# Firm-level Human Capital and Innovation: Evidence from China*

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**Abstract**

This paper explores firm-level innovation in a human capital view using two firm-level datasets from China, one from metropolitan cities and one from provincial middle cities. General human capital level can affect innovation directly and via R&D level indirectly; managerial human capital can affect firm innovation through their decision-making. We find that general human capital and managerial personnel's education has a significantly positive effect on innovation while the management team's age has a significantly negative effect on innovation. R&D has a larger effect in less developed areas. Finally, we also try IV estimation and the related results are discussed.

Keywords: Human capital, innovation, R&D

JEL classification: J24 I25 D22 L13

## I. Introduction

Why firms differ in innovation? Economists have long sought answers to this question because characteristics of innovative firms can have significant implications, not only for firm success but also the economic growth of a country. Along this avenue, literature on testing Schumpeterian hypotheses (Schumpeter, 1942), which argue that large firm operating in a concentrated market is the main engine of technological progress, has offered numerous insights as to how firm size and market structure affect firm innovation. Although it provides an effective framework for exploring the issue, the large body of work also leaves many questions unanswered. Most notably, the literature, which is almost exclusively on firm size, industry characteristics, market structure, and/or part of human capital information, seldom touches the characteristics of firms besides size and strategic choice. Moreover, leaving strategic choice outside the framework results in ignoring the interaction between a firm and its market environment. In this article, we attempt to fill those gaps first theoretically and then by exploiting the detailed and comprehensive firm-level data in Chinese manufacturing industry.

Traditionally, the most important explanatory factor of innovation is R&D spending because it is believed that R&D is the input in producing innovation[1]. However, in essence, those studies are deficient. First, they simply regard R&D as the most important input of innovation without going deeper into the details of R&D and the mechanisms of R&D in affecting innovation. Thus, they fail to take other firm resources, mainly a firm's general human capital, into consideration. Second, they ignore the non-R&D innovation, which is usually important to firm innovation.

[1] This idea is expressed through the knowledge production function by Griliches (1979) and has been followed by many studies (Pakes and Griliches, 1984; Hall, Griliches and Hausman, 1986; Hall and Ziedonis, 2001).

In reality, R&D encompasses a myriad of activities. Thus, R&D spending includes personnel salaries and wages, material and supplies, durable equipment, land and buildings, and other R&D costs such as energy, water and maintenance. Of them, salaries and wages account for around a third of total R&D expenditure cost (Soete, 1979)[2]. Therefore, we get two mechanisms through which R&D can affect innovation. First, R&D personnel can produce innovation directly using resources in the R&D department. However, even in this case, a successful innovation may involve participation of the firm's other human capital[3]. Second, R&D can facilitate non-R&D personnel, mainly engineers and managers, in improving process technology and product, and finally get new process technology and new product, i.e., innovation[4]. In this case, R&D and a firm's other resources, mainly human capital, are complementary.

In addition, innovation includes not only R&D innovation but also non-R&D innovation. Generally, there are three types of creative activities that do not require R&D. First, Kim and Nelson (2000) found that many imitative activities, including reverse engineering, do not require R&D, and the imitation is mainly dependent on the firm's technical personnel and engineers. Second, firms can make minor modifications or incremental changes to products and processes, relying on engineering human capital. Moreover, Hansen and Serin (1997) noted that the innovation process in low-and medium-technology sectors is more related to adaptation and learning by doing, based on design and process optimization, rather than from R&D. Third, firms can combine existing knowledge in new ways, for example in industrial design and engineering projects (Grimpe and Sofka, 2009). Due to the large share of firms that innovate without

[2] According to our own calculation, the ratio of salaries and wages in R&D is around 0.28 and 0.33 in Data 2000 and Data 2002, respectively.
[3] For example, it may need engineers to figure out the problems in the production process and customer service personnel to get consumer demand information.
[4] For example, R&D is critical to the absorptive capacity of a firm.

performing R&D[5], we can conclude that studies that only focus on R&D should not be enough to fully explain innovation differences across firms.

Several difficulties arise in our study. First, the form of R&D to be included in the empirical study is difficult to be determined, and what's worse, R&D may be endogenous. Lagged R&D expenditure may also affect a firm's number of patents, but R&D is highly correlated in a firm over time[6]. Simply including contemporary R&D and its lag may bring about serious multicollinearity. Also, we notice that R&D is a long-run plan and it may not distribute evenly over years[7]. Thus, we use average R&D over years in our estimation. Moreover, R&D may be endogenous in a firm's knowledge production function. To decrease the endogeneity of R&D, we exclude current R&D when calculating average R&D over time. To better deal with endogeneity, we also use both city average and industry average (both excluding the firm's own R&D) as instruments, and several techniques, GMM and control function, are used. Second, the endogeneity of general human capital may bias our estimates. We use instrumental estimates to solve this problem. The instruments we used are the number of job applicants for skilled worker positions and the number of weeks to fill the last job.

This paper makes three main contributions: (1) it provides both theory and theoretical framework for studying firm innovation in a human capital view, not only general human capital but also managerial human capital and R&D human capital. Growth theory only provides a theoretical framework to incorporate general human capital into innovation. Though there are a lot of empirical studies on firm innovation and firm human capital, there's no such theoretical framework support. (2) Using detailed firm-level data, we are able to study the effects of general

[5] We find that around 25% of firms with patents have no R&D spending in both of our data sets.
[6] In our datasets, we notice that R&D over time does correlate with each other highly. In fact the correlation coefficient is always above 0.90.
[7] For example, a firm may invest a lot of R&D in one year, but in the following two years, its R&D investment may be much less than this amount.

human capital, general manager's education and experience, and management team's education and age. (3) Two datasets from two different levels of cities, metropolitan cities and provincial middle cities enable us to examine the effect of market environment on firm innovation.

One of the limitations in our study is that patent is not a perfect measure of innovation. Pakes and Griliches (1980) observed that "patents are a flawed measure (of innovative output); particularly since not all new innovations are patented and since patents differ greatly in their economic impact". Thus, the relationship between human capital and patents cannot fully reveal how much human capital contributes to firm productivity via innovation. Moreover, the patent propensity rate for product and process innovation can differ a lot[8]. To better understand how firm human capital affects product innovation and process innovation, it is also interesting to study how human capital affects new product sales. We will pursue the productivity and new product sales in future research.

The paper is organized as follows. In Section 2, we present the theory on how firm human capital affects firm innovation and review related literature. Section 3 presents a theoretical framework where two firms Cournot compete with each other in a two-stage game. In Section 4 we introduce the data. Section 5 introduces our methodology strategy. In Section 6, we present our main results and interpret the findings. Section 7 presents further investigation. Section 8 concludes.

## II. Human capital and Innovation

What is the most important firm characteristic? Or in other words, why do different firms differ from each other? We believe that it is human capital. According to the resource-based view of

[8] Arundel and Kabla (1998) found that the propensity rate for product innovations is 35.9% on average and 24.8% for process innovation on average using Europe's largest industrial firms survey in 1993.

the firm, performance differences across firms can be attributed to the variance in the firms' resources and capacities. Resources that are valuable, unique, and difficult to imitate can provide the basis for firms' competitive advantages. Among all the resources in a firm, human capital has long been argued as a critical resource (Pfeffer, 1995). Although human resources may be mobile to some degree, because some capabilities are based on firm-specific knowledge, and others may only be valuable when integrated with additional individual capacities and specific firm resources that may not be mobile (Hitt *et al*., 2001), the idea that a firm's human capital is critical still holds. Moreover, upper echelon theory argued that organizations are just reflections of their top managers (Hambrick and Mason, 1984). Thus, given the importance of firm human capital, studying firm innovation from a human capital view becomes very natural.

There are three strands of studies that have touched innovation in human capital respect. First, human capital is introduced to firm innovation in endogenous growth theory (Romer, 1986, 1990; Lucas, 1993). Barro (2001) further proposed that higher human capital stock tends to generate higher growth through at least two channels: on the one hand, more human capital facilitates the absorption of superior technologies from leading countries, and for this channel, schoolings at secondary and higher levels should be especially important; on the other hand, human capital tends to be more difficult to adjust than physical capital. The endogenous growth theory takes human capital as one of the most important inputs in innovation from the macro level and this inspires us to notice the importance of human capital in firm innovation. However, it still cannot provide us a theoretical basis for firm innovation given the difference between micro and macro study[9]. Second, some of the Schumpeterian studies do include the number skilled workers in their studies, though only as a control variable (Acs and Audretsch, 1988). Notably, there's no mechanism of skilled workers analyzed; that is, there's no other explanation for including number of skilled workers in analysis other than "skilled workers are important to innovation."

Third, in management literature, there are some studies on firm innovation and characteristics of CEOs or management team[10]. The most related literature is Lin *et al*. (2011). They used World Bank survey data in 2002 (our Data 2002) to empirically examine the roles of managerial incentives and CEO characteristics in a firm's innovation activities. They concluded that CEO education and incentive scheme are positively associated with firm's innovation. However, they failed to include firms' general human capital and the characteristics of management team. The shortcoming of all these studies is that they seldom noticed the underlying economic theory and other factors that may affect innovation, and therefore failed to study the link between firm human capital and innovation in a systematic way, and thus there may exist bias.

We can see that, although in management literature there's a lot of studies on firm human capital and innovation, almost no economist pays enough attention to the link between firm-level human capital and innovation theoretically. In traditional economic theory, inputs are assumed to be homogenous, information perfectly available and evenly distributed, and profit maximization

[9] For example, human capital in a region or a country cannot be adjusted easily in a short run, while in a firm human capital can always be adjusted through hiring and firing workers and job training. Thus, human capital in a firm is more apt to suffer from endogeneity than in the country level. Moreover, in a firm, the role of the CEO or general manager and the whole management team can also be very important for firm innovation because they are related to the firm's innovation strategy and management.

[10] For example, Barker and Mueller (2002) analyzed CEO characteristics and firm R&D spending. They argued that a firm's R&D spending varies significantly with its CEO's characteristics even after controlling for the firm's corporate strategy, ownership structure, and other firm level factors.

central (Penrose, 2009). Therefore, when the traditional theory is applied to firms, we cannot identify what goes on inside firms (Nelson, 1991). Penrose (2009) argued that although markets set prices that influence resources allocation, those within the firms make decisions on what activities the firm will be involved in, how those activities will be performed, what resources are required, which resources are allocated to different activities and, ultimately, which resources are used are more important. As a consequence, internal processes and insights rather than external market prices and cost signals will largely influence a firm's growth (Darroch, 2005). Therefore, the study of firm strategy and performance should involve studying firm human capital.

