ADBI Working Paper Series

INNOVATION AND FIRM PERFORMANCE IN THE PEOPLE'S REPUBLIC OF CHINA: A STRUCTURAL APPROACH WITH SPILLOVERS

Anthony Howell

No. 805
February 2018

Asian Development Bank Institute

Anthony Howell is an assistant professor at the School of Economics of Peking University.

Suggested citation:

Howell, A. 2018. Innovation and Firm Performance in the People's Republic of China: A Structural Approach with Spillovers. ADBI Working Paper 805. Tokyo: Asian Development Bank Institute. Available: https://www.adb.org/publications/innovation-and-firm-performance-prc-structural-approach-spillovers

Please contact the authors for information about this paper.

Email: anthony.howell.pku@gmail.com

The author acknowledges funding support from the School of Economics at Peking University and the Natural Science Foundation of China No. 71603009.

Asian Development Bank Institute
Kasumigaseki Building, 8th Floor
3-2-5 Kasumigaseki, Chiyoda-ku
Tokyo 100-6008, Japan

Tel: +81-3-3593-5500
Fax: +81-3-3593-5571
URL: www.adbi.org
E-mail: info@adbi.org

Abstract

This paper adopts a structural framework to study the process of indigenous innovation and its impact on firm performance in the People's Republic of China (PRC). Informing the analysis is an unusually rich source of panel data comprising almost 70,000 private Chinese firms operating in the PRC from 2004 to 2007. Relying on a structural innovation framework, the focus is on estimating the effects of technological learning during each phase of the structural model: (i) the firm's decision to innovate; (ii) the innovation effort; (iii) the innovation throughput; and (iv) the firm performance. The results show that, in the early stages of innovation, Chinese firms fail to incorporate learning spillovers into their innovation effort, even when considering their absorptive capacity. Conversely, the study finds that, in the later stages of innovation, learning spillovers positively increase firms' innovation output as well as their performance, especially for firms with high absorptive capacity.

Keywords: innovation, firm performance, learning, agglomeration, institutions, People's Republic of China

JEL Classification: O30

Contents

1. INTRODUCTION

Researchers note that innovation is at the heart of economic growth and is essential for firms to maintain a competitive advantage in the market and to achieve long-term success (Porter 1990; Berthon, Hulbert, and Pitt 1999; Noble, Sinha, and Kumar 2002). In the literature, three dominant strands of research have emerged, focusing on different aspects of the innovation process: (i) the innovation–performance relationship, (ii) the knowledge production function, and (iii) the structural framework that links knowledge production to firm performance.

The first strand has led to a consensus that the role of innovation enhances firm productivity (Griliches 1958; Wakelin 2001; Wang and Tsai 2003; Griffith, Redding, and Van Reenen 2004). The second strand has developed largely from Pakes and Griliches's (1980) seminal paper. The authors ascribe the positive association between innovative inputs (R&D activities) and innovative outputs (patent activities) as the "knowledge production function." A slew of subsequent works links innovative inputs to innovative outputs (Zahra and George 2002; Roper, Du, and Love 2008; Love and Roper 2009).

In the third strand, Crépon, Duguet, and Mairesse (1998) extend the knowledge production framework of Pakes and Griliches (1980), embedding it into a recursive system of equations that links the knowledge production function to the firm performance (referred to as the CDM framework). The structural model is now a popular approach for examining the linkages between innovation and firm performance.[1] The main advantages of the CDM framework over previous approaches are that it corrects for the undesirable effects produced by selectivity and simultaneity bias (Lööf and Heshmati 2006); moreover, it is parsimonious and empirically tractable (Griffith et al. 2006).

Building on the structural approach, the current paper estimates an "augmented" version of the CDM model to examine the process of Chinese "indigenous" innovation and estimate its impact on firm performance. Informing our analysis is an unusually rich source of panel data comprising almost 70,000 private Chinese firms operating in the manufacturing sector in the People's Republic of China (PRC) from 2004 to 2007. Our data are unique not only because of their representativeness of Chinese firms during the time period but also because they provide the necessary detailed firm-level information—location, four-digit industry, innovative sales, R&D expenditures, value-added, gross output, and so forth—to carry out our analysis. Using panel data methods, we employ 3SLS with fixed effects to estimate the structural model, controlling for unobserved firm-specific effects, simultaneity, and endogeneity.

This paper makes contributions to the general innovation literature in the following ways. First, its theorization and subsequent empirical analysis of a complex set of direct and indirect effects that attempt to disentangle the sources of technological learning set it apart from previous structural approaches. We define technological learning as the process of building and accumulating technological capability: the ability to use technological knowledge effectively in production, engineering, and innovation to become competitive in the marketplace (Kim 2001).

[1] See Jefferson et al. (2002); Kemp et al. (2003); Arvanitis (2006); Griffith et al. (2006); Lööf and Heshmati (2006); Miguel Benavente (2006); Johansson and Lööf (2009); Hashi and Stojcic (2010); Antonietti and Cainelli (2011); and Howell (2017).

To disentangle the various sources of technological learning, we identify multiple learning interaction effects that take place (1) within the firm (learning by doing), (2) between the firm and the environment (learning by exporting and a firm's absorptive capacity to acquire intra- and inter-industry learning spillovers), and (3) external to the firm (intra- and inter-industrial learning spillovers mediated by institutions). We find these direct and mediating effects of learning to be important determinants of the innovation process and firm performance, although their respective impacts vary depending on both the different types of interactions and the stage of innovation under examination.

Making a second contribution to the literature, we apply the CDM framework to a transitioning and dirigiste economy, thereby extending the CDM model to a non-Western context. Johansson and Lööf (2009) argue that applying a "general structural model" to multiple (European) countries is problematic and infeasible for advanced econometric models that attempt to examine the particularities of the knowledge production function as part of the CDM model. It is even more important to examine the unique aspects of the innovative process in transitioning countries like the PRC, where substantial changes in political, economic, and legal institutions present new opportunities and challenges for enterprises to engage in innovative activities (Child and Tse 2001).

On a related point, a growing number of Chinese firm-level studies have emerged in the innovation literature (Tan 2001; Sun 2002; Zhou 2006; Guan et al. 2009; Naidoo 2010; Wang and Lin 2013). These studies largely confirm the positive role of innovation and the significance of location and policy instruments in enhancing firm performance; however, most of these empirical works fall into either the first or the second strand of the innovation literature, thereby restricting the investigation to studying the knowledge production function separately from its impact on firm performance (with the exception of Jefferson et al. 2002). The structural framework that this paper adopts—capable of studying the entire process of Chinese innovation and its impact on firm performance—improves the current literature on innovation in the PRC.

The outline of the paper is as follows. The next section discusses the relevant literature on the PRC's innovation strategy and its particularities. Section 3 develops the theoretical framework of the paper. Section 4 introduces the structural framework, modeling strategy, and variable development. Section 5 provides information on the summary statistics. Section 6 reveals the research findings from the structural model, and section 7 provides an overview of the main findings and concludes with some final remarks.

2. BACKGROUND: CHINESE INDIGENOUS INNOVATION

Since the PRC implemented economic reforms in 1978 and the subsequent large-scale dismantling of inefficient state-owned enterprises during the 1990s, the country has experienced tremendous economic growth and emerged as a key actor in the global economy. In 2000, the PRC's share of the global manufacturing output was approximately one-quarter of the US output, representing only 5.7%. By 2011, the PRC had surpassed the US to become the top global manufacturing producer, increasing its share to 19.8% of the global output (UNIDO 2011).

