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Abstract

This research aims to understand how industrial characteristics in Chinese industrial sectors are related to and affect innovation activities. Using Heckman's two-step procedure, this study contributes to examine firms' innovation determinants with a framework that clearly distinguishes between the two steps of innovation model: innovation propensity (probability of being innovative) and innovation performance (patents and innovation sales).In particular, the moderating effects of industrial characteristics on the relationships between R&D intensity, financial incentives and innovation performance are discussed. The findings show that different industrial characteristics generate different impacts on innovation propensity and innovation performance. Firms in capital intensive industries and relative monopoly industries are more likely to innovate. The findings also show that Direct Government Subsidy does not contribute significantly to improve economical innovation performance of firms and Indirect Government Subsidy on innovative economic performance is easier to be influenced by industry characteristics, which have important potential policy implications to guide innovation activities for Chinese policy makers as well as for Chinese firms.

Keywords: Industrial characteristics; R&D intensity; Financial incentives; Moderating effect.

1. Introduction

Increasing dynamic and complex external environment forces firms to innovate and mitigation competition for survival (Lodh, Nandy, & Chen, 2014).China, one of the leading rapidly-growing emerging economies, has been evolving from “imitation” to “innovation” (Dang & Motohashi, 2015; Lin et al., 2013). Innovation capabilities and performance in China have attracted attentions of scholars from many countries and regions all over the world. According to previous research, some of the innovation differentials among firms can be explained by differences in firms' contexts. One of the contexts in which firm's innovation takes place is provided by the industry in which firms operate (Tavassoli, 2015). Other performance variations are contributed by differences in characteristics and strategies of firms. Although considerable research efforts have been made to test whether the firm specific or industry factors more explain performance, the empirical findings are still inconclusive. Also, previous studies concern industrial characteristics have mainly focused on developed economies, characterized by well-established institutional environments, mature market-based competition and large pools of qualified knowledge workers (Guan et al., 2015; Frank et al., 2016). We thus in this paper respond to the lack of understanding of industry-level innovation determinants in China.

The large empirical literature concern the determinants of performance variations among firms have been conducted from the fields of industrial organization economics (IO) and resource-based views of the firm (RBV). From the perspective of IO, the structural characteristics of an industry influence the behavior of its component firms, which inevitably determines firm performance (Hawawini et al., 2003). In the early days, the effects of structural characteristics of particular industries on performance were more dominant than firm effects (Henderson & Mitchell, 1997; Stimpert & Duhaime, 1997). Nevertheless, the majority of recent studies have provided evidence of a more important firm-specific effect (Hawawini et al., 2003; Chen & Lin, 2010), this is in line with RBV. Different from IO insistence on making industry structure the main reason to explain variations in firm performance, RBV scholars focus increasingly on the heterogeneity of enterprise resources. However, few literatures have examined the link between industry characteristic and firm innovation behaviors. According to the theory of industry organization economics (IO), characteristics of an industry structure affect the conduct of firms (Guan et al., 2015). Considering that firms' innovation performance is strongly influenced by the determinants of innovation propensity and intensity, we thus assume that industry characteristic have an impact on firm's ability to benefit from innovation activities.

This paper shows the innovative behaviors of firms are affected by the industrial characteristics in China. In particular, it contributes to distinguish between determinants for innovation propensity and innovation performance. Further, the moderating effects of industrial characteristics on the relationships between R&D intensity, financial incentives and innovation performance are discussed. The analysis in the paper is important for the government in China to promote R&D activities and improve innovation performance. In line with the existing literature, we also examine the firm-level effect (e.g. firm age, firm size, R&D intensity and financial incentives) on the innovation performance. Thus, our paper not only contributes to the existing literature by providing a Chinese influence of industrial characteristics on firm's innovation process, but also has some implications for China's policy makers to improve the efficiency of financial incentives.

The study is organized as follows. Section 2 introduces the background and sets out the theoretical framing and the hypothesis. Section 3 outlines the data sources and analytical framework. Section 4 describes the variables and reports our empirical results, and Section 5 presents our conclusions and discussion.

2. Theoretical and conceptual background

2.1. Firm's innovation propensity and performance

There is a flourishing research-based literature on the firm innovation activity determinants. Various factors in micro, meso and macro level, such as firm size, capabilities, national support for research and development (R&D), market structures and geography, have found to be critical factors driving R&D input and influencing innovation performance(Tavassoli, 2015; Doh & Kim, 2014; Frank et al., 2016). However, the effects of potential factors on innovation propensity (probability of being innovative) may different from that on innovation performance (patents and innovation sales) (Tavassoli, 2015).The ratio of firms that have invested in R&D is relatively low in China (Feng & Ke, 2016). It is necessary to explore the determinants of innovation propensity. Also, there is likely to exist a "selection bias"(this will be discussed in Section 3) for many values of dependent variables in terms of innovation performance (patents and innovation sales) are not randomly missed (Heckman, 1979). We thus use Heckman's two-step procedure in this study to examine the effects of innovation determinants on the innovation propensity and innovation performance in a single model.

A variety of measurement methods over different innovation output indicators have been proposed (Guan & Ma, 2003; Tavassoli, 2015; Bronzini & Piselli, 2016; Frank et al., 2016). Patents and financial data associated with sales of new product are most common proxies for innovation performance. In prior studies, patent data have been traditionally used as a proxy for technological innovation output and new knowledge (Jaffe et al., 1993; Chen & Guan, 2011). Using patents as a proxy for innovation output has both advantages and disadvantages. On the one hand, it is well known that not all inventions are patentable and patented, and the patented inventions differ greatly in quality (Griliches, 1990). On the other hand, patents are more objective and reasonable compared with other proxies, for they are less exposed to personal or subjective considerations (Acs et al., 2002; Bronzini & Piselli, 2016). Moreover, the major purpose for a firm to engage in the innovative activities is to enhance their economic return through product or process innovation. Therefore, Innovation should to a greater extent meet and attract more customers' demand and obtain more economic profits (Chen & Guan, 2011). Financial data associated with sales of new product are considered to be a good indicator of economic innovation performance (Guan & Yam, 2015), because it can directly reflect the contribution of innovation output to economic growth of China (Zhang, 2015).

In this study, we use the number of applied patents and granted patents to proxy for technological innovation performance of the firms. New product sales are used as a proxy for economical innovation performance.

