Can innovation really bring economic growth? The role of social filter in China

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Abstract: This study explores the relationship between R&D investment and economic growth in China, using a newly collected panel data set. Specifically, we investigate how social filters are connected to R&D output. Instead of linking R&D investment directly to economic performance, we adopt a two-step strategy which identifies the impact R&D investment on R&D output, and then study the causal links between R&D output and economic development. Our results suggest that the relationship between R&D input, R&D output and economic growth diverges by different region and sectors. Most of positive associations stem from non-peripheral regions and non-state owned sectors. Social filters are also more effective under these circumstances. These results reveal the complexity of relationships between R&D efforts and economic performance and point to the important role of social filters in innovation and growth.

Keywords: R&D; Spillover; Social Filter; Economic Growth; China

1. Introduction

China has become one of the world's major economic powers with great potential, and the overall living standard has reached that of a fairly well-off society. In the past 30 years following the economic reform and opening-up in 1979 in particular, the Chinese economy has been developing at an unprecedented rate, and that momentum has been held steady into the 21st century. The Chinese economic growth however is mainly driven by export-oriented and labor-intensive manufacturing sectors, which is very vulnerable to external shocks such as the 2008 US sub-prime credit crisis and recent US-China trade war. To maintain sustainable economic growth in the future, China's policy makers believe that innovation plays a decisive role (Schaaper, 2009; Zhang et al., 2009). It is true that innovation generally is correlated with improved GDP-growth outcomes, but some empirical evidence shows that the causal link is not that obvious under certain circumstances. For instance, Jones (1995) indicated that although there was a tremendous rise in R&D input over the past 40 years for OECD countries, the GDP growth rates remain constant in many regions. Therefore, some scholars claim that R&D investment exerts only marginal effects on local development (Carlino and Hunt, 2007).

One possible explanation for the divergent results is the regional variation on R&D efficiency. According to Rodríguez-Pose (1999), some societies are innovation prone while some other societies are innovation averse due to the differences on social filters. Social filters are sets of socio-economic elements which favour or deter the development of a regional innovation system (Crescenzi and Rodríguez-Pose, 2013; Rodríguez-Pose, 1999). Therefore, R&D investment is not always positively related to economic development. In the theoretic front, it is also inappropriate to link R&D investment directly with economic performance. Although funding and personnel invested in R&D process may be associated with innovation, the R&D output does not necessarily lead to an increase of high-tech production so that it may not contribute to economic performance. Consequently, it is more reasonable to study each sets of causal links separately.

Our paper tries to provide empirical evidence on the relationship between R&D investment and economic development in China using a newly compiled data set. To our knowledge, despite the extensive literature on Chinese economic development and the impact of R&D, factors that determine R&D efficiency have not been thoroughly studied. Besides, the R&D efforts are assumed to be correlated directly to economic performance in previous Chinese studies. Therefore, there are still sizable gaps in research on R&D and economic growth. In this paper, we consider a two-step strategy which studies the correlation between R&D investment and R&D output as well as R&D output and economic development separately. We also incorporate social filter factors to see if the effect of R&D activity on economic development is contingent upon social and economic conditions. We argue social filters are important sources of 'codified' and 'non-codifiable' knowledge (Hodgson, 1988; Langlois, 2001; Gertler, 2003) in terms of understanding how things were typically done in different social and cultural contexts (Adams, 1992; Mayhew, 2001) and therefore the need to fully appreciate social filters in specific, localised contexts.

The rest of the paper is organized as following. Section 2 briefly reviews the literature on how R&D is related with economic performance, and the determinants of R&D efficiency. Our research framework is presented in Section 3 which provides an overview of a two stage strategy for the models used in the paper and the data set used. Section 4 presents the estimation results and highlights the main findings. Concluding remarks are summarized in the final section.

2. Literature Review

2.1 General relationship between R&D and economic performance

Scholars have long been interested in studying the engine of economic growth. With the popularity of endogenous growth theories, economists have realized that technological under-achievement is a major barrier to economic development, and R&D is a critical determinant on economic performance. As we all know, economic development is mainly about increasing the size of economy (Gross domestic output), which is normally measured by the final products and services people are willing to buy within a certain period of time. Since innovation is characterized by technical changes that result in better services, products and increasing productivities, there should be a positive correlation between R&D and economic development. Numerous models (e.g., Aghion and Howitt, 1992; Crossman and Helpman, 1991; Stokey,1995) have been constructed to highlight the significant role of R&D in promoting economic development, firm competitiveness and industrial dynamics (Coad *et al*, 2019).

In the empirical front, the positive relationship between R&D efforts and economic development has also been proved by scholars of various countries. For instance, early study of Horowitz (1967) found that regions with consistent growth rate of R&D activity are associated with consistent pattern of economic growth in America. Using panel data for OECD countries, Zachariadis (2007) has shown that R&D effort exerts strong positive effect on productivity and output. This result is supported by Falk (2007) who also found a positive relationship between R&D efforts in high-tech sectors and GDP per capita in OECD countries. Similar evidences have also been found in less developed countries. Kim (2011) argued that the overall contribution ratio of R&D to economic growth is about 35% in South Korea. Peng (2010) concluded that 1 percent of increase in R&D expenditures leads to 0.92 percent of increase in GDP level in China.

2.2 Social filter and R&D efficiency gear

Although the majority of the literature argues that R&D efforts are associated with regional economic performance, some scholars believe that not all the regions are capable of transforming R&D investment into real economic outcomes under any circumstance (e.g., Rodríguez-Pose, 1999; Shearmur and Bonnet, 2011). For instance, Zeng et al., (2019) proposed that absorptive capacity is an important moderator in the link between innovation input and output. It can act as a self-reinforcing mechanism for innovative activities. Duan et al. (2019) argued that the speed of inter-regional technology transfer is also important. A moderate level of transfer speed is more cable of promote the effect of innovation on growth. In an earlier study, Niu and Chen (2011) found that patent output is only significant in predicting growth in certain sector. As summarized by Crescenzi and Rodríguez-Pose (2013), factors such as social capital, human capital, institutional quality and cultural characteristics are critical in determining R&D efficiency. Therefore, "innovation is no longer explained by the sole combinations of tangible forms of capital (physical, financial, etc), but also by combinations of intangible forms of capital (Landry et al, 2002: 683)." Therefore, there always exist certain social and economic characteristics that may promote or hamper the impact of R&D on growth. The promoting effect thus cannot be taken as granted.

Social filters are sets of socio-economic elements which favour or deter the development of a regional innovation system (Crescenzi and Rodríguez-Pose, 2013; Rodríguez-Pose, 1999). Specifically, a region is considered to be innovation averse when it is characterized by strong social filter conditions, such as rigid labor market and shortage of skills. Contrarily, a region is considered to be innovation prone when it is characterized by weak social filter conditions, such as higher level of human capital (Rodríguez-Pose, 1999; Becker, 2009), institutional connectivity or 'thickness' (Amin, 1998). Strong social filters are associated with the institutionalist argument of institutional rigidity (Hodgson, 1989) whereby weak social filter are considered as conducive to change. In sum, innovation averse region are those with a thick wall between R&D input and output. Innovation actors in this case lack the capacity to transform innovation into value added economic activities. There will be lower returns yielded by the effort in R&D.