What accounts for the PRC's phenomenal growth in manufacturing in such a short period? The conventional view is that the PRC capitalizes on several advantages, such as a cheap, abundant labor supply, state subsidies, and a growing local demand for consumer items. While this perspective may partly explain the PRC's manufacturing success, it does not account for why other countries with low factor prices, state incentives, and even a large domestic market have not achieved the same level of success as the PRC.

Offering a new insight, Nahm and Steinfeld (2012) argue that "innovative manufacturing" is a critical part of and the missing explanatory factor that accounts for the PRC's economic growth story. This perspective is in stark contrast to the conventional view that the manufacturing–physical assembling process takes place in strict isolation from the innovation process (Steinfeld 2004a). Moreover, recognizing the important role of innovation in Chinese manufacturing challenges the stereotypical perceptions of the PRC as being merely "the world's factory"; rather, Chinese innovation, or "innovation with Chinese characteristics," explores the unique learning strategies that Chinese firms adopt.

According to the "innovative manufacturing" perspective, the accumulation of diverse, firm-specific know-how is a central component of the PRC's competitive specialization in manufacturing. This firm-specific knowledge, combined with the ability to access foreign technology and subsequently employ backward design strategies, enables Chinese firms to recreate "imitated" products at a cheaper cost, crowding out foreign suppliers (Howell 2016). Although other developing countries can make products at a lower cost, multi-national firms choose the PRC not only due to its cheap labor costs and emerging consumer market but also because of its engineering capabilities and quick tempo to reorient a product for large-scale production at the lowest cost possible.

The 2011 U.S.–China Economic and Security Review Commission Report confirms that Chinese innovation has made substantial inroads in a relatively short period of time, expanding into everything from design to genuine innovation, development, and commercialization of new products and processes. Based on this report, Nahm and Steinfeld (2012) argue that the PRC's place *within* global manufacturing is enabling it to develop the propriety know-how *beyond* manufacturing. In effect, Chinese firms are approaching tasks differently from pioneering firms from developed countries, leading to different learning outcomes, and, as Hall (1995) points out, this type of imitator strategy leads the imitating firms to become, in essence, innovators in their own way.

The innovative manufacturing perspective also complements the arguments of some Chinese scholars who claim that the PRC's learning process model of development is unique, deviating from that of other transitioning countries (Qian and Xu 1993; Chen and Qu 2003). For example, Chen and Qu (2003) argue that Chinese firms integrate operational, tactical, and strategic learning to produce a specific form of technological learning that differs from that of other newly industrializing economies (NIEs). As opposed to fitting the Chinese experience into that of other NIEs, a PRC-centric approach that accounts for the way in which Chinese firms incorporate technological learning into the innovation process provides the necessary contextualized knowledge regarding the PRC's spatial, institutional, and organizational features to account for its phenomenal growth.

2.1 Chinese Industrial Policy

The process of internationalization has exposed domestic Chinese firms to large amounts of foreign capital, reorienting them towards an export-based development strategy. Coinciding with the PRC's opening-up strategy, Chinese firms also face new, intense competition from foreign competitors. The increasing competition, in turn, has urged the Chinese authorities to focus on promoting indigenous innovation through strong state interventionist policies to protect local profits and preserve state revenues (Jefferson and Rawski 1994; Peng and Heath 1996).

For example, then Premier Wen Jiabao delivered a speech in 2006 emphasizing that the two main drivers of the PRC’s continued progress and development are the persistence in promoting opening and reform and the reliance “on the progress of science and technology and the strengths of innovation.” In the same year, the promotion of innovation received center stage in the PRC’s National Medium- and Long-Term Plan for the Development of Science and Technology (2006–2020) (Liu et al. 2011; Howell 2015). The plan unveiled the “blueprint” for innovation that will bring about the “great renaissance of the Chinese nation,” with stated goals of transforming the PRC into a technology powerhouse by 2020 and a global leader by 2050.

The industrial policy of the state buttresses the relative ease of access to foreign technology of Chinese firms’, which have relied on a “market-access-for-technology” strategy since the early 1990s. In 2011, the National Development and Reform Commission and the Ministry of Commerce issued a revised version (originally released in 1995) of the Catalogue of Industries for Guiding Foreign Investment. In that document, the Government identifies three categories in which foreign investment is “encouraged,” “restricted,” or “prohibited.”

The catalogue identifies over 450 industries, nearly 100 of which are subject to ownership restrictions that require foreign companies, for example, to form joint ventures—equity, cooperative, or contractual—with Chinese partners. To form a joint venture, it is often obligatory for foreign companies to transfer technology once they have established the joint venture as a precondition for its establishment (Shea 2012).

Scholars note several problems with the PRC’s industrial policy, which gives market access to foreign companies in exchange for tech transfer (Young and Lan 1997; Cheung and Lin 2004). According to Huang (2003), the return benefits to the PRC have been incommensurate with the deep discounts at which foreigners are able to purchase industrial assets and gain a foothold in the Chinese market. There is also growing recognition that Chinese firms may be over reliant on the transferring of the physical assets, overlooking the importance of the training and experience that are necessary to absorb those technologies.

For instance, Hu, Jefferson, and Qian (2005) suggest that the actual effect of FDI on improving the innovation capabilities of domestic Chinese firms is close to non-existent. From a different viewpoint, Young and Lan (1997) find that the potential for utilizing FDI as an instrument for technological development is greater than the theory suggests. Taking one step further, Liu and Buck (2007) find that the absorptive capacity of the firm positively mediates its utilization of the foreign knowledge inputs, leading to higher levels of innovation performance.

2.2 Institutional Barriers to Innovation

The legal and institutional environment is important, because investing in innovation is inherently risky and in theory can enhance firm performance or lead to financial distress and failure (Buddelmeyer, Jensen, and Webster 2010). The risk of engaging in innovative activities is comparatively high in the PRC compared with advanced market economies due to widespread intellectual property theft, unlawful abrogation of legal contracts and unfair competitive practices, the shortage of venture capital, poor institutional protection, and insufficient market demand (Guo 1997; Sun 2002; Wang and Lin 2008; Zhou 2008). These barriers not only increase the risk of innovation but also diminish the incentives for Chinese firms to pursue indigenous innovation activities relying on purely domestic inputs.

Building stable institutions can mitigate certain risks associated with pursuing innovation, whereas low state capacity leads to unclear rules, distrust, and rent-seeking activities, all of which impinge on the capacity and inclination of the firm to innovate (Steinfeld 2004b). Promoting the rule of law is an essential component of building institutions, incubating indigenous innovation, and promoting sustained growth. Taking into account the direct and mediating impact of institutions is an important issue for examining the innovation–performance linkages (Li and Atuahene-Gime 2001; Rodriguez-Pose and Crescenzi 2008) and helps to conceptualize the dynamic interplay between actors and structures (Geels 2004).

At present, as a result of poor institutional and legal frameworks in the PRC, innovative firms must depend heavily on state intervention and protectionism to survive (Li and Atuahene-Gime 2001). On the one hand, a strong state presence may increase the risk of innovation by undermining the benefits normally accrued from innovation in a competitive environment (Carlin, Schaffer, and Seabright 2004). Conversely, policy instruments may create a demand for technological learning and increase the supply of technological capability (Lall 1992), especially in certain key industries. For instance, He and Qing (2011) find that policy mechanisms exert a direct impact on the performance of industrial catching up for private Chinese firms in the telecommunication and automobile industries.