2.2. Industrial characteristics and firm innovation

As to what determine the firm-level performance variations, much evidence in the literature points towards industry-level differences. Kotha and Nair (1995) observed a high impact of industrial characteristics on firm performance in Japan. Lin, Chen, and Lo (2013) employed data from enterprises in China and find that industry influences tend to be more important than firm factors in the long-term competitive advantages of firms. Spanos and Lioukas (2001) suggested that industry and firm specific effects are both important but explain different dimensions of performance. The main purpose of this paper is to investigate how the innovative behaviors of firms are affected by the industrial characteristics. The industry structure is considered to be an important predictor of firm's conduct from the perspective of industrial organization economics (IO) (Lin, Chen, & Lo, 2013). Previous studies also have suggested a reciprocal relationship between the external contexts and the firm's strategy (Oliver, 1997; Hoskisson et al., 1999), and one of the contexts in which innovation happens is provided by the industry in which firms operate (Tavassoli, 2015). Therefore, industry specific factors tend to shape a firm's innovative behaviors that further affect its innovation performance. Moreover, firms in the same industry are likely to have similarities in products, markets, technologies, and resource bases, and thus tend to act similarly (Hannan & Freeman, 1977). Those similarities make it important for firms to choose external competitive environment.

The industry specific effect on innovation can also be studied in terms of the externalities. Dynamic externalities between institutions and business R&D activities influence knowledge creation and competition for new ideas (Varga, 1998; Greunz, 2003). There are two contra types of externalities: Marshall-Arrow-Romer (MAR) externalities associated with specialization, and Jacobs externalities associated with diversification. Supporters of The MAR model states that the concentration of an industry promotes knowledge spillovers between firms and thus facilitates innovation (Beaudry & Schiffauerova, 2009; Greunz, 2004), while the Jacobs(1969) externalities suggests that diverse knowledge environment, rather than similar knowledge and behavior of economic actors promotes creativity and as a consequence foster innovation.

In terms of industry characteristic, several different dimensions of indicators have been used. According to the structural forces developed by Porter, level of rivalry, market concentration and entry barrier, which determine the performance potential of firms competing in a given industry, are most common parts of the characteristics of an industry (Porter, 1980; Yurtoglu, 2004; Spanos et al., 2004). Those characteristics can further affect the firm's innovation performance by influencing the firm's innovation decision and innovation capability. In this paper, we assume that innovation is mainly driven by competition and knowledge spillovers (Cohen & Klepper, 1996). Empirical investigations also indicate that ownership is important for resource acquisition. We argue that industries with heterogeneous or homogenous industry structure as to firm characteristics (e.g. ownership) distribution would have an impact on innovation performance. We thus apply Ownership Structure, Capital Intensity and Monopoly Degree to describe characteristics of an industry.

2.2.1. Industry ownership structure and firm innovation

Corporate ownership research suggests that innovations are enabled by a conducive ownership structure, since ownership determines the allocation of the resources and the cooperation efficiency of owners and managers (Belloc, 2011; Jensen & Meckling, 1976). State-owned enterprises (SOEs) in China, controlled by either the central or the local governments at different levels, are still play a dominant role in many important sectors ((Lee, 2009; Feng & Ke, 2016). In this paper, we define Ownership Structure of an industry as the proportion of SOEs in an industry. Generally, SOEs are supposed to be more innovative and performance better in innovation for they can possess valuable resources from government and have a few notable advantages in innovation(Cohen & Levinthal, 1990; Van Wijk et al., 2008). However, it usually presents a negative picture with regard to the role of SOEs in innovation (Feng & Ke, 2016). Based on principal-agency theory, the owners and managers benefiting more from corporate profits are more likely to engage in innovative activities and monitor investment activities. However, managers in SOEs are separating between salary and firm performance; they thus lack the motivation to engage in innovation activities. SOEs also have a number of innovation disadvantages, such as rigidities and bureaucratic inertia, incentive systems unfavorable to innovation and change, and lack of managerial knowledge (Choi et al., 2011). Those disadvantages seriously block the innovation process of enterprises. Accordingly, SOEs are believed to be less efficient in improving and enhancing firm's performance than non-SOEs

(Zhang et al., 2007; Li & Xia, 2008).We thus argue that industries with high proportion of SOEs are likely to be devoid of innovative spirit and competiveness; thus hamper firms' innovation propensity. Generally, SOEs can retain more support and resources from government and other organizations than non state-owned enterprises. However, the ineffective structure and a lack of management, marketing and organization skills of SOEs automatically imply negative effects on the innovation performance of firms (Choi et al., 2011; Guan & Ma, 2003).Therefore, Firms in the industries with high ratio of SOEs tend to be less efficient in innovation output. In conclusion, the hypotheses are formulated as follows:

H1a: Ownership structure negatively affects firm's innovation propensity.

H1b: Ownership structure negatively affects firm's innovation performance.

2.2.2. Industry capital intensity and firm innovation

Capital intensity, which reflects the relative importance of factor endowments, has been identified as a determinant of innovation (Audretsch et al., 1996; Fu et al., 2010; Su, 2015). According to Brealey and Myers (1984) and Shapiro and Titman (1986), capital intensity often measured as fixed assets scaled by total assets or sales. In this paper, we define capital intensity as the ratio of total assets to sales revenue of in an industry. The high R&D costs and risks involved in innovation process keep many investors away. Smaller or less productive firms are less likely to conduct R&D (Feng & Ke, 2016). High capital intensity facilitates entry barriers and thus provides a group of firms with a competitive advantage over potential entrants (Lawless& Teagarden, 1991). Accordingly, firms located in industries with high capital intensity are able to invest more in R&D activities. Moreover, since the increasing complexity of technological development, external knowledge and technology acquisition has become more important for the innovative behaviors of a firm (Liu & Buck, 2007; Tsai et al., 2011). Capital is thus essential for enterprises to carry out R&D or introduce new technologies (Guan & Yam, 2015).The more innovation propensity is expected to those firms with more new knowledge and technology (Crepon, Duguet, & Mairesse, 1998; Hall & Mairesse, 2006). Thus, firms in capital intensive industries are likely to have a greater propensity to innovate, since they are considered to possess sufficient funds and unique technologies. Also, firms can enhance its innovation capabilities and create competitive advantages by introducing new technologies. Capital intensity is considered to reflect a firm's capacity to absorb, assimilate and develop new knowledge and technology (Bartel & Lichtenberg, 1987; Cohen & Levinthal, 1990). Moreover, capital intensive firms are supposed to be carriers of advanced technology. They can act as the potential generators of knowledge spillovers, and encourage the innovation performance of other firms in the same industry. Therefore, firms in capital intensive industries are likely to performance better in innovation. However, it is still not clear from the literature how the capital intensity of an industry influences firm's innovation propensity and innovation performance in the context of Chinese market. The hypotheses are formulated as follows:

H2a: Capital intensity positively affects firm's innovation propensity.

