China Economic Review 59 (2020) 101388

Contents lists available at ScienceDirect

China Economic Review

journal homepage: www.elsevier.com/locate/chieco

Firm-level human capital and innovation: Evidence from China

Xiuli Sun[a], Haizheng Li[b,d,*], Vivek Ghosal[c]

[a] School of Statistics, Southwestern University of Finance and Economics, Chengdu 611130, PR China
[b] School of Economics, Georgia Institute of Technology, Atlanta, GA 30332, USA
[c] Department of Economics, Rensselaer Polytechnic Institute, Troy, NY 12309, USA
[d] Hunan University, China

ARTICLE INFO

Keywords:
Patents
Innovation
Human capital
Skilled labor
Managerial human capital
Education
R&D
Geography

JEL classification:
J24
I25
D21
D22
L13
O32
O33

ABSTRACT

This paper examines the role of human capital in firms' innovation. Based on a World Bank survey of manufacturing firms in China, we use two firm-level datasets: one from large metropolitan cities, and one from mid-sized cities. Patents are used as an indicator of innovation. The human capital indicators we use include the number of highly educated workers, the general manager's education and tenure, and the management team's education and age. We use the Negative Binomial and Instrumental Variables estimators to estimate patent production function models that are augmented by our human capital variables. We also use the zero-inflated Negative Binomial model to examine the likelihood of innovation. We find that the human capital indicators play an important role in influencing patenting, and that some of the human capital variables appear to have a greater impact on patenting in mid-sized cities. Our human capital estimates are obtained after controlling for firms' R&D, size, market share, age, and foreign ownership, as well as fixed effects to control for industry-specific characteristics, and firms' location and geography.

1. Introduction

Identifying the underlying factors that make firms more innovative is of considerable importance and has seen substantial research. The literature has identified the roles played by R&D expenditures, firm size, financing constraints, among other characteristics. In part, driven by data availability, much of this literature has focused on firms in the relatively more developed countries.

Our focus in this paper is to examine some of the key determinants of firms' innovation output in a developing and rapidly growing large economy, China. More importantly, our objective is to focus on the contribution of various aspects of firms' human capital – as measured by the firms' managerial and workforce skill-levels – on their innovation output and on their heterogenous effects across different market environments. This is particularly important for a country like China which has made significant investments in R&D related resources to boost its development process, but still lags the developed economies. For example, China was ranked as the second largest R&D spender in the World in 2017.[1] However, in the Forbes 2018 list of the World's 100 most

* Corresponding author at: School of Economics, Georgia Institute of Technology, Atlanta, GA 30332, USA.
E-mail addresses: sunxl@swufe.edu.cn (X. Sun), haizheng.li@econ.gatech.edu (H. Li), ghosav@rpi.edu (V. Ghosal).

[1] OECD Main Science and Technology Indicators Database, February 2018. http://oe.cd/msti.

https://doi.org/10.1016/j.chieco.2019.101388
Received 20 February 2019; Received in revised form 20 November 2019; Accepted 27 November 2019
Available online 30 November 2019
1043-951X/

innovative companies, there are only 7 Chinese companies, while with 51 are from the U.S.[2]

At the macroeconomic level, human capital has been recognized as an important determinant of innovation (e.g., Gennaioli, La Porta, Lopez-de-Silanes, & Shleifer, 2012; Romer, 1990; Squicciarini & Voigtländer, 2015). At firm level, however, empirical studies on the relationship between firm innovation and human capital are somewhat lacking, especially in the context of a rapidly developing economy like China. Our study contributes to the extant literature by focusing on firm-level innovation in China, and, in particular, by investigating in detail the role played by human capital at various dimensions, including at the managerial level and in the firms' general workforce, as well as by examining how market environments affect the function of human capital. This comprehensive examination of the human factors can shed new light on the drivers of innovation in an important and rapidly developing economy.

The broader literature examining firm's innovation capacity and output has focused on a range of internal and external factors. One strand of literature related to firm level human capital considers highly skilled human capital as a crucial dimension of innovation processes for a firm (e.g., Kianto, Sáenz, & Aramburu, 2017; Snell & Dean Jr, 1992; Subramaniam & Youndt, 2005). Another strand of literature related to firms' innovation examines the management team (e.g., Lin, Lin, Song, & Li, 2011; McGuirk, Lenihan, & Hart, 2015; Zhang, Ou, Tsui, & Wang, 2017). However, many of the studies have focused either on skilled human capital, or on managerial human capital, and/or ignored external factors such as market structure (e.g., Lin et al., 2011; McGuirk et al., 2015).

In our study, we combine both internal and external factors to examine the determinants of a firm's innovation, with particular focus on how various aspects of workforce and managerial human capital contribute to firm innovation, and how the effects might differ across various market environments. Different facets of human capital are distinguished, measured and their roles are investigated, using different datasets and estimation methods.

The data we use are from a World Bank survey of firms in China. The data contain a rich set of variables related to labor force and innovation. Specifically, we study the manufacturing firms in China, because this sector has played a critical role in China's rapid economic growth, and accounts for about 40% of China's GDP. The World Bank survey contains two datasets from two different levels of cities - large metropolitan cities and mid-sized cities, which have very different market environments in China. The market environment can have a profound effect on a country's innovation system (Bosker & Garretsen, 2008). This further enables us to examine in detail the factors, especially human capital, affecting firms' innovation in different market environments.

Our estimates show that highly educated human capital plays an important role in both the probability of innovation and the quantity of innovation. However, there is variation on the impacts of the different human capital variables across the samples from the large versus mid-sized cities. The General Manager's (GM, hereafter) and management team's education levels have a positive and significant effect on firms' innovation output in mid-sized cities. The tenure of General Manager plays a positive role in large cities. The average age of a firm's management team appears to have a significant negative effect on innovation in all cities.

The paper is organized as follows. In Section 2 we briefly discuss the mechanisms of human capital on innovation at firm level. Section 3 presents the empirical models and estimation strategies, and the data and human capital measures are described in Section 4. Our estimates, using Negative Binomial (NB, hereafter), Instrumental Variables, and zero-inflated NB, are presented in Sections 5, 6 and 7. Section 8 concludes.

2. Firm level human capital and innovation

Studies in the field of industrial economics have mainly focused on external factors that affect firm innovation, such as market opportunities (Coad, Segarra, & Teruel, 2016), market structure and firm size (Hall & Ziedonis, 2001; Rogers, 2004), and modes of financing (Kortum & Lerner, 2000). Studies in the field of management have focused on various internal characteristics of firms that affect their innovation behavior such as those related to intellectual capital (Subramaniam & Youndt, 2005), employee incentives (Lin et al., 2011; Sauermann & Cohen, 2010), CEO characteristics (Lin et al., 2011), and task-based human capital (Fonseca, de Faria, & Lima, 2019).

Firm-specific human capital has been viewed as critical to fostering innovation and greater productivity. According to the *resource-based* theory, human capital is viewed as a critical resource, and performance differences across firms can be attributed to the variations in the firms' resources and capabilities (Custódio, Ferreira, & Matos, 2017; Hitt, Bierman, Shimizu, & Kochhar, 2001). Firms possess both tangible resources (such as physical capital and financial resources) and intangible resources (like human capital and brand equity). Intangible resources are more likely to produce a competitive advantage.

In this study, a firm's human capital includes firms' workforce human capital stock and managerial human capital. They represent a firm's resource as they provide competitive advantages for firms in terms of experience, skills and expertise, and also account for an important part of a firm's knowledge stock (Wright, Dunford, & Snell, 2001).

In the knowledge-based theory, the hallmarks of human capital are creative and skilled employees, who constitute the predominant source for new ideas and knowledge in an organization (Snell & Dean Jr, 1992). In particular, such intellectual capital influences incremental and radical innovative capabilities (Subramaniam & Youndt, 2005).[3]

We measure the firm's workforce human capital using the stock of highly educated workers. Those workers have close relationship

[2] Forbes. The World's Most Innovative Companies 2018. https://www.forbes.com/innovative-companies/#338aa51b1d65.

[3] Their human capital is constructed based on five self-evaluated items. The five items are: our employees are highly skilled; our employees are widely considered the best in our industry; our employees are creative and bright; our employees are experts in their particular jobs and functions; our employees develop new ideas and knowledge.

with absorptive capacity, which is a firm's ability to identify, assimilate, and exploit knowledge, and is considered a direct driver of innovation (e.g., Cohen & Levinthal, 1990). Moreover, highly educated workers play a vital role in combining, transforming and integrating external knowledge with the knowledge generated internally. Overall, highly educated human capital potentially implies greater learning-by-doing, and is complementary to a firm's R&D, and thus can help push the firm's innovation frontiers (e.g., Romer, 1990).[4]

Additionally, top managers of a firm influence the path and outcomes of firm innovation, through means such as building and managing an innovative culture, nurturing an innovative environment, and designing pro-innovation policies (Lin et al., 2011; McGuirk et al., 2015). The upper echelon theory (e.g., Zhang et al., 2017) argued that organizations are just reflections of their top managers, because the top management team has the task of formulating and implementing the firm's strategy on innovation. For instance, Wu, Levitas, and Priem (2005) showed that executive tenure is related to a company's patent approvals; Chen, Bu, Wu, and Liang (2015) found that top management team's attention to innovation influenced a firm's innovation activities; and Zhang et al. (2017) examined how CEO humility and narcissism affect firm innovation. Hu and Jefferson (2009) noted that more capable and motivated managers tend to conduct more R&D and be more aggressive in maintaining a portfolio of patents.

