

Research on the performance of industrial innovation of small and medium-sized enterprises in China

Guoqing Lu, Peng Dai and Xia Zhang
Hunan University, Changsha, China

Abstract

Purpose – The purpose of this paper is to test the relationship between innovation performance and innovation spillover effects, innovation inputs, innovation outputs and industrial effects.

Design/methodology/approach – The analysis framework including variables such as innovation spillover effect, innovation input, innovation output and industrial effect was constructed. Through the investigation and analysis of the innovation activities of China's GEM listed companies in 2014–2016, the innovation performance and the above factors were tested.

Findings – The research shows that enterprise performance has a significant positive correlation with innovation input and innovation output, but there is no significant correlation or even negative correlation with innovation environment and industry background such as government support and innovation opportunities, and the spillover effect is significant. The negative correlation is also negatively correlated with innovative human capital investment, company age and company Q.

Originality/value – Innovation is the real source of economic growth, and industrial innovation is the system integration of technological innovation, product innovation, market innovation, etc., which is the basic determinant of national competitiveness.

Keywords Innovation performance, Innovation spillover effect, Industrial innovation, GEM listed company

Paper type Research paper

1. Introduction

Since Schumpeter's innovation theory was put forward, the impact of innovation on economic growth has gained more and more attention from economists. The general view is that innovation is an important endogenous variable to economic growth (Baumol, 2002, 2007; Malerba and Brusoni, 2007; Peters, 2008). Baumol (2002) emphasized that innovation was the real source of unprecedented growth of capitalist economy, while small enterprises with proprietary innovation and large high-tech enterprises were the two wheels driving innovation forward.

Since the 18th National Congress of CPC, the Chinese Government has taken changing the mode of economic growth and structural adjustment as its strategic task to an unprecedented height, and in particular since the USA ban on ZTE sales after Sino – US trade war broke out in 2018, the proprietary innovation of key technologies and core industries has been highlighted as “pillars of a power.” The 13th Five-Year Plan put forward the important proposition of shaping the leading development by relying more on innovation and giving more play to the first-mover advantages. Either to replace old growth drivers with new ones or to achieve high-quality development, the essence is industrial upgrading and the fundamental path to industrial upgrading lies in industrial innovation. Freeman and Soete (1997), the author of the theory of national innovation, believes that the efficiency of industrial transformation depends on a country's industrial innovation



capability, and the core of national innovation is industrial innovation. He compared the former Soviet Union and Japan to illustrate the importance of industrial innovation in economic development. Japan lagged far behind the USA and other countries in technological innovation, especially major scientific and technological innovation. However, due to its strong industrial innovation capability, Japan's competitiveness in many industrial fields far exceeded that of the USA. Although the USA was the first innovator in these industries, Japan became the market leader. While the former Soviet Union could compete with the USA in technological innovation or invention, even surpassing the USA in some cutting-edge scientific and technological fields, however, due to its lack of innovative capability to transform advanced technologies into products and industries, most of its new and high-tech technologies only existed in laboratories or were used for military purposes and could not enter the major industrial sectors of the national economy. The lack of industrial innovation capability brought the economy of the former Soviet Union to the brink of collapse. Baumol (2007) also cited the four great inventions of ancient China. Although the talented Chinese people created these world-leading technologies, they lacked the capability to utilize them, or in today's term, the capability of industrial innovation. Whether it is the implementation of the major strategy of building an innovative country or the transformation of China's economic growth engines from old to new, it cannot be separated from the innovation practice of a large number of small- and medium-sized enterprises (SMEs) with industrial innovation capability. Looking at the history of the world capital market, the reason why GEM exists is simply to support the entrepreneurial innovation of SME. Innovation is the foundation of GEM's existence and also the source of GEM's development. China's GEM has existed for nearly ten years since its establishment in 2009, and about 700 SMEs have been successfully listed on the GEM, which highlights its remarkable achievement in terms of development speed. However, its development quality is not high, and has been criticized for the prevalence of market fraud, the large fluctuation of the index, the fact that the index has remained unchanged for ten years and the failure to cultivate a truly subversive and innovative company such as BATJ. At present, there is a lack of in-depth research on GEM innovation in theoretical circles and this paper attempts to make an empirical study on the innovation performance of listed companies on GEM, the pioneer of China's industrial innovation and its determinants.