H2b: Capital intensity positively affects firm's innovation performance.

2.2.3. Industry monopoly degree and firm innovation

Our paper learns from Lerner index to measure Monopoly Degree (Aghion et al., 2002). McKelvey (1997) argued that firms' development of capability is affected by competitive process at the industry level. Cohen and Klepper (1996) also indicated that firm's R&D input is related to the competitive condition of the industry in which the firm operates. Since the basic condition of

China is capital scarcity and labor abundance, funds and technology are still two of the biggest factors that impede Chinese firm's innovation propensity. Firms operate in an industry characterized by high monopoly degree are usually large and likely to possess sufficient funds and technologies (Fu et al., 2010). Moreover, Innovation is complex and requires firms to possess valuable and specific resources from other organizations or institutions (Howells, James, & Malik, 2003). Monopolists can rearrange R&D resources more efficiently and pursue frontier technology. Kamien and Schwartz (1982) indicated that monopolists face less market uncertainty and is more likely to innovate. Standard IO theory also argues that innovative activities may decline with competition. This is because more competition reduces the monopoly rents (Aghion et al., 2002). Thus, we suggest that Monopoly Degree of an industry positively associated with innovation propensity of the firms in this industry. However, in industries with high competition, firms face more pressure and are more likely to be involved in search behavior to enhance its innovation capabilities. The absence of competitive pressures may reinforce the organizational inertia and thus leads to large inefficiencies (Arrow, 1962). In addition, greater competition across firms facilitates the entry of new firms specializing in some particular product niche and thus exhibit high innovation performance. This is because the necessary complementary inputs and services are likely to be available from small specialist niche firms (Feldman & Audretsch, 1999). Therefore, the greater the degree of monopoly in an industry, the less likely it is that the firms in this industry to achieve effective innovation. The hypotheses are formulated as follows:

H3a: Monopoly degree positively affects firm's innovation propensity.

H3b: Monopoly degree negatively affects firm's innovation performance.

2.3. The moderating role of industrial characteristics

Industries with high proportion of SOEs are considered to be devoid of innovative spirit and competiveness. Firms in these industries have no incentives to innovate and acquire valuable technology (Ahn, 2002), and it will have a negative influence on the effect of R&D input. In addition, SOEs have priority in acquiring support and resources from government and other organizations in China. However, a lot of innovation disadvantages, such as management, marketing and organization skills of SOEs, automatically imply negative effects on the innovation performance of firms (Choi et al., 2011; Guan & Ma, 2003). Non-SOEs perform better in technological innovation but they are less likely able to retain sufficient support from government. We thus argue that firms in the industries with higher ratio of SOEs tend to be less efficient in utilizing the R&D input and financial incentives. Firms in capital intensive industries not only possess a number of technology and valuable information, and they also affect the technological base of industries and may generate positive technology spillovers for other firms in the same industries. External knowledge spillovers can enhance a firm's existing technical skills and, subsequently, generate important impact on innovation (Laursen and Salter, 2006; Tsai, Hsieh, & Hultink, 2011). Thus, firms in capital intensive industries can better utilize the R&D input and financial incentives, since these firms in capital intensive industries have advantages in technological base and innovation capabilities. Competition can increase innovation as it increases firm's incentive to obtain the leading position through technological innovation (Ahn, 2002). A firm that faces fierce competition is more likely to be involved in search behavior to enhance its innovation capabilities and is easier to be rewarded from its R&D investment and financial incentives. Thus, the absence of competition would leads to the inefficient utility of the R&D

input and financial incentives.

Based on the above arguments and discussions, we propose the following hypotheses on the moderating role of industrial characteristics:

H4a: Ownership Structure negatively moderates the relationship among R&D intensity, financial incentives and innovation performance.

H4b: Capital Intensity positively moderates the relationships among R&D intensity, financial incentives and innovation performance.

H4c: Monopoly Degree negatively moderates the relationships among R&D intensity, financial incentives and innovation performance.

A proposed theoretical framework for innovation propensity and innovation performance is showed in Fig.1. The framework proposes that the innovation propensity and innovation performance are affected by financial incentives and firm's R&D intensity. It further indicates that the relationship between financial incentives, R&D intensity and innovation performance is moderated by industrial characteristics.

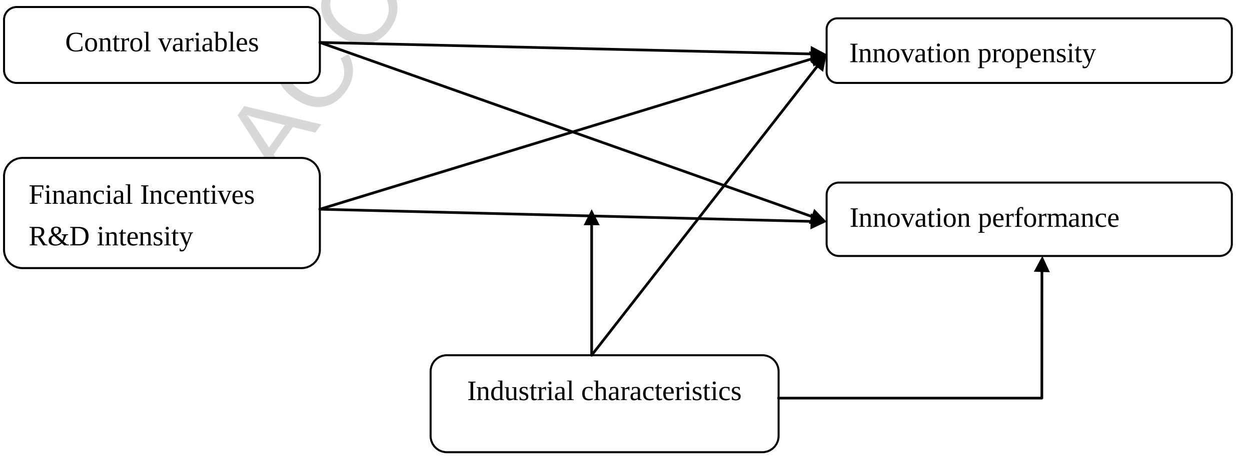

Fig 1. A proposed theoretical model for innovation propensity and innovation performance