Our human capital measures on management cover a range of attributes of the top management team, including GM's education and tenure, and the management team's average schooling and age. The managerial human capital as embodied in CEOs and top management team plays an important role in a firm's innovation. We analyze GM human capital separately to highlight its unique and critical role in determining firm innovation.

In a different strand of the literature, Santamaría, Nieto, and Barge-Gil (2009) emphasized the importance of various non-R&D factors that affect innovation. Rammer, Czarnitzki, and Spielkamp (2009) found that imitative activities mainly depend on the firm's technical personnel and engineers.[5] The non-R&D related informal knowledge production is especially important for firms in developing countries where small and medium enterprises (SMEs) tend to dominate. As a result, human capital contributes to firms' innovation directly through non-R&D innovation via learning by doing. Firms can make incremental changes to products and processes (Grimpe & Sofka, 2009), where highly educated human capital is vital to the adoption and adaptation processes (Santamaría et al., 2009). Explicitly incorporating human capital variables allows us to account for such non-R&D innovation.

The market environment can have a profound effect on innovation (Bosker & Garretsen, 2008). In our study, the two datasets cover firms from different types of cities, mid-sized and large cities, which have very different market environments in China. For example, the enforcement of intellectual property rights differs across cities due to uneven regional development in institutions and markets (Ang, Cheng, & Wu, 2014). Such differences will affect a firm's innovation. Further, the level of international openness is considerably higher in large cities. International openness and inward FDI can accelerate technological catch-up (Tödtling & Trippl, 2005) and stimulate innovation through spillovers, competition and demonstration effects (García, Jin, & Salomon, 2013). Additionally, the quality of human capital differs significantly across cities. Large cities usually have better educated labor force and more schools and colleges. As a result, firms in the large cities may behave differently in innovation compared to those in mid-sized cities.

Given the above considerations in this study we focus on the effects of human capital on firm's innovation. We contribute to the literature by including various dimensions of firm-specific human capital, and investigate the heterogenous effects of human capital across different market environments, represented by relatively more developed large metropolitan cities and less developed mid-sized cities in China. Given the drastic inequality in most developing countries, the varying roles human capital played in firm innovation in different environments will have important policy implications.

3. Empirical models and estimation strategies

Following a large literature in empirical microeconomics, we use firms' patents to proxy innovation. The specific approach we take is to augment the commonly-used patent production function (e.g., Hall & Ziedonis, 2001; Kortum & Lerner, 2000) by including a range of human capital indicators. More specifically:

$$E(Y_i) = \exp(X_i'\beta_X + H_i'\beta_H), \tag{1}$$

where Y_i is the count of patents of firm i, and the vector X_i includes a range of explanatory variables that affect firms' patent production.[6] H_i is the vector of human capital indicators.

The number of patents for a firm is a count variable. The limitation of the OLS estimator for count data is that it allows for negative values in its conditional mean function. However, the OLS estimator does not need distribution assumption. For count data models, the Poisson and Negative Binomial maximum likelihood estimators are two commonly used estimation strategies (e.g., Hall & Ziedonis, 2001; Hu & Jefferson, 2009; Kortum & Lerner, 2000). For the Poisson model, the variance is restricted to be equal to its mean, the so-called equi-dispersion, while the Negative Binomial model allows for over-dispersion.

[4] There's also a probability of "knowledge spillover channel" which means that when there's more highly educated human capital in a firm, there will be more internalization of outside R&D spillover or knowledge spillover into the firm.

[5] See Ghosal (2015) for issues related to incremental innovation in manufacturing firms.

[6] See, for example, Hausman et al. (1984), Kortum and Lerner (2000), Hall and Ziedonis (2001), and a brief review of the literature in Ghosal and Ni (2016).

3.1. Dealing with endogeneity using control function approach

At the firm level, human capital measures are likely to be endogenous. To take this into account, we also conduct Instrumental Variable estimation. For the NB model, due to its nonlinear nature, we apply the Control Function (CF) approach (Wooldridge, 2015) for the IV estimation. Specifically, let *pat* denote the dependent variable (the number of patents), and *h* the endogenous explanatory variables (included in *H*), and $\boldsymbol{z}$ the vector of exogenous variables and instruments. The mean function is:

$$E(pat \mid \boldsymbol{z}, h, v_1) = \exp(\boldsymbol{z}_1\delta_1 + \alpha_1 h + v_1), \tag{2}$$

where $\boldsymbol{z}_1$ is a strict subvector of z, and v_1 is the error term. Suppose that h has a standard linear form:

$$h = \boldsymbol{z}\boldsymbol{\pi}_2 + v_2, \tag{3}$$

and the joint distribution of v_1 and v_2 is independent of $\boldsymbol{z}$. Then we have

$$E(pat \mid \boldsymbol{z}, h) = E(\exp(\boldsymbol{z}_1\delta_1 + \alpha_1 h + v_1) \mid \boldsymbol{z}, h) = E(\exp(v_1) \mid v_2)\exp(\boldsymbol{z}_1\delta_1 + \alpha_1 h). \tag{4}$$

Using probability density function, we can show that $E(\exp(v_1)|v_2) = E(\exp(v_1|v_2)) = \exp(E(v_1|v_2))$. Moreover, if (v_1, v_2) are jointly normal, then $E(v_1|v_2)$ is linear in v_2. Under the assumption of zero mean of v_1 and v_2, we then get that $E(v_1|v_2) = \theta_1 v_2$, where θ_1 is a constant. Finally,

$$E(pat \mid \boldsymbol{z}, h) = \exp(\boldsymbol{z}_1\delta_1 + \alpha_1 h + \theta_1 v_2). \tag{5}$$

The above expectation suggests a two-step CF estimation procedure. The first step is to estimate the reduced form for h and obtain the residuals $\hat{v}_2$. Second, include $\hat{v}_2$, along with $\boldsymbol{z}_1$ and h, in the NB estimation.[7]

3.2. Zero-inflated Negative Binomial model

In the above models, firms with zero patents are treated as having no innovation. However, firms with zero patents are likely to be from two different data generating processes: (a) firms that don't innovate at all; (b) firms that attempt to innovate but fail to generate patents. It is important to distinguish between these two types to better understand their innovation behavior.[8]

Following Hu and Jefferson (2009), we distinguish them by applying the zero-inflated Poisson or NB approach, and model the two processes explicitly. If there exists overdispersion, then it is desirable to use zero-inflated NB instead of zero-inflated Poisson. In zero-inflated NB model, the *probability* of choosing to innovate or not is modelled in the inflated part using a logit model. The innovation outcome, i.e., the quantity of patent, is modelled by a NB process. The log likelihood function is thus constructed by combining the two processes.

The zero-inflated model supplements NB density $f_{NB}(\cdot)$ with a binary process that has density $f_B(\cdot)$. When firms do not attempt to innovate at all (i.e., the number of patents takes 0 with probability 1), the binary process takes value 0 with the probability $f_B(0)$. When firms do attempt to innovate, i.e., patent count takes value 0, 1, 2, …, the binary process takes value 1 with probability $f_B(1)$, eqaul to $1 - f_B(0)$. The density function is defined as:

$$g(pat_i) = \begin{cases} f_B(0) + (1 - f_B(0))f_{NB}(0) \text{ if } pat_i = 0 \\ (1 - f_B(0))f_{NB}(pat_i) \text{ if } pat_i \geq 1 \end{cases}, \tag{6}$$

and where $f_B(\cdot)$ is a logit model and $f_{NB}(\cdot)$ is the NB density given by:

$$f_{NB}(pat_i) = pr(Y = pat_i \mid \mu_i, \alpha) = \frac{\Gamma(pat_i + \alpha^{-1})}{\Gamma(\alpha^{-1})\Gamma(pat_i + 1)}\left(\frac{1}{1 + \alpha\mu_i}\right)^{\alpha^{-1}}\left(\frac{\alpha\mu_i}{1 + \alpha\mu_i}\right)^{pat_i}, \tag{7}$$

where $E(Y_i) = \mu_i = \exp(\boldsymbol{x}_i\beta)$.