2. Literature review

2.1 *The meaning of industrial innovation*

Schumpeter (1934) believed that the essence of innovation was "industrial mutation" or "creative destruction," while "creative destruction" was the fundamental driving force of economic growth. Since Schumpeter's theory of innovation, the theory and practice of innovation have made great achievements in the world, especially, the national innovation system, regional innovation system and innovation system of departments, industries and enterprises have attracted more and more attention. Schumpeter's innovation is actually the popular concept of "industrialization" in China's public opinion. In essence, industrialization is a "new combination" of factors of production, that is, the process of transforming results of technological innovation into commodities, which is the process of industrial innovation. Therefore, we can say that Schumpeter's concept of innovation is consistent with the connotation of industrial innovation. Freeman and Soete (1987, 1997) pointed out that industrial innovation was a systematic concept, and systematic factors were decisive factors to the success of industrial innovation. Lundvall (1992), Nelson (1993) and Malerba *et al.* (2004, 2007) also believed that innovation had systematic characteristics. Malerba *et al.* (2004, 2007) put forward the concept of sectoral systems of innovation based on the evolution theory. Malerba believes that sector is more accurate than industry in terms of innovation, as innovation system includes non-industrial organizations such as governments and

universities, and the sector innovation system includes three components: first, knowledge and technology; second, actors and networks; and third, the system (Malerba, 2004). From the content perspective, Malerba's concept of sector innovation is basically consistent with Freeman's industrial innovation theory. Scherer (1982) also suggested that sectors could reflect the characteristics and boundaries of R&D activities and technological activities more accurately than industries. However, up till now, both government statistics and stock exchange data have been based on industrial standards, and academic research in this field basically has been based on the definition of industry. Therefore, this paper believes that the concept of industrial innovation is more reasonable and easier for study. It can be said that industrial innovation is the systematic integration of technological innovation, product innovation, market innovation, etc. It is also the process that enterprises breaking the restrictions posed by structured industry and utilizing technological innovation, product innovation, market innovation or combination innovation to change the existing industrial structure or to create new industries, which is exactly what Schumpeter called the process of industrial mutation or creative destruction (Lu Guoqing, 2002).

2.2 Research progress at home and abroad

A great deal of empirical research shows that innovation is positively correlated with enterprise performance and its competitiveness (Peters, 2008), but there is also a research conclusion that R&D investment is weakly correlated with the performance of the enterprise, and innovation cannot explain all productivity growth of enterprises (Griliches, 1994). Peters (2008) made systematic investigation on the innovation performance of German enterprises, and his basic conclusion was that the labor productivity and the labor productivity growth were clearly positively correlated with the product innovation, but there is no conclusion between the process innovation and enterprise performance. The elasticity coefficient of knowledge capital output of German manufacturing enterprises is about 0.04, which is slightly lower than the output elasticity coefficient of existing R&D capital.