3. THEORETICAL FRAMEWORK: DISENTANGLING THE SOURCES OF LEARNING

Along with the institutional environment, the learning ability—absorptive capacity—of the firm becomes critical for its ability to capture and incorporate external knowledge inputs into its production function (Zahra and George 2002). According to Cohen and Levinthal (1990), "The premise of the notion of absorptive capacity is that the organization needs prior related knowledge to assimilate and use new knowledge." Geroski, Machin, and van Reenen (1993) highlight the importance of not only innovation in itself but also the learning process that takes place as a firm engages in innovative activities.

The literature identifies several potential sources that can facilitate a firm's learning process, which in turn can influence the process of innovation and firm performance. Pertinent to the scope of this paper, we identify the following sources of learning grouped into three categories: learning that is internal to the firm (learning by doing), firm–environment learning interaction (exporting by doing and the absorptive capacity of the firm mediated by learning spillovers), and learning that is external to the firm (learning spillovers mediated by institutions).

3.1 Learning I: Internal to the Firm

Learning by doing (LBD) is the process whereby the accumulation of production experience leads to increased performance and growth. The literature distinguishes between passive and active learning, with the former suggesting that LBD is an incidental and costless by-product of a firm's production activities and the latter occurring as the result of intentional activities of the firm to increase its organizational know-how, such as R&D investments (Thompson 2009). Early studies by Rapping (1965) and Sheshinski (1967) find evidence for significant learning effects as firms accumulate experience. Similarly, research confirms the positive and significant role of active learning, based on R&D investments, in firm performance (Jovanovic 1982; Pakes and Ericson 1998; Liu and Buck 2007).

3.2 Learning II: Firm–Environment Learning

In addition to LBD, the geographical environment is a potentially important source of supplemental knowledge generated outside the firm (Lööf and Nabavi 2013). Two main sources of firm–environment learning interactions are learning by exporting (LBE) and the absorptive capability of the firm to capture learning spillovers.

3.2.1 Learning by Exporting

LBE occurs as exporting firms benefit from their foreign buyers' technical and managerial expertise or the expertise from other foreign contacts, such as competitors, suppliers, or scientific agents (Rhee, Ross-Larsen, and Pursell 1984; Clerides, Lach, and Tybout 1998; Silva, Afonso, and Africano 2012). In addition, foreign buyers apply pressure to exporters to produce cheaper yet higher-quality products, generating incentives for exporting firms to become more efficient (Evenson and Westphal 1995). The accumulation of external knowledge inputs by exporting firms is not available to firms confined to the domestic market. Research considers this difference in access to external knowledge to be a key factor that explains why exporting firms tend to be more productive than non-exporters, although the direction of causality between exports and productivity is debatable (Balasubramanayam, Salisu, and Sapsford 1996). Despite the existence of anecdotal evidence purporting the significance of LBE, the econometric evidence so far provides little support (Salomon and Shaver 2005).

3.2.2 Geography of Learning Spillovers

The spatial concentration of economic activity is believed to be an essential aspect of the learning process and the generation of learning spillovers, which in turn foster growth, innovation, and productivity (Fujita and Thisse 2003; Henderson 2003, 2005; Acs, Armington, and Zhang 2007; Baldwin et al. 2008; Glaeser 2008; Kesidou and Romijn 2008; Rodriguez-Pose and Crescenzi 2008; He 2009). According to Keller (2010), the benefits derived from learning spillovers in urban regions can be as large as the return from firms' own investments.

Learning spillovers occur when a firm is able to incorporate these external knowledge inputs into its knowledge production function. Research based on the initial works of Cohen and Levinthal (1989, 1990) agree that the production of innovation and new technological knowledge increasingly depends on the firm's ability to search the external environment to access complementary knowledge inputs.

The literature discerns two types of externalities. Within-industry knowledge spillovers result from the spatial concentration of firms in the same industry, leading to localization economies, while the increased diversity of economic activity within a region leads to urbanization economies. Although a large literature examines the impact of spatial externalities on firm productivity, their relationship remains undetermined (Antonietti and Cainelli 2011).

On the one hand, learning spillovers are advantageous, because they enable a firm to overcome the financial and technological limitations of attempting to produce new knowledge solely based on in-house innovation (Antonellia, Patruccoa, and Quatraro

2011). At the same time, learning spillovers may cannibalize some of the benefits normally generated by the LBD process. As a greater stock of knowledge generated externally becomes freely available, the firm may avoid investing in learning opportunities, such as in-house R&D, as a cost-saving strategy (Ghemawat and Spence 1985; Barrios and Strobl 2004).

Several studies from developed countries find that learning spillovers result in positive firm performance (Gruber 1998; Thornton and Thompson 2001). In a study on Spain, Barrios and Strobl (2004) find that both firm-level LBD and learning spillovers positively influence firm performance. It is perhaps even more important to disentangle the sources of learning that are internal to the firm and those between the firm and the environment in developing countries, since these firms are much more likely to rely solely on learning spillovers in lieu of carrying out in-house R&D.

3.2.3 Learning III: External to the Firm

As developed in Section 2.2 above, the legal and institutional environment is also likely to have a direct impact on both the innovation process and the firm performance. Moreover, we expect the mediating impact of institutions on learning spillovers to facilitate the ease with which firms can transmit tacit knowledge at the organizational or industrial level. These expectations of institutions are in line with previous research that contends that it is not possible to understand the effects of innovation on firm performance and economic growth fully without considering the social and institutional conditions in an economy (Rodriguez-Pose and Crescenzi 2008).

4. THE STRUCTURAL FRAMEWORK OF INDIGENOUS INNOVATION

In the previous two sections, we identified several sources of learning, LBD, LBE, and learning spillovers, emphasizing the importance of a firm's experience and its absorptive capacity to utilize foreign knowledge inputs as well as acknowledging the Chinese state as a key player in the innovation and performance outcomes of the firm. Building on this theoretical groundwork, the current section introduces the structural model framework with learning, learning spillovers, and institutional effects.