To parameterize $f_B(0)$, i.e., the probability of choosing not to innovate by a firm, Hu and Jefferson (2009) assumed that the decision to innovate is determined by a logistic process as below:

$$f_B(0) = G(z'\gamma) = \frac{1}{1 - \exp(-z'\gamma)}, \tag{8}$$

where z includes variables that determine whether a firm chooses to innovate or not, and γ are the corresponding coefficients. The likelihood function becomes:

[7] One complication in the CF approach is that the estimation in the second stage involves generated regressors. We estimate the standard errors via the bootstrapping procedure.

[8] Some of the firm innovation studies like Autor, Dorn, Hanson, Pisano, and Shu (2017) focus on the set of firms who engage in innovation, or innovative firms, ignoring the set of firms who don't engage in innovation. Therefore, their research, and findings, mainly concentrates on the intensity of innovation in innovative firms rather than the probability of innovation.

$$L(\beta,\gamma;\boldsymbol{x}_i,z,pat_i)=\sum_{pat_i=0}\ln[\exp(z'\gamma)+(1+\alpha\exp(\boldsymbol{x}_i{}'\beta))]^{-\alpha^{-1}}+\sum_{pat_i>0}\sum\nolimits_{j=0}^{pat_i-1}\ln(j+\alpha^{-1})$$
$$+\sum\nolimits_{pat_i>0}\{-\ln(pat_i!)-(pat_i+\alpha^{-1})\ln(1+\alpha\exp(\boldsymbol{x}_i'\beta))+pat_i\ln(\alpha)+pat_i*\boldsymbol{x}_i{}'\beta\}+\sum\nolimits_{i=1}^{n}\ln(1+\exp(z'\gamma)). \tag{9}$$

The vector $\boldsymbol{x}$ includes those variables used in the model in the above section, and z and $\boldsymbol{x}$ are usually chosen to be identical.

4. Data and human capital measures

We use data from two unique surveys conducted by the World Bank.[9] The first one is "The Study of Competitiveness, Technology & Firm Linkage" conducted in 2002.[10] The second one is "Investment Climate Survey" conducted in 2003.[11] They form parts of surveys conducted by the World Bank on firms in China.[12] For both surveys, some quantitative questions (e.g., total sales, R&D, etc.) are covered not only for the survey year but also the previous 2 years in a retrospective way. Thus, there are 3 years of data available for these variables. Other questions are covered only for the survey year.

The first survey covers firms in five large cities including Beijing, Chengdu, Guangzhou, Shanghai, and Tianjin with most information for year 2000 (henceforth, we refer to this as *Data2000*). In this data set, there are 1548 firms surveyed and they belong to five manufacturing industries and five services industries. The second survey covers firms in 18 mid-sized cities with most information for year 2002 (henceforth, referred to as *Data2002*). The second survey includes 2400 firms from ten manufacturing and four services industries.

An advantage of using both data sets is that it allows us to examine the potentially different relationships between firms' human capital and innovation in large cities and in mid-sized cities. As discussed above, location and geography will influence the impact of human capital. Large cities are generally more developed with better infrastructure, market systems, and labor markets. In addition, they receive more FDI and thus have potentially larger spillover effects from foreign investment.

For the purpose of this study, we focus on manufacturing industries and exclude services industries as they may have very different mechanisms for innovation. Empirical studies in firm innovation commonly focus on manufacturing firms (Dang & Motohashi, 2015; Guo, Guo, & Jiang, 2016; Lin et al., 2011; Rupietta & Backes-Gellner, 2019). Traditionally, manufacturing is considered an important source of technological innovations and patenting, and a key driver of productivity.[13] Our samples, therefore, include industries like consumer products, electronic components, electronic equipment, and vehicles and vehicle parts.[14]

In selecting our final sample, for both datasets, we select firms with: (a) total assets (book value) no less than RMB 0.1 million[15]; (b) 20 or more total employees; and (c) 5 or more highly educated workers for the survey year. According to National Bureau of Statistics of China, manufacturing firms with < 20 employees are considered as micro firms, which are less likely to innovate and patent.[16] The final samples have 665 firms in Data2000 and 795 firms in Data2002.[17]

The human capital indicators we include are the total highly educated human capital, GM human capital, and the human capital of the management team. To measure highly educated human capital, we follow Fleisher, Hu, Li, and Kim (2011) and classify the employees into highly educated and use the number of highly educated workers as proxy.[18] This is consistent with the literature. For example, Schneider, Günther, and Brandenburg (2010) used the share of highly qualified workers as the measure of highly educated human capital. In our data, the highly educated group mainly consists of "engineering and technical personnel" and "managerial personnel (including sales)." By averaging the workers' schooling years for each occupation category over the sample, we designate each occupation level as highly educated if the average education is at the college level and above, and less educated, otherwise. The World Bank survey data only provide information on number of employees for different occupations for the years 2000 and 1998 in Data2000, and for the years 2001 and 2002 in Data2002. We imputed employment for different occupations for 1999 in Data2000 and year 2000 in Data2002.[19]

[9] Firm-level survey data in China are rare, especially data with detailed information on innovation and on labor force characteristics. The World Bank data are probably the most common data used in the literature (e.g., Ayyagari, Demirgüç-Kunt, & Maksimovic, 2011; Cull, Li, Sun, & Xu, 2015; Fleisher et al., 2011; Lin et al., 2011).

[10] The World Bank (2002). Study of Competitiveness, Technology & Firm Linkages. http://microdata.worldbank.org/index.php/catalog/651

[11] The World Bank (2003). Investment Climate Survey. http://microdata.worldbank.org/index.php/catalog/591

[12] Until now, this survey series have been conducted for four years, 2002, 2003, 2005 and year 2012. Only 2002 and 2003 waves are comparable, with the human capital information and detailed innovation variables. In the 2005 and 2012 survey, there is no information on innovation.

[13] We dropped the industries for producing apparel and leather goods.

[14] We further classify consumer products (i.e., household electronics), electronic components, electronic equipment into one category, named "electronics."

[15] In Year 2000 and 2002, the exchange rate is around RMB 8.28/$. All the monetary variables are real values, deflated to real values using city level inflation index (CPI) and year 2000 as base. During year 1998–2002 city-level PPI is not available. Provincial level PPI is only available since year 2001.

[16] Our results are not sensitive to other cutoffs (e.g., 50 total employees, 10 highly educated workers).

[17] The World Bank survey is designed to be representative. Missing values reduce the sample size. If missing values are not systematic created, i.e., they are random, the representativeness should not be affected.

[18] In both surveys, workers are classified into: basic production workers, auxiliary production workers, engineering and technical personnel, managerial personnel, service personnel, and other employees.

Table 1
Descriptive statistics.

	Obs.	Mean	S.D.
Data2000: All the values are in the survey year, year 2000			
Panel A: Human capital variables			
Number of highly educated workers in firm	664	1.66	3.19
GM's postgraduate dummy	663	0.17	0.38
Years of GM holding the position	664	5.27	4.07
Management team's average schooling	655	12.04	1.49
Management team's average age	654	36.28	6.71
Panel B: Firm characteristics			
R&D excluding labor compensation by firm	644	16.15	204.17
Total number of employees	665	7.32	14.13
Total assets	665	0.15	0.64
Firm's market share	630	17.05	21.10
Firm age	665	14.84	14.72
Foreign and private ownership	665	0.63	0.48
Other ownership	665	0.37	0.48
Subsidiary	665	0.07	0.26
Electronics industries	665	0.71	0.45
Vehicle industry	665	0.29	0.45
Data2002: All the values are in the survey year, year 2002			
Panel A: Human capital variables			
Number of highly educated workers in firm	791	1.47	3.48
GM's postgraduate dummy	790	0.16	0.37
Years of GM holding the position	788	5.65	4.51
Management team's average schooling	771	12.14	1.61
Management team's average age	770	36.95	5.57
Panel B: Firm characteristics			
R&D excluding labor compensation by firm	783	4.00	27.53
Total number of employees	795	9.50	99.33
Total assets	788	0.14	0.66
Firm's market share	795	9.17	15.97
Firm age	795	15.74	14.24
Foreign and private firm	795	0.48	0.50
Other ownership	795	0.52	0.50
Subsidiary firm	795	0.13	0.33
Electronics industries	795	0.60	0.49
Vehicle industry	795	0.40	0.49

Notes
1. Number of highly educated workers in a firm are measured in hundreds.
2. GM's postgraduate dummy =1 if postgraduate.
3. R&D expenditures excluding labor compensation are measured in million RMB.
4. Total number of employees are measured in hundreds.
5. Total assets are measured in billion RMB.

The General Manager's tenure and education, and the average age and education of management team are used as the indicators of managerial human capital. Education of the management team is defined as the average years of schooling of all managerial personnel in a firm.

Tables 1 provides the descriptive statistics. In Data2000, the average number of highly educated workers is 166, and it is 147 in Data2002, and the numbers vary dramatically across firms. GMs have > 14 years of schooling, 16–17% of them have a postgraduate degree, and, on average, hold the position for > 5 years.[20] The management team has more than high school education, and an average age of 37 years old.