It should be noted that, social filters are not about identifying how single factors are related to R&D efficiency. Contrarily, it seeks to find out whether the innovative region can be explained by a set of social conditions. Therefore, like Breschi and Lissoni (2001)'s studies on Innovation Milieux and Florida (1995)'s definition of learning Region, social filter theory is to investigate the role of the whole social settings in linking R&D to growth. As suggested by Rodríguez-Pose (1999), the most significant features for innovation averse societies are the lacks of ability to transform innovation into value added economic activities. Investment in R&D will only result in lower economic returns than in innovation prone region or in ordinary region. Based on this concept, social and economic conditions such as the availability of adequate skills in the labor force, the ability to use these skills in the market, the presence of a young and dynamic population, and a favorable sectorial structure can all be included into social filters

Several empirical evidences lend supports to social filter theory. Rodríguez-Pose (1999) found that non-favorable social filter conditions, such as low participation of women, aging of workforce, shortage of high skills are detrimental to innovation at peripheral regions. The inadequate social conditions further reduce the economic return of innovation. Crescenzi (2007) compared innovation in China and India. The results suggested that social filter conditions such as agglomeration effect on population and infrastructure endowments are of great importance in China. However in India, link to trade liberalization determines which specific regions move up in the world technology ladder. Based on panel data from 31 Mexican states, Rodríguez-Pose and Peralta (2015) found that economic growth in Mexico benefited from regions with favorable social filter conditions. In particular, it helps a region reap more benefit from additional investment in R&D.

The above discussion highlights the complicated causal link between R&D and growth, which should be a multi-step process. One of the best example in reality is the 'Swedish Paradox', which refers to the fact that higher levels of R&D effort in Sweden is not associated with production of high-tech products and higher level of high-tech exports (Edquist and Mckelvey, 1998; Pessoa, 2007; Ejermo and Kander, 2006). Instead of discussing the simple linear relationship, they identified four gears to capture the full process of how R&D efforts are related to local growth. Firstly, R&D efforts mainly contribute in the direction of invention (Gear A); inventive activity then is linked directly with innovation (Gear B) which affects high-tech production (Gear C), and ultimately in turn makes up part of GDP (Gear D)[1]. According to their findings, the causal link between each gear can not be taken for granted. For instance, entrepreneurial activities are critical for translating R&D effort into actual invention. Meanwhile, academic resource, i.e., a well functioned higher education system, is necessary to link invention with innovation. Moreover, innovation may not lead to high-tech production for small country where there are spillovers and imitations. The Swedish Paradox also has valuable implications for a wider audience as different countries may have problems in different gears. Therefore, it is no wonder that some previous studies found divergent result regarding the relationship between R&D efforts and growth.

2.3 R&D Spillover effect

In addition to the focus on the R&D activity itself, many papers look into the positive technology spillover effect, which commonly refers to 'stand on the shoulder effect.' As suggested by Mansfield (1985), due to the imperfect patenting and movement of skilled labor, knowledge of innovation leaks quickly between firms. Therefore, some firms hope to free ride on R&D activities carried out by other firms rather than innovate themselves (Griliches, 1988). At regional level, it has also been found that benefit deprived from foreign R&D is higher than self-dependent innovation for small countries (Helpman and Coe, 1995).

Empirical findings also lend support to these arguments. For example, Eaton and Kortum (1999) modeled the diffusion of new technologies across countries and provided a quantitative explanation of research effort, the growth of productivity and the spread of technology across countries. Roughly, according to their findings, research performed abroad is about two-thirds as potent as domestic research. The existing of international barriers to technological diffusion prevented the productivity growth. Funke and Niebuhr (2005) proposed robust estimation techniques to evaluate the research and development spillovers across west German functional regions between 1976 and 1996. In the paper, they built a quantitative model to capture regional technology spillover and found that regional growth was positively correlated with the R&D activity of neighboring regions, although the spillovers decreased rather quickly with distance. Their finding confirmed the hypothesis that proximity

[1] Although introducing new products to the market is the common way to reap benefit from R&D, one alternative is to license the technology to external actors. Both approaches should contribute to economic performance.

matters. More recently, Ang and Madsen (2012) investigated the economic growth of six Asian economies and found that international knowledge spillover on total factor productivities contributes a lot to Asian economic miracles.

2.4 Research framework

In our study, the relationship between R&D and growth can be roughly described as follows in Figure 1. Due to the limitation of data, we are only able to examine two sets of relationships (Gears) of R&D and growth. The *first* path deals with the link from R&D investment and R&D output. Although other informal input may also lead to inventive outcome, R&D investment generally refers to R&D funding and R&D personnel. Bilbao-Osorio and Rodríguez-Pose (2004) has already adopted this two-step strategy using EU samples. As documented earlier, the causal link between R&D investment and R&D output cannot be taken for granted. To what extent the R&D efforts can be transformed into innovation contingent on the social filter conditions. The *second* path refers to the link from R&D output to GDP growth. Similarly, social and economic conditions are critical for a region to derive economic benefits from innovations. Lastly, given the fact that technology spillover effect contributes to regional development, we could presume that it benefits local innovation and GDP growth synchronously.

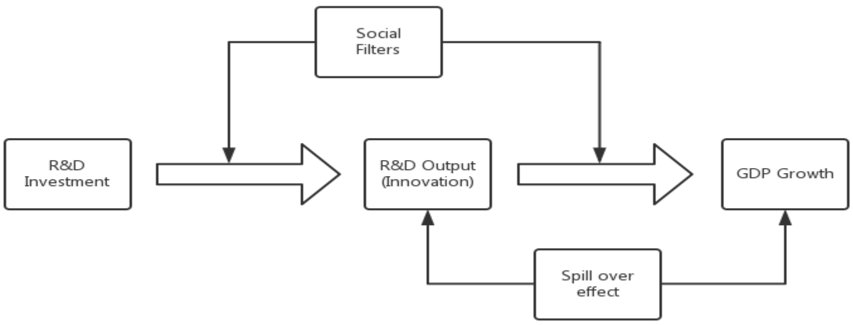

Figure 1. Path route of R&D investment and GDP growth

In this path route, we presume that external factors (e.g., social filters) are the major determinants of R&D efficiency. That is to say innovative actors (firm, government or university) always have strong motivation to commercialize its new technology and innovation. If R&D effort fails to exert influential impact on economic performance, we interpret it as a cause of unfavorable condition for innovation (strong social filter). One may question that internal factors, such as patent ownership, organizational structure and organizational culture also influence their commercialization strategy as indicated by previous studies (e.g., Lukas and Ferrell, 2000). However, from the long run perspective, the behavior of the organization is also a function of localized social settings. Therefore, there should not be fundamentally drawbacks for this ideal path route.

The primary aim of our paper is to study the above mentioned two paths controlling for spillover effect and local social-economic conditions using a China data set. Previous studies argued that R&D in China has three major characteristics.

(1) Chinese provinces differ a lot in their regional innovation abilities (Sun, 2000; Li, 2009, Fan et al., 2012). It has been found that the number of granted patents clusters in east coast China and the differences in innovation input are the major causes (Liu and White, 2001). This implies that higher level of R&D endowment leads to higher level of output according to previous studies. Other factors such as government support and industry specific environment (e,g.,Li,2009); Intermediary organization (e.g., Wu and Xu, 2013), and return migration (e.g., Sternberg and Müller, 2005) have also been found to be correlated with R&D efficiency in China.