With the growth of new economy, there are three new dynamics in the field of innovation economics, which are the impact of spreading effect on productivity, the different forms of research and development cooperation and the role of patents in promoting innovation when innovation grows (Sena, 2004). The spreading effect has become the hot spot in foreign innovation research. In the endogenous growth model, the technology spillover or R&D spillover as important factor has gained wide attention (Grossman and Helpman, 1991). Since endogenous growth theory was born, knowledge innovation and spillover have been considered to have a significant impact on economic growth. Indeed, in the endogenous growth model, the focus is that individual companies' innovative behavior can contribute to sustained long-term economic growth through intra-industrial spreading effect (Romer, 1986; Grossman and Helpman, 1991). Bernstein and Nadiri (1988, 1991) found that the spreading effect was statistically significant for all US industries in that if companies in different fields were technically similar or share the same technological base, R&D's spreading effect in the industry would be produced; they found that in all industries, spreading effect could reduce variable costs and increase output, thus cutting product price. Jaffe (1986, 1989) concluded that an enterprise productivity growth was positively related to its own R&D and R&D of its similar enterprises in the same technical field. Aiello and Cardamone (2009) studied the panel data of 1,203 Italian manufacturing enterprises from 1998 to 2003 and concluded that the spillover effect of R&D had a positive correlation with enterprise performance. In short, a large number of empirical studies show that the spillover effect of R&D has a positive impact on enterprise production (Griliches, 1991; Wieser, 2005; Aiello and Cardamone, 2009).

Entering the twenty-first century, China's innovation-driven development strategy and development of innovation economy have provided a lot of new topics for innovation

economics research. However, despite the voluminous and diverse foreign innovation research literature, it cannot answer the innovation-related questions in China's rapid economic growth. Chinese scholars have begun to transfer their research on innovation from macro-economic level to micro-enterprise level. The two key areas are: first, the micro-level of enterprise innovation such as R&D strategy and patents. An Tongliang and others analyzed the behavior characteristics of Chinese enterprises like R&D strategies and R&D subsidies (An Tongliang, 2006, 2009), and conducted a micro-level survey through questionnaires on the R&D behavior of Jiangsu manufacturing enterprises. Alcorta *et al.* (2008) studied several behavioral characteristics in Chinese companies' innovation. Second, industrial policies and innovation subsidy performance of China's innovation support. Quite a few scholars have studied this and have generally concluded that government innovation support and innovation subsidies play a certain role in promoting the growth of emerging industries (Lu Guoqing *et al.*, 2014; Zhang Jie *et al.*, 2015), but have not significantly improved the quality of innovation, that is, they have not notably promoted substantive innovation or disruptive innovation (Li Wenjing and Zheng Manni, 2016; Zhou Yahong *et al.*, 2012). Regardless of the theoretical studies' conclusion, the reality is that the quantity and variety of innovation in China are unprecedented in the world, so there is no reason to doubt the innovation capability of Chinese enterprises and the fact that the wave of industrial innovation has already emerged in China. As Bloom's research suggested, China had rapidly developed into the world's largest trading country since joining the WTO, greatly pushing forward not only the technological progress of its own enterprises but also the technological innovation of developed countries in Europe and North America (Bloom *et al.*, 2016).

On the whole, the current domestic research on enterprise innovation is mainly questionnaire survey and macro-level industrial research, while the research on industrial innovation, especially on micro-enterprise-level innovation performance, is basically blank. This paper attempts to make an empirical analysis on the innovation performance of GEM listed companies, the most active, successful and influential group in China's industrial innovation, referring to domestic and foreign innovation research, and adopting the micro-subject method commonly used internationally in innovation research. The main reason for selecting GEM listed companies as research samples is that SMEs, especially listed small- and medium-sized companies, are the activists and winners of industrial innovation, the leaders of their industries, and the pioneers of industrial innovation. As Baumol (2007) put it, small enterprises (defined as "fewer than 500 employees in size") basically monopolized innovative activities with revolutionary breakthrough.

3. The performance of industrial innovation and its measurement methods

3.1 Model design

Innovation as a hot topic for theoretic research as it is, far too little research has been conducted on industrial innovation performance. For long, people have been accustomed to R&D investment and patent statistics as indicators to innovation performance, which has limitations. Not only the research on R&D activities' output has seriously underestimated the return of them, the metrics of innovative output measurement themselves also exist major defects (Peters, 2008). Griliches (1994) believed that R&D – based input–output indicators could only partially reflect innovation performance. First of all, R&D investment is not the only way for enterprises to develop new products or processes, and R&D indicators will especially underestimated innovation performance of SMEs and service industries (Peters, 2008). Second, patents do not fully reflect the innovative output (Griliches, 1990). The innovation process itself is of the black box nature, which always puzzles research on innovation performance. The general conclusion is that R&D has a positive correlation with productivity, and process-related R&D is more conducive to productivity improvement than product-related R&D (Griliches and lichten Berg, 1984). However, the CDM model coined