Regarding R&D, to avoid double counting, we use R&D expenditures by excluding the R&D-personnel related compensation. There is a very large difference in R&D between two datasets, with approximately RMB 16 Million on average in Data2000 and approximately RMB 4 Million on average in Data2002. As expected, firms in the large cities invest a lot more on R&D than those in mid-sized cities.

As we noted earlier, R&D has been included as a key variable in patent production function models. Much of the early work used a lag structure of R&D in estimating the patent production function (e.g., Hausman, Hall, & Griliches, 1984).[21] However, the

[19] We impute the data using the average weighted by employment in other two years.

[20] According to the survey instruction, a person with high school education has approximately 10 years of schooling; and a person with undergraduate education has approximately 14 years of schooling.

[21] This is due to the gap between when the R&D is conducted and the eventual generation of a patent. Also, see Barker III and Mueller (2002) and Ghosal and Ni (2016) for a discussion of this literature.

Table 2
Patent applications and patents granted.

	Data2000		*Data2002*	
	Year	Percentage of Firms with patents	Year	Percentage of Firms with patents
Patent applications	2000	13.08%	2002	13.21%
	1999	12.93%	2001	10.57%
	1998	11.43%	2000	10.06%
Patents granted	2000	12.03%	2002	13.58%
	1999	12.93%	2001	10.44%
	1998	10.23%	2000	10.94%

Notes: Due to time needed in patent examination, the number of patents granted in a year comes from patent applications in previous years. It is therefore possible that in some years the patents granted can be larger than applications in that year.

subsequent literature found that one-lag R&D expenditures performed as well as a more lagged structure in explaining the patents-R&D relationship. As discussed by Hall and Ziedonis (2001), using deeper lags of R&D provides no useful information beyond including the most current R&D data. As the World Bank survey data have only 3-years of information on R&D, we use the average of lagged values of R&D expenditures (excluding R&D-labor compensation) over the past 2 years. This helps average out the fluctuations in R&D expenditure across years within a firm and saves the degree of freedom by not having to include two lags. Overall, lagged R&D is less likely to be endogenous to current patenting (Dang & Motohashi, 2015).

Firm size is measured by total assets (gross book value). The market share data provided in the survey are self-reported by each firm. In Data2000, firms have higher market share on average (17.05%) than for the firms in Data2002 (9.17%). This is likely because firms in large cities are bigger players in the industry. The ownership structure in the two datasets differs significantly, with a much high proportion (63%) of foreign and private firms in Data2000. This is probably due to supportive policies, infrastructure, and business environment in big cities.

Patents are a commonly used proxy for innovation (e.g., Hsu & Ziedonis, 2013). We measure innovation activities based on firms' annual patent applications. The number of patent applications are expected to reflect the totality and the timing of a firm's patenting strategy. The very fact that a firm undergoes the process of applying for a patent signals some underlying innovation activity. As a robustness check, we also used patents granted to estimate the model, and our inferences are similar. The correlation between patents applied for and granted is high: 0.875 in Data2000 and 0.830 in Data2002, respectively. The patents information is presented in Table 2. The proportion of firms applying for patents is in the range of 10–14%. In both datasets, there is an upward trend.

In terms of dynamics, average patent applications (among firms with nonzero patents), proportion of firms with patents (i.e., the ratio of firms with nonzero patents to all firms in the datasets), highly educated human capital, and R&D all tend to increase over the years, except for highly educated workers from year 2001 to 2002 in Data2002.

Table 3 presents the differences in human capital indicators between firms with and without patents. For both datasets, the firms with a higher number of patents generally have more highly educated workers, better educated GM and management team, and younger management team, and all differences are statistically significant.

Looking ahead to our estimation, we note an important point. In our samples from the two datasets, the broad industries included are consistent, with both samples including consumer products, electronic components, electronic equipment, and vehicles and vehicle parts. Thus, the potential heterogeneity in our estimated effects is less likely to arise at least from the broader industry differences. However, it is possible that the broad industry classification may conceal compositional differences within the broader

Table 3
Human capital indicators comparison between firms with patents and without patents.

	Data2000			*Data2002*		
	Firms with patents	Firms without patents	Difference	Firms with patents	Firms without patents	Difference
Number of highly educated workers in firm	4.04	1.30	2.74*** (0.35)	4.01	1.08	2.93*** (0.35)
GM's postgraduate dummy	0.30	0.16	0.14*** (0.043)	0.32	0.14	0.18*** (0.038)
Years of GM holding the position	5.84	5.19	0.65 (0.47)	5.94	5.61	0.33 (0.48)
Management team's average schooling	12.70	11.93	0.77*** (0.17)	12.70	12.06	0.64*** (0.17)
Management team's average age	34.21	36.60	−2.39*** (0.77)	35.33	37.21	−1.88*** (0.59)

Notes
1. See Table 1.
2. Standard errors in parentheses: *$p < .10$, **$p < .05$, ***$p < .01$. Two-sided t-test is used to compare the difference.

category. As an example, consider an industry classification: 'motor vehicles and parts.' This is a standard classification in, for example, the U.S. SIC code. But this broader classification conceals differences between say firms that may make spark plugs, steering wheel related components, final assembly of the vehicles, among many other components. This type of compositional differences may vary across regions across the country. The World Bank datasets we use simply do not have enough information to control for such 'within-industry-category' compositional differences. This is an interesting avenue for future research, based on the availability of more detailed datasets.

5. The estimated effects of human capital on patents

Based on the discussions above, we specify the empirical model as:

$$\log(pat_i) = \beta_0 + \beta_1 HC_i + \beta_2 \log(RD_i) + \beta_3 SZ_i + \beta_4 MKTSHR_i + \beta_5 W_i + u_i, \tag{10}$$

where pat_i is the number of patent counts of firm i, HC_i represents human capital indicators, RD_i is R&D expenditures, SZ_i is firm size, $MKTSHR_i$ is market share, W_i stands for other control variables, and u_i is the firm-specific error term.[22]

Explanatory variables include the human capital measures we noted earlier. Other variables include R&D expenditures, firm size, market share, firm age, ownership, etc. They have been commonly used in the literature in patent production models (e.g., Blundell, Griffith, & Van Reenen, 1999; Eberhardt, Helmers, & Yu, 2016; Hall & Ziedonis, 2001; Kortum & Lerner, 2000). R&D is clearly an input for generating patents. For market structure and firm age, Schumpeterian hypotheses argued that large firms in concentrated markets are the main engine of technological progress. Empirical studies have offered numerous insights as to how firm size and market structure affect firms' innovation (e.g., Raymond, Mairesse, Mohnen, & Palm, 2015). Additionally, theory and evidence also indicate that entrants generally invest more in R&D than incumbents (Coad et al., 2016; Czarnitzki & Kraft, 2004). This suggests that old firms may be less innovative than their younger counterparts, and thus age may affect innovation. Ownership determines the governance structure of a firm and thus will affect innovation behavior. For example, empirical studies have shown that state-owned enterprises (SOEs) in China have lower R&D efficiency than non-state firms, and foreign firms have higher R&D efficiency than domestic firms (Zhang, Zhang, & Zhao, 2003). Given the importance of knowledge spillover in firm innovation (Audretsch & Feldman, 2004), we also include *city-fixed effects* and *industry-fixed effects*. These fixed effects are designed to capture spatial effects, spillover effects, and other city/industry factors, such as those related to market conditions, economic and regulatory policies, among others.[23]

Table 4 reports the regression results based on OLS, Poisson and Negative Binomial (NB) estimation.[24] Although the OLS estimation is the simplest approach, it requires less restrictive assumptions, such as the distribution assumption in Poisson/NB estimation. Our analysis and discussion will be based on the NB results.

The results in Table 4, using the NB estimates, show that *highly educated human capital* has a positive and significant effect on patent applications in both datasets. More specifically, when the number of highly educated workers increases by 10 people, the number of patents is expected to increase by 3.6% in the NB model in Data2000. Evaluating at the sample average of number of patents (0.88), the number of patents is expected to increase by 0.032. Results are similar for mid-sized cities (column 6), but a somewhat smaller effect. In particular, when the number of highly educated workers increases by 10, the number of patent applications is expected to increase by 2.46%. Evaluating at the sample average patent counts (0.82), patent counts are expected to increase by 0.020.[25] The broad conclusions we draw from these estimates are similar in spirit to Bosetti, Cattaneo, and Verdolini (2015), who found that highly educated labor has a positive effect on innovation.