How do different types of human capital affect firm innovation? Top executives have the discretion to control R&D expenditure in firms. Also, because R&D expenditure is a long-term investment that is considerably risky with high failure rates, top managers monitor R&D expenditure closely and adjust its level based on their preferences. Moreover, top management teams have the task of formulating and implementing the firm's strategy (Hambrick and Mason, 1984), and as part of their leadership function, CEOs must coordinate and control team behaviors.

The mechanisms between general human capital in a firm and innovation can be in two channels. First, higher general human capital means higher ability of learning by doing and thus can improve a firm's innovation ability. The relationship between learning-by-doing and patents has been studied by Lieberman (1987), and it found that patenting in process innovation in the chemical industry was largely an outgrowth of "learning by doing." Second, general human capital and a firm's R&D together affect the firm's innovation through R&D innovation. The complementary relationship is modeled by Romer (1990), where innovation is produced by combining R&D and human capital together[11].

For general human capital in a firm, following Schumpeterian studies, we define it based on education level and define it as the number of highly educated workers; it mainly includes managerial personnel and technical and engineering personnel in a firm. For managers, research examining the relationship between managers' personal characteristics and organizational outcomes has taken two different approaches. One approach is to directly assess the psychological attributes of the managers and examine their link to outcomes (Miller et al., 1982). Another approach is to assess demographic characteristics (such as age and education), making the assumption that such characteristics are related to cognitive abilities, attitudes, and expertise (Bantel and Jackson, 1989). In this study, we use the demographic characteristics because it is more practical.

To better explain how different types of human capital influence firm innovation, a theoretical framework using game theory is given in the next section.

## III. Theoretical framework

This section presents our theoretical framework. The model serves three purposes. First, it describes the mechanisms through which different kinds of human capital affect a firm's innovation. Second, its equilibrium conditions suggest that a firm's strategic R&D investment might be the reason why firms from different market environments differ greatly with respect to

[11] There's also a probability of "knowledge spillover channel" which means that when there's more general human capital in a firm, there will be more internalization of outside R&D spillover or knowledge spillover into the firm. This has been explained in knowledge spillover literature, such as Audretsch and Feldman (1996). We will save this for future study.

R&D investment. Third, it allows us to see how firms choose their R&D investment, and thus we can derive expressions for firm innovation, which we estimate in the empirical part.

Our framework is based on Rosen (1991) and Howitt and Mayer-Foulkes (2005). We examine firm innovation using a duopoly model with risk-neutral firms in a two-stages game[12]. In the first stage, the firms invest in a risky R&D project. After conducting the research and observing the outcome of all investments, the firms play an output game in the production stage. Human capital enters in innovation through three channels: general human capital increases the firm's cost directly but can also decrease the firm's cost indirectly through innovation; managerial human capital affects the firm's innovation via project choice and the choice of R&D investment level in that better managerial capacity approaches optimal choice closer; R&D human capital directly affects innovation.

A. Production stage

Since backward induction can give us subgame-perfect equilibrium, we consider first the output market decision in production stage. We consider an industry consisting of two firms with Cournot competition. The firms produce a single homogenous good and each maximize its single-period profit. Let $q_i \geq 0, (i = 1,2)$ be the output of the $i$th firm and $Q = q_i + q_j, (i, j = 1, 2 \; and \; i \neq j)$ be the total industry output. Function $P(Q) = a - bQ$, where $a > 0$ and $b > 0$ are demand parameters, is the industry demand curve. To simplify, we assume that there's no fixed cost and a firm's marginal cost $c_i = C_i + \delta(S_i)$. $C_i$ is determined by a firm's technology level and can be reduced by innovation. $C_i$ decreases with technology level. That is, the more

[12] Firms engage in innovation because a successful project lowers their production cost in the sequent output market competition. To simplify our analysis, we follow Spence (1984) and Rosen (1991) and use cost-reducing technology to represent innovation because we can always break a product into a Lancasterian bundle of services and model product improvement as a reduction in the cost of producing services.

advanced technology, the smaller $C_i$. $S_i$ is a firm's general human capital level, and $\delta(S_i)$ stands for a firm's expenditure on skilled workers, and we have $\frac{\partial\delta(S_i)}{\partial S_i} > 0$, implying that higher general human capital costs the firm more . Given the same technology level, a firm with higher general human capital level will have a higher cost.

The single period profits of the $i$th firm are given by

$$\Pi_i(q_i, q_j) = P(q_i + q_j)q_i - c_i q_i \qquad (1)$$

Based on price and each firm's equilibrium quantity, we can get firm $i$'s profit at equilibrium as $\Pi_i = \frac{[a-2c_i+c_j]^2}{9b} = bq_i{}^2$, implying that firm $i$'s profit is proportional to its squared quantity and that the firm's profit will increase with its own innovation success but decrease with its rival's innovation success.

B. Innovation stage

In this stage, the two firms choose their own R&D project and the level of R&D investment (scale) simultaneously. Moreover, we assume that they conduct their own projects at the same time and are completed before the start of the output game. Two outcomes may arise for each project: either it succeeds or it fails. The set of R&D strategies from which the firms choose and the outcome of innovation are common knowledge.

There are two substages in the innovation stage. First, both firms choose projects $p^i$ $(i = 1, 2)$ from the continuum of projects, $\alpha$, in the set $(0,1)$. Higher values of $\alpha$ represent projects that have a greater chance of success at any fixed level of investment. $\alpha$ is chosen by a firm's managers, and thus it is a function of a firm's managerial human capital, $\alpha(M_i)$, where $M_i$ is a firm's managerial human capital and we have that the larger $M_i$ is, the closer $\alpha(M_i)$ is to the optimal value. If a project $\alpha$ yields a successful innovation for a firm, then the firm's cost is reduced by $\gamma(\alpha)$, where $\gamma$ is differentiable in $\alpha$ and $\gamma'(\alpha) < 0$, which means that as $\alpha$ increases from 0 to 1, the cost reduction will decrease. Therefore, if firm $i$ succeeds in innovation, its marginal cost will become $c_i - \gamma(\alpha_i)$ and if it fails its marginal cost will still be $c_i$. Projects should be made based on the existing technology base, the firm's human resources, and the market. Optimal project should enable the firm to generate the maximum of expected profit.

Second, for each project $\alpha$, managers can choose R&D level. We know that innovation as a way of knowledge creation is an activity with a basic element of uncertainty (Maskell and Malmberg, 1999). For project $\alpha$, based on Howitt and Mayer-Foulkes (2005), we also assume that the success probability of a certain project at time $t$ in firm $i$ is given by

$$\mu_i = S_i R_i \qquad (2)$$

Where $R_i$ is firm $i$'s R&D expenditure and $S_i$ is firm $i$'s general human capital that can promote innovation. Note that both $S_i$ and $R_i$ are standardized into values with range $[0,1]$.

Thus, the success probability of innovation in firm $i$ is

$$I_i = \alpha_i(M_i) S_i R_i \qquad (3)$$

This means that a firm's innovation depends not only on its R&D investment $R_i$, but also the firm's general human capital and whether or not it chooses the "right" project, which is determined by its managerial human capital $M_i$. The extreme case is that even when a firm has a very high human capital capacity and invests heavily in R&D, if it chooses the "wrong" project, it still has a high probability of unsuccessful innovation. If we take the log for equation (3) at both sides and also control for other firm characteristics, such as firm size and firm age, and market structure, an estimation based on (3) is just what is used by Schumpeterian studies without including managerial human capital.

However, an estimation based on (3) can be biased because R&D is usually endogenous. That is, R&D is one of the most important, if not the only, decision in a firm in terms of innovation. Next, we will examine how firms make their R&D decisions. We still use backward induction to study the innovation stage. That is, a firm first takes a project as given and choose its optimal R&D level, $R_i$, and then based on the optimal R&D level, it chooses optimal project, $\alpha_i$. Given project $\alpha_i$, firm $i$ will maximize its expected profit

$$\Pi_i = \alpha_i \mu_i \pi_i^S + (1 - \alpha_i \mu_i) \pi_i^F - R_i \qquad (4)$$

where $\pi_i^S$ is the profit firm $i$ will get if its innovation is successful and $\pi_i^F$ is its profit if its innovation fails. Equation (4) states that the expected profit is the firm's expected profit after innovation minus its expenditure on innovation, R&D.

The firm's after-innovation profit $\pi_i^S$ and $\pi_i^F$ are determined not only by firm $i$'s innovation, but also firm $j$'s ($j \neq i;\ i, j = 1,2.$) innovation because the two firms Cournot compete with each other in the same market. Firm $j$ also may succeed or fail in innovation; thus, we will have

$$\pi_i^S = \alpha_j \mu_j \pi_i^{SS} + \left(1 - \alpha_j \mu_j\right) \pi_i^{SF} \qquad (5)$$

$$\pi_i^F = \alpha_j \mu_j \pi_i^{FS} + \left(1 - \alpha_j \mu_j\right) \pi_i^{FF} \qquad (6)$$

where $\pi_i^{SS}$ is firm $i$'s profit when both firms succeed in their innovation, $\pi_i^{SF}$ is firm $i$'s profit when firm $i$ succeeds while firm $j$ fails, $\pi_i^{FS}$ is firm $i$'s profit when firm $i$ fails while firm $j$ succeeds, and $\pi_i^{FF}$ is firm $i$'s profit when both firms fail.

We then plug (5) and (6) into (4), and then take the derivative with respect to $R_i$ and thus we get the reaction function of firm $i$. Following the same procedure, we then get the reaction function of firm $j$. Combine the two reaction functions together and we then solve for the optimal R&D, $R_i$, given $\alpha_i$,

$$R_i = \frac{-9b + 4\alpha_j\gamma(\alpha_j)S_j(a + c_i - 2c_j + \gamma(\alpha_j) + \delta(S_i) - 2\delta(S_j))}{4\alpha_i\alpha_j\gamma(\alpha_i)\gamma(\alpha_j)S_iS_j} \qquad (7)$$

Equation (7) shows that a firm's R&D spending is determined not only by demand function $(a, b)$ and its own and rival's technology level (cost function) $(\gamma(\alpha_i), \gamma(\alpha_j), \delta(S_i), \delta(S_j))$, but also both firms' general human capital level and their project choices $(S_j, S_j, \alpha_i, \alpha_j)$. The implication is that the rival's information can be used as instruments for the firm's R&D in empirical study. More specifically, we use the rival firm's R&D as an instrument.