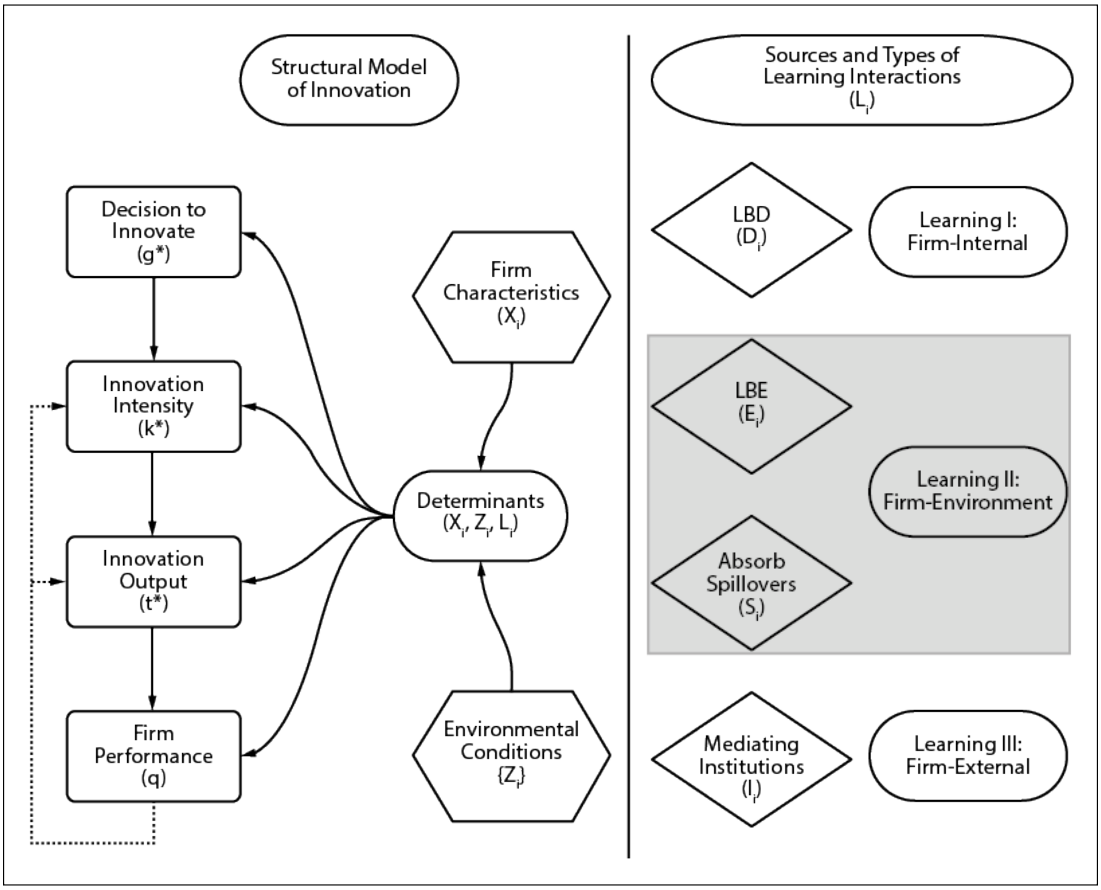
4.1 Modeling Strategy

In the spirit of Crépon, Duguet, and Mairesse (1998), we model the process of innovation using four main equations. Equation (i) is the firm's decision to engage in innovation determined by a positive value for R&D expenditure. Equation (ii) is the intensity of the firm's R&D effort, and equation (iii) is the knowledge production function based on the intensity of new product or process sales. Equation (iv) is the performance equation, in which knowledge is an input for a firm's total factor productivity (TFP).

The model combines aspects of the original CDM model along with the adapted CDM model of Antonietti and Cainelli (2011), which controls for spatial externalities. Developing our own structural model of innovation, we estimate firm characteristics, environmental conditions, and learning interactions at each stage of the model (Figure 1).

Three sets of learning interactions take place that account for learning by doing (D_i), learning by exporting (E_i) and the absorptive capacity to utilize foreign knowledge inputs (S_i), and the effect of mediating institutions (I_i). Both S_i and I_i include two learning spillover terms, one for intra-industry spillovers and another for inter-industry spillovers. In total, our model takes into account six learning interaction effects.

Figure 1: Augmented Structural Model of Innovation with Learning Interactions



To estimate the model, we employ panel 3SLS with fixed effects to control for unobserved firm-specific effects, simultaneity, and endogeneity. This is a modest improvement over the original CDM model (and many of the related empirical works thereafter), which relies on cross-sectional data and is thus incapable of accounting for specific effects across firms. Similar to the CDM model, we assume innovation to be endogenous in the performance equation (iv) and R&D intensity to be endogenous in the innovation equation (iii). We develop proper instruments to control further for this endogeneity—the firm's market share, the distance to a port, the industry, and year dummies. We assume the remaining explanatory variables to be exogenous, which is a difficult assumption to make. Therefore, when possible, we lag the assumed exogenous variables by one year.

In line with Griffith et al. (2006), we estimate the CDM model for all firms, not just those with positive innovation sales. That is, we estimate the R&D equations and use the predicted values for all firms as the proxy for the innovation effort in equation (iii). This approach departs from the majority of the other studies and is based on the idea that all firms exert an (imitative) innovative effort to some extent but not all firms report their efforts (Griffith et al. 2006).

4.2 Structural Equations

First we will introduce the set of four structural equations, along with the dependent variables and latent independent variables. Following the explanation of the models, we will explain and discuss the set of independent variables {X_i, Z_i, L_i}. Lower case denotes logged values.

To obtain the innovation effort of the firm, we employ the estimation method that Wooldridge (1995) developed based on the Heckman two-step procedure (Heckman 1976). In the first step, we use the maximum likelihood to estimate the panel probit model with fixed effects—a firm's decision to invest in R&D (1=yes, 0=no). In the second step, we use pooled OLS to estimate the linear regression model for firms with a positive value of R&D, with the dependent variable being the ratio of expenditures on research and development (R&D) to the number of employees.

The first equation relates to the decision to pursue innovation, and the second equation relates to the intensity of resources—R&D expenditures divided by total sales—utilized in the innovation process. g_i^* is the unobserved dependent variable indicating whether a firm invests in innovation, and k_i^* is the latent or true intensity of a firm's investment in innovation, with g_i and k_i being their observed counterparts. We define the first equation as follows:

$$g_i^* = x_{i0}b_0 + z_{i0}\gamma_0 + l_{i0}\eta_0 + u_{i0} \quad (1)$$

and

$$k_i^* = x_{i1}b_1 + z_{i1}\gamma_1 + l_{i1}\eta_1 + u_{i1} \quad (2)$$

where x_{i0} and x_{i1} are vectors of firm characteristics and b_0 and b_1 are their corresponding coefficient vectors. z_{i0} and z_{i1} represent the environmental conditions of the firm, with γ_0 and γ_1 as the associated vector coefficients. l_{i0} and l_{i1} are the learning interaction terms, and η_0 and η_1 are the associated vector coefficients. We assume marginal normality for u_0 and a linear conditional mean assumption for u_1.

In the innovation equation, we assume that t_i^* is the latent dependent variable for innovation output based on the new product and process sales divided by the number of employees. k_i^* is the predicted values for R&D obtained from equation 2. We can express the equation as follows:

$$t_i^* = \alpha_k k_i^* + x_{i2}b_2 + z_{i2}\gamma_2 + l_{i2}\eta_2 + u_{i2} \quad (3)$$

We use total factor productivity (TFP) to measure firm performance, which represents the contribution from technological progress or institutional change and is the difference between the output growth and the weighted average of the growth rate of the input factors. To construct the TFP variable, we follow Olley and Pakes's (1996) semi-parametric approach, grouping firms into the same two-digit industry to control for technological differences, and estimate the TFP for each enterprise. t_i^* is the predicted value of innovation sales generated from equation 3 above.

The performance equation is:

$$tfp_i = \alpha_l t_i^* + x_{i3}b_3 + z_{i3}\gamma_3 + l_{i0}\eta_3 u_{i3} \tag{4}$$

where tfp are estimates of the firm's TFP, derived from Olley and Pakes's (1998) method. The other coefficients have the same interpretation as before.