The effect of *GM's tenure* is positive and significant. When the GM's tenure increases by one additional year, the number of patent applications is expected to increase by 13.5% for Data2000. The estimated effect is much smaller for Data2002, with the expected increase of 5.0% (based on the NB estimation).[26] One possible explanation is that the large cities have more developed markets, with higher level of competition, and these markets are more likely to reward experienced managers who innovate. Another possibility is that the composition of the firms and industries differ across mid-sized and large city markets, with the latter being more technologically advanced, resulting in higher incentives and premiums on innovation. Based on Lin et al. (2011), shorter tenured GMs might have greater incentives to focus on short-term outcomes in order to build their reputation and therefore might be less willing to invest in high-risk long-horizon R&D projects.

---

[22] Our way of measuring R&D and high skilled workers is consistent with an important strand of the literature: Hu and Jefferson (2009); Dang and Motohashi (2015); Hu, Zhang, and Zhao (2017); Fleisher et al. (2011), to name a few. Because the dependent variable is the number of patents and patenting propensity, it is better to use the magnitude measures to study their effects, and consistent with the papers we note above.

[23] We also tried to use some city-level variables to control for city-level spillovers, such as number of college students in a city. Generally, the results are consistent with those using fixed effects. The advantage of using city level spillover measures is to save degree of freedom.

[24] In the regression, we cannot use panel data because most variables needed are only available for one year, and accordingly, we use year 2000 for Data2000 and year 2002 for Data2002.

[25] Additionally, we apply the idea of standardized coefficient regression to make approximate comparison of estimated parameters from the two datasets. When the number of highly educated workers increases by one standard deviation, the number of patents is expected to increase by 114.84% in the NB model in Data2000, and it is expected to increase by 85.61% in Data2002. If we evaluate at the same sample average of 0.88, the effect is 1.01 and 0.75 increase respectively in patent applications, and the conclusions remain unchanged.

[26] That is, when GM's tenure increases by one standard deviation, the number of patent applications is expected to increase by 54.9% and 22.55% in Data2000 and Data2002 respectively.

Table 4
OLS, Poisson and Negative Binomial estimation results.

Dependent variable: patents applied	*Data2000*			*Data2002*		
	(1) OLS	(2) Poisson	(3) NB	(4) OLS	(5) Poisson	(6) NB
Panel A: Human capital variables						
Number of highly educated workers	0.432**	0.0949***	0.362***	0.519	0.102***	0.246***
	(0.167)	(0.0171)	(0.0766)	(0.319)	(0.0218)	(0.0553)
General Manager with a postgraduate degree	0.588	0.438	0.0333	0.922*	0.774**	1.059***
	(0.515)	(0.353)	(0.319)	(0.531)	(0.347)	(0.279)
General Manager's tenure	0.127***	0.119***	0.135***	0.0384	0.00984	0.0499*
	(0.0431)	(0.0353)	(0.0391)	(0.0253)	(0.0355)	(0.0262)
Management team's average schooling	0.0236	0.0823	0.121	0.0809	0.128	0.312***
	(0.0845)	(0.108)	(0.129)	(0.0745)	(0.0835)	(0.102)
Management team's average age	−0.0645**	−0.0618**	−0.162***	−0.00969	−0.0677***	−0.100***
	(0.0281)	(0.0290)	(0.0276)	(0.0274)	(0.0262)	(0.0243)
Panel B: R&D and firm characteristics						
Average (log) R&D excluding labor compensation in previous 2 years	0.0189	0.0379	0.0401*	0.0178	0.0952***	0.0865***
	(0.0268)	(0.0315)	(0.0239)	(0.0256)	(0.0322)	(0.0202)
Market share	0.0121	0.0126**	0.0191***	0.00661	0.0167***	0.0225***
	(0.00962)	(0.00612)	(0.00651)	(0.00874)	(0.00581)	(0.00606)
Total assets	−0.482	0.00905	−0.846***	0.0352	0.0869	−0.271**
	(0.369)	(0.133)	(0.298)	(0.562)	(0.0777)	(0.130)
Firm age	−0.00737	−0.00877	0.0136	−0.0178	−0.00532	0.0154
	(0.00991)	(0.0150)	(0.0127)	(0.0136)	(0.0115)	(0.0109)
Foreign and private ownership	0.191	0.0682	0.446	0.226	−0.225	0.0239
	(0.296)	(0.368)	(0.334)	(0.319)	(0.316)	(0.314)
Subsidiary	0.604	0.355	−1.064*	1.231*	0.862**	0.198
	(1.242)	(0.819)	(0.632)	(0.664)	(0.396)	(0.380)
*ln*alpha			2.374***			1.991***
			(0.149)			(0.143)
City dummies	Yes	Yes	Yes	Yes	Yes	Yes
Industry dummies	Yes	Yes	Yes	Yes	Yes	Yes
Constant	Yes	Yes	Yes	Yes	Yes	Yes
Number of observations	608	608	608	737	737	737
Adjusted R^2	0.126			0.196		

Notes
1. See Table 1. Subsidiary = 1 if the firm is a subsidiary.
2. Standard errors in parentheses: $^{*}p < .10$, $^{**}p < .05$, $^{***}p < .01$.
3. Columns (1) and (4) are the results of the OLS estimates, and columns (2) and (5) are the estimated based on Poisson model, and Columns (3) and (6) are estimated using negative binomial (NB) model.
4. *ln*alpha is the log-transformed over-dispersion parameter, with a positive and significant value favoring NB model to Poisson model.

Interestingly, the *education of GM* (post-graduate degree or not) has an insignificant effect in Data2000, but is highly significant in Data2002. It is likely that generally more educated executives may have more knowledge and higher ability to absorb new ideas and therefore have a higher propensity to accept innovations (King, Srivastav, & Williams, 2016; Sunder, Sunder, & Zhang, 2017). Such knowledge may command a higher premium in mid-sized cities which, on average, have lower levels of education, and affect firms' ability to adopt and use more advanced technologies relative to their counterparts in the relatively larger and developed cities.[27]

The *management team's average age* has a negative and significant effect in both datasets. This implies that younger managerial teams lead to greater innovation and patenting efforts. Older management teams tend to be more conservative and risk averse, and often less inclined to push on risky and expensive innovation projects (e.g., Barker III & Mueller, 2002).

The estimated effect of the *management team's average education* is not significant in Data2000, but is positive and significant in Data2002. Consistent with the results noted above regarding GM's education, the management team's education seems to be more important in mid-sized cities.

R&D spending has a positive and significant effect on patents in both datasets, consistent with a large previous literature (e.g., Akcigit & Kerr, 2018; Hall & Ziedonis, 2001). Market share has a positive effect on patenting, as found in the literature Cohen and Levinthal (1990), and the results in Blundell et al. (1999), Lee, Veloso, and Hounshell (2011), and Hashmi and Biesebroeck (2016). Larger firms (as measured by the total firm assets variable) patent less than smaller firms. Firm age and foreign ownership do not appear to have a significant effect on patenting.

[27] For example, in 2000, the proportion of labor force with a college degree or above in one of the survey cities in Data2000, Shanghai, is 13.35%. Due to the lack of similar data for mid-sized cities, we considered Henan province as a comparable example and its proportion of college degree or above is merely 3.58% for the same year.

Finally, a subsidiary firm could promote innovation through internal knowledge diffusion, but can also be constrained because innovations may be arranged mostly in the parent firm. Our estimates show that being a subsidiary firm has a negative effect in Data2000 (but statistically insignificant effect in Data2002).[28]

Innovative activities as well as the components of human capital might vary between state owned enterprises (SOEs) and non-SOEs (Zhang et al., 2003). We then estimate models with subsamples for state-owned enterprises (SOEs) and non-SOEs. The results are showed in Table 5. The results are generally comparable, but still show interesting differences between SOEs and Non-SOEs. In particular, for highly educated human capital, in mid-sized cities, its effect is insignificant in SOEs, while for non-SOEs remains highly significant. One possible explanation is that in mid-sized cities, the market system is not as developed that in large cities. Therefore, the hiring decision in those SOEs may be less market oriented and the size of the skilled workers does not reflect its function (e.g., it is well-known that SOEs have large number of redundant workers).

Another major difference is on the effect of GM's tenure, which has a negative and significant effect in SOEs but positive effect in non-SOEs, both in large and mid-sized cities. It is likely that the appointment for GM at a SOE is more politically driven and longer tenure may reduce the incentive to take risk for innovation due to political concerns. This possibility may also help explain why average education of the management team shows no significant effect in mid-sized cities for SOEs. Additionally, one puzzling result is that R&D shows negative and significant effect for SOEs in the large cities. It may be related to political motives on R&D spending given the nature of state-ownership.

6. Results from control function approach

Some human capital variables, such as number of skilled workers and GM's education, are likely to be endogenous. For example, a firm that tends to promote innovation may be more likely to hire a GM with a certain level of education, and thus the GM's education can be correlated with unobservable firm-specific characteristics related to innovation. Similarly, factors affecting a firm's workforce is likely to be related to a firm's innovation profile so that the number of highly educated workers can be endogenous as well (Thoenig & Verdier, 2003).[29] Our estimated specifications above include both city-fixed effects and industry-fixed effects. These fixed effects are likely to sweep out myriad spatial, industry-specific technology and related effects, and alleviate the omitted variable bias.