3. Methodology and data

3.1. Data and sample

Our study uses a combined dataset of firm information provided by Zhongguancun Management Committee and industry data provided by the National Bureau of Statistics of China, which covers the period between 2012 and 2014. The scene is set at the major industrial firms in Zhongguancun for following reasons. First, Zhongguancun Science Park, which located in the Chinese capital city, is recognized as the first National Independent Innovative Demonstration Zones of the country. Zhongguancun also has become the second largest innovation area at the global level. In addition, Beijing, the capital city of China, has a number of top organizations and institutions that help firms to decode and appropriate flows of information, such as technological change and sources of technical assistance, thus strengthening firms' competitive advantage and innovation performance in Zhongguancun. Finally, Substantial national innovation policies are first implemented in Beijing. Many central government policies designed to spur innovation in enterprises were based on innovative experiences in Beijing, particularly from the city's high-tech development zone (Guan & Yam, 2015). Firms in Zhongguancun are more likely to receive government funding.

According to the classed criteria in the China Statistics Yearbook on industrial sector, the final sample contains 1,935firms across 27 industry classifications.

3.2. Selection of industrial characteristics variables

Among the different issues summarized by the National Bureau of Statistics of China, we focused on three types of variables that describe industrial characteristics: (i) Ownership Structure (OS); (ii) Capital Intensity (CI); and (iii) Monopoly Degree (MD). Ownership Structure variable describes the proportion of SOEs in an industry. Capital Intensity reflects the relative importance of factor endowments (Fu et al., 2010), which is often measured as the ratio of the industry's total fixed assets of the industry to total assets or sales (Lawless and Teagarden, 1991). The Lerner Index measures the strength of monopoly power in the market by calculating the degree that price deviates from marginal cost. Through adjusting Lerner index and establishing the econometric model, this paper empirically studies the influence of industry monopoly degree on firm's innovation. Monopoly Degree is calculated using the following equation:

$$MD = \frac{POR - \mathrm{OC}}{POR} \quad (1)$$

According to Eq. (1), POR is calculated for the prime operating revenue of an industry, while OC refers to operating cost of the industry.

3.3. Methodology

Previous research has suggested that the ratio of firms that have invested in R&D is relatively low in China (Feng&Ke, 2016). Also, in this paper, many values of firm's R&D input are not observed. Firm's innovation performance is the function of innovation inputs and innovation activities (Tavassoli, 2015). While some firms choose to engage in innovative activities, a considerable number of other enterprises have not been willing to innovate. Various factors have been found to be influential on firm's innovation propensity (probability of being innovative). Thus, there is likely to exist a "selection bias" for many values of innovation performance (patents and innovation sales) are not randomly missed (Heckman, 1979).Heckman's procedure can explicitly resolve the potential sample selection bias inherent in data.

This paper adopts Heckman two-step approach, which consists of two equations, to examine how industrial characteristics affect a firm's innovation propensity and performance. The first step of the Heckman procedure is a probit equation (selection equation), which is responsible for determining whether a firm is an innovative firm or not (Tavassoli, 2015).A selection bias control factor, which is also called Lambda, is constructed through the first-stage probit analysis. This factor, equivalent to the Inverse Mill's Ratio (IMR), is calculated to reflect the unobserved effects in the first-step model. In the second-step model, an OLS regression analysis of the effects of explanatory variables on innovation performance is performed. The Lambda is used as an additional independent variable to correct potential sample selection bias in the second equation.

In order to analyze the effects of industrial characteristics on innovation propensity, the first equation of our model is expressed as follows:

$$Innovation_p = \alpha_1 + \beta_1 Firmage + \beta_2 Firmsize + \sum \beta_i FI_i + \sum \mu_k IC_k + \sigma_1 \qquad (2)$$

The dependent variable $Innovation_p$ is an innovation dummy, which indicates whether a firm innovates or not. $Innovation_p$ takes on a value of one if a firm have R&D expenditures and zero otherwise, which is actually unobservable in practice (Tavassoli, 2015) . $Firmage$ and $Firmsize$ are included in Eq. (2) as firm-level control variables. $Firmage$ is measured as the age of each firm been in business. Since the size threshold is judged more on the basis of revenues and assets than employment, $Firmsize$ is measured by the natural logarithm of total assets in this paper (Qiao et al., 2014). FI measures the financial incentives, which consists of Financial Loan (FL), Direct Government Subsidy (DGS) and Indirect Government Subsidy (IGS). Financial Loan is measured as the loans from banks. Direct Government Subsidy is expressed as the fund of scientific and technical activities from government, while Indirect Government Subsidy is expressed as the tax exemption or reduction. There are three industrial characteristics (IC) variables included in Eq (2), where α_1 is the intercept, $\sigma_1$is residuals, and β, μ represent the regression coefficient.

To examine the impacts of industrial characteristics on economical performance of innovation, the second equation of the model is developed:

$$\begin{aligned} &Innovation_o = \alpha_2 + \beta_1 Firmage + \beta_2 Firmsize + \beta_3 RDI + \\ &\sum \beta_i FI_i + \sum \mu_k IC_k + \sum \delta_r MV_R + \beta_4 Lambda + \sigma_2 \end{aligned} \quad (3)$$