by Crépon *et al.* (1998) has effectively overcome the black box confusion in the innovation process. The CDM model incorporates innovation input, innovation output and productivity indices in the same model for the first time, and applies Community Innovation Survey data in the efficiency research of product and process innovation via knowledge production function. Lööf and Heshmati (2002) revised the CDM model by replacing R&D investment with innovation investment (Peters, 2008). Third, innovation, especially industrial innovation, shares the characteristics of public goods. Recent research shows that traditional methods generally underestimate the return of R&D activities, mainly because they neglect the spillover effect of these activities (Mairesse and Mohnen, 2005; Aiello and Cardamone, 2009). Aiello and Cardamone (2009) perfected the CDM model based on the above research and established a new model that contains the innovation spillover effect.

3.2 *The measurement of the spillover effect*

According to the CDM model, an enterprise decision on whether to invest on innovation or not depends on the cost comparison between acquiring technology from outside and developing technology itself. The measurement of spillover effect is a difficult point in the measurement of industrial innovation performance, and no recognized methods are available yet. Aiello and Cardamone (2009) measured the spillover effect of enterprise innovation with the company's technical similarity and its geographical consistency, solving the problem of measuring spillover effect that has long confused the enterprise innovation performance research. The author believes that Aiello's and Cardamone's measurement has two defects. First, the company's technical similarity index is in fact Jaffe's (1989) consistency index, which essentially reflects the vector's uncentered correlation and does not truly reflect innovation spillover effect. Based on industrial economic analysis, the spillover effect of industrial innovation mainly depends on the similarity of the industry that the enterprise is in and its influence on other industries. Therefore, it is more reasonable to replace the company's technical similarity index with the industrial similarity and industrial influence coefficient in the modern industrial organization theory. Second, it is also problematic for Aiello and Cardamone to measure the company's geographical consistency with mere spatial distances. The results of regional innovation theory indicate that the spillover effect of an industry's innovation activities not only has something to do with the influence of the industry itself, and the most important external environmental factor is the influence coefficient of the region where the innovation activities take place. For example, the spillover effect of innovation in an industrial cluster should be much larger than that in a single company. Thus, pure spatial distances cannot fully indicate the innovation spillover effect. Borrowing from the research results of regional innovation economics and industrial geographical concentration theory, further revising the gravity model improved by Aiello and Cardamone (2009) based on China's reality and the data availability by replacing the company's geographical consistency index in spillover effect calculation with the regional innovation radiating capability index in China's regional innovation capability evaluation system (Zhao Yanyun *et al.*, 2009), measuring the company's technical similarity by the industrial influence coefficient, combining the National Input-Output Table 2015 and applying Formula 3.37 (Liu Zhibiao and An, 2009) of "An Analysis of Modern Industrial Economy," we can calculate the spillover effect of enterprise industrial innovation through the following formula:

$$S = i \text{ enterprise's industrial influence coefficient} \\ \times i \text{ enterprise's regional innovation radiation coefficient} \times R,$$

where S represents the spillover effect of innovation; R represents R&D investment; and i represents the company.

3.3 Selection of indicators

This paper selects the indicators in Table I by referring to the definition of relevant indicators in the OECD Innovation Survey Manual (OECD and Eurostat, 2005) and taking into consideration of the accessibility of data.

The innovation input in this paper selects two indicators including R&D investment and human resources investment (the share of employees with bachelor's degree or higher).