We conduct IV estimation to assess the robustness of our results. Given the nature of our dataset based on the World Bank survey, it is challenging to find good instruments. In Data2000, for highly educated workforce, we follow Fleisher et al. (2011) and use the 'number of applicants for highly educated positions' and the 'average number of weeks those positions are vacant' as instruments. A firm with more highly educated human capital is more likely to attract more applicants and thus less vacant weeks for those positions. Meanwhile, the number of applicants and vacant weeks are expected to be determined by the broader economic factors related to labor markets and by the supply-side considerations of job seekers, and thus they are likely exogenous to a firm.

For Data2002, we do not have the same information on the number of applicants and vacant weeks. However, in the survey, firms are asked if they have labor shortage in skilled employees, and if they have, what is the percentage. The shortage reflects the broader demand and supply characteristics of the labor market. If the labor market experiences shortage of skilled workers, it is likely to affect the size of skilled workers in one firm. Therefore, we use the percentage of firms with shortage in skilled workers in a city, *excluding the firm itself as the instrument*. Whether other firms in the same labor market are short of highly educated workers is related to the broader characteristics of the labor market and should be exogenous to the specific firm under consideration.

Additionally, for both datasets, we also use lagged values of the number of highly educated workers as instruments.[30] It is common to use lagged variable as instruments in the literature (e.g., Cameron, Proudman, & Redding, 2005; Dang & Motohashi, 2015; Goñi & Maloney, 2017). The standard argument is that previous values have already been set and should not be correlated with the current errors, like the assumptions of strictly exogeneity and sequential exogeneity commonly used in panel data models. We believe this argument is applicable to our case: i.e., the previous year's highly educated workforce cannot be adjusted due to the current disturbance term, and thus we use it as IV.[31]

To find instruments for GM's education, we follow the approach in Lin et al. (2011) and use industry-city averages of GM's years of schooling (excluding the firm itself). If the endogeneity problem is specific for firms, then netting out this firm-specific component yields a measure that only depends on the underlying characteristics inherent to the particular industry and/or city. However, in our context, other firms in the same industry and/or same city may influence the choice of the GM for a particular firm due to labor market connection and competition.

The IV results of the NB model estimated by Control Function approach are reported in Table 6. The results related to human capital effects are similar to the Negative Binomial results discussed in the above section.[32] More specifically, for highly educated

[28] The evidence on the relationship between subsidiary firms and innovation is rather mixed. For example, De Marchi (2012) examining environmental innovation finds that the subsidiary effect is insignificant.

[29] For other human capital measures, GM's tenure and the average age of the management team are unlikely to be endogenous. For the average schooling of the management team, because the impact of any particular personnel adjustment on the average schooling of the entire team is generally very small, we believe it is unlikely to be endogenous either.

[30] As discussed in the data section, the number of highly educated workers are available for two years in each survey. We used the number of highly educated workers lagged two years as instrument.

[31] We realize that complications may exist with our choice of this instrument, for example, due to potential error term serial correlation. The potential limitation that is arising likely cannot be addressed due to the nature of the World Bank dataset. More detailed and longer time-series data may allow one to better control for some of the effects we estimate.

Table 5
NB regression by ownership.

	Data2000		*Data2002*	
	(1) SOE	(2) Non-SOE	(3) SOE	(4) Non-SOE
Number of highly educated workers	0.379***	0.323***	−0.0422	0.372***
	(0.106)	(0.0749)	(0.0781)	(0.0912)
General Manager with a postgraduate degree	−1.296	0.0489	1.864***	0.876**
	(1.411)	(0.346)	(0.684)	(0.413)
General Manager's tenure	−0.441***	0.227***	−0.254**	0.0774**
	(0.159)	(0.0437)	(0.113)	(0.0304)
Management team's average schooling	0.876**	0.283*	0.0570	0.273**
	(0.410)	(0.161)	(0.221)	(0.115)
Management team's average age	−0.400***	−0.149***	−0.248***	−0.0935***
	(0.155)	(0.0296)	(0.0594)	(0.0270)
Average (log) R&D excluding labor compensation in previous 2 years	−0.169**	0.0293	0.184***	0.0647***
	(0.0851)	(0.0245)	(0.0663)	(0.0227)
Number of observations	122	486	169	568

Note:
1. For each dataset, we divided the sample into two groups: SOE and non-SOE. The results are estimated by NB.
2. The specification in Table 5 is the same with that in Table 4. To save the space, we only show the results of human capital measures and R&D.
3. Standard errors in parentheses: $^{*}p < .10$, $^{**}p < .05$, $^{***}p < .01$.

human capital, when the number of highly educated workers increase by 10, the number of patents is expected to increase by 3.52% in Data2000 and 3.26% in Data2002, respectively.

Regarding the GM's tenure, the IV results show positive and significant estimates in Data2000 and positive but insignificant in Data2002. For the effect of GM education, IV estimates are insignificant for both years.[33] Management team's age has a significant and negative effect on firm innovation in both datasets, and the management team's education shows a positive and significant effect in Data2002. The estimates for other variables are generally comparable with the baseline results reported earlier.

In CF estimation, we can test the endogeneity of the suspect variable by testing the significance of the residuals from the first stage, as shown in Table 6. They are insignificant in both datasets. In particular, the Wald test cannot reject the null that the residuals are insignificant.[34] Therefore, we cannot reject that the suspect variables are exogenous. Overall, the potential endogeneity does not appear to meaningfully bias the results in the baseline model estimation, and the test on endogeneity cannot reject the baseline results.

7. Innovation propensity and intensity

In our dataset, only a fraction of firms (about 13%) have nonzero patent applications. Given this feature of the data, we use the zero-inflated Negative Binomial model to simultaneously examine firms' propensity to innovate and the intensity of innovation. This deepens our understanding of firms' innovation. We estimate the model using zero-inflated NB based on the potential over-dispersion.[35] The estimation results are presented in Table 7.[36] Columns (1) and (3) present the results on the *quantity* of patents, and Columns (2) and (4) show the effects on the *probability* to innovate.

The results show that more highly educated workers result in not only a higher quantity of patent applications but also a higher probability to innovate in both datasets. In particular, when the number of highly educated workers increases by 10, patent applications increase 1.1% and 0.927% respectively, in large and mid-sized cities, respectively, and on average the probability to innovate increases by 0.77 and 3.45 percentage points, respectively, evaluating at sample means. It appears that highly educated human capital has a larger effect in promoting the propensity to innovate in mid-sized cities, while a greater effect in increasing the intensity of innovation in the large cities. Compared to results reported in Table 4, we can see that, after netting out the *probability* effect, the effect of highly educated workers on the *quantity* of innovation is much smaller.

[32] We did not run IV estimation for Zero-inflated models because, to the best of our knowledge, such technique is not available yet.

[33] One possibility of the insignificance is the relative inefficiency of IV.

[34] The Wald test of the joint significance of the residuals is 1.51 with *p*-value 0.4703 for Data2000 and is 1.35 with p-value 0.5082 for Data2002. We are not aware of overidentification test in the CF framework. Therefore, in order to conduct the overidentification test, we run the regression using 2SLS, assuming that the test result from the 2SLS is a good indicator (because the OLS is still consistent in count data estimation). The overidentification test does not reject the null that the over-identifying instruments are valid, assuming a subset of the instruments is valid and identified the model. In particular, in Data2000, the overidentification test based on 2SLS is 1.181 with *p*-value 0.5542, and in Data2002, the test statistic is 2.875 with p-value 0.2375.

[35] We use LR to test if the overdispersion parameter is equal to 0. The likelihood ratio test statistic is 303.81 with p-value equal to 0.000 in Data2000 and is 201.36 with p-value 0.0000 in Data2002, indicating that zero-inflated NB model is preferred.

[36] In addition, we test the specification between the standard NB model and the zero-inflated NB model. BIC corrected Vuong test z equal to −3.90 with p-value 0.00 for Data2000, and it is −4.27 with p-value 0.00 in Data2002, indicating that zero-inflated NB is favored than a standard NB.

Table 6
IV estimation results.