When we take derivatives with respect to different variables and parameters respectively, we can analyze a firm's R&D behavior more specifically[13]. When we define $c = c_i + c_j$, we find that the derivative of $R_i$ with respect to $c_i$ is smaller than zero, implying that R&D is decreasing with average production cost of firms in a market. That is, firms in a market with laggard technology have less R&D investment than firms in a market with advanced technology. This is consistent with our data. When we define $S = S_i + S_j$, we get that the derivative of $R_i$ with respect to $S_i$ is bigger than zero, implying that R&D is increasing with average human capital level of firms in a market. That is, firms in a market with higher human capital level have more R&D investment than firms in a market with lower human capital level. This is consistent

[13] They are too complex to present in this paper. Available upon request.

with our data. In the datasets, firms in metropolitan cities, like Beijing, have four times more R&D than firms in provincial cities, like Benxi.

Moreover, we get that $R_i$is a convex function in terms of $\alpha_i$ and there's an optimal project corresponding to the minimum of $R_i$. That is, if a manager chooses the "wrong" project, the firm will invest too much R&D and there will be a loss in profit. Moreover, we find that a firm's R&D is increasing with its general human capital. That is, a firm with higher general human capital level tends to be more innovative than a firm with lower general human capital.

Plug (7) into (3), we get that the expression for firm innovation, indicating that when we treat a firm's R&D as endogenous, instead of R&D as a factor affecting the firm's innovation, now market environment, the other firm's cost and human capital will affect the firm's innovation together with its own cost ($c_i$), human capital ($S_i$) and market demand ($a, b$).

In sum, our theoretical framework indicates that a firm's innovation is determined by a combination of the firm's general human capital, managerial human capital, firm R&D, and market demand. When we treat R&D as endogenous, the rival firm's human capital and cost function will also affect the firm's innovation. Thus, in our empirical study, we not only need to include a firm's general human capital, managerial human capital, firm's R&D, firm characteristics and market share in our estimation, but also market environment. We use firm characteristics to control for the firm's cost and market share for the firm's demand. Moreover, we use two datasets to control for the effects of market environment (or the other firm) on firm innovation.

## IV. Empirical strategy

A. Specification

From our theoretical model, general human capital in a firm and its managerial human capital together with firm R&D all are vital for a firm's innovation. Thus, they should be included in studying a firm's innovation. In addition, firm characteristics, i.e., firm size, firm age and ownership structure, market structure, industry fixed effect, and city fixed effect are also controlled.

The knowledge production function in our study is specified as

$$\log(pat_{it}) = \beta_0 + \beta_1 HC_{it} + \beta_2 \log(RD_{it}) + \beta_3 SZ_{it} + \beta_4 MKTSHR_{it} + \beta_5 W_{it} + u_{it} \quad (8)$$

where $pat_i$ is the number of patents applied for in China, $HC_i$ is human capital indicators, $RD_i$ is R&D expenditure, $SZ_{it}$ is firm size, $MKTSHR_{it}$ is market share, $W_{it}$ is some control variables, such as industry and city fixed effect, and $u_i$ is a disturbance term, assumed to be distributed independently but not necessarily identically across firms, for firm $i = 1,2, \dots, n$.

Though patent number is not a perfect measure for innovation output as we mentioned before, it still constitutes a relevant measure of the technological effectiveness of R&D activity (Griliches, 1990). We use the number of patents applied for in China as our dependent variable though there are data for both number of patents applied for and actually granted in our dataset[14]. There are two reasons for us to use number of patents applied for. One is to decrease the effect of external patent offices across different areas. The other is that in our database, the two variables differ very little and give us similar results[15]. By using patents applied for we implicitly assume that firms apply patent honestly, that is, firms only apply patents when they feel their innovation can meet the criterion for a patent. This is not an unreasonable presumption since patent application has its cost and firms will not waste its resources.

[14] In addition, we have patented data applied for and actually granted in US, but there's too little useful value and thus we only use patent data in China.
[15] The results are available upon request.

We use general human capital, GM's tenure and education, and the average age and education of management team as our human capital indicators. GM's tenure is the years he holds his position. We use number of highly educated workers or skilled workers to measure a firm's general human capital. We use GM's graduate degree dummy to account for his education. Education of management is the average years of schooling of the management team.

However, an identification problem, ignored by almost all Schumpeterian studies, arises as we include a firm's general human capital level in our estimation because factors affecting a firm's workforce adjustment are very likely to be related to factors affecting the firm's innovation. For example, a firm that wants to be active in innovation tends to hire more highly educated workers. Thoenig and Verdier (2003) mentioned that by employing a larger share of skilled labor, firms can reduce informational leakages and spillovers, which can be freely acquired by outside competitors, and thereby lessen the threat of imitation and technological leapfrogging because of tacit knowledge and non-codified know-how embedded in skilled workers. Moreover, successful innovation may also increase the proportion of skilled workers in the whole workforce (Krueger, 1993) because more advanced technology needs to be complementary to be productive. The endogeneity of skill adjustments in response to technological changes within a firm is also mentioned by Fleisher *et al*. (2011). Following their method, we use the number of applicants for the positions and the average number of days those positions are vacant as instruments.

Another important variable in the patent production function is R&D spending by the firm. However, how to include R&D in the patents estimation equation is still a question. Much of the early work focused on how the lag structure of R&D affects patents (Pakes and Griliches, 1980; Hausman, Hall and Griliches, 1984). They largely concluded that the lag structure is very poorly identified because of the high within-firm correlation of R&D expenditure over time. Moreover, when many lags are included in the model, the estimate of the sum of the coefficients is roughly the same as the estimated coefficient of contemporaneous R&D when no lags are included. Following their conclusion, some literature use only contemporaneous level of R&D in their specification (Hall and Ziedonis, 2001). However, by doing so, two problems might arise. First, R&D expenditure is a *long-term* investment (Barker and Mueller, 2002). Thus, only including contemporaneous R&D cannot capture a firm's real innovation efforts[16]. In this point of view, an average R&D over years rather than R&D of a certain year is a better innovation input measure for the firm[17]. Second, contemporaneous R&D is very likely to be endogenous. That is, there is a possible correlation between unobserved innovation productivity shocks and R&D level. Thus, we exclude current R&D from the averages to lessen endogeneity. Though there are many studies on patent-R&D relationship but there are few on the endogeneity of R&D. Among them, Jaffe (1986) treated firm R&D as endogenous and used corresponding industry average as an instrument. Following their method, we use both industry and city averages as instruments.

Firm size is measured by the log of total assets rather than the log of total sales to lessen the correlation between firm size and other variables. Intuitively, firms with more resources will tend to innovate more because it has the ability to innovate. Generally, we expect a positive effect of firm size and when human capital is considered. We use two approaches to study the effect of market environment on innovation. First, we include market share of each firm in our model to account for a firm's market position. Second, we use two datasets, one from

[16] Specifically, if a firm decides to develop a new product, its R&D investment structure over time may be a combination of a large initial R&D spending in the first year and some additional R&D investment in the following years. In this case, the R&D level in a certain year cannot represent the firm's innovation endeavor.
[17] For example, in our data, there's a firm with R&D in 1998 of RMB 944.660 million and its R&D in year 1999 and year 2000 are RMB 249.075 million and RMB 191 million, respectively.

metropolitan cities and the other from provincial middle cities, to examine how firms in different markets, a more advanced one and a less advanced one, innovate.

B. Estimation

The number of patents applied for by a firm is a count variable with many zeros, so we use Poisson based econometric models and estimation methods. A simple investigation will reveal that there is overdispersion that violates the regular equidispersion assumption in Poisson. Because of overdipersion, instead of using ordinary Poisson estimation, we can use Quasi-likelihood Maximum Estimation (QMLE) Poisson by Wooldrige or Pseudo Maximum Likelihood Method by Gourieroux, Montfort and Trognon (GMT, 1984). QMLE Poisson model assumes that the variance of the disturbance is proportional to the mean of the dependent variable and weights the observations accordingly. GMT have shown that since the Poisson model belongs to the linear exponential family, the coefficient estimates from the Poisson model should be consistent if the mean specification is correct and the robust errors are consistent even under misspecification of the distribution. In application, because it is only ordinary Poisson with robust error, we still call it Poisson in our results analysis. Another common used way to deal with overdispersion is Negative Binomial regression (NB thereafter) (see, Yang and Huang, 2013). The NB model generalizes the Poisson QMLE model by allowing for an additional source of variance.

Let Y be a random variable such that $E(Y) = \mu$; in QMLE Poisson the variance is assumed as $Var_P(Y) = \theta\mu$ and in NB as $Var_{NB}(Y) = \mu + \kappa\mu^2$, where $\mu > 0$ and overdispersion parameter $\theta > 1$, and $\kappa > 0$. We can see that the variance of Poisson is assumed to be linearly related to the mean, whereas the variance of NB is quadratic in the mean. Besides the difference of variance assumption, the other difference between QMLE and NB is that the regression coefficients are fitted differently because different weights are used when estimated and these weights are inversely proportional to the variance. We estimate QMLE and the NB model by standard maximum likelihood techniques. The disadvantage of NB is that if the assumption of variance form does not hold, then the estimate is inconsistent. However, NB is more efficient than Poisson generally. Moreover, zero-inflated models are also used to deal with overdispersion if there are excess zeros in data. In our datasets, there are about 90% observations with zero patents. Therefore, zero-inflated models are also a possible choice but in our analysis they play no roles in improving our model[18]. Therefore, we still choose the most basic one, NB, to analyze our results.

## V. Data

In this paper, we use data from two surveys. The first is "The Study of Competitiveness, Technology & Firm Linkage" conducted by the World Bank in China in 2002. The second is "Investment climate survey" conducted also by the World Bank in 2003. Though with different names, these two surveys are very similar[19]. The first dataset was carried out in 2001-2002, covered firms in five big cities, Beijing, Chengdu, Guangzhou, Shanghai, and Tianjin[20]. Most quantitative questions covered the period 1998-2000; most qualitative questions covered only the time of the survey, 2000 (We call the first dataset as Data 2000, thereafter). The second dataset was conducted in 2003 and covered firms in 18 cities[21], smaller than the cities surveyed in 2000. Most quantitative questions covered the period 2000-2002; most qualitative questions covered

[18] The criterion we use is the sum of the absolute differences between predicted value and the observed value.
[19] Both of them collected information on innovation and technology, firm productivity, finance, labor, and the obstacles to doing business, etc. Both are filled up by the senior manager of the main production facility of the firm and the accountant and/or personnel manager of the firm.
[20] The sample includes 1548 observations and 1206 variables.
[21] The 18 cities are: Benxi, Changchun, Changsha, Chongqing, Dalian, Guiyang, Haerbin, Hangzhou, Jiangmen, Kunming, Lanzhou, Nanchang, Nanning, Shenzhen, Wenzhou, Wuhan, Xi'an and Zhengzhou. This sample includes 2400 establishments and 1073 variables.

only year 2002 (We call the second dataset as Data 2002, thereafter). Both samples consist of both manufacturing and service firms[22].