(2) Spillover is critical for China's innovation and growth (e.g., Wang et al., 2015; Shang et al., 2012; Jiang et al., 2010). However, to what extent the recipient regions benefit from technology spillover is contingent on its ability to identify and exploit foreign knowledge (Cohen and Levinthal, 1990), which commonly refers to absorptive capacity. Using province level data covering the period 1996-2002, Lai, et al. (2006) argued that the absorptive capability in China depended on the human capital investment and degree of openness. Jiang et al. (2010) indicated that telecommunications and human mobility are also of great importance in enhancing absorptive ability.

(3) One of the major challenges of the Chinese innovation system is its over-reliance on government sector. According to the data in China Statistics Year Book 2014, government funded R&D accounts for 21.5% of total R&D expenditures and enterprise funded R&D accounted for 78.5%. The proportion of government directly funded R&D in China is not significantly higher than the western countries. However, State-owned enterprises (SOEs) take a relatively larger part of enterprise supported R&D funding (55%). Meanwhile, it has also been found that SOEs are not efficient users of knowledge. Using panel data in China, Yang et al (2012) found that higher ratio of SOEs R&D lowers local innovative ability due to the inefficiency of

SOEs. Therefore, policies that benefit SOEs may have crowded out support to non-SOEs in China (OECD, 2008:p42).

Generally, these studies are in line with our framework. Innovation in China is driven primarily by R&D investment and technology spillover exerts critical influence on innovation and growth. The relationship between R&D and economic performance may not be taken for granted in China as government sector plays a significant role in national innovation system and is considered to be less efficient. Although previous studies have found some other factors that are associated with innovation efficiency in China, the social filter conditions (social settings as a whole) have not been extensively studied. Further, to our knowledge the multi-step strategies have not been adopted in studying relationships between R&D efforts – Innovation – Growth. Therefore, it is still unclear how R&D is related to economic development in China.

3. Data Description and the Model

In this paper, we use a newly collected panel data set covering 31 provinces, autonomous regions and centrally-administered municipalities in China, with the time spans from 1998 to 2013, 16 years in total. The data for R&D Funding by Region and R&D Personnel by Region are from China Statistical Yearbook on Science and Technology, various years. The data for Trade Openness from 1998 to 2004 are from China Compendium of Statistics 1949 – 2004, various years. All the other data used in the analysis are from the China Statistical Yearbook, various years. To select appropriate proxy variables, our selection is based on the following criteria: (1) the proxy variables must be comparable across regions; (2) they must address the characteristics of R&D conditions in China; (3) the proxy variables should be estimable, and data are available.

3.1 Specification of Equation I

As documented earlier, this paper aims at investigating R&D activities and economic performance, endogenous growth catch-up model is thus employed. As suggested by Schumpeter (1966), although innovation is likely to increase the technological gap, regions with lower level of technology may catch up with advanced region via knowledge diffusion and imitation or ‘late comer advantage’ (Lin, 2012). Therefore, economic growth can be explained by both technology gap and the ability to exploit the gap. Fagerberg (1987) argues that, in general this model contains three elements: the potential for imitation, the innovating activity, and the efforts mobilized in exploiting technological gap. Rodríguez-Pose and Peralta (2015) incorporates social filter factors into this approach and modified the model as

Equation I:

$$\ln(RGDPC)_{i,t} = \beta_1 \ln(RGDPC)_{i,t_0} + \beta_2 \ln(FPAT)_{i,t\text{-}3} + \beta_3 \ln(SF)_{i,t} + \beta_4 \ln(INV)_{i,t} + \beta_5 \ln(ExRGDPC)_{i,t} + \beta_6 \ln(n+g+\delta) + \beta_7 \ln(ExPAT) + \varepsilon_{i,t}$$

$RGDPC_{i,t}$ is the real gross domestic product (GDP) per capita in region *i* and in year *t*. One of the main implications of the neoclassical growth theory and models that exhibit transitional dynamics is that the growth rate depends on the initial condition of the economy. The main idea of “conditional convergence” hypothesis is that an economy grows faster the further it is from its own steady-state value (Barro and Sala-i-Martin, 2004). So we include the initial position of the economy by including the (log of the) initial level of real GDP per capita in the set of explanatory variables. $ExRGDPC_{i,t}$ refers to the potential spillovers linked to the wealth of neighboring states as suggested by Rodríguez-Pose and Peralta (2015). The national mean and standard deviation of real GDP per capita is RMB 18,199.04 yuan and RMB 15,373.86 yuan as indicated by table 1. For different regions, the mean real GDP per capita is RMB 33,073.78 yuan for the non-peripheral provinces and RMB 12,893.93 yuan for the peripheral provinces. It is obvious that the eastern China develops much better than the central and western China, with the real GDP per capita in the eastern more than twice as much as that of the central and western[2].

Table 1. Summary Statistics by Main Variables

Variable	Region	NOB	Mean	Standard Deviation	Minimum	Maximum
Fund (%)	National	496	1.12	1.07	0.01	7.78
	Non Peripheral	126	2.06	1.6	0.19	7.78
	Peripheral	370	0.8	0.51	0.01	2.98
RDPersonR(%)	National	496	0.15	0.2	0.01	1.15
	Non Peripheral	126	0.35	0.3	0.03	1.15
	Peripheral	370	0.08	0.05	0.01	0.25
Patent(%)	National	496	2.66	5.06	0.03	36.81

[2] We have to admit that dividing peripheral and non-peripheral regions based on the geography location is somewhat rough. There are some area in western regions are relatively developed. However, western regions enjoyed different institutional settings compared with eastern regions (known as The Western Development Policy in China). These policy settings include tariff reduction, tax exemption and one on one support from eastern regions, etco this end, we treat the Eastern China as non-peripheral regions and the Western China as peripheral regions.

	Non Peripheral	126	6.67	8.19	0.31	36.81
	Peripheral	370	1.03	1.31	0.03	8.36
RGDPC	National	496	18199.04	15373.86	701.43	83448.43
	Non Peripheral	126	33073.78	19763.68	8103.54	83448.43
	Peripheral	370	12893.93	8968.28	701.43	57864.32
PGrow(‰)	National	496	5.96	3.26	0.01	13.87
	Non Peripheral	126	4.43	2.97	0.01	13.51
	Peripheral	370	8.42	4.31	1.46	13.87
INV(%)	National	496	51.1	12.52	33.44	119.9
	Non Peripheral	126	48.2	7.63	35.3	76.9
	Peripheral	370	52.49	13.86	33.44	119.9
Open (%)	National	496	31.41	40.53	3.16	164.91
	Non Peripheral	126	87.13	44.7	19.22	164.91
	Peripheral	370	12.31	7.76	3.16	42.74
Education level	National	496	8.05	1.24	2.94	11.93
	Non Peripheral	126	8.89	1.23	6.62	11.93
	Peripheral	370	7.74	1.13	2.94	10.03
Employment	National	496	56.13	16.17	14.04	89.6
	Non Peripheral	126	72.94	17.56	19.5	89.6
	Peripheral	370	39.06	10.32	14.04	66.54
Urbanization	National	496	49.27	16.17	14.04	89.06
	Non Peripheral	126	44.63	10.78	14.04	66.54
	Peripheral	370	61.63	17.56	19.85	89.06

$(FPAT)_{i,t}$ is the flow of new knowledge/ideas which is measured by number of patent granted per 10 thousand people in region *i* in time *t*. The national mean is 2.66 with standard deviation 5.06, and the difference in R&D among different regions is quite large. During the 16 years we studied, eastern China have average 6.67 domestic patents granted each year, peripheral China have average 1.03, which is about 15% of eastern China. Since knowledge may take years to realize economic value, we thereby impose a lag of three years between number of patent and economic growth to be consistent with Porter and Stern (2000).