4.3 Variable Development

The set of firm characteristics (x_i*'s*) includes: market share, distance to port, age, *age squared*, R&D intensity, export intensity, direct subsidy intensity, and leverage of the firm (assets-to-debt). We report all the firm-level variables in one-year lags.[2] We exclude the market share from the second R&D equation as an exclusion restriction. The literature assumes and supports the idea that the market share—an indicator of firm size—is related to the decision to engage in R&D but not the R&D intensity (Griffith et al. 2006). We identify the market share and distance to a port as instrumental variables for equations 3 and 4, respectively, along with industry and year dummies. Therefore, except for the exclusion of the market share and distance to a port, $x_{i0} = x_{i1} = x_{i2} = x_{i3}$.

The set of environmental conditions (z_i) consists of proxies for state industrial protection, local regional protection, the quality of institutions, and learning spillovers. We use the same set of environmental conditions in all the phases of the model. That is, $z_{i0} = z_{i1} = z_{i2} = z_{i3}$. To control for potential endogeneity, we report learning by exporting and spatial externalities in one-year lags; we report institutional development in four-year time lags times a constant value in 2004.

The set of learning interactions (z_i*'s*) is equivalent for all four models and includes the following six terms: learning by doing (LBD), learning by exporting (LBE), the absorptive capacity of a firm to capture intra- and inter-industry spillovers, and the mediating effects of institutional quality on intra- and inter-industry spillovers. We obtain learning by doing by multiplying the firm's experience (age) by its labor productivity in the previous year. We calculate learning by exporting by interacting the firm's experience with its export intensity in the prior year.

As a proxy for the spatial concentration of economic activity, we construct the EG index of Ellison and Glaeser (1997) to capture the localization economies generated from the Marshall–Arrow–Romer (MAR) externalities.

Our second agglomeration proxy—labor density—is calculated as the size of the working population in each city divided by the area of the city (km^2). This proxy captures the urbanization economies that knowledge spillovers generate that result from the diversity of local industries. Moreover, labor density relates to the size of the agglomeration, the significance of the collective resources and information, and the size of the local labor market (Antonietti and Cainelli 2011).

We develop a simple proxy for institutional quality based on the average spending on labor insurance (2001–2003) multiplied by a constant of the proportion of union workers in the labor force in 2004 for each city. No proxy for institutional quality is perfect. The main drawback of our proxy is that neither higher labor insurance expenditures nor greater proportions of union workers in the labor force necessarily equate to stronger structural support for innovation, such as the protection of

[2] See Table 7 in the Appendix for a description of the variables, summary statistics, and correlation details.

intellectual property laws or infrastructure that facilitates technology transfers. Despite its drawbacks, our institutional proxy captures the aspects of institutional building that improve employment and social protection, which are likely to be attractive to highly skilled workers engaged in innovative activities. Moreover, our proxy takes into account the lagged time effects that usually occur with institutional change. Our choice of a four-year time lag seems to be reasonable and is partially due to data availability.

Besides issues with proxy variables, a primary concern is that the addition of interaction terms leads to inefficient coefficients due to the presence of high collinearity. To alleviate this concern, we exclude all the interaction terms in a baseline model that does not suffer from collinearity problems (see Panel B in Table 7, Appendix A). In general, the subsequent inclusion of interaction terms does not lead to serious disturbances within the model, although we interpret some coefficients with caution in some cases.

5. DATA AND SUMMARY STATISTICS

This study utilizes the Annual Report of Industrial Enterprise Statistics (ASIF) that the State Statistical Bureau of China compiled for the years 2004–2007. The data comprise all firms with an annual turnover of approximately 5 million renminbi (approx. $600,000), accounting for 95% of the industrial output in the PRC (Lu and Tao 2009; Brandt, Van Viesebroeck, and Schott 2012). The data contain an unusually rich set of variables, including information on R&D investments, total sales, gross output, employment, geographic location, industry affiliation, new product or process sales, and sources of finance.

The scope of our paper encompasses the process of Chinese “indigenous” innovation and its impact on firm performance; therefore, we restrict our sample to domestic Chinese firms in which the majority of the capital is privately owned. We construct a balanced panel, resulting in approximately 70,000 domestic Chinese firms born in 1990 or later. We exclude firms with missing information or illogical negative values (i.e. for R&D, new product sales, etc.) from the sample.

Table 1 presents the annual size-weighted means for the four dependent variables that we use in the structural model. The average percentage change in TFP from 2004 to 2007 is just under 7%. R&D witnessed the highest average percentage change, increasing by 115% over the 2005–2007 period. The 40% increase in the number of firms that chose to invest in RD in part facilitated this large percentage change in R&D intensity, as well as firms investing a larger percentage of sales in R&D activities.

Table 1: Summary Information for Dependent Variables

	2004	**2005**	**2006**	**2007**	**AvgChge** (%)
TFP	2.59	2.62	2.65	2.68	6.91
Innov	...	9.20	12.30	14.64	91.31
RDint	...	0.29	0.37	0.52	115.14
RDchoice	...	0.09	0.10	0.11	39.22

Table 2 reports a summary of firm persistence in R&D and innovation intensity over the 2005–2007 period. Less than 18% of firms report positive R&D sales and less than 17% report positive innovation sales. Of the firms engaged in innovation-related activities, 8.46% undertake R&D activities and 6.81% report positive innovation sales for at least one of the observed periods. Slightly less than half of those respective firms report positive R&D expenditures and innovation sales for all three reporting periods.

Table 2: Firm Innovation Persistence

Innovation Effort	N	Percent	Innovation Output	N	Percent
RD-3Yrs	2,999	4.38	Innov-3Yrs	2,569	3.76
RD-2Yrs	3,033	4.43	Innov-2Yrs	3,945	5.77
RD-1Yr	5,785	8.46	Innov-1Yr	4,660	6.81
RD-None	56,594	82.73	Innov-None	57,237	83.67
Total	**68,411**	**100%**	**Total**	**68,411**	**100%**

Table 3

SIC	Industry	Firms	TFP	% $\Delta TFP04-07$	Innov	% $\Delta Innov05-07$
13	Agro-food processing	2.1	2.4	2.4	4.1	34.8
14	Food manufacturing	1.8	1.1	−6.8	11.9	35.9
15	Beverage manufacturing	1.1	1.2	−2.4	10.7	116.8
17	Textiles	12.5	2.8	0.2	8.9	104.9
18	Textiles, garments, shoes, hat manufacturing	3.8	3.1	4.5	5.3	17.1
19	Leather, fur, feather products	2	2.5	2.2	7.8	120.9
20	Wood processing/wood, bamboo, rattan, brown, grass products	2.8	1.8	11	7.3	149.8
21	Furnish Making	1.3	2.5	1.6	8.7	88.4
22	Paper/Paper products	3.7	2.1	1.1	4.8	40.1
23	Printing/record medium reproduction	2	1.2	−10.3	9.5	17.9
24	Educational/sports goods	1.1	3.5	4.8	9.3	34.6
26	Chemical materials/chemical products	7.2	2.4	1	14.7	30.6
27	Pharmaceutical manufacturing	1.8	1.5	0.7	35.5	51
28	Chemical fiber	0.5	2.9	−3.5	6.6	48.6
29	Rubber products	1.4	2.3	4.3	7.6	58.8
30	Plastic products	5.4	2.8	1.3	9.9	66.5
31	Nonmetallic minreal products	8.8	2.5	4.2	7.8	42.7
32	Ferrous metal smelting/rolling processing	2.1	1.9	8.7	5.9	70.3
33	Nonferrous metal smelting/rolling processing	0.3	2.8	−9.9	9.4	158.2
34	Metallic mineral products	6.6	2.8	2.6	9.0	50.5
35	General equipment manufacturing	10.1	3.0	4.8	12.2	72.1
36	Special equipment manufacturing	4.5	3.1	5	21.9	82.5
37	Transportation equipment	4.9	2.1	2.7	17.5	64.8
39	Electrical machinery/equipment manufacturing	6.9	3.9	9.7	21.5	73.2
40	Communications equipment, computers/other electronic equipment	2.4	2.2	6	31.5	55.1
41	Instruments, meters, cultural/office machinery	1.3	2.8	1.7	33.7	68
42	Artwork/other manufacturing	1.7	3.5	2.8	7.8	124.4