The data are randomly selected from all firms in their respective cities and industries. The resulting size range is extreme, with the reported number of production workers ranging from 3 to 83542 in Data 2000 and from 1 to 70169 in Data 2002. In order to reduce the heterogeneity among firms, we restrict our data only in manufacturing industry and also confine our research to the subsample with at least 50 total workers, at least 10 highly educated workers and 10 less educated workers and RMB 3000,000 sales. As a result, there are 624 firms in Data 2000 and 913 firms in Data 2002.

In the survey, there is information on average education level for each occupation[23]. Following Fleisher *et al*. (2011), we classify the employees into two categories: highly educated and less educated workers. By averaging the workers' schooling codes for each occupation over sample[24], we designate each occupation level as either highly educated or less educated based on the average schooling of workers in the occupation. Consistent with Fleisher *et al*. (2011), our highly educated group mainly consists of "engineering and technical personnel" and "managerial personnel (including sales)." We then use number of highly educated workers ($L_s$) as our general human capital measure in a firm. Note that the survey data only provide us the information on number of employees for different occupation for the years 2000 and 1998. We impute

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[22] The industries cover electronic components, autos and auto parts, clothing and leather products, electronic and communication equipment, household electrical goods, information technology services, accounting, auditing, and nonbank financial services, business logistics services, advertising and marketing services, and communication services. In Data 2002, chemical products and medicine, biotech products and Chinese medicine, and metallurgical products are also included.

23 In both surveys, workers are classified into: basic production workers, auxiliary production workers, engineering and technical personnel, managerial personnel, service personnel and other employees. Moreover, there is no explicit explanation for "other employees".

[24] We average years of schooling both over the whole sample and over industries, and both indicate the same classification.

employment for different occupations for 1999 in Data 2000 and year 2000 in Data 2002[25]. Finally, we round them to get $L_s 2000$.

We use self-reported market share to account for market structure. The self-reported market share is rarely used in literature, but it is much better than calculated market share used in previous literature (e.g., Blundell et al., 1999) because to calculate, one needs first to define the market which is usually not an easy task. By using self-reported market share, we don't need to define the market, and moreover the "market" definition used here is related to the firm the most, and thus we can get the real market effect on the firm.

We use number of patents applied for in China as our dependent variable. There is also information about number of patents applied for in the US and number of patents actually granted in the US; however, useful values are too few[26]. Here, we have two measures of patent, number of patents applied for by firms and number of patent actually granted in China. However, the two measures are very similar[27]. Moreover, when we try to use the two measures as our dependent variables we get similar results. Thus, in this paper, we only present empirical analysis using patent applied for in China as our dependent variable.

We then present a statistics summary for the full sample in Table 1 (Data 2000) and Table 2 (Data 2002). We can see that firms in Data 2000 do better than firms in Data 2002 even if there is a time trend in Data 2002 with average 0.84 patents in year 2000 in Data 2000 and

[25] We use weighted average employment of 2000 and 1998, using ratio of total employment of 1999 to 2000 and 1999 to 1998 as weights to impute employment for 1999 in Data 2000. Similarly, for Data 2002, we impute the employment for different occupation for year 2000 using weighted average employment of 2002 and 2001 and use the ratio of total employment of 2000 to 2002 and 2001 to 2002 as weights.

[26] In Data 2000, number of nonzero values for number of patents applied for in US are 2,4,3 for year 2000, 1999 and 1998, respectively; number of nonzero values for number of patent actually granted in US are 4,5,4 for year 2000, 1999 and 1998, respectively. In Data 2002, number of nonzero values for number of patents applied for in US are 2,1,1 for year 2002, 2001 and 2000, respectively; number of nonzero values for number of patent actually granted in US are 2,1,1 for year 2002, 2001 and 2000, respectively.

[27] There are around 8.5%-11% firms apply for patents in 2000 Data while around 7%-9% firms apply for patents in 2002 Data. Meanwhile, there are around 7%-10% firms are actually granted patents in 2000 Data while 7%-9% firms in 2002 Data actually granted a patent.

average 0.74 patents in year 2002 in Data 2002. Also, we can see that for both datasets, number of patents increases over time. Generally, firms are bigger in Data 2002 and they have more highly educated workers and more total workers, with around 180 highly educated workers and 950 total employment in Data 2000 and around 162 highly educated workers and 750 total workers in Data 2002. We can see that sales of firms in metropolis (Data 2000) are more than firms in provincial big cities (Data 2002), though the different is not big, all around 0.3 Billion RMB. However, there's very large difference in R&D between two datasets, with around 15-19 Million RMB in Data 2000 and around 2-4 Million RMB in Data 2002. Another important difference between two datasets is that firms in Data 2000 have a higher market share (16.13%) than in Data 2002 (9.01%). In addition, there's little difference in General Manager's education and experience and the firm's age.

## VI. Results

Without controlling for city and industry effects, Table 3 reports the results from regressing number of patents applied for on human capital and a firm's other characteristics using three different regression specifications: OLS, Poisson and Negative Binomial. For all the specifications, the number of patents applied for in China is used as the dependent variable. Columns (1)-(3) in part I in Table 3 (the left half) are estimated using only cross-sectional data in year 2000 in Data 2000 while in columns (4)-(6) in part II in Table 3 (the left half), Data 2002 is used and only cross-sectional data in year 2002 in Data 2002 are used because our human capital indicators are only available for the survey year. All specifications include city dummy variables and industry dummy variables. OLS estimator is the simplest to use and requires the least requirements to be consistent, but it ignores the count nature of the data. Table 4 is the same as Table 3 except that Table 3 doesn't control for city and industry effects. Poisson with robust errors and Negative Binomial estimates take into both count data nature and overdispersion into account. To get consistent estimates, the Poisson model only requires that the conditional mean is correctly specified while Negative Binomial estimates require not only correctly specified mean condition but also variance condition. This stronger assumption can lead to more efficient estimation, but if the variance condition is not correctly specified, the estimates become inconsistent. Negative Binomial model fits data better[28], and thus our analysis will be based on it.

We noticed that the estimates without city and industry effects controlled (Table 3) are generally a little bit smaller than estimates with city and industry effects controlled (Table 4), implying that city and industry effects may bias down the coefficients. However, the differences are very small. This indicates that by only including fixed city effect and industry effect, we fail to identify their effect in affecting firm's innovation. In addition, because of the small differences, to avoid including too many variables in the model that may make maximum likelihood estimation fail to converge, we will base our analysis on models without city and industry effects (Table 3).

The first important result we can see is that the number of highly educated workers has a positive and significant coefficient across all models and both datasets, suggesting a positive effect of general human capital on innovation. That is, when a firm has more general human capital, it will tend to have more innovation. Specifically, we get a coefficient of 0.285 using year 2000 data and a coefficient of 0.154 using year 2002 data and both are significant at 1% level, indicating that other things equal, when highly educated workers increase 100 people, the number of patents will increase 28.5 % in Data 2000 and 15.4% in Data 2002, respectively. We can see that the effect of general human capital is quite significant both statistically and

[28] Our criterion is the sum of the absolute differences between predicted value and observed value.

economically, and it is robust across both datasets. This is consistent with previous studies. Audretsch and Acs (1991) also concluded that skilled labor has a positive effect on innovation using industry level data[29]. Their results indicated that other things equal, when number of skilled labor increases, innovation would also increase. Very interestingly, we notice that the effect of general human capital has a larger effect in Data 2000 than in Data 2002 even when there's a time trend in Data 2002, implying how market environment might influence the effect of general human capital on innovation.

General manager's experience is positive and significant both statistically and economically in Data 2000. In NB model, we find the coefficient is around 0.166, which means that when general manager holds the position for one additional year, the number of patent application will increase 16.6%. This is consistent with Lin *et al.* (2011) that showed that general manager's tenure has a positive effect on R&D expenditure. The reason why we get a positive effect of GM's tenure might be that a GM with longer tenure can be more experienced with the firm and the market structure and the technology opportunity in this industry, and he can thus have a good judgment regarding a firm's innovative capacity and market demand. This is especially true for firm innovation that is full of uncertainty. However, there are also some studies that found that general managers tend to make fewer changes in strategy as their tenure increases. Hambrick and Fukutomi (1991) claimed that this lack of change occurs because when tenure increases, GM became conservative and more strongly committed to implementing their own paradigm for how the organization should be run[30]. The positive effect of GM tenure in our

[29] Similarly, they defined skilled labor as the percentage of employment consisting of professional and kindred workers, plus managers and administrators, plus craftsmen and kindred workers.
[30] Moreover, there are some researchers who found that CEOs tend to make fewer changes in strategy as their tenure increases. One reason is that with each increasing year of tenure, CEOs have less interest in pursuing strategies of innovation through higher R&D expenditure, preferring instead to emphasize stability and efficiency (Barker and Mueller, 2002). The other reason is that longer-tenured CEOs may lose touch with their organization's environments and therefore may not make the changes and investments desired to keep the firm evolving over time.

study indicates that the effect of good judgment is larger than the effect of conservative leadership.

Instead of including GM's college degree in the estimation as in other literature (e.g., Lin *et al*., 2011), we include GM's postgraduate degree to indicate GM's education because there are more than 70% of firms' GM with a college degree and thus under this situation, the study of a postgraduate degree will be more meaningful. Table 3 shows that GM graduate is insignificant in NB model in Data 2000 while it is significant both in Poisson model and NB model in Data 2002. In NB model, the coefficient of postgraduate degree is 0.852 indicating that when a firm's GM with postgraduate degree, its innovation will increase 85.2% compared to firms having GM only with college degree. This means that compared to college education, postgraduate education of GM is more important to innovation.