$ExPAT_{i,t}$ is the regional technology spillover effect, which is the possibility that regions benefit from spatial spillovers. The idea is that provinces can benefit from external stock of knowledge. The knowledge spillovers approach has been adopted by economists using different quantitative methods, while the spillover effect arises mainly from the positive externality of adjoining regions' R&D activity. In this paper, we follow Funke and Niebuhr (2005) and Kuo and Yang (2008), denote the region knowledge spillover as:

$$ExPAT_i = \sum_{\substack{j=1 \\ j \neq i}}^{N} SPAT_j \cdot \exp\left[-\beta_E \cdot d_{ij}\right] = \sum_{\substack{j=1 \\ j \neq i}}^{N} SPAT_j \cdot \exp\left[\frac{\ln(1-\gamma_E)}{\overline{D}_{AVR}} \cdot d_{ij}\right]$$

where $SPAT_j$ measures the stock of patents in province *j*. d_{ij} is the distance between the centers of the regions *i* and *j*. In this paper, we choose the railway distances, rather than straight line distances, between the capital cities of regions *i* and *j*, since it gives a more realistic representation of the cost of interaction across spaces. $\overline{D}_{AVR}$ is the average railway distance between the capital cities of immediately adjacent provinces, and γ_E is a transformed distance decay parameter. As is customary in the literature, we choose $\gamma_E = 0.5$, since similar estimates for the spillover effects have been found when various distance decay parameters according to Kuo and Yang (2008).

$INV_{i.t}$ is the investment savings ratio in region i and in year t. In Fagerberg (1987)'s work, investment refers to the efforts in exploiting the technology gap. We follow Li and Huang (2008) to use the share of investment spending in GDP as proxy for investment savings ratio. The national mean for the investment rate is 51.10% with standard deviation 12.52%. The average ratios for non-peripheral and peripheral regions are 48.20% and 52.49%, respectively, which are very close to each other. These show that the investment is quite balanced among different regions.

ln(n+g+d) is the workforce growth in region i and in year t with value equal to the summary of population growth rate, depreciation rate and technological growth progress. For the sum of the depreciation rate and technological progress, we follow the approach in Makiw et al. (1992), in which it is assumed to be 0.05 and is the same for all provinces and all years.

$SF_{i,t}$ refers to social filter variable which measure the ability of a region to transform innovation to economic activity. As suggested by Rodríguez-Pose (1999); Bilbao-Osorio and Rodríguez-Pose (2004) and Crescenzi and Rodríguez-Pose (2013) social filter is related to labor market structure, demographics and educational attainment. To be consistent with these studies, we adopt several variables to measure social filter: (1)urbanization rate, which is calculated by proportion of citizens that live in urban area. (2) Social capital, which is measured by number of social organizations per 10 thousand people. (3) Privatization, which is measured by proportion of private fixed investment. (4) Financial development index from NERI INDEX of Marketization of China’s Provinces Report 2011. (5) Property right development index from NERI INDEX of Marketization of China’s Provinces Report.

The first two variables are identical with that of Crescenzi and Rodríguez-Pose (2013)’s study. It has been also found that urbanization is associated with creativity due to the agglomeration effect (Andersson et al., 2005). Meanwhile, social capital contributes to innovation as it facilitates diffusion of knowledge and valuable information (e.g., Landry et a, 2002). We thereby incorporate social organization and urbanization as one of dimensions of social filter variables. Numerous studies highlight the critical role of institution such as contract law, property rights or privatization in innovation (e.g., Markusen 2001; Tan et al,2015). Therefore, three institutional indicators: privatization, property rights and financial development were included. Finally, we adopt principal component analysis (PCA) to convert the seven indicators into two uncorrelated variables (see the appendix for details).

3.2 Specification of Equation II

The equation I mentioned above deals with the casual link from R&D output to economic performance. Knowledge production function is then adopted to identify how R&D input is related to R&D output. According to Romer (1990) and Jones (1995) the basic form of knowledge production function is given as $\dot{A}_{it} = \delta L_{it}^{\lambda} A_{it}^{\phi}$. In this model knowledge is a function of the number of idea workers (L) and the stock of knowledge (A). λ refers to the efficiency parameter of knowledge worker, whereas ϕ refers to the feasibility of long-term knowledge-based growth. The knowledge production function has been extensively studied and extended by numerous scholars. For instance, Porter and Stern (2000) emphasize the “raising the bar effect”, arguing that a region is benefited from ideas that new to the local but not necessarily new to the world. Cheung and Lin (2004) systematically studies how international trade and foreign direct investment (FDI) is embedded in innovation process. Therefore, the knowledge production function can be extended as: $\dot{A}_{it} = \delta L_{it}^{\lambda} A_{it}^{\phi} R_{it}^{\kappa} A_{-it}^{\varphi} F_{it}^{\mu} T_{it}^{\nu}$. In this model, flow of knowledge is a function of idea workers (*L*), expenditure spend on creating new idea (*R*), stock of knowledge (*A*), stock of knowledge in neighboring region (A_{-i}), volume of international trade (*T*) and volume of FDI (*F*). Therefore, when social filter is incorporated, the regression model can be given as Equation II:

$$
\begin{aligned}
\ln(FPAT)_{i,t+3} = {} & \beta_1 \ln(SPAT)_{i,t} + \beta_2 \ln(ExPAT)_{i,t} + \beta_3 SF_{i,t} + \beta_4 \ln(Fund)_{i,t} + \beta_5 \ln(Person)_{i,t} \\
& + \beta_6 \ln(Open)_{i,t} + \beta_7 \ln(FDI)_{i,t} + \omega_{i,t}
\end{aligned}
$$

$SPAT_{i,t}$ refers to stock of patent discovered in local region which is calculated through perpetual inventory method: $SPAT_{i,t+1} = (1-d)SPAT_{i,t} + FPAT_{i,t}$ as suggested by Pessoa (2005). In this equation, stock of patent is determined by stock of patent in previous year; depreciation rate and flow of patent in current year. To be consistent with Pessoa (2005)'s study, we set the depreciation rate as 5% in baseline model and as 0% as well as 10% in robustness check.

$Open_{i.t}$ and $FDI_{i.t}$ measures the international trade openness in region i and in year t. The former is calculated by the volume of trade (export plus import) over GDP. Since we are studying all the provinces within the same country, it is not necessary to adjust the proxy variable for whether it is landlocked, and for whether it is an oil exporter like other cross-country empirical studies. The rationale that we want to include the international trade openness is that we want to use this variable to capture possible effects of international technological spillovers. For the trade openness proxy variable, trade/GDP, the national mean is 31.41% with standard deviation 40.52%. The non-peripheral regions which includes mainly coastal provinces has a much more prosperous trade, with mean 87.13%, than its central and western counterparts, with mean 12.31%. This data indicates that during the past decade, the exports and imports are mainly concentrated along the eastern seaboard.

$Fund_{i,t}$ and $Person_{i,t}$ refers to R&D funding out of GDP and R&D personnel out of population. For the R&D Funding out of GDP, the national mean is 1.12% with standard deviation 1.07%. For the non-peripheral region (Eastern China) and peripheral region, the R&D Funding out of GDP ratios are 2.06% and 0.81%, respectively. The higher ratio in eastern China indicates that non-peripheral region takes more effect in R&D investment. For the R&D personnel out of population, the national mean is 0.15% with standard deviation 0.20%. The mean for non-peripheral region (eastern) and peripheral region are 0.35% and 0.08%, respectively. These give the similar picture as the R&D funding out of GDP, that the eastern China has much better R&D resources and devote more efforts than other two regions.