The direct output of innovation is measured by the number of patents. For a long time, people feel that high-growth industries and high-tech industries embrace innovation with investment of higher frequency and stronger intensity. Therefore, three important industry variables are added to this model to verify the conventional views. These industry variables include industry effects, opportunity windows for industrial innovation and learning by export, which are employed to reflect the industry environment and innovation opportunities when enterprises engage in innovative activities. These three industry variables are of particular importance to listed companies, due to the distinct industry differences (in industry effects) in China's securities market. Even if hype is not considered, the P/E ratio and P/B ratio vary considerably in different industries and thus the listed companies in different industries enjoy different innovation opportunities and accessible resources. Industry effects can be measured by Tobin's Q (McGahan, 1999), which is calculated by reference to the calculation method of Chung and Pruitt (1994). The opportunity windows for industrial innovation are measured by the proportion of sales revenue of new product in total sales revenue. The Learning by Export is measured by the proportion of export revenue of new products in total sales revenue:

$$\ln y = \alpha_0 + \alpha_q \ln q + \alpha_h h + \alpha_r \ln r + \alpha_l \ln l + \alpha_s \ln s + \alpha_a \ln a + \alpha_g \ln g + \alpha_i \ln i + \alpha_e \ln e + \alpha_p \ln p + \mu.$$

4. Data sources and data processing

The GEM board is designed to provide financing and space of growth for small- and medium-sized growth companies and high-tech companies outside the main board. Since its establishment in 2009, it has maintained a high level of innovation investment and innovation output and showed sound momentum of rapid development and increasing

Indicators	Meaning
Profit from main operations (<i>y</i>)	An enterprise's annual profit from main operations, serving as a comprehensive indicator reflecting the enterprise's business performance and innovation performance
Tobin's Q (<i>q</i>)	$Q = (\text{total market value} + \text{gross liability}) / \text{total assets}$; total market value = market value of circulating shares + preference shares
High-tech enterprises (<i>h</i>)	1 represents high-tech enterprises; 0 represents non-high-tech enterprises
R&D investment (<i>r</i>)	An enterprise's annual total investment in R&D
Human resources investment (<i>l</i>)	Share of employees with bachelor's degree or higher in an enterprise on December 31st every year
Spillover (<i>s</i>)	Regional innovation radiation capacity coefficient × industry influence coefficient × R&D investment
Age of enterprise (<i>a</i>)	Number of years between the founding of the enterprise to the end of this year
Government support (<i>g</i>)	Government subsidy/total amount of R&D
Opportunity windows (<i>i</i>)	New product sales revenue/total sales revenue, reflecting the innovation opportunities in the industry
Learning by export (<i>e</i>)	New product export revenue/total sales revenue, reflecting the learning by export effects
Number of patents (<i>p</i>)	Patents the company obtains within the year

Table I. Meanings of indicators

vitality of innovation. It collects more complete information on innovation input and output than the main board. Therefore, this paper selects GEM listed companies as research samples.

The data spans three consecutive years including 2014, 2015 and 2016. It is in line with the conventions of international innovation survey (OECD and Eurostat) to select the data of three years for innovation studies. As of December 31, 2014, there were 412 companies listed on the GEM board. After excluding sample companies with incomplete data and no innovation output (with zero patent), this paper obtains 256 valid samples in the manufacturing sector. The specific distribution is shown in Table II.

The data of the sample enterprises are directly obtained from CSMAR database and iFind database, which are derived from such published documents as the prospectus and annual report of listed companies. The original data of government subsidies, which is utilized to measure government support, are derived from the “non-operating income” account of the financial statements. When the information of patent number is not complete, further manual efforts are made to search in the company’s daily disclosure information and website. Information on new product sales revenue, new product export volume and total sales revenue is from Gtafe database. When the data are incomplete, we further refer to the China Statistical Yearbook on Science and Technology for additional information. Industry data are obtained from the China Statistical Yearbook on Science and Technology, China Statistical Yearbook on High-tech Industry, Innovation Survey of Industrial Enterprise Nationwide and Statistics on Scientific and Technological Activities of Industrial Enterprises among others. Due to the endogenous feature of innovation, a 3SLS regression calculation of the above model is performed by the Stata software.