Table 3 presents the market share and size-weighted averages for TFP and innovation effort by industry. The textile industry (12.5%) is the largest industry represented in the sample, followed by general equipment manufacturing (10.1%). Electrical machinery and equipment manufacturing achieved the highest average TFP (3.9) as well as the highest average percentage change (9.7%). Pharmaceutical manufacturing reported the highest average innovation sales (35.5), followed by instruments, meters, and office machinery (33.7) and communications, computers, and electronics (31.5). The fastest movers in innovation output occurred in the resource-intensive industries, non-ferrous metal smelting and processing (158%), and wood processing (149%). Interestingly, all the industries showed positive changes in innovation output, indicating growing reliance on developing new products or processes.

6. RESULTS

In the baseline model, we are most interested in the role of LBD (proxied by age), the absorptive capacity of the firm (AbsCap), the export intensity (Exp), learning spillovers (EG3 and labor density), and institutional effects at each stage of the innovation. To take into account learning interaction effects, we subsequently estimate additional models.

The Learning I model offers an improved proxy for LBD by interacting a firm's experience in years with its previous year's labor productivity (learning interaction internal to the firm). The Learning II model further examines the potential for learning spillovers conditioned on the firm's absorptive capacity (firm–environment learning interaction). The Learning III model adds an additional interaction term for learning spillovers mediated by institutions (learning interaction external to the firm). We briefly discuss each of the four model specifications for each stage of the innovation process.

6.1 Innovation Effort Equations

The R&D equations relate to the firm's innovation effort (Table 4). We find that firms with larger market shares are more likely to choose to innovate. The distance from a port (the proxy for access to foreign knowledge) does not affect the decision to innovate, but a larger distance tends to reduce the R&D intensity.

Older firms are more likely to choose to innovate, but younger firms pursue a more intensive innovative strategy. Allowing for non-linear effects of experience, we find the opposite relationship. The most experienced firms are less likely to choose to innovate but pursue more intensive innovation strategies. Three of the four models confirm this result and provide mixed results with regard to LBD expectations. While we expect age to enhance a firm's R&D capabilities through learning effects, it may also impair the R&D strategy as a result of organizational sclerosis.

Absorptive capacity plays a positive role in both the firm's decision to innovate and the intensity of R&D activities. The higher the export intensity, the more likely it is that the firm will choose to innovate but with less intensive R&D. Direct subsidies increase both the likelihood of choosing to innovate and the R&D intensity. A higher debt-to-equity ratio (leverage) increases the likelihood that a firm will choose to innovate but reduces the R&D intensity.

Table 4: RD Equations

	Baseline		Learning I		Learning II		Learning III	
	Probit	Tobit	Probit	Tobit	Probit	Tobit	Probit	Tobit
(Intercept)	−1.687***	0.271***	−1.460***	0.119***	−1.457***	0.112***	−1.437***	0.113***
	(0.139)	(0.018)	(0.139)	(0.018)	(0.139)	(0.018)	(0.139)	(0.018)
mrktshr	0.221***	...	0.268***	...	0.267***	...	0.267***	...
	(0.004)	...	(0.005)	...	(0.005)	...	(0.005)	...
DistPrt	0.005	−0.002***	0.000	−0.001***	0.000	−0.001**	−0.002	−0.001**
	(0.003)	(0.000)	(0.003)	(0.000)	(0.003)	(0.000)	(0.003)	(0.000)
age	0.139*	−0.007	0.482***	−0.049***	0.481***	−0.049***	0.482***	−0.049***
	(0.059)	(0.007)	(0.062)	(0.007)	(0.062)	(0.007)	(0.062)	(0.007)
age2	0.005	0.001	−0.035*	0.006***	−0.037*	0.007***	−0.036*	0.007***
	(0.015)	(0.002)	(0.015)	(0.002)	(0.015)	(0.002)	(0.015)	(0.002)
AbsCap	1.393***	0.353***	1.464***	0.392***	1.581***	0.458***	1.547***	0.458***
	(0.042)	(0.007)	(0.042)	(0.007)	(0.076)	(0.012)	(0.076)	(0.012)
Exp	0.422***	−0.022***	0.344***	0.008*	−0.031	0.105***	−0.046	0.105***
	(0.028)	(0.004)	(0.029)	(0.004)	(0.200)	(0.028)	(0.200)	(0.028)
Subs	2.785***	0.288***	2.734***	0.411***	2.738***	0.413***	2.719***	0.411***
	(0.143)	(0.022)	(0.143)	(0.022)	(0.143)	(0.022)	(0.143)	(0.022)
Levg	0.293***	−0.023***	0.236***	−0.001	0.236***	−0.001	0.239***	−0.001
	(0.048)	(0.006)	(0.049)	(0.006)	(0.049)	(0.006)	(0.049)	(0.006)
EG3	0.286	−0.046	0.089	−0.014	0.219	−0.021	0.167	−0.019
	(0.242)	(0.031)	(0.243)	(0.031)	(0.245)	(0.032)	(0.245)	(0.032)
Den	0.052***	−0.012***	0.051***	−0.009***	0.052***	−0.008***	0.065***	−0.008***
	(0.011)	(0.001)	(0.011)	(0.001)	(0.011)	(0.001)	(0.011)	(0.001)
IndProt	0.041***	0.005***	0.055***	0.005***	0.055***	0.005***	0.056***	0.005***
	(0.009)	(0.001)	(0.009)	(0.001)	(0.009)	(0.001)	(0.009)	(0.001)
RegProt	0.008	−0.009***	0.018	−0.010***	0.018	−0.010***	0.020	−0.010***
	(0.012)	(0.001)	(0.012)	(0.002)	(0.012)	(0.002)	(0.012)	(0.002)
InstQ	0.022***	0.002**	0.023***	0.002***	0.023***	0.002***	0.077***	0.000
	(0.004)	(0.001)	(0.004)	(0.001)	(0.004)	(0.001)	(0.008)	(0.001)
LrnDo	...	...	−0.105***	0.015***	−0.105***	0.015***	−0.106***	0.015***
	...	...	(0.005)	(0.001)	(0.005)	(0.001)	(0.005)	(0.001)
LrnExp	...	...	...	...	0.338	−0.069**	0.358*	−0.069**
	...	...	...	...	(0.179)	(0.021)	(0.179)	(0.021)
AbsCap*EG3	...	...	...	...	−6.127**	0.204	−5.979**	0.183
	...	...	...	...	(1.990)	(0.283)	(1.991)	(0.283)
AbsCap*Den	...	...	...	...	0.018	−0.184***	0.073	−0.185***
	...	...	...	...	(0.133)	(0.020)	(0.133)	(0.020)
EG3*InstQ	...	...	...	...	...	...	−0.219	0.087***
	...	...	...	...	...	...	(0.198)	(0.026)
Den*InstQ	...	...	...	...	...	...	−0.099***	0.001
	...	...	...	...	...	...	(0.011)	(0.001)
IMR	−0.102***	...	−0.154***	...	−0.102***	...	−0.101***	...
	(0.003)	...	(0.003)	...	(0.003)	...	(0.003)	...
Adj. R2	...	0.122	...	0.119	...	0.119	...	0.119
Num. obs.	205,233	205,233	205,233	205,233	205,233	205,233	205,233	205,233
Num. Firms	68,411	68,411	68,411	68,411	68,411	68,411	68,411	68,411
LL	...	–60,777.6	...	–60,593.3	...	–60,583.8	...	–60,546.6