4. Estimation Results

As a preliminary examination of the relationships among the key variables we studied, correlation analysis is adopted. From the correlation matrix in Table 2, we find the correlation relationships are consistent with our expectation. The $Patent$ is positively related to $Fund$ and $Person$. On the other hand, $Patent$ is also positively correlated with $RGDPC$ (correlation coefficient 0.8855). The relationship between SF and $Patent$ is also positive, suggesting that a region scoring higher in social filter may be able to produce more patents[3]. Finally, our results suggest a positive relationship between technology $ExPAT$ and $Patent$ as well as $RGDPC$. However, the coefficient is relatively smaller comparing with other variables.

Table 2. Correlation Analysis

	Patent	Person	Fund	RGDPC	SF	RDRSP
Patent						
Person	0.8768					
Fund	0.7398	0.8921				
RGDPC	0.8855	0.7959	0.6105			
SF	0.8029	0.8268	0.7023	0.7796		
ExPAT	0.5493	0.4595	0.4306	0.5757	0.3407	1.0000

In the regression analysis, we will first conduct baseline model using standard OLS estimation, fixed effect estimation, random effect estimation. Quadratic term of explanatory variables are then introduced to see if there is a U-shaped relationship between R&D input and output as well as R&D output and economic development. We finally incorporate social filter variable to study if the U-shaped relationship is caused by social-economic factors.

In robustness check, we adopt dynamic panel GMM estimation to capture the potential endogeneity problem (Blundell and Bond, 2000); and control for time effect in panel fixed and random model to capture the time trend. In addition, to have an overall picture of the impact of R&D investment on economic growth, we also divide our sample into peripheral and non-peripheral regions in robustness check. The non-peripheral region refers to eastern region including 10 provinces, and the peripheral region covers the rest of Chinese provinces. Most of Chinese studies (e.g., Li and Huang, 2008), divide the 31 provinces, autonomous regions and centrally-administered municipalities into three groups[4], the eastern, the central and the western based on their geographical locations, according to the definition by the Nation Bureau of Statistics of China. However, from the perspective of economic development, the middle,

[3] In the correlation analysis, social filter variable (SF) is treated as numerical variable, the value of which is the score of PCA.
[4] Eastern China: Beijing, Fujian, Guangdong, Hainan, Hebei, Jiangsu, Liaoning, Shandong, Shanghai, Tianjin, Zhejiang; Central China: Anhui, Guangxi, Heilongjiang, Henan, Hubei, Hunan, Inner Mongolia, Jiangxi, Jilin, Shanxi; Western China: Chongqing, Gansu, Guizhou, Ningxia, Qinghai, Shannxi, Sichuan, Tibet, Xinjiang, Yunnan.

western and northeast China share lots of similarities and therefore can be classified as one group.

4.1 R&D investment and R&D output

Model I in Table 3 is obtained by including variables of lagged value of Real GDP per capita, regional technology spillover effects, social filter, and R&D investment as the baseline model. The coefficients on R&D personal ($\ln(Person)$) is positive and significant while the coefficients on R&D funding ($\ln(Fund)$) turn out to be negative and insignificant, suggesting that R&D funding is not positively correlated to R&D output in OLS estimation. The coefficient on social filter variable ($SF = 1$) is also positive and significant suggesting that province positioned as weak social filter region are capable of producing more innovation. Note that social filter variable is treated as categorical variable in our estimation. The lagged value of Real GDP per capita (ln(RGDPD)) and technology spillover effect (ln(ExPAT)) are both positive and significant, which indicate that R&D output is promoted by regional technology spillover effect and previous economic achievement. In column 2 and 3 of model I, fixed effect and random effect model are employed and the results are similar to OLS estimation. R&D personnel positively related to granted patent number, while R&D funding still exhibit a negative sign; lagged value of Real GDP per capita , spillover effect and social filter is positively related to granted patent number. According to the result of Hausman test, fixed effect model is more valid than OLS and random effect estimation.

In model II, we incorporate quadratic term of R&D funding ($[\ln(Fund)]^2$) and R&D personnel ($[\ln(Person)]^2$). This is to study if the relationship between R&D investment and R&D output are curvilinear. As aforementioned, not all the regions are capable of generating R&D output through R&D investment. The OLS estimation in column1 reveal that both R&D personnel and R&D funding is having a positive effect on R&D output. Meanwhile, the quadratic term of these two variables also exhibit a positive sign, suggesting that R&D investment is positively related to R&D output in OLS estimation. Control variables also exhibit positive and significant sign as previous regression. In column 2 and 3 of model II, fixed and random effect model is employed. The result shows that R&D personnel exert a strong positive impact on R&D output as $\ln(\mathrm{Person})$ and $[\ln(Person)]^2$ both exhibit a positive and significant sign. A U-shaped relationship might exist between R&D funding and R&D output as $\ln(RDFundR)$ exhibit a negative sign and $[\ln(Fund)]^2$ exhibits a positive sign. Hausman test suggests that random effect model is preferred in this case.

Lastly in model III, the interaction term of R&D investment variable and social filter variable is introduced, so as to investigate if certain social-economic factors are able to mediate the relationship between R&D investment and R&D output. As suggested by columns 2 and 3 of model III, interaction term ($\ln(Fund)*SF$) exhibit a positive and significant sign, which indicate that region positioned as weak social filter region (SF=1) are better able to convert R&D expenditure into output. Regarding R&D personnel, its interaction term with social filter variable exhibits a positive sign but not significant, suggesting that the relationship between R&D personnel and R&D output is less likely to be influence by social filter variables.

Overall, our results show that the causal link between R&D input and output is complicated. For R&D personnel, our results indicate a clear and straightforward positive causal link with coefficient ranging from 0.45 to 0.9. Since we take logarithmic form on the both sides of equation, the result suggested that 1% of increase in R&D personnel leads to 0.45% to 0.9% of increase in patent number. For R&D funding alone, 1% of increase in R&D funding may lead to 0.3% of decrease in patent number. However, with the help of Social filter conditions, 1% increase in R&D funding leads to 0.245% (=0.523-0.278) of increase in R&D output. In consistent with previous study (e.g., Shang et al., 2012), regional spillovers exerts positive impact on regional innovation. 1% increase outside patent stock is associated with 0.5% increase in patent number. Therefore, proximate location to innovative neighbors can help to raise the innovation capability of a province.