5. Empirical analysis

5.1 Relevance and endogeneity test

Table III shows the Pearson correlation coefficient between the explained variable and the explanatory variable. The test results show that innovation performance, which is measured by $\ln y$ (profit from main operation), has a remarkable correlation of above 10 percent between the majority of explanatory variables including $\ln q$ (Tobin’s Q value), $\ln r$ and $\ln s$. There is also certain correlation among explanatory variables, but the correlation coefficients stay at a relatively low level. To further test the multicollinearity among the

Industry	Number	Percentage
Agriculture, forestry, animal husbandry and fishery products and services	1	0.39
Food and cigarettes	4	1.56
Textile, garment, shoes, hats, leather, feather and relevant products	1	0.39
Papermaking, printing and cultural and educational products	1	0.39
Chemical products	36	14.06
Non-metallic minerals	11	4.30
Metal smelting and calendaring processing	2	0.78
Metal ware	2	0.78
General-purpose equipment	19	7.42
Special-purpose equipment	42	16.41
Transport and communication equipment	7	2.73
Electric machinery and equipment	33	12.89
Communication devise, computers and other electronic equipment	57	22.27
Instruments and apparatus	16	6.25
Other manufacturing products	23	8.98
Electricity and heat generation and supply	1	0.39
Total	256	100

Table II.
Industrial distribution
of sample companies

	lny	lnq	h	lnr	lnl	lns
lny	1					
lnq	-0.158***	1				
h	0.151***	-0.102***	1			
lnr	0.740***	-0.206***	0.183***	1		
lnl	-0.003	0.208***	-0.024	0.125***	1	
lns	0.624***	-0.133***	0.210***	0.730***	0.057	1
lna	0.094***	-0.018	0.037	0.070*	0.013	0.104***
lng	-0.039	0.049	0.049	-0.156***	0.049	-0.208***
lni	0.051	0.058	-0.030	0.174***	0.097***	0.116***
lne	-0.018	0.081**	-0.071**	0.160***	0.061*	0.048
lnp	0.339***	-0.091**	0.089**	0.416***	0.050	0.155***
	lna	lng	lni	lne	lnp	
lna	1					
lng	0.019	1				
lni	-0.145***	0.033	1			
lne	-0.161***	0.003	0.884***	1		
lnp	-0.026	0.073**	0.165***	0.166***	1	

Notes: * $p < 0.1$; ** $p < 0.05$; *** $p < 0.01$

Table III. Pearson correlation coefficient

explanatory variables, the variance inflation factor (VIF) is employed and the results are shown in Table IV. The results show that the VIF of each explanatory variable is less than 10 and with no multicollinearity.

Missing variables and other situations may lead to correlation between the explanatory variables and the disturbance terms and therefore cause endogenous problems. A Hausman's endogeneity test is applied to the variables in the model. If the result is at a significance level lower than 5 percent, this paper rejects the null hypothesis that "all explanatory variables are exogenous" and tests all the explanatory variables one by one. The results show that both lnq and lnr are endogenous. Therefore, the first-lagged variables of lnr and lnq are used as instrumental variables (not related to the disturbance terms, but related to the explanatory variables) and the model is subjected to a two-stage least squares regression calculation.

5.2 Estimated results and analysis

This paper uses the first-lagged variable as instrumental variables, employs the Stata 14 to estimate the cross-section data in 2014, 2015 and 2016 and gets the estimated results for three consecutive years (see Table V).