The dependent variables, $Innovation_o$, in Eq. (3)represent the technological performance and economical performance of innovation. Technological performance of innovation indicates new or improved technology or product prototypes resulted from the innovation inputs (Chen & Guan, 2011). The extant empirical evidence suggests that patents might indeed be a fairly reliable and meaningful indicator of innovation (Acs et al., 2002; Chen & Guan, 2011; Dang & Motohashi, 2015). Patent can reflect the quality of an innovation for it has been examined by experts who judge its novelty and utility (Bronzini & Piselli, 2016). In this study, we use the number of applied patents and granted patents to proxy for technological performance of innovation, while the economical performance of innovation is measured as the natural logarithm of new product sales to correct for skewness. Many of the differential advantages between firms derive from firm size and R&D intensity (Mairesse & Mohnen, 2001; Walter, 2012). Concerning the latter, firm's R&D intensity is a crucial factor in technology licensing as it not only generates innovative technologies and products with a potential to license out, but also determines the firm's absorptive capacity, which enables the firm to more easily assimilate, combine, and utilize technologies obtained through inward licensing. The R&D intensity (RDI) is a proxy variable for R&D investment, which is measured as the natural logarithm of R&D expenditure divided by R&D personnel at the firm. Generally, the definition of R&D intensity is based on R&D expenditure or R&D personnel (Guan & Yam, 2015; Doh & Kim, 2014). In this paper, we use RDI to avoid a potential issue of endogeneity as R&D intensity may be closely related to innovation. MV expressed as the interaction terms of FI*IC (Financial incentives *Industrial characteristics) and FI*RDI (Financial incentives * R&D intensity), captures the moderating effects of industrial characteristics on firm innovation performance. Lambda is the inverse Mill's ratio produced by the first probit estimation. σ_2 is the vector of disturbance term. The coefficient of Lambda significantly different from zero means $\sigma_1$and σ_2 are correlated. It also indicates a sample selection bias is present but corrected (Tavassoli, 2015).

4. Analysis and results

4.1. Descriptive statistics

Detailed descriptive statistics for the main variables are provided in Table1. The variation coefficient for the firm size variable is rather large, which indicates that the sample has a high degree of dispersion in size. The firms in our sample applied an average of 21.106 patents over three years. The values of granted patens change from 0 to 957. Innovation sales are measured using the natural logarithm of new product sales, which vary between 0 and 17.4. VIF (variance inflation factor) values in Table 2 are far less than the widely accepted threshold of 5, which indicates multicollinearity is not a serious problem in our sample.

Table 1 Summary statistics of variables.

Variables	**Min**	**Max**	**Mean**	**SD**	**VIF**
Firm age	1	105	12.660	7.268	1.03
Firm size	4.972	17.387	10.995	1.996	1.93
R&D intensity	0	8.342	2.826	2.591	1.51
FL	0	15.832	3.629	4.732	1.36
DGS	0	13.755	1.407	2.834	1.30
IGS	0	13.327	3.395	3.646	1.68
OS	0.004	0.606	0.048	0.043	1.73
CI	0.075	5.181	0.822	2.447	1.83
MD	0.080	0.294	0.164	0.046	1.09

Applied patents	0	7384	21.106	203.654	-
Granted patents	0	957	4.329	28.712	-
Innovation sales	0	17.400	5.485	5.372	-

Notes:

FL, DGS and IGS are abbreviations for Financial Loan, Direct Government Subsidy (DGS) and Indirect Government Subsidy (IGS), respectively. OS, CI and MD are abbreviations forOwnership Structure, Capital Intensity and Monopoly Degree, respectively.

Table 2 reports the Pearson correlation coefficients of major variables used in the analysis. The correlation coefficients between Financial Loan (FL), Indirect Government Subsidy (IGS) and Firm Size are pretty high. This indicates that the lager the firm size, the more possibility to receive financial support in China. The correlation coefficient between Ownership Structure (OS) and Capital Intensity (CI) is rather large. This is perhaps because the basic condition of China is capital scarcity and labor abundance, and SOEs can retain more support from government and thus tend to account for a certain proportion in capital intensive industry. As showed in this table, the dependent variables in terms of innovation performance are negatively and significantly correlated with Ownership Structure (OS) and Monopoly Degree (MD), but positively and significantly correlated with Capital Intensity (CI).

Table 2 Pearson Correlation coefficients of major variables used in the model.

Variables	**Firm age**	**Firm size**	**R&D intensity**	**FL**	**DGS**	**IGS**	**OS**	**CI**	**MD**	**Applied patents**	**Granted patents**	**Innovation sales**
Firm age	1.000											
Firm size	0.187***	1.000										
R&D intensity	0.079***	0.461***	1.000									
FL	0.040***	0.500***	0.292***	1.000								
DGS	0.097***	0.394***	0.393***	0.282***	1.000							
IGS	0.094***	0.564***	0.508***	0.317***	0.371***	1.000						
OS	0.007	0.090***	-0.001	0.037	0.024	0.031	1.000					
CI	-0.024	0.047**	0.056**	0.026	0.070***	0.024	0.636***	1.000				
MD	0.018	0.026	0.051**	-0.028	0.038*	0.002	0.081***	0.256***	1.000			
Applied patents	0.069***	0.540***	0.544***	0.403***	0.501***	0.580***	0.011	0.065***	-0.042*	1.000		
Granted patents	0.087***	0.538***	0.487***	0.379***	0.508***	0.544***	0.010	0.068***	-0.035	0.832***	1.000	
Innovation sales	0.118***	0.493***	0.541***	0.325***	0.322***	0.545***	-0.054**	-0.018	-0.048**	0.515***	0.470***	1.000

Note:

FL, DGS and IGS are abbreviations for Financial Loan, Direct Government Subsidy (DGS) and Indirect Government Subsidy (IGS), respectively. OS, CI and MD are abbreviations forOwnership Structure, Capital Intensity and Monopoly Degree, respectively.
*p<.1；**p<.05；***p<.01.

4.2. Regression analysis and results

This paper use Heckman's two-step procedure to accommodate the selection bias. The impacts of industrial characteristics on innovation propensity are examined using a probit regression model and the results are shown in the first column of Table 3. With regard to the first column, most of the explanatory variables at firm-level have statistically significant influences on the innovation propensity of a firm. Financial incentives (FL, DGS and IGS) can positively and significantly affect firms' innovation propensity. Industrial characteristics also have the expected

Table 3 Heckman two-step estimates of applied patents.

