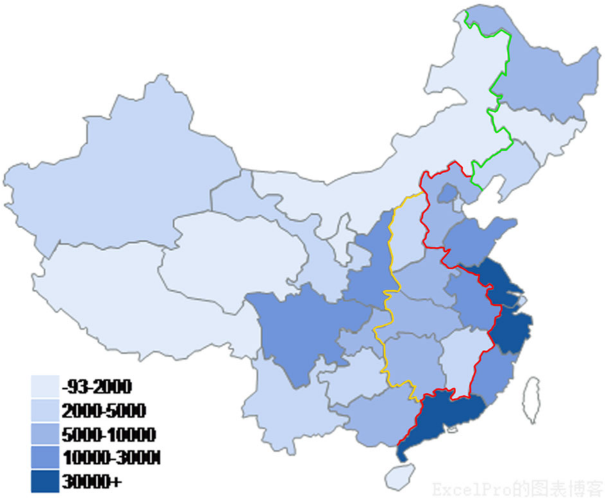

Fig. 4 Spatial distribution of patent applications variation (2012–2013)

Table 6 Average values of the decomposition results of innovation performance (2000–2012)

	Average	Regional economic structure (%)	R&D intensity (%)	Innovation efficiency (%)	Economic development (%)
Patent count					
East	2.0539	0.06	31.30	55.12	13.52
Central	0.5055	−1.04	29.26	49.18	22.60
West	0.4364	−0.49	−1.08	40.32	61.25
Northeast	0.5150	−2.96	62.20	−3.14	43.90
$(Patent\ count)_{t+1}$					
East	2.3588	0.38	34.10	50.30	15.22
Central	1.3974	−1.04	27.79	50.65	22.60
West	0.5838	−0.49	−1.21	43.17	58.53
Northeast	0.5681	−2.96	61.02	−0.83	42.77

In line with the practice in Sect. 3.2, we only interpret the first case, taking no consideration of the time lag. The average increases in patent count in the East, Central, West, and Northeast areas are all positive. Since the 2000s, all four areas have experienced an improvement in innovation performance, although the pace of improvement varied. The average increase in patent count in the East is the best at 2.0539; significantly behind are the Central at 0.5055, West at 0.4364, and Northeast at 0.5150. Considering the patent count and its increase in various regions, China's innovation may be experiencing a "Matthew effect" (Merton 2010), meaning that the innovation ability of the developed East is getting stronger, while the West is getting weaker, causing greater polarization in China's regional innovation performances. If no effective measures are taken to promote innovation in the Central, West, and Northeast areas, China's long-term sustainable development and innovation-driven strategy will be hindered. The comparisons of the decomposition results have shown substantial differences in innovation performance among areas. In the East, the four factors are all positive drivers, especially innovation efficiency and R&D intensity, which contribute more than 80% of the total effect. The regional economic structure factor has a negative effect in the Central area. The regional economic structure and R&D intensity in the West are negative drivers. The increase in innovation output depends primarily on economic development in the West. The most powerful driver in the Northeast is R&D intensity, whose contribution rate is 62.20%, with economic development contributing 43.90% and the effects of regional economic structure and innovation efficiency being negative.

4.1 The innovation drivers in the East

In terms of the East, the average contribution rate of regional economic structure is positive only in the East, at 0.06%. R&D intensity got stronger starting in 2000, rising from 1.37 to 2.36% in 2012. Innovation efficiency also improved, from 2.09 to 5.52%. R&D intensity and innovation efficiency are ahead of other three areas. If we consider innovation output measured by patent applications, whether the total or the increase, the East has an evident advantage. Since China's reform and opening up policy started in 1978, China has promoted a regional development strategy gradually from the coast to the interior. The eastern coastal areas took the lead in the economic system reform and opening-door policy (Li 2009). A series of preferential policies covering openness to other countries, plus finance, taxation, investment, and credit were first offered there. With such national policy advantages, the East continues to play a leading role in China's economic development. GDP and per capita GDP of the East are ahead of other areas, and the tertiary industry represented by the service industry is developing rapidly, further optimizing the industrial structure. Besides, the East has a solid infrastructure and its talents, R&D conditions, and several other factors all rank first of the four areas. In the most recent 10 years, China has been vigorously developing an export-oriented economy. Regions in the southern part of the East area make full use of their excellent geographical location, and technology transfer from developed countries, affecting the breadth, depth, and effect of innovation. Flexible innovation mechanisms and a strong market economic role make enterprises in these regions become innovators. These advantageous conditions promote the implementation of the eastern innovation-driven strategy.