Moreover, Table 3 presents that management team's average age has a negative and significant coefficient in both datasets while their average schooling tends to have a positive coefficient among all the models though it is only significant in column (3). Thus, we can get that management team's average age has negative effect on innovation while their average education has a positive effect on innovation. Specifically, the coefficient of management team's average age in column (5), -0.0545, means that other things equal, when management team's average age increases one year, the firm's number of patents will decrease 5.45%. Our results are consistent with our intuition and previous management studies. Older executives tend to be more conservative (Hambrick and mason, 1984) and empirical studies have found that older top managers tend to be risk averse (Barker and Mueller, 2002) and follow lower-growth strategies (Child 1974). One reason is that older executives have less of the physical and mental stamina needed to implement organizational changes (Child, 1974). Another reason is that older managers may have greater difficulty grasping new ideas and learning new behaviors (Hambrick and Mason, 1984) because some cognitive abilities seem to diminish with age, including learning ability, reasoning, and memory. Finally, younger managers are likely to have received their education more recently than older managers, so their technical knowledge should be superior (Bantel and Jackson, 1989).

Meanwhile, Table 3 shows that management team's average schooling has a positive effect and is significant in negative binomial model in part I, implying that the higher education of management team, the more innovation a firm can have. The importance of the top manager's education has been studied in a number of studies. Attained education level is always assumed to be correlated with cognitive ability, and higher levels of education should be associated with higher ability to generate (and implement) creative solutions to complex problems. Hitt and Tyler (1991) found that more educated executives have greater cognitive complexity and such cognitive complexity provides greater ability to absorb new ideas and therefore increases the tendency toward accepting innovations.

R&D in Part II in Table 3 has a positive effect, consistent with previous studies (e.g., Pakes and Griliches, 1980; Scherer, 1983; Brouwer and Kleinknecht, 1999). The coefficient is 0.112, implying that when R&D increase 1%, other things equal, the number of patents will increase 0.112%, which is comparable to Hall and Ziedonis (2001) which reported the coefficient of the log form of R&D is 0.196 using Poisson model[31]. However, we failed to find a significant effect of R&D in Part I in Table 3. Like us, Lieberman (1987) also failed to detect a strong R&D effect, and they argued that their failure might stem from the poor quality of the available R&D data. Different from him, we claim that the relationship between R&D and

[31] The relationship between patents and R&D has also been studied at the firm level and they reveal a strong link between total corporate R&D expenditure and patents (e.g., Bound et al., 1984; Pakes and griliches, 1984).

innovation, when measured by patents, may be affected by market environment. In theoretical part, we have showed that market environment with advanced technology and more human capital stimulates firm R&D. Also, in the datasets R&D in Data 2000 is around 5 times R&D in Data 2002. Thus, we conclude that it might be that all firms have more than enough R&D over what is needed so the variation in R&D is not the reason why our dependent variable, number of patents, varies.

Market share has a positive effect across all models and is significant in Poisson in Part I and significant in Poisson and Negative Binomial in Part II, strongly supporting Schumpeterian hypotheses. This is not hard to understand. With bigger market share, firms can have more profit, and thus firms can have more resources to put into R&D. This is important because possible failures in financial markets may force firms to rely on their own supra-normal profits to finance the search for innovation (Bhattacharya and Ritter, 1983). Also, with bigger market share, firms can appropriate more profits from more sales using innovation[32].

Firm size tends to have a positive effect and is significant in Poisson model in Part I in Table 3, and this is consistent with Schumpeterian hypothesis and the literature (e.g., Scherer, 1983); that is, larger firms tend to have more innovation. Holding R&D expenditures constant, large firms are more likely to apply for patents than small firms. The reason may be that larger firms are more likely to have the specialized staff and legal departments that facilitate filing and enforcement of a patent claim (Lieberman, 1987). The coefficient is 0.299 in Poisson in Part I, comparable to Brouwer and Kleinknecht (1999) where the coefficient for firm size is 0.38-0.62 for different datasets, and industry dummies and R&D collaboration are controlled.

## VII. Further Investigation

[32] See Blundell, Griffith and Reenen (1999) for more reasons.

In estimating our equation, we face a possible econometric problem concerning the potential correlation between the independent variables, general human capital and R&D, and unobservable or unmeasurable firm-specific characteristics, such as the quality of human capital. The ordinary Poisson and NB estimates would then be subject to omitted-variable misspecification and bias. One of the traditional ways to correct the bias is to use panel data. With panel data, we can de-mean the variables and thus all time-invariant firm-specific characteristics would be removed. If none of the unobservable or unmeasurable firm-specific characteristics change over time, we will get unbiased estimates. However, for our data, a three-year panel data, most variation of the data is cross-sectional. Applying the de-mean method will then wipe out useful interfirm variation. Thus, in our study, we use cross-sectional data that make the best use of information on firm characteristics.

Though we can always use GMM to deal with endogeneity in nonlinear model, our main method, control function approach, can be more efficient. Let $y_1$ denote the response variable, $y_2$ the endogenous explanatory variable, and $\boldsymbol{z}$ the $1 \times L$ vector of exogenous variables (which includes unity as its first element). Consider the model

$$E(y_1|\boldsymbol{z}, y_2, r_1) = \exp(\boldsymbol{z}_1\delta_1 + \alpha_1 y_2 + r_1) \tag{9}$$

where $\boldsymbol{z}_1$ is a $1 \times L_1$ strict subvector of $z$ that also includes a constant and $r_1$ is the error term. Suppose first that $y_2$ has a standard linear reduced form with an additive and independent error

$$y_2 = \boldsymbol{z\pi}_2 + v_2 \tag{10}$$

$$D(r_1, v_2|\boldsymbol{z}) = D(r_1, v_2) \tag{11}$$

so that $(r_1, v_2)$ is independent of $\boldsymbol{z}$. Then

$$E(y_1|\boldsymbol{z}, y_2) = E(y_1|\boldsymbol{z}, v_2) = E(\exp(r_1)\,|v_2)\exp(\boldsymbol{z}_1\delta_1 + \alpha_1 y_2) \qquad (12)$$

If $(r_1, v_2)$ are jointly normal, then $E(\exp(r_1)\,|v_2) = \exp(\theta_1 v_2)$, where we set the intercept to zero, assuming $\boldsymbol{z}_1$ includes an intercept. This assumption can hold more generally, too. Then

$$E(y_1|\boldsymbol{z}, y_2) = E(y_1|\boldsymbol{z}, v_2) = \exp(\boldsymbol{z}_1\delta_1 + \alpha_1 y_2 + \theta_1 v_2) \qquad (13)$$

This expectation immediately suggests a two-step estimation procedure. The first step is to estimate the reduced form for $y_2$ and obtain the residuals. Second, include $\hat{v}_2$, along with $\boldsymbol{z}_1$ and $y_2$, in Poisson QMLE or Negative Binomial.

Though in the linear model, control function estimates are identical to 2SLS estimates, in the exponential model, we can obtain a more efficient estimator via control function method. Moreover, we can still take the count data feature and overidentification feature in the second stage of control function by using Poisson QMLE and Negative Binomial model.

Table 5a and 5b show the results of IV estimation. The difference is that in Table 5a, we only treat R&D as endogenous while in Table 5b we treat both R&D and general human capital level as endogenous. The results of the first stage regression suggest that we are using reasonably "strong" instruments. We also partially test the validity of the instruments by the over-identification test and do not reject the null that the over-identifying instruments are valid assuming a subset of the instruments is valid and identified the model. The IV results in Table 5a are generally consistent with those in Table 3. That is, the effects of human capital indicators stay similar. However, we find that now R&D is also not significant in Data 2002. This indicates that R&D is indeed endogenous and determined by other factors. In Table 5b, we only present results from Data 2000 because we don't have information on job application in Data 2002.

From Table 5b, we find that general human capital becomes insignificant now, but other human capital indicators remain quite similar effects as in Table 3. This implies that in the long run if we take the endogeneity of general human capital into account, it might have no effect on innovation.

## VIII. Conclusion

We first explain the reason why we need human capital in our firm innovation study. First, a firm's human capital is its one of the most important resources, and thus it is how we can differentiate firms. This is from resource-based theory. Second, traditional economic theory assumes that firms are homogenous except for market share and firm size. We emphasize that the characteristics of a firm's decision makers, GM and management team, will largely affect their decision-making and thus the firm's performance and other aspects of the firm. Moreover, upper echelon theory argues that a firm is a reflection of top managers. Human capital plays its role in three ways. First, general human capital affects a firm's success probability directly, and it can also affect the firm's success probability indirectly via affecting the firm's R&D level choice. Second, R&D human capital determines innovation directly. Third, managerial personnel can affect a firm's project choice and R&D choice. Better managerial personnel will make decisions closer to optimal levels.

Our major findings are as follows. General human capital has a positive effect in both datasets and the effect in Data 2000 is much larger. Moreover, we find that GM's education and experience have positive and significant effects on innovation. Management team's education has a positive effect on innovation while the team's average age has a negative and significant effect on firm innovation. Notably, R&D has a positive and significant effect on innovation in Data 2002 while it is insignificant in Data 2000.

Implications from our results are that: (1) human capital, general human capital and characteristics of managerial personnel, is very important in determining firm's innovation. Without considering them, the study of firm innovation may be biased because of heterogeneity. Moreover, when both variables are included, human capital can account for the impact of other innovation, i.e. all the other "on the job learning" or "learning by doing". (2) Controlling only market share or market fixed effect is not enough for firm innovation study. Comparing firm innovation in different market environments is essential to studying how market environment affects a firm's innovation. Thus, besides knowledge spillover, we find that the strategic choice of a firm plays an important role in how the market environment affects firm's innovation. This is consistent with Grabowski (1968) which stated that firm decisions on R&D are strongly influenced by the behavior of competitors. (3) R&D and general human capital level might be endogenous in long run. Without dealing with this problem, we might misinterpret their effects.

Our results are subject to two caveats that warrant further research: one relating to innovation measure; the other relating to innovation strategies. First, as we admitted previously, patent number is not a perfect measure for firm innovation because value of patents varies and a lot of innovation is not patented. Further studies on new product sales and Total Factor Productivity (TFP) might provide us with more insights into firm innovation. Second, in our study, we only focus on firm's R&D and non-R&D innovative activities in house without considering a firm's other innovative strategies, like R&D cooperation and licensing from other firms, and so forth. However, in reality, firms will choose their innovative method among all the possible strategies.