Regression variables	**Model 1**	**Model 2**	**Model 3**	**Model 4**	**Model 5**	**Model 6**
	N=1935	Uncensored obs=1080				
Con	-2.291(.300)***	-2.959(.763)***	-3.517(.963)***	-2.515(.681)***	-3.160(.789)***	-3.381(.790)***
Firm Characteristics						
Firm age	.074(.068)	-.134(.082)	-.133(.082)	-.133(.082)	-.135(.083)	-.117(.083)
Firm size	.110(.022)***	.263(.034)***	.262(.034)***	.265(.034)***	.267(.034)***	.274(.035)***
R&D intensity		.116(.050)**	.109(.051)**	.115(.050)**	.113(.050)**	.114(.050)**
FL	.018(.008)**	.043(.009)***	.044(.009)***	.044(.010)***	.044(.010)***	.045(.010)***
DGS	.133(.016)***	.137(.020)***	.138(.020)***	.139(.020)***	.141.020)***	.145(.020)***
IGS	.132(.011)***	.146(.026)***	.149(.026)***	.148(.026)***	.153(.026)***	.158(.027)***
Industrial Characteristics						
OS	-2.624(.988)***	-3.230(1.796)*	-3.700(1.972)**	-3.423(1.815)*	-3.378(1.823)*	-3.784(2.014)*
CI	.430(.187)**	.683(.263)***	.731(.266)***	.773(.293)***	.702(.288)**	.762(.267)***
MD	1.399(.764)*	-3.102(.841)***	-2.981(.847)***	-3.147(.852)***	-2.751(.863)***	-2.793(.863)***
Interaction Term						
OS*RDI			2.186(2.433)			
CI*RDI			-.275(.358)			
MD*RDI			-1.631(1.033)			
OS*FL				-.388(.335)		
CI*FL				.047(.049)		
MD*FL				-.215(.157)		
OS*DGS					.101(.662)	
CI*DGS					-.016(.086)	
MD*DGS					-.484(.234)**	

OS*IGS						-.052(.530)
CI*IGS						.049(.071)
MD*IGS						-.644(.214)***
Lambda		.829(.353)**	.864(.354)**	.863(.354)*	.929(.359)**	1.002(.364)***
Wald Chi-square	285.14***	165.65***	168.87***	167.57***	166.21***	166.70***

Notes:

Model 1 of the table reports the first-stage probit regression analysis with the dependent variable innovation dummy (corresponding to innovation propensity). Model 2 to Model 6 report the second-stage estimates with dependent variable applied patents (corresponding to technological innovation performance).

*p<.1；**p<.05；***p<.01.

and significant influence on the likelihood of been innovative. Capital Intensity (CI) and Monopoly Degree (MD) exhibit positive effects on firm’s innovation propensity. In other words, firms in the capital intensive industry and monopoly industry are more likely to innovate. This could be because firms in those industries have sufficient funds and advanced technology to engage in innovation activities. However, Ownership Structure (OS) is negatively influential to innovation propensity.

4.2.1 Impact of industrial characteristics on the number of applied patents

The second-stage of truncated regression analysis examines the impacts of industrial characteristics on innovation performance. Specifically, Model 2 to Model 6 of Table 3 report the second-stage estimates with dependent variable applied patents, which correspond to technological performance of innovation. The results of second column “Model 2” in Table 3 indicate that Firmsize, R&D intensity and financial incentives can positively and significantly explain applied patents. With regard to Model 2, Capital Intensity (CI) has significant and positive effect on firm’s applied patents, while Ownership Structure (OS) and Monopoly Degree (MD) negatively affect the dependent variable. We add three moderating variables (RDI*OS, RDI*CI, RDI*MD) to Model 3 to examine moderating effect of those industry characteristics. The result from Model 3 of Table 3 shows that none of these industrial characteristics can significantly affect the relationship between R&D intensity (RDI) and applied patents. Model 4 to Model 6 of Table 3 examine separate moderating effects of industrial characteristics between three different financial incentives and innovation performance. The results in Model 5 and Model 6 reveal that Monopoly Degree (MD) negatively affects the relationship between financial incentives and applied patents, although sometimes not to a significant degree. Lambda (inverse Mills' ratio) is significantly different from zero. This indicates the existence of selectivity bias and necessity of using the Heckman's two-step procedure.

4.2.2 Impact of industrial characteristics on the number of granted patents

Table 4Heckman two-step estimates of granted patents

Regression variables	Model 1	Model 2	Model 3	Model 4	Model 5
	Uncensored obs=1080				
Con	-3.016(.559)***	-3.225(.697)***	-3.145(.569)***	-3.183(.579)***	-3.432(.582)***
Firm Characteristics					
Firm age	-.056(.060)	-.054(0.060)	-.053(.060)	-.057(.061)	-.040(.061)
Firm size	.248(.025)***	.247(.025)***	.250(.025)***	.252(.025)***	.259(.025)***
R&D intensity	.013(.036)	.009(.036)	.012(.036)	.010(.036)	.010(.036)
FL	.019(.007)***	.020(.007)***	.020(.007)***	.020(.007)***	.021(.007)***
DGS	.110(.014)***	.111(.014)***	.112(.015)***	.113(.015)***	.117(.015)***
IGS	.102(.018)***	.106(.019)***	.105(.019)***	.109(.019)***	.113(.020)***
Industrial Characteristics					
OS	-3.689(1.298)***	-3.950(1.351)***	-3.725(1.311)***	-3.830(1.320)***	-4.071(1.435)***
CI	.684(.191)***	.721(.193)***	.760(.213)***	.696(.211)***	.761(.195)***
MD	-2.036(.617)***	-1.909(.623)***	-2.090(.628)***	-1.728(.634)***	-1.741(.639)***
Interaction terms					
OS*RDI		.727(1.727)			
CI*RDI		-.117(.255)			
MD*RDI		-2.113(.743)***			
OS*FL			-.107(.242)		
CI*FL			.005(.035)		
MD*FL			-.237(.114)**		
OS*DGS				.083(.486)	
CI*DGS				-.009(.063)	
MD*DGS				-.420(.172)**	
OS*IGS					-.032(.379)
CI*IGS					.064(.051)

MD*IGS					-.640(.155)***
Lambda	.306(.367)	.739(.258)***	.741(.259)***	.780(.262)***	.860(.267)***
Wald Chi-square	176.72***	184.17***	178.99***	177.24***	181.38***

Notes:

The table reports the second-stage estimates with dependent variable granted patents (corresponding to technological innovation performance).

*p<.1； **p<.05； ***p<.01.