Variable	VIF	1/VIF
lne	4.860	0.206
lni	4.820	0.207
lnr	2.900	0.345
lns	2.440	0.411
lnp	1.320	0.758
lnq	1.130	0.884
lnl	1.100	0.910
lng	1.090	0.920
h	1.080	0.930
lna	1.040	0.957
Mean	VIF	2.180

Table IV. Test of multicollinearity

Table V.
Model
calculation results

	2014		2015		2016	
	Coefficient	Z-test	Coefficient	Z-test	Coefficient	Z-test
<i>lnq</i>	0.0986	(0.74)	-0.000485	(-0.00)	0.102	(0.86)
<i>h</i>	-0.0419	(-0.58)	-0.0398	(-0.55)	-0.0932	(-1.44)
<i>lnr</i>	0.883***	(9.25)	0.862***	(8.50)	0.849***	(9.53)
<i>lnl</i>	-0.0964*	(-2.31)	-0.112**	(-2.73)	-0.130***	(-3.54)
<i>lns</i>	-0.0152	(-0.28)	0.0555	(1.02)	0.0826	(1.73)
<i>lna</i>	0.0669	(0.52)	0.0333	(0.23)	-0.0119	(-0.09)
<i>lng</i>	0.0797*	(2.18)	0.0950*	(2.41)	0.0931*	(2.42)
<i>lni</i>	0.267*	(2.09)	0.345*	(2.28)	0.262*	(2.01)
<i>lne</i>	-0.210***	(-3.30)	-0.251***	(-3.69)	-0.242***	(-3.67)
<i>lnp</i>	0.0133	(0.39)	0.0197	(0.53)	0.00820	(0.25)
<i>_cons</i>	3.672***	(5.58)	2.693*	(3.76)	2.092	(1.80)
<i>n</i>	256		256		256	

Notes: * $p < 0.05$; ** $p < 0.01$; *** $p < 0.001$

6. Conclusion

Following conclusions are drawn based on the model evaluation and tests illustrated above.

First, there is significant positive correlation between innovation performance and R&D inputs of companies listed on the GEM Board. The significance test at 0.1 percent level is passed and the correlation coefficient is 0.8, the highest among all factors. This suggests that the increase of R&D investments remains to be the most important way to improve performance of companies listed on the GEM Board and it is also the internal driving force for the sustainable growth of the company, which is in line with the view of traditional innovation economics. However, negative correlation is observed between innovation performance and inputs in human resources among all other innovation inputs. Human resources inputs, represented by the proportion of staff with higher education or above in the entire staff population, are negatively correlated to the profits of the company's main business, suggesting that companies with higher investments in human resources have lower performance. In other word, the value of human capital, instead of boosting the performance of the listed companies, becomes burdens of the companies. This is probably because in SMEs costs of highly educated staff usually account for a large share in the overall costs of human resources. Moreover, the economic utility of inputs in human capital cannot be released in the short-term, but evaluation of innovation performance happens within three years upon the inputs are made, and as a result there is a negative correlation between the two factors. In addition, investing in human capital means something deeper for China's listed SMEs. For example, if an enterprise intends to apply for the state's funding for technologically innovative programs, a critical indicator is the research team or personnel and it is usually the key factor to determine whether an enterprise gets the funding. In this sense, direct economic reward from human capital inputs does not look as important as it really is.

Second, companies listed on the GEM Board are all emerging enterprises at the growing stage of booming development. It is logically justifiable that the age of a company is positively correlated to the company's performance. The negative correlation emerging in 2017 is in line with the enterprise life cycle theory. There is positive correlation between government support and innovation performance of the enterprises, but the coefficient is rather small, suggesting that government subsidies provide some but not significant incentives to enterprise innovation. It can be seen from the raw data that government subsidies to the sampled companies/enterprises are far smaller than the R&D investments made by the companies/enterprises themselves and therefore have relatively small impact