Dependent variable: patents applied		
	Data2000	*Data2002*
Panel A: Human capital variables		
Number of highly educated workers	0.352***	0.326***
	(0.131)	(0.0963)
General Manager with a postgraduate degree	−3.136	−3.602
	(3.467)	(4.708)
General Manager's tenure	0.142***	0.0373
	(0.0504)	(0.0385)
Management team's average schooling	0.331	0.285*
	(0.209)	(0.171)
Management team's average age	−0.106***	−0.121***
	(0.0309)	(0.0354)
Panel B: R&D and firm characteristics		
Average (log) R&D excluding labor compensation in previous 2 years	0.0493	0.123***
	(0.0370)	(0.0416)
Market share	0.0312***	0.0277***
	(0.00763)	(0.0106)
Total assets	−0.190	−0.188
	(0.675)	(0.615)
Firm age	−0.0138	0.00287
	(0.0178)	(0.0185)
Foreign and private firm dummy	−1.848***	−0.0835
	(0.685)	(0.366)
Subsidiary	0.143	−0.233
	(0.357)	(0.613)
Residual from first stage regression of highly educated human capital	−0.262	−0.169
	(0.284)	(0.251)
Residual from first stage regression of GM's education	3.856	4.740
	(3.864)	(4.229)
lnalpha	2.074***	2.172***
	(0.174)	(0.174)
Number of observations	396	732

Notes
1. City and industry dummies and the intercept are not reported. Standard errors in parentheses: *$p < .10$, **$p < .05$, ***$p < .01$.
2. The variables, highly educated human capital and GM's postgraduate degree, are treated as endogenous.
3. For data2000, the sample size is much smaller compared to that in the OLS estimation in Table 4. This is because of the missing value in IVs. For example, the instrument “the number of applicants for highly educated positions” has 202 missing values.
4. The results are estimated using the Control Function method. Bootstrapped standard error is reported due to the generated regressors in the model. In Data2000, the Wald test of the joint significance of the residual is 1.51 with p-value 0.4703. In Data2002, the Wald test is 1.35 with p-value 0.5082. Thus, we cannot reject the null hypothesis.

The effect of GM's postgraduate degree found in mid-sized cities reported in Table 4 seems to be driven by its effect on innovation intensity, i.e., 142.8% increase with a postgraduate degree GM. In other words, GM education does not seem to increase the propensity to innovate, but when they innovate, it promotes the quantity. Additionally, GM's tenure plays a role in how much to innovate in both large and mid-sized cities. Specifically, when GM's tenure increases one additional year, the patent applications increases 12.1% in the large cities while it increases 6.03% in mid-sized cities.

As in the NB estimation results reported in the above section, management team's age has negative effect on innovation. However, the results here show a big difference between large and mid-sized cities. In particular, it is only significant in Data2000. The older the management team, it is less likely that the firm will innovate in the large cities.

Overall, the above results indicate that the stock of highly educated workers has positive and significant effect on both the innovation propensity and intensity in all samples. However, managerial human capital shows different impacts on the propensity to innovate and on the intensity to innovate between large and mid-sized cities.

8. Concluding remarks

In this study, we examine an important question about how human capital affects a firm's innovation. In particular, we investigate how various aspects of human capital contribute to firm innovation, and how its effects differ in various market environments, using the World Bank's survey on firms in China. We examined the impact of human capital on firms' innovation using two datasets: one containing a sample of firms in large metropolitan cities, and the other containing firms in mid-sized cities.

We used the Negative Binomial procedure as well as Instrumental Variable estimation via the Control Function approach to estimate the patent production function models. Additionally, we employ the zero-inflated NB model to examine firms' propensity to

Table 7
Zero-inflated NB results.

Dependent variable: patents applied	*Data2000*		*Data2002*	
	(1) Patent applications	(2) Probability to innovate	(3) Patent applications	(4) Probability to innovate
Panel A: Human capital variables				
Number of highly educated workers	0.110**	0.576*	0.0927**	6.786**
	(0.0507)	(0.343)	(0.0440)	(2.684)
General Manager with a postgraduate degree	0.387	0.351	1.428***	−4.920
	(0.437)	(0.657)	(0.328)	(3.351)
General Manager's tenure	0.121**	0.0858	0.0603*	0.0500
	(0.0599)	(0.0580)	(0.0344)	(0.111)
Management team's average schooling	−0.0905	0.243	0.0282	0.946
	(0.159)	(0.198)	(0.124)	(0.777)
Management team's average age	−0.0961***	−0.0554	−0.0385	−0.385
	(0.0368)	(0.0425)	(0.0503)	(0.318)
Panel B: R&D and firm characteristics				
Average (log) R&D excluding labor compensation in previous 2 years	−0.00293	0.0569	0.0957***	−0.215
	(0.0375)	(0.0475)	(0.0302)	(0.229)
Market share	0.00833	0.0179	0.00848	0.0744
	(0.00790)	(0.0137)	(0.0102)	(0.0881)
Total assets	−0.140	−1.085	0.139	−18.07**
	(0.478)	(0.780)	(0.334)	(7.094)
Firm age	0.0138	−0.0201	−0.0221*	0.0623
	(0.0137)	(0.0270)	(0.0122)	(0.0798)
Foreign and private firm dummy	0.930	−0.637	0.281	−2.685
	(0.659)	(0.770)	(0.423)	(2.137)
Subsidiary	0.343	−1.607	−0.237	2.104
	(0.909)	(1.224)	(0.448)	(2.507)
lnalpha	0.967**		1.690***	
	(0.428)		(0.158)	
City dummies	Yes	Yes	Yes	Yes
Industry dummies	Yes	Yes	Yes	Yes
Constant	Yes	Yes	Yes	Yes
Number of observations	608	608	737	737

Notes
1. See Tables 1, 4 and 6.
2. Standard errors in parentheses: *$p < .10$, **$p < .05$, ***$p < .01$.

innovate and the intensity of innovation.

We find that more highly educated workers result in a higher quantity of patents and a higher probability to innovate, irrespective of whether they are in large or mid-sized cities. However, the education of the GM and the management team is more important for firms in mid-sized cities, and the GM's tenure plays a more important role in firm innovation in large cities. Moreover, the GM's postgraduate degree seems to be more effective in increasing innovation productivity compared to innovation propensity; a similar effect can be found in relation to the GM's tenure. Additionally, the management team's average age appears to have a negative effect on firm innovation in all cities.

Our results indicate that human capital plays an important role in promoting innovation for firms in China. Therefore, effective policies for innovation include strengthening the skills of the workforce and increasing the incentive of the firm management to innovate. For example, in selecting a management team, firms in mid-sized cities can pay more attention to the education background of the GM and management team, while in large cities, it is desirable to focus on a longer tenure for the GM. Additionally, forming a younger management team is better for firm innovation. China has already spent a large amount on R&D, and our findings support that policies should not only focus on R&D but also on the human capital aspects of innovation.

Acknowledgements

We are grateful to our three anonymous referees for their exceptionally thoughtful review of earlier versions of the paper and the Editor for suggestions on improving our arguments and presentation. We thank participants at the Econometric Society Meetings (Hong Kong), Workshop on Applied Microeconomics, Center for Economic Studies (Munich), Industry Studies Association Conference (Washington D.C.), Centre for European Economic Research (ZEW, Mannheim), and Patrick S. McCarthy, Shatakshee Dhongde, Xiaoming Huo, and Gene Chang for helpful comments. We gratefully acknowledge partial financial support from the National Natural Science Foundation of China (Grant #71773151).