4.2 The innovation drivers in the Central area

The Central area is the geographical heart of China, playing an important role in linking the East and the West for China's development. Only when the Central area develops can China develop sustainably and in a healthy manner. The effect of regional economic structure in the Central area was negative from 2000 to 2005, becoming positive and having its contribution rate increase after 2005. This improvement may be due to “the rising strategy of central China” put forward in 2004. The six province-level regions of the Central area are adjusting and optimizing their economic structures, which is making its regional economic structure become more reasonable. Patent applications totaled 234,599 in 2013, 14.4 times that in 2000 (16,335 items). In 2013, R&D intensity was 1.28%, only about half that of the East, and innovation efficiency was 4.78%, less than the East. While the factors of the Central area as a whole promote innovation performance, its innovation outlook is not optimistic. The number of patent applications in the Central area accounted for only 11.6% of the national total in 2012, which may be related to its industrial structure which features a high proportion of primary industry and traditional industry, with a lack of high-tech enterprises.

4.3 The innovation drivers in the West

Since the implementation of the “develop-the-west strategy,” which started in 2000, the Chinese Party Central Committee has been boosting investment in the West, speeding up its economic and social development (Shenggen and Zhang 2004). Economic growth has become the most powerful driver of western innovation performance. The number of patent applications in 2012 was 206,046 items, 12.6 times of that in 2000 (16,381 items). The regional economic difference is narrowing. The reduced to 0.799 in 2012, compared to 0.965 in 2000. The contribution of regional economic structure turned from negative to positive. In terms of innovation efficiency, the West is similar to the Central area. Although R&D intensity increased from 0.7 to 0.9%, it is still at the lowest level of the four major areas. Since the transportation networks are concentrated in the eastern coastal areas, the East’s transportation costs in the processes of production and distribution are low. According to location theory of Alfred Webber, the nature of profit tracing and “polarization effect” of the East accelerates the “polarization” of the West. The limited funds flow from the West to the East through market intermediaries, which seriously impedes the infrastructure investment in the West. The West has an obvious disadvantage in technological innovation. Full-time equivalent of R&D personnel in the East accounted for 64.69% of the whole country in 2013, while the West had only 12.49%. Looking at education, workers educated at the college and higher level accounted for 12.94% of the population in the East, while in the West figure is 9.72%. Without skilled scientists and engineers operating in an environment with access to cutting-edge technology, it is unlikely that any area will produce an appreciable amount of new-to-the-world innovative output (Furman et al. 2002; Hendricks 2002). The lack of funds and highly trained personnel in the West leads to poor innovation investment, and prospects for innovation-driven strategy development are not optimistic.

4.4 The innovation drivers in the Northeast

The number of patent applications in the Northeast was 80,933 in 2012, 6.3 times higher than in 2000 (12,758 items). Because there are only three province-level regions in the Northeast, the economic disparity among regions is not big, and the CV_W is between 0.3 and 0.5. The contribution of regional economic structure and the CV_W

is roughly in opposite directions. Since 2004, R&D intensity has been around 1.15%, which is a great improvement compared with 0.70% in 2000. However, the innovation efficiency effect of the Northeast is negative. This condition is consistent with the research conclusion that the innovation ability not only depends on R&D inputs, but also relies on the enhancement of R&D efficiency (Chiu et al. 2012). If an area endowed with good innovation resources has low efficiency, its innovation ability is limited, and the economic growth will be restricted. Fritsch and Slavtchev (2009) argued that factors such as enterprise property, industrial structure, regional economic system, and enterprise system can influence regional innovation efficiency. Generally, the innovation frequency in light industry is greater than in heavy industry, and light industry has a shorter innovation cycle compared with heavy industry. The incentive system for state-owned enterprises or R&D organizations lacks flexibility, resulting in low levels of technological innovation efficiency. In a large firm, there is a good deal more bureaucracy, which leads to more difficult communication and coordination of R&D. The Northeast has been the concentration zone of heavy industry for a long time but it is lacking a transmission mechanism to transform innovation input into actual output. It has a high proportion of large- and medium-sized enterprises and insufficient market competition, so the change of innovation efficiency negatively effects innovation output.