Table 3. The Effect of R&D Investment on R&D Output

	Model I			Model II			Model III		
	OLS	Fixed	Random	OLS	Fixed	Random	OLS	Fixed	Random
ln(Fund)	-0.088	-0.078	-0.090	0.144*	-0.052	-0.008	-0.199	-0.278***	-0.299***
	(0.136)	(0.166)	(0.201)	(0.065)	(0.342)	(0.521)	(0.154)	(0.003)	(0.004)
ln(Person)	0.781***	0.495***	0.481***	0.732***	0.793***	0.952***	0.552***	0.563***	0.730***
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.003)	(0.006)
ln($RGDPC_1$)	0.535***	0.117***	0.199***	0.797***	0.478***	0.589***	0.489***	0.099**	0.160**
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.026)	(0.034)
ln(ExPAT)	0.108***	0.608***	0.402***	0.069***	0.383***	0.258***	0.130***	0.552***	0.405***
	(0.003)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
SF=1	0.199***	0.077	0.102*	0.012	0.032	0.034	0.076**	0.073	0.181
	(0.000)	(0.121)	(0.073)	(0.231)	(0.342)	(0.481)	(0.045)	(0.231)	(0.182)
$[\ln(Fund)]^2$				0.013	0.022	0.028**			
				(0.322)	(0.279)	(0.092)			
$\ln[(Person)]^2$				0.061*	0.088***	0.103***			

				(0.078)	(0.001)	(0.004)			
ln(Fund)*SF							0.340**	0.523***	0.578***
							(0.033)	(0.002)	(0.001)
ln(Person)*SF							0.162*	0.053	0.028
							(0.071)	(0.241)	(0.187)
CONSTANT	-4.272	-5.627	-3.799	-6.983	-6.902	-6.33	-4.787	-4.911	-3.752
NOB	496	496	496	496	496	496	496	496	496
Adjusted R^2	0.849	0.889	0.879	0.877	0.905	0.904	0.861	0.914	0.901
Prob>F(chi2)	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00
Hausman test	-	79.77	-	-	5.69	-	-	-17.55	-

1. The t-statistics are reported in the parentheses. *p<0.90; **p<0.95; ***p<0.99.

2. Negative values in Hausman test indicate that the data fails to meet its asymptotic assumptions.

4.2 R&D output and economic development

In this section we will investigate how R&D output (measured by number of granted patent) is related to economic development. Although a positive correlation has been generally proved in theoretic front, previous literatures also point out that the R&D investment alone is not sufficient to predict economic performance. What equally important is social, economic and institutional conditions (See a summary of Crescenzi and Rodríguez-Pose, 2013).

As documented earlier, the model employed in this section is derived from neoclassical growth model. Except for regional R&D investment we will focus on technology spillover effect as well. Model I in Table 4 present the estimation result without social filter variable using OLS, fixed and random effect model. The results suggest that number of granted patent ($\ln(Patent)$) is not significant in predicting economic development, while regional technology spillover effect ($\ln(ExPAT)$) exerts only a weak impact. Control variables such as lagged value of GDP per capita ($\ln(RGDPC)$), investment ratio ($\ln(INV)$) and openness ($\ln(Open)$) exhibit a positive sign. The coefficients on the workforce growth ($\ln(n+g+\delta)$) are negative and significant, which is consistent with the result of McDonald and Roberts (2002). In column 2 and 3, fixed and random effect model is employed which produce similar results as OLS estimation, except for that number of granted patents is slightly negative related to economic development. The Hasuman test however suggests that fixed effect model is more valid.

Model II adds quadratic term of number of patents ($[\ln(Patent)]^2$) into the base model to evaluate whether the relationship between R&D output and economic development is curvilinear. As usual, OLS is conducted first and followed by fixed and random effect model.

The result shows that both $\ln(Patent)$ and $[\ln(Patent)]^2$ exhibits a significant negative sign which implies that the relationship between R&D outputs and economic development is negative. In model III, social filter variable and its interaction term with R&D output variable ($\ln(Patent)*SF$) is introduced. The regression results show that R&D output is not significantly related to GDP per capita, and the ability of reaping economic benefit from patent is also not significantly different in innovation averse and innovation prone region in China.

Table 4. The Effect of R&D Output on Economic Development

	Model I			Model II			Model III		
	OLS	Fixed	Random	OLS	Fixed	Random	OLS	Fixed	Random
ln(Patent)	0.019	-0.026***	-0.019***	-0.013***	-0.018**	-0.013	0.006	-0.004	0.006
	(0.251)	(0.001)	(0.002)	(0.000)	(0.015)	(0.037)	(0.311)	(0.278)	(0.244)
ln(ExPAT)	0.005**	0.005*	0.005**	0.007***	-0.001	0.007***	0.007*	-0.004	0.007*
	(0.032)	(0.052)	(0.041)	(0.000)	(0.172)	(0.000)	(0.064)	(0.171)	(0.083)
ln($RGDPC_1$)	1.031***	1.057***	1.034***	1.026***	1.037***	1.026***	1.029***	1.034***	1.029***
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
ln(INV)	0.049***	0.046***	0.049***	0.061***	0.047***	0.061***	0.056***	0.048***	0.055***
	(0.001)	(0.002)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
ln(Open)	0.002	0.058*	0.013	0.005	0.064*	0.005	-0.008	0.064***	-0.008
	(0.141)	(0.080)	(0.229)	(0.182)	(0.071)	(0.236)	(0.201)	(0.001)	(0.381)
ln(n+g+d)	-0.031***	-0.026***	-0.031***	-0.027***	-0.025***	-0.027***	-0.029***	-0.024***	-0.029***
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.002)	(0.000)	(0.000)
ln[(Patent)]^2				-0.007***	-0.005**	-0.006***			
				(0.000)	(0.021)	(0.000)			
SF=1							0.006	0.019**	0.007
							(0.161)	(0.034)	(0.241)
ln(Patent)*SF							-0.038***	-0.028***	-0.003
							(0.004)	(0.005)	(0.216)
CONSTANT	-0.401	-0.696	-0.403	-0.422	-0.652	-0.398	-0.311	-0.528	-0.331
NOB	496	496	496	496	496	496	496	496	496
Adjusted R^2	0.952	0.941	0.711	0.955	0.967	0.938	0.955	0.966	0.712
Prob>F(chi2)	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00
Hausman test		70.01			76.72			78.42	

1. The t-statistics are reported in the parentheses. *p<0.90; **p<0.95; ***p<0.99.

2. Negative values in Hausman test indicate that the data fails to meet its asymptotic assumptions

4.3 Additional regressions and robustness check

To make in-depth analysis on the role of social filters, we hereby process data with sub samples. The first strategy is to divide our samples into non-peripheral region and peripheral region. The non-peripheral region in China refers to eastern province whereas the peripheral region refers to the rest provinces in china. As aforementioned, Eastern and Western China face relatively different institutional settings and social filters may plays a different role. Second, we divide sample into SOEs and non-SOEs. After economic reform, the overall number of SOEs decreased a lot. However, remaining SOEs became bigger and stronger and they occupied large amount of subsidies and bank loans (Chen and Lai, 2015). It should be noted that social filter theory is based on western context where economic activities are dominated by private sectors. Those social filter conditions may play different role in promoting innovation in private or non-private sectors. IV estimation is finally employed to address the problem of edogeneity.