Table 4 shows the second-stage of truncated regression analysis examining the impacts of industrial characteristics on granted patents. The results of Model 1 in Table 4 indicate that some firm-level characteristics of firm size, financial incentives have positively significant influence on granted patents, and another part of firm's characteristics, such as firm age and R&D intensity, have no significant influence on firm's granted patents. That is, once a firm choose to invest in R&D activities, its R&D intensity is unlikely to increase the number of granted patents. Model 1 of Table 4 also shows that both Ownership Structure (OS) and Monopoly Degree (MD) have significant and negative impacts on Granted Patents, while the impact of Capital Intensity (CI) on Granted patents is significantly positive. Similar to the impacts on the relationship between financial incentives and applied patents, Monopoly Degree (MD) exhibits significant and negative effect on the contributions of R&D intensity and financial incentives to granted patents.

4.2.3 Impact of industrial characteristics on new product sales

Table 5 shows the second-stage of truncated regression analysis using the new product sale as dependent variable. The results of Model 1 in Table 5 indicate that most of firm's characteristics, i.e. Firm age, Firm size, R&D intensity, Financial Loan (FL) and Indirect Government Subsidy (IGS) have positively significant influence on new product innovation, whereas Direct Government Subsidy (DGS) can not affect economical performance of innovation significantly. This is somehow in line with the previous empirical evidence showing that financial support from the government failed to enhance innovative economic performance for Chinese manufacturing firms (Guan & Yam, 2015). In addition, Ownership Structure (OS) and Monopoly Degree (MD) have significant and negative impacts on the economical performance of innovation. However, Capital Intensity (CI) became an insignificant moderator. Model 2 and Model 3 in Table 5 reveal that the interaction of R&D intensity, Financial Loan (FL)，Government Subsidy (DGS) and industrial characteristics are insignificant. The results in Model 6 suggest that the effect of Indirect Government Subsidy (IGS) on new production innovation is negatively moderated by Ownership Structure (OS) and Monopoly Degree (MD). Capital Intensity (CI) can positively affect the impact of Indirect Government Subsidy (IGS) on new product sales. In particular, the coefficient of Lambda in Table 5 is not significant. This non-significant coefficient may suggest that there is no serious sample selection bias in the estimation.

Table 5 Heckman two-step estimates of new product sales

Regression variables	**Model 1**	**Model 2**	**Model 3**	**Model 4**	**Model 5**
	Uncensored obs=1080				
Con	-2.386(2.575)	-4.834(3.334)	-1.972(2.602)	-2.571(2.599)	-1.601(2.666)
			Firm Characteristics		
Firm age	.745(.275)***	.725(.275)***	.727(.275)***	.785(.275)***	.738(.275)***
Firm size	.560(.115)***	.563(.114)***	.554(.115)***	.578(.115)***	.587(.115)***
R&D intensity	.395(.181)**	.385(.181)**	.387(.180)**	.385(.180)**	.361(.180)**
FL	.062(.032)*	.063(.032)**	.059(.032)*	.062(.032)*	.063(.032)**
DGS	.039(.066)	.038(.066)	.034(.066)	-.085(.120)	.051(.066)
IGS	.304(.087)***	.306(.087)***	.292(.087)***	.302(.088)***	.309(.088)***
			Industrial Characteristics		
OS	-13.822(6.296)**	-17.045(6.542)***	-14.535(6.341)**	-16.233(6.798)**	-12.563(6.328)**
CI	.186(.904)	.169(.913)	.115(1.003)	.730(.968)	.209(.908)
MD	-9.323(2.804)***	-8.703(2.814)***	-9.183(2.827)***	-10.081(2.860)***	-9.214(2.823)***
			Interaction terms		
OS*RDI		10.677(8.835)			
CI*RDI		.371(1.291)			
MD*RDI		-5.227(3.631)			
OS*FL			-1.412(1.172)		
CI*FL			.223(.170)		
MD*FL			.834(.539)		

OS*DGS				-2.748(2.205)	
CI*DGS				.148(.286)	
MD*DGS				.510(.784)	
OS*IGS					-4.786(1.889)**
CI*IGS					.803(.253)***
MD*IGS					-1.219(.736)*
Lambda	-.268(1.204)	-.256(1.204)	.059(1.204)	.303(1.214)	.393(1.221)
Wald Chi-square	95.69***	100.33***	101.86***	99.74***	107.55***

Notes:

The table reports the second-stage estimates with dependent variable new product sales (corresponding to economical innovation performance).

*p<.1; **p<.05; ***p<.01.

We thus apply simply OLS regression on the sample of innovative firms. The results of OLS regression are presented in Table 6. According to Table 6, we can find that the OLS regression results are very similar to those obtained using Heckman's second-step truncated regression.

Table 6 OLS regression of new product sales

Regression variables	Model 1	Model 2	Model 3	Model 4	Model 5
	Uncensored obs=1080				
Con	-1.901(1.377)	-4.381(2.578)	-1.865(1.427)	-2.428(1.412)	-1.601(2.666)
Firm Characteristics					
Firm age	.738(.274)***	.718(.275)***	.725(.274)***	.777(.275)***	.738(.275)***
Firm size	.550(.105)***	.553(.106)***	.552(.106)***	.566(.106)***	.587(.115)***
R&D intensity	.389(.179)**	.886(.461)*	.386(.179)**	.378(.180)**	.361(.180)**
FL	.059(.029)**	.061(.029)**	.058(.029)**	.059(.029)**	.063(.032)**
DGS	.029(.043)	.027(.043)	.032(.043)	.032(.043)	.051(.066)
IGS	.287(.043)***	.289(.043)***	.288(.044)***	.283(.044)***	.309(.088)***
Industrial Characteristics					
OS	-13.822(6.296)**	-17.045(6.542)***	-14.535(6.341)**	-13.268(5.961)**	-12.563(6.328)**
CI	.186(.904)	.169(.913)	.115(1.003)	.647(.913)	.209(.908)
MD	-9.323(2.804)***	-8.703(2.814)***	-9.183(2.827)***	-10.243(2.800)***	-9.214(2.823)***
Interaction terms					
OS*RDI		10.715(8.888)			
CI*RDI		.377(1.298)			
MD*RDI		-5.198(3.651)			
OS*FL			-1.413(1.179)		
CI*FL			.223(.171)		
MD*FL			.836(.541)		
OS*DGS				-2.707(2.211)	

CI*DGS				.143(.287)	
MD*DGS				.536(.782)	
OS*IGS					-4.790(1.901)**
CI*IGS					.805(.254)***
MD*IGS					-1.178(.729)
F	31.87***	24.28***	24.42***	24.22***	24.98***
R^2	.211	.215	.216	.214	.219
Adjusted R^2	.205	.206	.207	.205	.211

Notes:

The table reports the results of OLS regression with dependent variable new product sales (corresponding to economical innovation performance).