5 Robustness check

In this section, we replicate the LMDI decomposition model using different measures to prove the consistency and reliability of the empirical results. We consider several robustness checks to address this concern.

5.1 R&D personnel as the innovation input

Prior studies typically use R&D expenditure and R&D personnel to measure the inputs of innovation (Cruz-Cázares et al. 2013; Griliches 1979; Hong et al. 2016; Wang et al. 2016). As a robustness check to study the stability and significance of the results, we can estimate the LMDI model with the variable R&D computed as the Full-time equivalent of R&D personnel (R&D FTE). R&D FTE has been widely used as a measure of innovation input although not as commonly as the expenses for internal R&D activities (Guan and Chen 2010; Hong et al. 2015). The main results are robust to the alternative measure of innovation input (see Table 7 in “Appendix”).

5.2 Scientific papers as the innovation output

As innovation includes technological and scientific aspects, we also can perform a robustness test of our model using the publication of scientific papers as the proxy for innovation output (Wang and Huang 2007). The measure “scientific papers” is calculated as the total number of papers published in Science Citation Index (SCI) international journals and in Engineering Index (EI) international journals[4]. As a robustness check, we report the results through two specifications, one considers no time lag for scientific papers and the other uses a 1-year lag for scientific papers. The sign and the relative importance of different components are not changed by using the scientific papers measure (see Table 8 in "Appendix").

6 Concluding remarks

Despite high interest in innovation performance, few empirical studies address influencing factors from both systematic and dynamic perspectives. As today's China is in transition, the analysis of influencing factors of innovation may have important implications for the formulation of government policy. Drawing upon the extended Kaya identity, this paper applies the LMDI model to analyze the driving factors of innovation performance and their respective contributions using a panel dataset of 30 Chinese provincial-level regions during 2000–2012. First, the study examines innovation-driven activities in the whole country, and investigates the influencing factors, regional economic structure, regional R&D intensity, regional innovation efficiency, and national economic development. Then, the 30 provincial-level regions are divided into four groups to discuss the different impacts on different areas. Over the entire study period, China's innovation output rose by an average of 1.0834 patent applications per 10,000 annually. R&D intensity, innovation efficiency, and economic development had positive impacts. The contribution rate of positive drivers was 101.69%. The innovation performance was primarily driven by the innovation effect (R&D intensity effect and innovation efficiency effect), the contribution rate of which was 81.78%. Nationally, the contribution rate of the economic development was 19.92%, which means that China's innovation performance is closely related to its economic development. In terms of innovation effect, the contribution rate of R&D intensity was 27.49% and the innovation efficiency was 54.28%. The decomposition of this proposed indicator allows us to identify the channels through which entities conduct their innovation activities. That is, heavy R&D investment, although necessary for implementing an innovation-driven strategy, does not necessarily bring high efficiency in innovation and cannot guarantee success in innovation (Chen and Guan 2012). More attention should be paid to improving the R&D efficiency for better innovation performance. The regional economic structure has a negative impact, indicating the imbalanced regional development in China. But the negative contribution rate is far lower than that of positive factors, so China's innovation output was increasing throughout the period 2000–2012.

Looking at individual areas, the impacts of the four driving factors on innovation performance vary significantly among China's four major economic areas. The East has a better innovation foundation and a higher innovation ability than the other areas; the Central, West, and Northeast areas are relatively backward. The innovation performance of the West mainly depends on economic development and its R&D intensity is

[4] The Social Science Citation Index (SSCI) papers is also widely recognized as the academic achievements from R&D activities. Due to the lack of SSCI data, the current study takes no consideration of SSCI.

insufficient, which hinders the sustainable growth of its innovation output. Due to the industrial structure of the Northeast, the negative innovation efficiency effect needs to be evaluated carefully. Since noticeable differences among four areas in terms of realizing paths for innovation in China are observed during 2000–2012, policy makers should formulate appropriate innovation policies for each area according to its resource endowment and environmental capacity as well as its development stage, rather than treat them uniformly.