Table 5. The effect of R&D input on output (Sub-sample of SOEs and Non-SOEs)

	Peripheral			Non-peripheral		
	OLS	Fixed	Random	OLS	Fixed	Random
ln(Fund)	0.121**	-0.087*	-0.099*	0.181**	0.122**	0.105**
	(0.033)	(0.056)	(0.073)	(0.013)	(0.033)	(0.041)
ln(Person)	0.892***	0.324***	0.511***	0.489***	0.601***	0.681***
	(0.000)	(0.010)	(0.003)	(0.000)	(0.003)	(0.000)
ln($RGDPC_1$)	0.535***	0.672***	0.418***	0.489***	0.198**	0.160**
	(0.000)	(0.000)	(0.000)	(0.000)	(0.014)	(0.022)
ln(ExPAT)	0.179**	0.421***	0.381***	0.122***	0.319***	0.327***
	(0.023)	(0.002)	(0.001)	(0.000)	(0.000)	(0.000)
SF=1	0.102**	0.077	0.102*	0.076**	0.087**	0.273**
	(0.047)	(0.181)	(0.083)	(0.045)	(0.031)	(0.021)
ln(Fund)*SF	0.298**	0.393**	0.448***	0.329**	0.505***	0.544***
	(0.043)	(0.022)	(0.001)	(0.033)	(0.002)	(0.001)
ln(Person)*SF	0.162*	0.053	0.088	0.144*	0.043	0.079
	(0.061)	(0.199)	(0.154)	(0.051)	(0.198)	(0.125)
CONSTANT	-4.644	-5.234	-3.123	-4.475	-4.475	-3.754
NOB	370	370	370	126	126	126
Adjusted R^2	0.811	0868	0.893	0.857	0.906	0.917
Prob>F(chi2)	0.000	0.000	0.000	0.00	0.00	0.00
Hausman test	-	69.97	-	-	-10.45	-

1.The t-statistics are reported in the parentheses. *p<0.90; **p<0.95; ***p<0.99. Left three columns report estimations in Peripheral regions and right side columns report estimations in Non-peripheral regions.

2. Negative values in Hausman test indicate that the data fails to meet its asymptotic assumptions.

Table 6. The effect of R&D output on economic development (Sub-sample of SOEs and Non-SOEs)

	Peripheral			Non-peripheral		
	OLS	Fixed	Random	OLS	Fixed	Random
ln(Patent)	0.018	-0.046***	-0.071***	0.056***	0.074***	0.082***
	(0.311)	(0.004)	(0.001)	(0.011)	(0.001)	(0.000)
ln(ExPAT)	0.007**	0.008**	0.009**	0.005***	0.022**	0.031**
	(0.022)	(0.042)	(0.033)	(0.002)	(0.021)	(0.013)
ln($RGDPC_1$)	1.129***	1.200***	0.933***	1.380***	1.422***	1.291***
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
ln(INV)	0.032**	0.074**	0.098**	0.057***	0.066***	0.071***
	(0.057)	(0.012)	(0.010)	(0.000)	(0.000)	(0.000)
ln(Open)	0.002	0.052**	0.078**	-0.008	0.024	0.008
	(0.158)	(0.040)	(0.019)	(0.201)	(0.301)	(0.381)
ln(n+g+d)	-0.021***	-0.033***	-0.041***	-0.008***	-0.019***	-0.012***
	(0.000)	(0.000)	(0.000)	(0.002)	(0.000)	(0.000)
SF=1	0.081	0.101	0.122*	0.116**	0.120**	0.133**
	(0.141)	(0.102)	(0.078)	(0.033)	(0.019)	(0.016)
ln(Patent)*SF	0.031***	0.021***	0.019***	0.078***	0.044***	0.059***
	(0.004)	(0.011)	(0.026)	(0.001)	(0.005)	(0.002)
CONSTANT	-0.321	-0.501	-0.322	-0.261	-0.642	-0.592
NOB	370	370	370	126	126	126
Adjusted R^2	0.921	0.910	0.899	0.929	0.940	0.891
Prob>F(chi2)	0.000	0.000	0.000	0.000	0.000	0.000
Hausman test		69.01			82.48	

1. The t-statistics are reported in the parentheses. *p<0.90; **p<0.95; ***p<0.99. Left three columns report estimations in peripheral regions and right side columns report estimations in Non-peripheral regions.

2. Negative values in Hausman test indicate that the data fails to meet its asymptotic assumptions.

Table 5 reports estimations on both peripheral and non-peripheral region and the result is different from the full sample. For instance, in non-peripheral regions, 1% increase in R&D funding and R&D personnel lead to 0.1% and 0.7% of increase in patent number respectively. However in peripheral regions, R&D funding is insignificant in predicting R&D output. For social filter conditions, the positive effect observed in previous section resides only in non-peripheral. Regarding other variables, our result indicates that innovation in peripheral region relied more on regional spillover. 1% of increase in external patent stock leads to 0.4%

of increase in R&D output. Table 6 reveals the interplay between R&D output and growth. The result again implies a huge regional disparity in China. In line with the study of Chen et al., (2009) east China is more capable of reaping benefit from innovation.

Table 7. The effect of R&D input on output (Sub-sample of SOEs and Non-SOEs)

	SOEs			Non-SOEs		
	OLS	Fixed	Random	OLS	Fixed	Random
ln(Fund)	0.012	-0.022	-0.031	0.178	0.212	0.189
	(0.189)	(0.120)	(0.105)	(0.022)	(0.008)	(0.013)
ln(Person)	0.521***	0.211***	0.178***	0.448***	0.418***	0.420***
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
ln($RGDPC_1$)	0.321***	0.322***	0.299***	0.278***	0.307***	0.265***
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
ln(ExPAT)	0.201**	0.329***	0.285***	0.155**	0.134*	0.129*
	(0.023)	(0.002)	(0.001)	(0.043)	(0.062)	(0.071)
SF=1	0.087	0.099	0.104	0.110**	0.140**	0.132**
	(0.152)	(0.181)	(0.153)	(0.044)	(0.029)	(0.032)
ln(Fund)*SF	0.079**	0.032	0.021	0.084***	0.052**	0.033**
	(0.043)	(0.109)	(0.121)	(0.004)	(0.019)	(0.031)
ln(Person)*SF	0.002	0.002	0.003	0.162**	0.123**	0.182***
	(0.201)	(0.231)	(0.214)	(0.061)	(0.032)	(0.004)
CONSTANT	-2.851	-4.019	-4.291	-2.977	-3.491	-4.190
NOB	496	496	496	496	496	496
Adjusted R^2	0.903	0.849	0.879	0.884	0.921	0.904
Prob>F(chi2)	0.000	0.000	0.000	0.000	0.000	0.000
Hausman test	-	57.18	-	-	-2.45	-

1. The t-statistics are reported in the parentheses. *p<0.90; **p<0.95; ***p<0.99. Left three columns report estimations in SOEs samples and right side columns report estimations in Non-SOEs samples.

2. Negative values in Hausman test indicate that the data fails to meet its asymptotic assumptions.

Table 8. The effect of R&D output on economic development (Sub-sample of SOEs and Non-SOEs)

	SOEs			Non-SOEs		
	OLS	Fixed	Random	OLS	Fixed	Random
ln(Patent)	0.017	0.032	0.015	0.076**	0.109***	0.097***
	(0.201)	(0.281)	(0.301)	(0.011)	(0.001)	(0.000)
ln(ExPAT)	0.006**	0.019**	0.029**	0.003***	0.068*** (0.007)	0.080***

	(0.012)	(0.031)	(0.017)	(0.002)		(0.002)
$\ln(RGDPC_1)$	1.201***	1.309***	1.112***	1.117***	1.287***	1.101***
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
ln(INV)	0.044**	0.059**	0.072***	0.057**	0.064**	0.056**
	(0.022)	(0.012)	(0.004)	(0.002)	(0.018)	(0.020)
ln(Open)	0.012	0.049	0.039	-0.008	0.031	0.018
	(0.133)	(0.109)	(0.120)	(0.157)	(0.202)	(0.271)
ln(n+g+d)	-0.026***	-0.040***	-0.033***	-0.019***	-0.033***	-0.044***
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
SF=1	0.075	0.138*	0.174**	0.121**	0.156**	0.144**
	(0.129)	(0.055)	(0.031)	(0.029)	(0.010)	(0.014)
ln(Patent)*SF	0.031**	0.041**	0.094***	0.133***	0.144***	0.152***
	(0.028)	(0.022)	(0.002)	(0.000)	(0.000)	(0.000)
CONSTANT	-0.501	-0.482	-0.378	-0.484	-0.521	-0.390
NOB	496	496	496	496	496	496
Adjusted R^2	0.894	0.928	0.904	0.905	0.920	0.901
Prob>F(chi2)	0.000	0.000	0.000	0.000	0.000	0.000
Hausman test		44.81			67.51	

1. The t-statistics are reported in the parentheses. *p<0.90; **p<0.95; ***p<0.99. Left three columns report estimations in SOEs samples and right side columns report estimations in Non-SOEs samples.