References

Akcigit, U., & Kerr, W. R. (2018). Growth through heterogeneous innovations. *Journal of Political Economy, 126*(4), 1374–1443.
Ang, J. S., Cheng, Y., & Wu, C. (2014). Does enforcement of intellectual property rights matter in China? Evidence from financing and investment choices in the high-tech industry. *Review of Economics and Statistics, 96*(2), 332–348.
Audretsch, D. B., & Feldman, M. P. (2004). Knowledge spillovers and the geography of innovation. *Handbook of regional and urban economics*. *Vol. 4*. *Handbook of regional and urban economics* (pp. 2713–2739). Elsevier.
Autor, D., Dorn, D., Hanson, G. H., Pisano, G., & Shu, P. (2017). Foreign competition and domestic innovation: Evidence from US patents. *NBER working paper* No. w22879.
Ayyagari, M., Demirgüç-Kunt, A., & Maksimovic, V. (2011). Firm innovation in emerging markets: The role of finance, governance, and competition. *Journal of Financial and Quantitative Analysis, 46*(6), 1545–1580.
Barker, V. L., III, & Mueller, G. C. (2002). CEO characteristics and firm R&D spending. *Management Science, 48*(6), 782–801.
Blundell, R., Griffith, R., & Van Reenen, J. (1999). Market share, market value and innovation in a panel of British manufacturing firms. *The Review of Economic Studies, 66*(3), 529–554.
Bosetti, V., Cattaneo, C., & Verdolini, E. (2015). Migration of skilled workers and innovation: A European perspective. *Journal of International Economics, 96*(2), 311–322.
Bosker, M., & Garretsen, H. (2008). Economic development and the geography of institutions. *Journal of Economic Geography, 9*(3), 295–328.
Cameron, G., Proudman, J., & Redding, S. (2005). Technological convergence, R&D, trade and productivity growth. *European Economic Review, 49*(3), 775–807.
Chen, S., Bu, M., Wu, S., & Liang, X. (2015). How does TMT attention to innovation of Chinese firms influence firm innovation activities? A study on the moderating role of corporate governance. *Journal of Business Research, 68*(5), 1127–1135.
Coad, A., Segarra, A., & Teruel, M. (2016). Innovation and firm growth: Does firm age play a role? *Research Policy, 45*(2), 387–400.
Cohen, W. M., & Levinthal, D. A. (1990). Absorptive capacity: A new perspective on learning and innovation. *Administrative Science Quarterly, 35*(1), 128–152.
Cull, R., Li, W., Sun, B., & Xu, L. C. (2015). Government connections and financial constraints: Evidence from a large representative sample of Chinese firms. *Journal of Corporate Finance, 32*, 271–294.
Custódio, C., Ferreira, M. A., & Matos, P. (2017). Do general managerial skills spur innovation? *Management Science, 65*(2), 459–476.
Czarnitzki, D., & Kraft, K. (2004). An empirical test of the asymmetric models on innovative activity: Who invests more into R&D, the incumbent or the challenger? *Journal of Economic Behavior & Organization, 54*(2), 153–173.
Dang, J., & Motohashi, K. (2015). Patent statistics: A good indicator for innovation in China? Patent subsidy program impacts on patent quality. *China Economic Review, 35*, 137–155.
De Marchi, V. (2012). Environmental innovation and R&D cooperation: Empirical evidence from Spanish manufacturing firms. *Research Policy, 41*(3), 614–623.
Eberhardt, M., Helmers, C., & Yu, Z. (2016). What can explain the Chinese patent explosion? *Oxford Economic Papers, 69*(1), 239–262.
Fleisher, B. M., Hu, Y., Li, H., & Kim, S. (2011). Economic transition, higher education and worker productivity in China. *Journal of Development Economics, 94*(1), 86–94.
Fonseca, T., de Faria, P., & Lima, F. (2019). Human capital and innovation: The importance of the optimal organizational task structure. *Research Policy, 48*(3), 616–627.
García, F., Jin, B., & Salomon, R. (2013). Does inward foreign direct investment improve the innovative performance of local firms? *Research Policy, 42*(1), 231–244.
Gennaioli, N., La Porta, R., Lopez-de-Silanes, F., & Shleifer, A. (2012). Human capital and regional development. *The Quarterly Journal of Economics, 128*(1), 105–164.
Ghosal, V. (2015). Business strategy and firm reorganization: Role of changing environmental standards, sustainable business initiatives and global market conditions. *Business Strategy and the Environment, 24*(2), 123–144.
Ghosal, V., & Ni, J. (2016). Competition and innovation in automobile markets. *CESifo Working Paper Series No. 5504*.
Goñi, E., & Maloney, W. F. (2017). Why don't poor countries do R&D? Varying rates of factor returns across the development process. *European Economic Review, 94*, 126–147.
Grimpe, C., & Sofka, W. (2009). Search patterns and absorptive capacity: Low and high-technology sectors in European countries. *Research Policy, 38*(3), 495–506.
Guo, D., Guo, Y., & Jiang, K. (2016). Government-subsidized R&D and firm innovation: Evidence from China. *Research Policy, 45*(6), 1129–1144.
Hall, B. H., & Ziedonis, R. H. (2001). The patent paradox revisited: An empirical study of patenting in the US semiconductor industry, 1979-1995. *RAND Journal of Economics,* 101–128.
Hashmi, A. R., & Biesebroeck, J. V. (2016). The relationship between market structure and innovation in industry equilibrium: A case study of the global automobile industry. *Review of Economics and Statistics, 98*(1), 192–208.
Hausman, J., Hall, B. H., & Griliches, Z. (1984). Econometric models for count data with an application to the patents-R&D relationship. *Econometrica,* 909–938.
Hitt, M. A., Bierman, L., Shimizu, K., & Kochhar, R. (2001). Direct and moderating effects of human capital on strategy and performance in professional service firms: A resource-based perspective. *Academy of Management Journal, 44*(1), 13–28.
Hsu, D. H., & Ziedonis, R. H. (2013). Resources as dual sources of advantage: Implications for valuing entrepreneurial-firm patents. *Strategic Management Journal, 34*, 761–781. https://doi.org/10.1002/smj.2037.
Hu, A. G., & Jefferson, G. H. (2009). A great wall of patents: What is behind China's recent patent explosion? *Journal of Development Economics, 90*(1), 57–68.
Hu, A. G., Zhang, P., & Zhao, L. (2017). China as number one? Evidence from China's most recent patenting surge. *Journal of Development Economics, 124*, 107–119.
Kianto, A., Sáenz, J., & Aramburu, N. (2017). Knowledge-based human resource management practices, intellectual capital and innovation. *Journal of Business Research, 81*, 11–20.
King, T., Srivastav, A., & Williams, J. (2016). What's in an education? Implications of CEO education for bank performance. *Journal of Corporate Finance, 37*, 287–308.
Kortum, S., & Lerner, J. (2000). Assessing the contribution of venture capital to innovation. *RAND Journal of Economics,* 674–692.
Lee, J., Veloso, F. M., & Hounshell, D. A. (2011). Linking induced technological change, and environmental regulation: Evidence from patenting in the US auto industry. *Research Policy, 40*(9), 1240–1252.
Lin, C., Lin, P., Song, F. M., & Li, C. (2011). Managerial incentives, CEO characteristics and corporate innovation in China's private sector. *Journal of Comparative Economics, 39*(2), 176–190.
McGuirk, H., Lenihan, H., & Hart, M. (2015). Measuring the impact of innovative human capital on small firms' propensity to innovate. *Research Policy, 44*(4), 965–976.
Rammer, C., Czarnitzki, D., & Spielkamp, A. (2009). Innovation success of non-R&D-performers: Substituting technology by management in SMEs. *Small Business Economics, 33*(1), 35–58.
Raymond, W., Mairesse, J., Mohnen, P., & Palm, F. (2015). Dynamic models of R&D, innovation and productivity: Panel data evidence for Dutch and French manufacturing. *European Economic Review, 78*, 285–306.
Rogers, M. (2004). Networks, firm size and innovation. *Small Business Economics, 22*(2), 141–153.
Romer, P. M. (1990). Endogenous technological change. *Journal of Political Economy,* S71–S102.
Rupietta, C., & Backes-Gellner, U. (2019). Combining knowledge stock and knowledge flow to generate superior incremental innovation performance—Evidence from Swiss manufacturing. *Journal of Business Research, 94*, 209–222.
Santamaría, L., Nieto, M. J., & Barge-Gil, A. (2009). Beyond formal R&D: Taking advantage of other sources of innovation in low-and medium-technology industries. *Research Policy, 38*(3), 507–517.
Sauermann, H., & Cohen, W. M. (2010). What makes them tick? Employee motives and firm innovation. *Management Science, 56*(12), 2134–2153.
Schneider, L., Günther, J., & Brandenburg, B. (2010). Innovation and skills from a sectoral perspective: A linked employer–employee analysis. *Economics of Innovation and New Technology, 19*(2), 185–202.
Snell, S. A., & Dean, J. W., Jr. (1992). Integrated manufacturing and human resource management: A human capital perspective. *Academy of Management Journal,*

35(3), 467–504.
Squicciarini, M. P., & Voigtländer, N. (2015). Human capital and industrialization: Evidence from the age of enlightenment. *The Quarterly Journal of Economics, 130*(4), 1825–1883.
Subramaniam, M., & Youndt, M. A. (2005). The influence of intellectual capital on the types of innovative capabilities. *Academy of Management Journal, 48*(3), 450–463.
Sunder, J., Sunder, S. V., & Zhang, J. (2017). Pilot CEOs and corporate innovation. *Journal of Financial Economics, 123*(1), 209–224.
Thoenig, M., & Verdier, T. (2003). A theory of defensive skill-biased innovation and globalization. *American Economic Review,* 709–728.
Tödtling, F., & Trippl, M. (2005). One size fits all?: Towards a differentiated regional innovation policy approach. *Research Policy, 34*(8), 1203–1219.
Wooldridge, J. M. (2015). Control function method in applied econometrics. *Journal of Human Resources, 50*(2), 420–444.
Wright, P. M., Dunford, B. B., & Snell, S. A. (2001). Human resources and the resource based view of the firm. *Journal of Management, 27*(6), 701–721.
Wu, S., Levitas, E., & Priem, R. L. (2005). CEO tenure and company invention under differing levels of technological dynamism. *Academy of Management Journal, 48*(5), 859–873.
Zhang, A., Zhang, Y., & Zhao, R. (2003). A study of the R&D efficiency and productivity of Chinese firms. *Journal of Comparative Economics, 31*(3), 444–464.
Zhang, H., Ou, A. Y., Tsui, A. S., & Wang, H. (2017). CEO humility, narcissism and firm innovation: A paradox perspective on CEO traits. *The Leadership Quarterly, 28*(5), 585–604.