on the companies'/enterprises' performance. In addition, the current paper takes into account only the direct subsidies from the government rather than the entire basket of government supporting policies such as tax reduction, which is another important reason why government support does not have great impact on enterprise performance. It is indeed that there is no significant correlation between high-and-new-tech enterprises listed on the GEM Board and innovation performance, and a negative correlation is even observed between the two. It is traditionally believed that high-and-new-tech enterprises, usually with strong innovative inputs and sound operational performance, should be positively correlated to innovation performance in one way or another and a negative correlation is never possible. However, the conclusion drawn by this paper is completely different from the traditional view. This can be understood from two perspectives: even though innovative inputs of high-and-new-tech enterprises are usually higher than those of ordinary innovative enterprises, high-and-new-tech companies do not have business performance significantly higher than the average level of innovative enterprises in general. Preferential treatment for those enterprises, such as tax reduction, government subsidies or R&D subsidies, do not tend to increase the profits of major business of those enterprises on a large margin. This is because China has a system to certify high-and-new-tech companies, which has clear specifications on how much innovation inputs an enterprise should make for it to be qualified as a high-and-new-tech company. But the system does not set any requirement on business performance; and if certified as a high-and-new-tech company, the company can enjoy a lot of direct and indirect benefits such as tax reduction, government subsidy and financing facility. Therefore, it is rather tempting for an enterprise to get certified as high-and-new-tech company. Since high innovative input is regarded by the government as a must-have condition for a company to be certified as high-and-new-tech company, statistics related to innovative inputs are inevitably over-decorated or even faked in the application process. In this sense, it is understandable why there is the negative correlation between high-and-new-tech companies and innovation performance.

Third, innovation performance and spillover effect are not significantly correlated, and there even emerged negative correlation. Based on the definition of spillover effect as given in this paper, the negative correlation is justifiable. As is known to all, the process of innovation comes with certain degree of externality or spillover effect (Romer, 1986), which usually happens when a company uses the research findings of another company without sharing the research costs or when the production or innovation are quite universal. Spillover effect usually emerges because a company cannot possess all the benefits brought by the innovation made by itself. Since innovation is public good that spreads, it is not possible for the innovator to take all the benefits as a result of the innovation, which will reduce the performance of innovation. Even though the innovator is granted the right to possess the innovative achievements all by himself/herself, for example, in the case of a patent, he/she is able to use the innovation exclusively just for a certain period of time. This is rather unfavorable and inefficient for an enterprise. As a result, a commonly accepted view in literature of industrial organization is that the existence of spillover effect is regarded as the primary reason for the optimal R&D investment in the equilibrium condition, and that the spillover effect is one of the sources hindering R&D investments. This is why the benefits of innovation cannot be exclusively enjoyed by the innovator and the spillover effect ensures that the innovative achievements spread to the entire society, which will enrich the overall knowledge reserve of the society.

Fourth, innovation performance is positively correlated to the innovation opportunity windows, is negatively correlated to the Learning by Export effect and is not significantly correlated to the Tobin's Q ratio of the company. The positive correlation between innovation performance and the window of innovation opportunity means that the enterprise seizes the opportunity of innovation and finds the right direction in the

transformation and upgrading of industrial structure. The negative correlation between innovation performance and the Learning by Export effect is quite contrary to traditional views. Generally speaking, export companies can draw upon advanced management experience and production technologies from abroad, which should be conducive to the company's performance. But the Learning by Export effect is closely related to economic condition and market environment. Although trade in export facilitates the production efficiency of Chinese enterprises by certain extent, the impact has significantly diminished since China joined the WTO. As China became the world's second largest exporter of goods, enterprises have been increasingly reliant on trade in export and more sensitive to policies on external trade. At the same time, the fact that enterprises listed on the GEM Board are mostly SMEs with weak Learning by Export capability, the existence of technological spillover in the export process and the uncertainties of trade policies have also helped to explain the negative correlation between the Learning by Export effect and company performance. Tobin's Q ratio is a market-based indicator of the operational performance, innovation performance and productive effect of an enterprise. Just like the P/B ratio of a public company, a higher Tobin's Q ratio suggests higher premium on assets. China's stock market is speculative where high P/E ratios are quite prevalent for companies listed on the SME Board and the GEM Board, and it is common when the stock price of a company is deviated from its performance. As a result, a company's Tobin's q ratio is not necessarily related to the current performance of that company.

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Corresponding author

Guoqing Lu can be contacted at: lgq5766@163.com