2. Negative values in Hausman test indicate that the data fails to meet its asymptotic assumptions.

In table 7 and 8, we differentiate innovation in SOEs from non-SOEs. As suggested in the result, R&D personnel is significant in predicting output in SOEs but to a lesser extent compared with non-SOEs (2% compared with 4%). Social filter conditions increase the positive impact of SOEs sample only. 1% increase R&D personnel leads to around 6% increase in patent number with both main effect and interaction effect. Innovation in non-SOEs contributes to regional growth significantly. Innovation in SOEs however exerts limited impact. Despite economic reform, the SOEs are still relatively less efficient compared with non-SOE sectors, a point which has been extensively mentioned in previous studies (Yang et al., 2012; Chen and Lai, 2015).

Finally, IV estimation is employed to deals with the problem of two-way causality. In consistent with Xiong et al.(2017), the longitudes and latitude of capital city in each province is used as instrumental variables. As suggested by Bjørnskov and Méon (2015), geographic conditions have a profound impact on social activities of human beings. For instance, habitants in cold regions are more prone to cooperate with others so as to survive from bad weather. This acts as a necessary prerequisite to higher levels of general trust. Agriculture and farming is more common in warm and wet regions, which produces mainly particular trust with kinship ties. In China, regions with higher levels of longitude are generally close to sea which formed marine civilization. Therefore, it can be predicted that habitants in high longitude and low latitude area relied more on bridging social capital, an important element in promoting innovation efficiency (Akcomak and Weel, 2008). Therefore, geographic conditions have a profound impact on social and economic conditions but are not strongly related to regional development in nowadays. The results confirm our estimations in previous section and social filters conditions indeed exert positive impact under certain circumstance.

Table 9. Robust Check for the sample in different regions

	Model 1	Model 2	Model 3	Model 4
ln(FundR)	0.122**		0.115**	
	(0.033)		(0.042)	
ln(PersonR)	0.401***		0.881***	
	(0.003)		(0.000)	
ln($RGDPC_1$)	0.121**	0.921***	0.106**	1.211***
	(0.021)	(0.000)	(0.043)	(0.000)
ln(ExPAT)	0.041***	0.076**	0.068**	0.043***
	(0.006)	(0.022)	(0.030)	(0.000)
IV.SF	0.241**	0.145**	0.177**	0.109**
	(0.017)	(0.073)	(0.031)	(0.082)
ln(INV)		0.021		0.049***
		(0.165)		(0.000)
ln(Open)		0.121***		0.102**
		(0.000)		(0.033)
ln(n+g+d)		-0.048***		-0.024***
		(0.001)		(0.000)
ln(Patent)		0.073*		0.025**
		(0.061)		(0.033)
Longitude	-0.004***	-0.004***	-0.004***	-0.004***
	(0.002)	(0.002)	(0.002)	(0.002)
Latitude	0.003*	0.003*	0.003*	0.003*
	(0.047)	(0.047)	(0.047)	(0.047)
NOB	126	126	496	496
Adjusted R^2	0.837	0.844	0.892	0.901
Prob>F(chi2)	0	0	0	0
Hansen J	9.809	12.392	11.221	10.291

1. The t-statistics are reported in the parentheses. *p<0.90; **p<0.95; ***p<0.99. Model 1 and model 2 refers to estimations on non-peripheral

regions. Model 3 and 4 refers to estimations on non-SOEs. Since Social filters conditions in peripheral sample and SOEs samples are not that significant, it is no need to apply IV approach.

5. Conclusions

In the paper, we look at the relationship between R&D investment and economic growth in China, using a newly collected panel data. We conduct analysis which examines the association between R&D investment and innovation output as well as innovation output and economic development respectively. Social filters conditions have been incorporated as one of the main independent variables. The results imply a complex relationship between R&D investment and economic performance in China. R&D input is related to R&D output only in non-state sectors and non-peripheral regions. Meanwhile, patent number is not able to contribute growth for state sectors and peripheral regions. The promoting effects of social filters conditions have also been confirmed under certain circumstance. Therefore, R&D investment is only conditionally related to innovation and economic growth.

Two reasons can account for this. First, it has been found that that R&D activities in China's state owned sectors are less efficient. Previous studies show that patent in R&D covered by government financial support is less likely to be commercialized due to the moral hazard problem. Owner of the government funded patent thus is less motivated to commercialize its innovation (Svensson, 2006). Using data set in China, Peng and Yu (2013) indicate that government financial support is effective in promoting growth of Small and medium sized enterprise and exert no significant or negative impact on the growth of state-controlled enterprises. Second, there exist huge disparities in different regions in China. When operating as a entirety, China made great achievement in innovation. However, only few regions can be highlighted as innovation prone provinces. Investment and international trade is still the most contributors to growth in middle and west China.

If China wishes to develop its knowledge economy and reap more benefit from innovation, more comprehensive policy is needed rather than simply increasing R&D input. Social economic conditions such as labor market, urbanizations are of great importance. For instance social filters increase the positive effect of R&D funding on output by another 0.4%. Therefore, regional government should focus on a series of factors that support the overall innovation system. Due to the large regional disparities, policies that promote innovation and growth should also consider localized factors. In middle and west China, the growth mode is still in its primary stage which may need further reform. Besides, since large numbers of R&D activities in China are funded directly or indirectly by the government, there should be some initiatives to motivate the owner of these patents to commercialize their innovations.

Our paper is, of course, not without drawbacks. First, we have only examined two sets of relationship due to data limitation. According to Ejermo and Kander (2006), the whole innovation process involves four gears: R&D investment-invention (Gear A); invention-innovation (Gear B), innovation-production (Gear C) and production-economic growth (Gear D). The results of our paper suggest that China seems to have problem in Gear C or Gear D. However, we are not able to clearly identify which gear is primarily responsible for the problem. Second, we proxy social filter with three indicators proposed by existing studies based on principal component analysis. Relevant theory in Chinese context has not been well established. One possible weakness is that we might overlook some critical localized conditions. Taken all these into consideration, future research on R&D and economic performance should focus on the whole picture of innovative growth and incorporate more localized factors.

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Appendix Principal Component Analysis for Social Filter

	Comp1	Comp2	Comp3	Comp4	Comp5
Urbanization	0.669	0.1371	0.3896	-0.1646	0.5946
Social Organization	0.5964	0.0655	-0.1559	0.6765	-0.3976
Privatization	-0.4338	0.2989	0.5284	0.6191	0.245
Property Right	-0.0668	0.0659	-0.6783	0.0805	0.4025
Financial Development	0.0543	0.7216	0.2907	-0.3542	-0.5161

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