*** *p*<0.001, ** *p*<0.01, * *p*<0.05.

Interestingly, industrial specialization does not have an impact on the choice to innovate or the R&D intensity, whereas labor density increases the likelihood that a firm will choose to innovate but leads to lower levels of R&D intensity. State industrial subsidies increase both the probability that a firm will choose to innovate and the R&D intensity. On the other hand, regional protectionism does not influence the choice to innovate and exerts a negative impact on R&D intensity. The quality of institutions increases both the decision to innovate and the R&D intensity.

In the subsequent models—Learning I, II, and III—we add the learning interaction terms. Learning by doing diminishes the need for firms to invest in innovative activities, yet firms that are able to benefit from learning by doing will dedicate a larger amount of resources to R&D intensity. Conversely, we find that learning by exporting does not affect the choice to innovate and reduces the R&D intensity.

A greater firm ability to absorb knowledge from spatial externalities reduces the likelihood of choosing to carry out internal R&D in the case of knowledge generated from industrial specialization and reduces the R&D intensity in the case of knowledge generated from labor density. The building of strong institutions plays an important role in giving firms the confidence to combine knowledge absorbed from spatial externalities with internal R&D expenditures. In other words, specialization and location in a region with strong institutions lead to greater R&D intensity.

6.2 Innovation Output Equation

In all four models, R&D intensity increases the innovative output. With regard to firm experience, we find that older firms are less likely to innovate, yet the firms with the most experience are associated with higher levels of innovation. We find that the absorptive capacity of the firm increases the innovation output statistically in all four models. We also find that export intensity is positively associated with innovation output in all three models. The financial structure of the firm plays an important role in innovation. Both direct subsidies and access to loans lead to positive effects on innovation. We find that both industrial specialization and labor density lead to increased innovation output, although industrial specialization plays a much stronger role in facilitating knowledge spillovers. Interestingly, industrial protectionism does not persist through the innovation effort stage, having no effect on the innovation output. Regional protectionism, on the other hand, remains significant, increasing the innovative output.

The institutional quality does not have an impact on the innovation output, except in the last model. One way to understand this finding is that, for policy and infrastructure to have a positive effect on innovation, the enterprises within a particular region must have the appropriate absorptive capabilities and resources (Guan et al. 2009). We should interpret the statistically negative coefficient in the last model with caution, considering that it only becomes significant when we enter the interaction term with institutions into the model.

The Learning I, II, and III models add the learning interaction effects. We find that learning by doing leads to greater innovation output in all three models. Learning by exporting remains insignificant. The institutional quality further mediates the role of spatial externalities. Firms that are located in specialized industries and receive support from strong local institutions will generate higher levels of innovative output.

Table 5: Innovation Equations

	Baseline	Learning I	Learning II	Learning III
(Intercept)	1.106***	1.098***	1.109***	1.105***
	(0.086)	(0.086)	(0.086)	(0.086)
RDint	1.404***	1.370***	1.368***	1.368***
	(0.012)	(0.012)	(0.012)	(0.012)
Age	−0.112**	−0.270***	−0.270***	−0.270***
	(0.037)	(0.038)	(0.038)	(0.038)
age2	0.047***	0.067***	0.066***	0.066***
	(0.010)	(0.010)	(0.010)	(0.010)
AbsCap	0.286***	0.267***	0.809***	0.815***
	(0.035)	(0.035)	(0.062)	(0.062)
Exp	0.677***	0.699***	0.631***	0.629***
	(0.020)	(0.020)	(0.154)	(0.154)
Subs	1.017***	1.062***	1.055***	1.054***
	(0.114)	(0.114)	(0.114)	(0.114)
Levg	0.144***	0.156***	0.158***	0.157***
	(0.033)	(0.033)	(0.033)	(0.033)
EG3	1.354***	1.430***	1.345***	1.370***
	(0.171)	(0.171)	(0.172)	(0.172)
Den	0.087***	0.087***	0.102***	0.101***
	(0.007)	(0.007)	(0.007)	(0.007)
IndProt	0.002	−0.001	−0.001	0.000
	(0.006)	(0.006)	(0.006)	(0.006)
RegProt	0.106***	0.106***	0.108***	0.108***
	(0.008)	(0.008)	(0.008)	(0.008)
InstQ	0.000	0.000	0.000	−0.017**
	(0.003)	(0.003)	(0.003)	(0.005)
LrnDo	...	0.045***	0.045***	0.045***
	...	(0.003)	(0.003)	(0.003)
LrnExp	...	...	0.186	0.188
	...	...	(0.116)	(0.116)
AbsCap*EG3	...	...	6.451***	6.263***
	...	...	(1.545)	(1.545)
AbsCap*Den	...	...	−1.704***	−1.709***
	...	...	(0.108)	(0.108)
EG3*Inst	...	...	...	0.656***
	...	...	...	(0.142)
Den*Inst	...	...	...	0.011
	...	...	...	(0.008)
Adj. R2	0.089	0.090	0.092	0.092
Num. obs.	205,233	205,233	205,233	205,233
Num. Firms	68,411	68,411	68,411	68,411

*** p<0.001, ** p<0.01, * p<0.05.

Industrial specialization positively mediates firms with greater absorptive capacity. Surprisingly, we find that labor density has negative mediating effects on a firm's absorptive capabilities. One explanation for this unlikely finding lies in the construction of the absorptive capacity variable, which itself is interacted by the proportion of professional staff in 2004 and the annual amount of spending on professional training from 2005 to 2007. A possible interpretation of the coefficient is that urbanization economies lead to higher levels of innovation for low-skilled, labor-intensive firms. This finding is consistent with the innovative manufacturing perspective that, even in remedial tasks, such as assembly, Chinese firms create new processes or products to reduce costs.

6.3 Firm Performance Equation

Innovation intensity is statistically significant and leads to higher TFP performance in all four models. Similar to the innovation equation, we find the same relationship between firm experience and TFP. Older firms tend to be less productive, but the most experienced firms are the most productive. The absorptive capacity of the firm is statistically significant and positive in the baseline and Learning I models but becomes insignificant once the learning interaction terms are included in the Learning II and III models.

The role of exports in firm performance remains a puzzle. In the baseline model, the export intensity decreases the TFP output, but it increases the TFP when we include the learning by doing interaction term in the model and then becomes insignificant once we include the other learning and institutional interaction terms. One interpretation of this finding suggests that exporting firms that exhibit learning by doing are able to become more productive than exporting firms that fail to learn from their experiences.