This study's empirical research results lead to interesting findings regarding the policy implications of China's innovation activities. First, our study indicates that the unbalanced structure of a regional economy inhibits innovation output growth, which is consistent with the findings of many previous research publications. This finding supports the usefulness and justification of the state policy to narrow regional gaps. There are invisible barriers hindering the flow of resources that affect the technological innovation flow among different administrative regions in China, such as local protectionism, scientific research systems, and household registration systems, leading to unbalanced regional economic development. Given the rising regional inequality in China, it is difficult to change the regional economic structure in China in the short term. If these differences increase further, they may result in serious social problems such as social unrest. It is necessary for the Chinese government to balance equity and efficiency, and to work on addressing this problem. In addition, traffic and information networks should be constructed to accelerate innovation diffusion, helping to realize coordinated development. To further develop China's national regional development strategy, the Chinese government should promote its develop-the-west strategy, fully revitalize Northeast China, promote the rise of the Central area, and actively support the transformation and upgrading of the East, with the overall goal of narrowing the regional gap.

Second, our results suggest that innovation performance is primarily driven by the innovation effect (R&D intensity effect and innovation efficiency effect), which means that China's innovation performance is closely related to its economic development. In terms of innovation effect, the contribution rate nationally of R&D intensity is 27.49% and rate of the innovation efficiency is 54.27%. Therefore, heavy R&D investment, although necessary for implement innovation-driven strategy, does not necessarily bring high efficiency for innovation and cannot guarantee success in innovation, which quantitatively supports the argument of Chen and Guan (2012). Those findings remind us that increasing investment in R&D may not be an optimal policy instrument to promote innovation performance, and that other incentive policy instruments to improve the innovation efficiency would be preferable. Such alternatives could include the promoting of state-owned enterprise reform, staff training, infrastructure construction, an incentive mechanism for technology innovation, the establishment of a more effective legal and financial system, and so on (Hendricks 2002; Porter and Millar 1985; Ren et al. 2012).

Third, the role of influencing factors varied significantly among the four major economic regions, which indicates the necessity for consideration of regional disparity. Many previous studies have pointed out the existence of regional inequality (Cheong and Wu 2014; Jian et al. 1996; Li and Gibson 2013), so when assessing the local government, the central government should follow the principle of seeking truth from facts and scientific development needs, and implement a classification evaluation. The East should give priority to innovation-driven indices such as independent innovation and independent brand innovation. On this basis, Beijing and Shanghai should increase their evaluation weights of cultural industry. The Central area should focus on economic development, using economic development as the key indicator. The Northwest should develop its science and technology for regional ecological restoration, maximizing the ecological restoration index. On the basis of the reconstruction of its old industrial base, the Northeast should vigorously promote S&T innovation in heavy industry, and insist on the road of independent innovation and independent brand construction.

As with most studies, this research is not free of limitations and offers several useful directions for future study. First, as discussed extensively in Sect. 2.2, using patent applications as proxy of innovation can be criticized because not all the patents can be commercialized successfully (Yang and Yang 2015). Because of the unavailability of data, this current study focuses on the R&D stage and leaves aside the commercialization stage, thereby following the approach in mainstream economic literature (Bronzini and Piselli 2016; Li 2009). Future study can go one step further and take the economic performance into account. Second, this paper studies innovation activities from the perspective of regional disparity. According to the work of Li et al. (2014), the industrial structure is also an important factor affecting innovation performance. There is regional and industrial diversity within a nation, especially in transitional economies, so it is better to take the industrial structure into consideration and thus to provide a comprehensive picture or story of innovation performance in China. Third, as the reasons for regional disparity are multifaceted, ranging from economic to political circumstances, future research should further refine the impact of regional economic structure. Despite the limitations, this study makes a significant contribution to innovation activities by extending the LMDI decomposition model to investigate the driving factors of innovation performance in China. This provides an in-depth and systematic analysis of the role of regional structure, innovation effect, and economic development. Moreover, it enriches the empirical study of the factors and yields implications for the formulation of government policies.

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Appendix

See Tables 7, 8.

Table 7 Decomposition results of China's innovation performance (R&D personnel as the innovation input)