## References


1. Acs, Z. J., & Audretsch, D. B. (1988). Innovation in large and small firms: an empirical analysis. *The American Economic Review*, 678-690.
2. Arundel, A., & Kabla, I. (1998). What percentage of innovations are patented? Empirical estimates for European firms. *Research Policy*, *27*(2), 127-141.
3. Audretsch, D. B., & Acs, Z. J. (1991). Innovation and size at the firm level. *Southern Economic Journal*, 739-744.
4. Audretsch, D. B., & Feldman, M. P. (1996). R&D spillovers and the geography of innovation and production. *The American Economic Review*, 630-640.
5. Bantel, K. A., & Jackson, S. E. (1989). Top management and innovations in banking: does the composition of the top team make a difference? *Strategic Management Journal*, *10*(S1), 107-124.
6. Barker III, V. L., & Mueller, G. C. (2002). CEO characteristics and firm R&D spending. *Management Science*, *48*(6), 782-801.
7. Barro, R. J. (2001). Human capital and growth. *American Economic Review*, 12-17.
8. Bhattacharya, S., & Ritter, J. R. (1983). Innovation and communication: Signaling with partial disclosure. *The Review of Economic Studies*, *50*(2), 331-346.
9. 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.
10. Bound, J., Cummins, C., Griliches, Z., Hall, B. H., & Jaffe, A. B. (1984). Who Does R&D and Who Patents?. In *R & D, Patents, and Productivity* (pp. 21-54). University of Chicago Press.
11. Brouwer, E., & Kleinknecht, A. (1999). Innovative output, and a firm's propensity to patent.: An exploration of CIS micro data. *Research Policy*, *28*(6), 615-624.
12. Child, J. (1974). Managerial and organizational factors associated with company performance part I. *Journal of Management Studies*, *11*(3), 175-189.
13. Darroch, J. (2005). Knowledge management, innovation and firm performance. *Journal of knowledge management*, *9*(3), 101-115.
14. 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.
15. Gourieroux, C., Monfort, A., & Trognon, A. (1984). Pseudo maximum likelihood methods: Applications to Poisson models. *Econometrica: Journal of the Econometric Society*, 701-720.
16. Grabowski, H. G. (1968). The determinants of industrial research and development: A study of the chemical, drug, and petroleum industries. *The Journal of Political Economy*, 292-306.

17. Griliches, Z. (1979). Issues in assessing the contribution of research and development to productivity growth. *The Bell Journal of Economics*, 92-116.

18. Griliches, Z. (1990). Patents Statistics as Economic Indicators: A Survey. *Journal of Economic Literature*, *28*(4), 1661-1707.

19. Grimpe, C., & Sofka, W. (2009). Search patterns and absorptive capacity: Low and High-technology sectors in European countries. *Research Policy*, *38*(3), 495-506.

20. 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.

21. Hall, B. H., Griliches, Z., & Hausman, J. A. (1986). Patents and R&D: Is there a lag?. NBER working paper.

22. Hambrick, D. C., & Fukutomi, G. D. (1991). The seasons of a CEO's tenure. *Academy of Management Review*, *16*(4), 719-742.

23. Hambrick, D. C., & Mason, P. A. (1984). Upper echelons: The organization as a reflection of its top managers. *Academy of Management Review*, *9*(2), 193-206.

24. Hansen, P. A., & Serin, G. (1997). Will low technology products disappear?: The hidden innovation processes in low technology industries. *Technological Forecasting and Social Change*, *55*(2), 179-191.

25. Hausman, J., Hall, B. H., & Griliches, Z. (1984). Econometric Models for Count Data with an Application to the Patents-R & D Relationship. *Econometrica: Journal of the Econometric Society*, 909-938.

26. Hitt, M. A., & Tyler, B. B. (1991). Strategic decision models: Integrating different perspectives. *Strategic Management Journal*, *12*(5), 327-351.

27. Hitt, M. A., Biermant, 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.

28. Howitt, P., & Mayer-Foulkes, D. A. (2005). R&D, Implementation, and Stagnation: A Schumpeterian Theory of Convergence Clubs. *Journal of Money, Credit and Banking*, *37*(1), 147-77.

29. Jaffe, A. (1986). Technological Opportunity and Spillovers of R&D: Evidence from Firms' Patents, Profits, and Market Value. *American Economic Review*,*76*(5), 984-1001.

30. Kim, L., & Nelson, R. R. (Eds.). (2000). *Technology, learning, and innovation: Experiences of newly industrializing economies*. Cambridge University Press.

31. Krueger, A. B. (1993). How Computers Have Changed the Wage Structure: Evidence from Microdata, 1984-1989. *The Quarterly Journal of Economics*, *108*(1), 33-60.

32. Lieberman, M. B. (1987). Patents, learning by doing, and market structure in the chemical processing industries. *International Journal of Industrial Organization*, *5*(3), 257-276.

33. 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.

34. Lucas Jr, R. E. (1993). Making a miracle. *Econometrica: Journal of the Econometric Society*, 251-272.

35. Maskell, P., & Malmberg, A. (1999). Localised learning and industrial competitiveness. *Cambridge journal of economics*, *23*(2), 167-185.

36. Miller, D., De Vries, M. F. K., & Toulouse, J. M. (1982). Top executive locus of control and its relationship to strategy-making, structure, and environment. *Academy of Management journal*, *25*(2), 237-253.

37. Nelson, R. R. (1991). Why do firms differ, and how does it matter?. *Strategic Management Journal*, *12*(S2), 61-74.

38. Pakes, A., & Griliches, Z. (1980). Patents and R&D at the firm level: A first report. *Economics Letters*, *5*(4), 377-381.

39. Pakes, A., & Griliches, Z. (1984). Patents and R&D at the firm level: a first look. In *R & D, Patents, and Productivity* (pp. 55-72). University of Chicago Press.

40. Penrose, E. (2009). *The Theory of the Growth of the Firm*. Oxford University Press.

41. Pfeffer, J. (1995). *Competitive Advantage Through People: Unleashing the Power of the Work force*. Harvard Business Press.

42. Romer, P. M. (1986). Increasing returns and long-run growth. *The Journal of Political Economy*, 1002-1037.

43. Romer, P. M. (1990). Endogenous technological change. *Journal of Political Economy*, S71-S102.

44. Rosen, R. J. (1991). Research and development with asymmetric firm sizes. *The RAND Journal of Economics*, 411-429.

45. Scherer, F. M. (1983). The propensity to patent. *International Journal of Industrial Organization*, *1*(1), 107-128.

46. Schumpeter, J. A. (1942). *Socialism, capitalism and democracy*. Harper and Brothers.

47. Soete, L. L. (1979). Firm size and inventive activity: The evidence reconsidered. *European Economic Review*, 12(4), 319-340.

48. Spence, M. (1984). Cost reduction, competition, and industry performance. *Econometrica: Journal of the Econometric Society*, 101-121.

49. Thoenig, M., & Verdier, T. (2003). A theory of defensive skill-biased innovation and globalization. *American Economic Review*, 709-728.

50. Yang, C. H., & Huang, C. H. (2013). Is Taiwan's R&D productivity in decline? A microeconometric analysis. *Journal of Business Economics and Management*,*14*(1), 137-155.

Table 1 Descriptive Statistics (Data 2000)

| Variable | Year | obs | Mean | Std. Dev. | Min | Max |
|---|---|---|---|---|---|---|
| Number of patents applied by firm in China | 2000 | 624 | 0.84 | 4.28 | 0 | 50 |
| | 1999 | 624 | 0.67 | 3.43 | 0 | 38 |
| | 1998 | 624 | 0.39 | 1.89 | 0 | 20 |
| Number of patents applied by firm in China with patents>0 | 2000 | 74 | 7.11 | 10.56 | 1 | 50 |
| | 1999 | 74 | 5.66 | 8.46 | 1 | 38 |
| | 1998 | 66 | 3.73 | 4.64 | 1 | 20 |
| Number of patents actually granted to firms in China | 2000 | 624 | 0.55 | 3.07 | 0 | 48 |
| | 1999 | 624 | 0.53 | 2.62 | 0 | 33 |
| | 1998 | 624 | 0.33 | 1.71 | 0 | 20 |
| Number of patents actually granted to firms in China with patents>0 | 2000 | 69 | 4.96 | 8.00 | 1 | 48 |
| | 1999 | 75 | 4.43 | 6.35 | 1 | 33 |
| | 1998 | 58 | 3.53 | 4.51 | 1 | 20 |
| Number of highly educated workers in firm (Hundred) | 2000 | 623 | 1.84 | 3.25 | 0.1 | 41.33 |
| | 1999 | 619 | 1.76 | 2.83 | 0.1 | 24.96 |
| | 1998 | 623 | 1.81 | 2.79 | 0.1 | 27.31 |
| Number of applicants for skilled position (Hundred) | 2000 | 418 | 0.37 | 1.30 | 0 | 15.95 |
| Number of weeks to fill last job for skilled positions | 2000 | 431 | 3.78 | 7.73 | 0.5 | 87.5 |
| Total number of employees (Hundred) | 2000 | 624 | 9.45 | 15.05 | 0.5 | 170.98 |
| | 1999 | 623 | 9.12 | 14.59 | 0.5 | 184.66 |
| | 1998 | 621 | 9.46 | 15.12 | 0.5 | 180.59 |
| R&D expenditure by firm (Thousand RMB) | 2000 | 603 | 18996.44 | 237062.50 | 0 | 5673039 |
| | 1999 | 611 | 15204.81 | 194832.00 | 0 | 4618865 |
| | 1998 | 610 | 15309.83 | 183430.50 | 0 | 4238681 |
| Average R&D excluding current year(Thousand RMB) | | 610 | 15252.81 | 188559.90 | 0 | 4428773 |

| | | | | | | |
|---|---|---|---|---|---|---|
| Average R&D across cities excluding current year (Thousand RMB) | | 610 | 15260.58 | 19973.09 | 787.62 | 53919.59 |
| Average R&D across industries excluding current year (Thousand RMB) | | 610 | 15268.49 | 18242.56 | 79.26 | 45231.12 |
| Value of total sales (Million RMB) | 2000 | 624 | 334.31 | 1828.58 | 3 | 31600 |
| | 1999 | 624 | 318.91 | 1933.77 | 3.01 | 32200 |
| | 1998 | 614 | 253.86 | 1613.49 | 3.04 | 28900 |
| Total net assets (Million RMB) | 2000 | 622 | 102.79 | 430.07 | 0.013 | 7554.332 |
| Years of schooling of General Manager (GM) | 2000 | 622 | 14.03 | 2.30 | 5 | 18 |
| Years of GM holding the position | 2000 | 623 | 5.69 | 4.44 | 0 | 30 |
| GM's postgraduate dummy (=1, postgraduate) | 2000 | 622 | 0.16 | 0.37 | 0 | 1 |
| Management team's average age | 2000 | 614 | 36.29 | 6.63 | 18 | 54 |
| Management team's average schooling | 2000 | 615 | 11.88 | 1.50 | 8 | 18 |
| Firm's market share | 2000 | 583 | 16.13 | 20.53 | 0.1 | 98 |
| Firm age | 2000 | 624 | 17.81 | 17.37 | 0 | 92 |
| Shareholding firms dummy | 2000 | 624 | 0.16 | 0.37 | 0 | 1 |
| State-owed firms dummy | 2000 | 624 | 0.24 | 0.43 | 0 | 1 |
| Foreign invested firms dummy | 2000 | 624 | 0.39 | 0.49 | 0 | 1 |
| Other firms dummy | 2000 | 624 | 0.21 | 0.41 | 0 | 1 |