*p<.1；**p<.05；***p<.01.

5. Discussion and conclusions

Our results suggest that several firm-level determinants could explain the innovative propensity and innovation performance of firms in Chinese industrial sectors. The central question in this paper, however, is whether these Chinese firms are also influenced by the meso-level context in which the firms operate and innovate. Using Heckman's two-step procedure, our study examines the effects of firm-level factors and industrial characteristics on firm’s innovation. We further analyze the moderating roles of industrial characteristics on the relationships between R&D intensity, financial incentives and innovation performance.

The results suggest that most of firm-level and industry-level determinants have significant impact on the firm’s innovation propensity and performance. With regard to innovation propensity, firm size and financial incentives have found to be significant and positive. Ownership Structure (OS) is shown to have a negative effect on innovation propensity. This could be because industries with high proportion of SOEs are likely to be devoid of innovative spirit and competiveness, thus firms in these industries are less likely to innovate. However, the effects of Capital Intensity (CI) and Monopoly Degree (MD) on innovation propensity are significantly positive, which is in line with the findings of Romano (1987). Since the basic condition of China is capital scarcity and labor abundance, funds and technology are still two of the biggest factors that impede Chinese firm's innovation propensity. Firms in capital intensive industries and monopoly industry are considered to possess sufficient funds and technology. More innovation propensity is expected to those firms with more new knowledge and technology (Crepon, Duguet, & Mairesse, 1998; Hall & Mairesse, 2006). Thus, firms in capital intensive industries and monopoly industry are likely to have a greater propensity to innovate.

With regard to innovation performance, our results indicate that industries with high proportion of SOEs or absence of competition tend to impedes firm's innovation performance and leads to large inefficiencies. Capital Intensity (CI) generates a positive effect in terms of perceived technological performance of innovation, but fails to enhance innovative economic performance. These findings also suggest that industrial characteristics could produce different influences on each step of innovation. Monopoly Degree (MD) not only affects the innovation performance directly, it sometimes also can negatively moderate the relationships between financial incentives and innovation performance. This paper also indicates that Ownership Structure (OS) and Capital Intensity (CI) fail to moderate the relationships between R&D intensity, Direct Government Subsidy (DGS) and innovation performance. In terms of Ownership Structure (OS), the possible reason may be that state-owned firms (SOEs) in China retain more support from government than non state-owned enterprises but present a negative picture with regard to the role of SOEs in innovation on the one hand (Feng & Ke, 2016).Thus, firms in the industries with high ratios of SOEs tend to be less efficient in utilizing R&D input and financial incentives to innovate. But on the other hand, Most of SOEs in China spent a lot of their innovation cost in the acquisition of key equipment (Guan et al., 2006). They can act as the potential generators of knowledge spillovers, and positively influence the innovation performance of other firms in the same industry. In terms of Capital Intensity (CI), firms in capital intensive industries can better utilize the R&D input and financial incentives, since they can enhance its innovation capabilities by introducing new technologies. But on the other hand capital intensity is associated with high investment in fixed assets. This leads to innovation strategies are usually constrained by past resource commitments (Datta and Rajagopalan, 1998).Compared to Financial Loan (FL) and Direct Government Subsidy (DGS), the effect of Indirect Government Subsidy (IGS) on innovative economic performance is easier to be influenced by industrial characteristics.

This study provides some implications for policy makers in China. The first stems from the fact that firms in capital intensive industries and relative monopoly industries are more likely to innovate, while firms in the industry with high proportion of SOEs tend to impede innovation propensity and innovation performance. Considering that firms in capital intensive industries and monopoly industry are supposed to possess sufficient funds and technology, we argue that firms are more likely to engage in innovative activities if they can obtain sufficient support from government or organizations. In addition, SOEs not only affect the innovation performance of their own firms, but also significantly and negatively affect other local firms. Thus, the implication is that Chinese government should reinforce its financial support to non-state owned enterprises （NSOEs）to encourage innovative activities and speed up for the adjusting of industrial ownership structure and reforming of SOEs to increase innovation efficiency. Second, Capital Intensity (CI) positively moderates the relationship between Indirect Government Subsidy (IGS) and innovation performance. In other words, Indirect Government Subsidy affects firms in capital intensive industries more strongly. Thus, Chinese government should increase its Indirect

Government Subsidy, such as tax reliefs, to firms in capital intensive industries. Third, the evidence shows that Direct Government Subsidy does not contribute significantly to improve economical innovation performance of firms. This is perhaps because the utilization of Direct Government Subsidy is more affected by government purpose. Generally, Government prefers to innovations that have long-term strategic value. Although these innovations may also have economic values in the future, but their gain is limited in the short term. Chinese government may need to change its innovation funding mechanism from Direct Government Subsidy to a more competitive system commonly adopted in market-driven economies.

Limitations of this paper, which are necessary to be pointed out for future research, are obvious. This paper has only provided a short-term and relative static perspective on industrial sectors that cannot reflect the change of innovative activities for the Chinese firms. For example, we use the cross-sectional data to examine the effects of industry characteristics on innovation performance, however, we aware that patenting procedure and commercialization phase last some time. The non-significant R&D intensity could also be caused by the time lag of patent licensing. This limitation is basically derived from the data available, since SSB only provide a three-year industrial sectors data. This limitation may change our findings and will be an interesting topic to discuss in future research. There is another thing that must be noticed: we only consider the quantity of patents while the quality issue of patent has been neglected. However, Kim et al. (2012) indicate the quality of patent is also important in promoting economic growth. The intensive study about the quality issue should be carried out in evaluating innovation performance and efficiency in the future, if data are available. In addition, we do not consider the industrial firms outside our sample. The issue could also be investigated in the future research.

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Highlights

1. A two-step approach is used to differentiate between the two sets of innovation determinants.
2. Industry characteristics have different impacts on the two steps of innovation model.
3. Industry characteristics moderate the relations between financial incentives and innovation performance.
4. R&D intensity does not contribute significantly to the granted patents in China.