	Total effect	Regional economic structure	R&D intensity	Innovation efficiency	Economic development
$Patent\ count + R\&D\ FTE$					
2000–2001	0.1628	0.0038	0.0153	0.1310	0.0127
2001–2002	0.2941	0.0422	0.0893	0.1301	0.0325
2002–2003	0.3315	0.0065	−0.0198	0.2833	0.0615
2003–2004	0.2028	−0.0092	0.0004	0.0609	0.1507
2004–2005	0.7930	−0.0085	0.3021	0.3413	0.1581
2005–2006	0.6406	0.0041	0.2672	0.2718	0.0975
2006–2007	0.8675	−0.0134	0.5066	0.2189	0.1554
2007–2008	0.9638	−0.0523	0.3835	0.2925	0.3401
2008–2009	1.1858	−0.0073	0.9775	0.1931	0.0225
2009–2010	1.6829	−0.0288	0.2913	0.8720	0.5484
2010–2011	2.9112	−0.0827	0.3359	1.8208	0.8372
2011–2012	2.9640	−0.0744	1.4192	1.4459	0.1733
Mean	1.0833	−0.0183	0.3807	0.5051	0.2158
$(Patent\ count)_{t+1} + R\&D\ FTE$					
2000–2001	0.2974	0.0049	0.0231	0.2540	0.0154
2001–2002	0.3351	0.0522	0.1100	0.1324	0.0405
2002–2003	0.2037	0.0086	−0.0229	0.1458	0.0722
2003–2004	0.7708	−0.0096	−0.0033	0.5951	0.1886
2004–2005	0.6743	−0.0083	0.4021	0.0735	0.2070
2005–2006	0.8720	0.0066	0.3294	0.4143	0.1217
2006–2007	0.9769	−0.0162	0.6143	0.1851	0.1937
2007–2008	1.1936	−0.0615	0.4818	0.3534	0.4199
2008–2009	1.6906	0.0013	1.2293	0.4318	0.0282
2009–2010	2.9083	−0.0270	0.3834	1.8282	0.7237
2010–2011	2.9882	−0.0987	0.4229	1.5610	1.1030
2011–2012	2.3307	−0.0806	1.7319	0.4679	0.2115
Mean	1.2701	−0.0190	0.4752	0.5369	0.2771

The data of full-time equivalent of R&D personnel (R&D FTE) are collected from the China Statistical Yearbook on Science and Technology 2001–2013

Results for the four major areas are not reported to save space

Table 8 Decomposition results of China's innovation performance (scientific papers as the innovation output)

	Total effect	Regional economic structure	R&D intensity	Innovation efficiency	Economic development
Scientific papers					
2000–2001	0.1060	0.0032	0.0095	0.0902	0.0031
2001–2002	0.0722	0.0277	0.0126	0.0230	0.0089
2002–2003	0.1076	−0.0002	0.0177	0.0731	0.0170
2003–2004	0.0997	−0.0018	0.0252	0.0324	0.0439
2004–2005	0.3520	−0.0129	0.0524	0.2614	0.0511
2005–2006	0.0945	0.0010	0.0227	0.0393	0.0315
2006–2007	0.1392	0.0001	0.0150	0.0789	0.0452
2007–2008	0.1861	−0.0135	0.0449	0.0632	0.0915
2008–2009	0.1479	0.0031	0.2002	−0.0610	0.0056
2009–2010	0.2281	−0.0066	0.0144	0.0964	0.1239
2010–2011	0.1346	−0.0119	0.0332	−0.0470	0.1603
2011–2012	0.1553	−0.0012	0.1251	0.0041	0.0273
Mean	0.1519	−0.0011	0.0477	0.0545	0.0508
$(Scientific\ papers)_{t+1}$					
2000–2001	0.0730	0.0043	0.0132	0.0513	0.0042
2001–2002	0.1087	0.0332	0.0170	0.0473	0.0112
2002–2003	0.1002	−0.0002	0.0231	0.0563	0.0210
2003–2004	0.3450	−0.0023	0.0346	0.2517	0.0610
2004–2005	0.1051	−0.0162	0.0683	−0.0139	0.0669
2005–2006	0.1397	0.0012	0.0249	0.0782	0.0354
2006–2007	0.1891	0.0001	0.0183	0.1186	0.0521
2007–2008	0.1487	−0.0146	0.0525	0.0065	0.1043
2008–2009	0.2287	0.0035	0.2282	−0.0094	0.0064
2009–2010	0.1314	−0.0071	0.0162	−0.0163	0.1386
2010–2011	0.1574	−0.0121	0.0364	−0.0408	0.1739
2011–2012	0.5120	−0.0009	0.1473	0.3336	0.0320
Mean	0.1866	−0.0009	0.0567	0.0719	0.0589

The data of scientific papers for a given year are reported in the China Statistical Yearbook on Science and Technology for the subsequent two years. We use the statistics from 2001 to 2014

Results for the four major areas are not reported to save space

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