Table 2 Descriptive Statistics (Data 2002)

| Variable | Year | obs | Mean | Std. Dev. | Min | Max |
|---|---|---|---|---|---|---|
| Number of patents applied by firm in China | 2002 | 910 | 0.71 | 3.68 | 0 | 77 |
| | 2001 | 910 | 0.50 | 2.29 | 0 | 31 |
| | 2000 | 910 | 0.44 | 2.12 | 0 | 28 |
| Number of patents applied by firm in China with patents>0 | 2002 | 114 | 5.68 | 8.97 | 1 | 77 |
| | 2001 | 94 | 4.85 | 5.48 | 1 | 31 |
| | 2000 | 90 | 4.48 | 5.28 | 1 | 28 |
| Number of patents actually granted to firms in China | 2002 | 910 | 0.67 | 2.86 | 0 | 30 |
| | 2001 | 910 | 0.47 | 2.09 | 0 | 24 |
| | 2000 | 910 | 0.47 | 2.15 | 0 | 30 |
| Number of patents actually granted to firms in China with patents>0 | 2002 | 122 | 4.98 | 6.33 | 1 | 30 |
| | 2001 | 97 | 4.41 | 4.87 | 1 | 24 |
| | 2000 | 96 | 4.43 | 5.15 | 1 | 30 |
| Number of highly educated workers in firm (Hundred) | 2002 | 904 | 1.57 | 2.86 | 0.1 | 42.81 |
| | 2001 | 902 | 1.58 | 3.07 | 0.1 | 53.83 |
| | 2000 | 899 | 1.59 | 3.19 | 0.1 | 60.86 |
| Total number of employees (Hundred) | 2002 | 909 | 7.36 | 13.21 | 0.5 | 155 |
| | 2001 | 908 | 7.45 | 13.46 | 0.5 | 199.06 |
| | 2000 | 904 | 7.38 | 13.65 | 0.5 | 220.44 |
| R&D expenditure by firm (Thousand RMB) | 2002 | 904 | 4140.77 | 26450.19 | 0 | 534973.4 |
| | 2001 | 892 | 3787.40 | 32729.11 | 0 | 782405.7 |
| | 2000 | 891 | 2527.87 | 17935.78 | 0 | 451204 |
| Average R&D excluding current year (Thousand RMB) | | 889 | 3166.79 | 24973.85 | 0 | 616804.9 |
| Average R&D across cities excluding current year (Thousand RMB) | | 892 | 3191.77 | 2947.75 | 98.99 | 10086.07 |

| | | | | | | |
|---|---|---|---|---|---|---|
| Average R&D across industries excluding current year (Thousand RMB) | | 892 | 3187.61 | 3323.36 | 128.41 | 12957.13 |
| Value of total sales (Million RMB) | 2002 | 909 | 271.05 | 1246.51 | 3.11 | 29700 |
| | 2001 | 906 | 224.28 | 938.37 | 3.09 | 21300 |
| | 2000 | 901 | 198.78 | 763.11 | 3.01 | 15800 |
| Total net assets (Million RMB) | 2002 | 905 | 96.52 | 411.77 | 0.11 | 8207.21 |
| Years of schooling of General Manager (GM) | 2002 | 903 | 14.15 | 2.23 | 5 | 18 |
| Years of GM holding the position | 2002 | 901 | 5.86 | 4.47 | 1 | 23 |
| GM's incentive income dummy | | 910 | 0.30 | 0.46 | 0 | 1 |
| GM's postgraduate dummy (=1, postgraduate) | 2002 | 903 | 0.17 | 0.37 | 0 | 1 |
| Management team's average age | 2002 | 879 | 36.50 | 5.31 | 20 | 51 |
| Management team's average schooling | 2002 | 883 | 12.13 | 1.50 | 8 | 18 |
| Firm's market share | 2002 | 884 | 8.96 | 16.38 | 1 | 99.46 |
| Firm age | 2002 | 910 | 15.96 | 14.34 | 2 | 52 |
| Shareholding firms dummy | 2002 | 910 | 0.29 | 0.45 | 0 | 1 |
| State-owned firms dummy | 2002 | 910 | 0.26 | 0.44 | 0 | 1 |
| Foreign invested firms dummy | 2002 | 910 | 0.22 | 0.41 | 0 | 1 |
| Other firms dummy | 2002 | 910 | 0.24 | 0.42 | 0 | 1 |

Table 3 Estimation Results without controlling for city and industry effects

| | I: Year 2000 (Data 2000) | | | II: Year 2002 (Data 2002) | | |
|---|---|---|---|---|---|---|
| | OLS | Poisson | NB | OLS | Poisson | NB |
| | (1) | (2) | (3) | (4) | (5) | (6) |
| Number of highly educated workers | 0.420** | 0.0792*** | 0.285*** | 0.530* | 0.0928*** | 0.154*** |
| (Hundred) | (0.164) | (0.0171) | (0.0782) | (0.312) | (0.0258) | (0.0405) |
| General Manager's experience (years) | 0.190** | 0.205*** | 0.166*** | 0.0122 | -0.00040 | 0.0167 |
| | (0.0848) | (0.0444) | (0.0415) | (0.0231) | (0.0301) | (0.0295) |
| General Manager's postgraduate degree | 1.000 | 0.966** | 0.360 | 0.598 | 0.589* | 0.852*** |
| dummy (=1 if has a postgraduate degree) | (0.667) | (0.434) | (0.381) | (0.433) | (0.328) | (0.286) |
| Management team's average age | -0.0367 | -0.0363 | -0.101*** | -0.0146 | -0.0545** | -0.0858*** |
| | (0.0319) | (0.0381) | (0.0298) | (0.0188) | (0.0253) | (0.0268) |
| Management team's average schooling | 0.0785 | 0.133 | 0.246* | 0.0380 | 0.0893 | 0.0519 |
| | (0.0598) | (0.0905) | (0.145) | (0.0611) | (0.102) | (0.0983) |
| Market Share | 0.0152 | 0.0124** | 0.0208*** | 0.0120 | 0.0182*** | 0.0308*** |
| | (0.0101) | (0.00562) | (0.00719) | (0.00820) | (0.00477) | (0.00551) |
| Log (average R&D excluding current year) | 0.00497 | 0.0196 | 0.0279 | 0.0306* | 0.108*** | 0.112*** |
| | (0.0333) | (0.0389) | (0.0290) | (0.0161) | (0.0274) | (0.0213) |
| Firm Size (log (total net assets)) | -0.00223 | 0.299** | -0.00648 | -0.111 | 0.0950 | 0.0283 |
| | (0.147) | (0.144) | (0.153) | (0.167) | (0.101) | (0.0954) |
| Firm Age (year) | -0.00777 | -0.0161 | 0.00104 | -0.00813 | -0.00654 | -0.00107 |
| | (0.00815) | (0.0133) | (0.0126) | (0.00851) | (0.0137) | (0.0129) |
| Shareholding firms dummy | -0.281 | -0.361 | -0.0896 | -0.154 | -0.130 | 0.0337 |
| | (0.556) | (0.727) | (0.460) | (0.205) | (0.316) | (0.351) |
| State-owned firms dummy | -0.141 | -0.176 | 0.275 | -0.575* | -0.721 | -1.074** |
| | (0.462) | (0.535) | (0.573) | (0.323) | (0.520) | (0.449) |
| Foreign invested firms dummy | 0.0665 | 0.0964 | 0.328 | 0.439 | 0.0376 | -0.483 |
| | (0.583) | (0.710) | (0.473) | (0.450) | (0.408) | (0.399) |
| Constant | -0.753 | -5.560* | -2.327 | 0.974 | -1.367 | 0.446 |
| | (2.402) | (3.071) | (2.528) | (1.116) | (1.427) | (1.669) |
| City dummies | No | No | No | No | No | No |
| Industry dummies | No | No | No | No | No | No |
| Number of observations | 562 | 562 | 562 | 824 | 824 | 824 |

Note: Standard errors in parentheses: $p < 0.10$, $^{**}$ $p < 0.05$, $^{***}$ $p < 0.01$

Table 4 Estimation Results controlling for city and industry effects

| | I: Year 2000 (Data 2000) | | | II: Year 2002 (Data 2002) | | |
|---|---|---|---|---|---|---|
| | OLS | Poisson | NB | OLS | Poisson | NB |
| | (1) | (2) | (3) | (4) | (5) | (6) |
| Number of highly educated workers | $0.425^{***}$ | $0.0831^{***}$ | $0.292^{***}$ | $0.536^{*}$ | $0.0910^{***}$ | $0.182^{***}$ |
| (Hundred) | (0.162) | (0.0172) | (0.0766) | (0.319) | (0.0229) | (0.0548) |
| General Manager's experience (years) | $0.201^{**}$ | $0.200^{***}$ | $0.171^{***}$ | 0.0161 | -0.0158 | 0.0191 |
| | (0.0856) | (0.0328) | (0.0404) | (0.0225) | (0.0298) | (0.0285) |
| General Manager's postgraduate degree | $1.004^{*}$ | 0.638 | 0.353 | 0.633 | $0.541^{**}$ | $0.902^{***}$ |
| dummy (=1 if has a postgraduate degree) | (0.609) | (0.398) | (0.365) | (0.440) | (0.271) | (0.258) |
| Management team's average age | -0.0552 | -0.0397 | $-0.0853^{***}$ | -0.00273 | $-0.0595^{**}$ | $-0.0674^{***}$ |
| | (0.0392) | (0.0327) | (0.0290) | (0.0230) | (0.0234) | (0.0249) |
| Management team's average schooling | 0.0370 | 0.114 | $0.354^{***}$ | 0.0981 | 0.122 | 0.116 |
| | (0.0749) | (0.0897) | (0.136) | (0.0841) | (0.0905) | (0.0975) |
| Market Share | 0.0156 | 0.00899 | $0.0242^{***}$ | 0.0124 | $0.0210^{***}$ | $0.0311^{***}$ |
| | (0.0102) | (0.00640) | (0.00754) | (0.00775) | (0.00468) | (0.00521) |
| Log (average R&D excluding current year) | -0.00874 | -0.0142 | -0.0211 | $0.0294^{*}$ | $0.100^{***}$ | $0.112^{***}$ |
| | (0.0317) | (0.0311) | (0.0282) | (0.0162) | (0.0250) | (0.0197) |
| Firm Size (log (total net assets)) | 0.0355 | $0.346^{***}$ | 0.0872 | -0.122 | 0.164 | 0.0262 |
| | (0.141) | (0.127) | (0.137) | (0.186) | (0.103) | (0.0928) |
| Firm Age (year) | -0.00278 | -0.00532 | 0.00505 | -0.0149 | -0.0142 | -0.00739 |
| | (0.00840) | (0.0126) | (0.0113) | (0.00952) | (0.0112) | (0.0106) |
| Shareholding firms dummy | 0.0483 | 0.103 | -0.307 | -0.0966 | -0.0368 | -0.134 |
| | (0.539) | (0.599) | (0.528) | (0.224) | (0.332) | (0.338) |
| State-owned firms dummy | 0.0246 | -0.261 | 0.0464 | -0.451 | -0.618 | $-0.872^{**}$ |
| | (0.447) | (0.440) | (0.466) | (0.314) | (0.412) | (0.363) |
| Foreign invested firms dummy | -0.00906 | -0.186 | -0.406 | 0.426 | -0.201 | $-0.940^{**}$ |
| | (0.513) | (0.545) | (0.472) | (0.448) | (0.425) | (0.387) |
| Constant | 0.134 | $-6.317^{**}$ | $-6.289^{**}$ | -0.356 | $-17.82^{***}$ | $-16.17^{***}$ |
| | (2.808) | (2.549) | (2.576) | (1.296) | (1.597) | (1.860) |
| City dummies | Yes | Yes | Yes | Yes | Yes | Yes |
| Industry dummies | Yes | Yes | Yes | Yes | Yes | Yes |
| Number of observations | 562 | 562 | 562 | 824 | 824 | 824 |

Note: Standard errors in parentheses: $p < 0.10$, $^{**}$ $p < 0.05$, $^{***}$ $p < 0.01$

Table 5a IV estimation Results: Only R&D is endogenous

| | I: Year 2000 (Data 2000) | | | | II: Year 2002 (Data 2002) | | | |
|---|---|---|---|---|---|---|---|---|
| | 2SLS | Poisson CF | GMM | NB CF | 2SLS | Poisson CF | GMM | NB CF |
| | (1) | (2) | (3) | (4) | (5) | (6) | (7) | (8) |
| Number of highly educated workers | $0.421^{***}$ | $0.332^{***}$ | $0.0866^{***}$ | $0.288^{***}$ | $0.544^{*}$ | $0.192^{*}$ | $0.0629^{***}$ | 0.114 |
| (Hundred) | (0.163) | (0.108) | (0.0213) | (0.0804) | (0.314) | (0.106) | (0.0243) | (0.0711) |
| General Manager's experience (years) | $0.191^{**}$ | $0.166^{***}$ | 0.0843 | $0.166^{***}$ | 0.0136 | 0.0100 | 0.0245 | 0.0122 |
| | (0.0833) | (0.0407) | (0.101) | (0.0418) | (0.0231) | (0.0451) | (0.0391) | (0.0313) |
| General Manager's postgraduate degree | 1.011 | 0.588 | $1.014^{*}$ | 0.381 | 0.653 | $1.013^{**}$ | 0.397 | $0.715^{*}$ |
| dummy (=1 if has a postgraduate degree) | (0.689) | (0.568) | (0.587) | (0.418) | (0.485) | (0.465) | (0.312) | (0.384) |
| Management team's average age | -0.0358 | $-0.119^{***}$ | -0.0253 | $-0.0993^{***}$ | -0.0177 | $-0.0995^{**}$ | -0.0229 | $-0.0769^{**}$ |
| | (0.0309) | (0.0357) | (0.0557) | (0.0352) | (0.0194) | (0.0451) | (0.0329) | (0.0301) |
| Management team's average schooling | 0.0838 | $0.442^{*}$ | 0.242 | 0.257 | 0.0499 | 0.0772 | -0.108 | 0.0162 |
| | (0.0858) | (0.240) | (0.181) | (0.195) | (0.0611) | (0.137) | (0.229) | (0.101) |
| Market Share | 0.0154 | $0.0271^{**}$ | $0.0156^{**}$ | $0.0214^{***}$ | 0.0140 | $0.0298^{**}$ | 0.00654 | $0.0256^{***}$ |
| | (0.0106) | (0.0129) | (0.00663) | (0.00817) | (0.00930) | (0.0124) | (0.00964) | (0.00940) |
| Log (average R&D excluding current year) | -0.000302 | -0.0386 | 0.0227 | 0.0133 | -0.000134 | 0.276 | 0.762 | 0.199 |
| | (0.0543) | (0.173) | (0.0862) | (0.115) | (0.0699) | (0.171) | (0.656) | (0.135) |
| Firm Size (log (total net assets)) | 0.00389 | 0.0594 | 0.0914 | 0.0127 | -0.0880 | -0.273 | -0.363 | -0.0368 |
| | (0.141) | (0.278) | (0.192) | (0.211) | (0.173) | (0.194) | (0.427) | (0.142) |
| Firm Age (year) | -0.00792 | 0.00279 | -0.00840 | 0.000382 | -0.00768 | 0.0246 | -0.00866 | -0.00230 |
| | (0.00804) | (0.0177) | (0.0124) | (0.0132) | (0.00845) | (0.0167) | (0.0117) | (0.0129) |
| Shareholding firms dummy | -0.271 | 0.509 | -0.344 | -0.0625 | -0.155 | 0.313 | 0.0354 | 0.0551 |
| | (0.558) | (0.710) | (0.808) | (0.471) | (0.203) | (0.471) | (0.369) | (0.348) |

| | | | | | | | | |
|---|---|---|---|---|---|---|---|---|
| State-owned firms dummy | -0.135 | 0.847 | -0.817 | 0.289 | -0.610$^{*}$ | -1.810$^{***}$ | -0.285 | -0.969$^{**}$ |
| | (0.448) | (0.762) | (0.978) | (0.588) | (0.337) | (0.645) | (0.413) | (0.467) |
| Foreign invested firms dummy | 0.0599 | 0.408 | -0.516 | 0.303 | 0.399 | -0.955 | 0.0318 | -0.373 |
| | (0.590) | (0.721) | (0.828) | (0.485) | (0.449) | (0.597) | (0.457) | (0.465) |
| Constant | -0.916 | -5.210 | -4.408 | -2.738 | 0.681 | 3.158 | -0.0393 | 1.287 |
| | (2.522) | (5.455) | (4.783) | (4.577) | (1.246) | (3.113) | (1.630) | (2.005) |
| City dummies | No | No | No | No | No | No | No | No |
| Industry dummies | No | No | No | No | No | No | No | No |
| Number of observations | 562 | 562 | 562 | 562 | 824 | 824 | 824 | 824 |

Note: (1) Standard errors in parentheses: $p < 0.10$, $^{**}\, p < 0.05$, $^{***}\, p < 0.01$

(2) In this model, R&D is treated as endogenous, and we use the corresponding city average R&D and industry average R&D as instruments. Moreover, a firm's own R&D needs to be excluded from the average.

Table 5b IV estimation Results: Both R&D and general human capital are endogenous

| | Year 2000 (Data 2000) | | | |
|---|---|---|---|---|
| | 2SLS | Poisson CF | GMM | NB CF |
| | (1) | (2) | (3) | (4) |
| Number of highly educated workers | 0.185 | 0.0524 | 0.0170 | 0.127 |
| (Hundred) | (0.178) | (0.248) | (0.0635) | (0.145) |
| General Manager's experience (years) | 0.137$^{***}$ | 0.190$^{**}$ | 0.145$^{***}$ | 0.179$^{***}$ |
| | (0.0519) | (0.0793) | (0.0538) | (0.0577) |
| General Manager's postgraduate degree | 1.596$^{*}$ | 0.586 | 0.958$^{***}$ | 0.669$^{*}$ |
| dummy (=1 if has a postgraduate degree) | (0.819) | (0.507) | (0.288) | (0.376) |
| Management team's average age | -0.0183 | -0.0644$^{*}$ | -0.0341 | -0.0441 |
| | (0.0406) | (0.0390) | (0.0315) | (0.0319) |
| Management team's average schooling | 0.142 | 0.198 | 0.112 | 0.156 |
| | (0.115) | (0.278) | (0.159) | (0.195) |
| Market Share | 0.0205 | 0.0294$^{**}$ | 0.0139$^{**}$ | 0.0225$^{***}$ |
| | (0.0130) | (0.0124) | (0.00590) | (0.00870) |
| Log (average R&D excluding current year) | -0.00416 | -0.0818 | 0.102 | -0.0732 |
| | (0.0835) | (0.157) | (0.135) | (0.112) |
| Firm Size (log (total net assets)) | 0.185 | 0.338 | 0.197 | 0.197 |
| | (0.235) | (0.304) | (0.158) | (0.213) |
| Firm Age (year) | -0.0245 | -0.0137 | -0.0252 | -0.0143 |
| | (0.0161) | (0.0261) | (0.0160) | (0.0191) |
| Shareholding firms dummy | 0.0263 | 0.372 | -0.203 | 0.0231 |
| | (0.819) | (0.907) | (0.620) | (0.535) |
| State-owned firms dummy | -0.695 | 0.484 | -0.918 | -0.0203 |
| | (0.460) | (0.901) | (0.732) | (0.687) |
| Foreign invested firms dummy | -0.697 | -0.579 | -0.422 | -0.367 |
| | (0.888) | (0.739) | (0.565) | (0.499) |
| Constant | -2.905 | -5.686 | -3.689 | -4.389 |
| | (3.051) | (5.715) | (3.258) | (4.208) |
| City dummies | No | No | No | No |
| Industry dummies | No | No | No | No |
| Number of observations | 358 | 358 | 358 | 358 |

Note: (1) Standard errors in parentheses: $p < 0.10$, $^{**}$ $p < 0.05$, $^{***}$ $p < 0.01$.

(2) In this model, both R&D and general human capital (number of highly educated workers) are treated as endogenous. We use the corresponding city average R&D and industry average R&D as instruments for R&D. Moreover, a firm's own R&D needs to be excluded from the average. We use the number of job applicants for skilled worker positions and the number of weeks to fill the last job as instruments for general human capital.