Unlike the situation in the innovation effort stage, subsidized and indebted firms experience lower levels of TFP. Similarly, we find that industrial specialization diminishes the TFP in the baseline model but becomes insignificant in the subsequent models. The statistically significant negative coefficient in the baseline model is likely to reflect the "competition effect" generated by industrial specialization, which leads to greater entry rates and lower productivity output. We find that labor density increases the TFP output in all the model estimations and that state industrial protection reduces the TFP and is significant in three of the four models. Likewise, regional protectionism harms the TFP output but is significant in only the baseline model. Quality institutions exert a positive impact on TFP performance and are significant in all four models.

Including the learning interaction terms, we find that learning by doing leads to higher levels of TFP, whereas there is no evidence to suggest that learning by exporting leads to increased TFP. Although industrial specialization (above) resulted in lower TFP output, we find that firms with a highly skilled labor force will absorb intra-industry knowledge spillovers, which in turn increase the TFP performance. There is no evidence to suggest that labor density interacted with the absorptive capacity of the firm has an impact on the TFP. In the Learning III model, we find that institutional quality positively mediates both industrial specialization and labor density, leading to higher levels of TFP.

Table 6: TFP Equations

	Baseline	Learning I	Learning II	Learning III
(Intercept)	0.694***	0.730***	0.603***	0.611***
	(0.029)	(0.025)	(0.035)	(0.035)
Innov	0.115***	0.031***	0.088***	0.085***
	(0.005)	(0.005)	(0.014)	(0.014)
Age	−0.011	−0.779***	−0.781***	−0.781***
	(0.012)	(0.011)	(0.011)	(0.011)
age2	0.013***	0.109***	0.110***	0.110***
	(0.003)	(0.003)	(0.003)	(0.003)
AbsCap	0.171***	0.030**	−0.008	−0.001
	(0.011)	(0.010)	(0.019)	(0.019)
Exp	−0.114***	0.015*	−0.004	−0.002
	(0.007)	(0.006)	(0.045)	(0.045)
Subs	−0.654***	−0.464***	−0.459***	−0.453***
	(0.038)	(0.034)	(0.034)	(0.034)
Levg	−0.176***	−0.110***	−0.109***	−0.109***
	(0.011)	(0.010)	(0.010)	(0.010)
EG3	−0.275***	0.082	0.076	0.087
	(0.056)	(0.050)	(0.050)	(0.050)
Den	0.049***	0.054***	0.054***	0.052***
	(0.002)	(0.002)	(0.002)	(0.002)
IndProt	−0.003	−0.018***	−0.018***	−0.018***
	(0.002)	(0.002)	(0.002)	(0.002)
RegProt	−0.009***	0.000	0.000	0.001
	(0.003)	(0.002)	(0.002)	(0.002)
InstQ	0.030***	0.031***	0.031***	0.021***
	(0.001)	(0.001)	(0.001)	(0.002)
LrnDo	...	0.215***	0.215***	0.215***
	...	(0.001)	(0.001)	(0.001)
LrnExp	...	...	0.020	0.018
	...	...	(0.034)	(0.034)
AbsCap*EG3	...	...	1.038*	0.995*
	...	...	(0.451)	(0.451)
AbsCap*Den	...	...	0.048	0.039
	...	...	(0.032)	(0.032)
EG3*Inst	...	...	...	0.093*
	...	...	...	(0.042)
Den*Inst	...	...	...	0.019***
	...	...	...	(0.002)
Adj. R2	0.327	0.468	0.468	0.468
Num. obs.	205,233	205,233	205,233	205,233
Num. Firms.	68,411	68,411	68,411	68,411

*** p<0.001, ** p<0.01, * p<0.05.

7. SUMMARY OF THE RESULTS AND CONCLUDING REMARKS

The structural innovation framework that this paper introduces helps to reveal the mediating effects of learning spillovers on Chinese innovation and firm performance. Consistent with the existing literature, firms that engage in indigenous research and development increase their innovative throughput, which in turn increases firm performance. Moreover, firms' learning by doing helps to spur each stage of innovation, while we find that learning by exporting has no effect. The lack of learning by exporting supports previous studies that question the effectiveness of the PRC's market-access-for-foreign-capital strategy (Young and Lan 1997; Cheung and Lin 2004), as domestic Chinese firms do not appear to benefit from their interactions with foreign buyers' technical and managerial expertise.

In the early stages of innovation, there is no evidence to suggest that Chinese firms are capturing spillovers and incorporating them into their innovation effort, even when we take their absorptive capacity into account. Conversely, in the later stages of innovation, we find that learning spillovers positively increase firms' innovation output, as well as their performance, especially for firms with high absorptive capacity. This result confirms previous work that suggests that the effects of learning spillovers on innovation vary according to the stage of innovation (Ghemawat and Spence 1985; Barrios and Strobl 2004): the presence of learning spillovers reduces the firm's incentives to invest in innovation—in-house R&D—yet leads to higher levels of innovation output—imitation—and enhances firm productivity.

In view of the firm's inability to integrate learning spillovers by pursuing indigenous innovation strategies, the role of the state becomes particularly important. The state plays a key role in encouraging firms to pursue innovation through various policy tools, including subsidies for firms that open R&D labs, tax breaks, and unfettered access to loans, especially for firms in strategic industries. From this perspective, the industrial policy and local protectionism may help to minimize the high risks associated with pursuing innovation as well as mitigating the negative effects of potential market failures that disrupt the transfer of tacit knowledge from the environment to the firm.

To become a global "innovative powerhouse," the results presented in this paper highlight the importance of institution building along with contemporaneous efforts to reduce the role of the state and local governments in the market. Building a solid institutional environment reduces the high risks associated with pursuing innovation and will help to facilitate the transferring of tacit knowledge, leading to both intra- and inter-industrial spillovers, thereby reducing firms' dependency on state protectionism and spurring their competitiveness. Combined with the limited strategic policy instruments and further accumulation of learning by doing, Chinese firms will better absorb learning spillovers and integrate them with in-house R&D activities. In time, it is likely that the PRC will continue to contribute widely to the global stock of knowledge and increase its value-added at all points of the global production chain.

REFERENCES

Acs, Z. J., C. Armington, and T. Zhang. 2007. "The Determinants of New-Firm Survival across Regional Economies: The Role of Human Capital Stock and Knowledge Spillover." *Papers in Regional Science* 86 (3): 367–91.

Antonellia, C., P. P. Patruccoa, and F. Quatraro. 2011. "Productivity Growth and Pecuniary Knowledge Externalities: An Empirical Analysis of Agglomeration Economies." *Economic Geography* 87: 23–50.

Antonietti, R., and G. Cainelli. 2011. "The Role of Spatial Agglomeration in a Structural Model of Innovation, Productivity and Export: A Firm-Level Analysis." *Annals of Regional Science* 46 (3): 577–600.

Arvanitis, S. 2006. *Innovation and Labour Productivity in the Swiss Manufacturing Sector: An Analysis Based on Firm Panel Data*. KOF Working Paper 149.

Balasubramanayam, V. N., M. Salisu, and D. Sapsford. 1996. "Foreign Direct Investment and Economic Growth in EP and IS Countries." *Economic Journal* 106: 92–105.

Baldwin, J. R., D. Beckstead, W. M. Brown, and D. L. Rigby. 2008. "Agglomeration and the Geography of Localization Economies in Canada." *Regional Studies* 42 (1): 117–32.

Barrios, S., and E. Strobl. 2004. "Learning by Doing and Spillovers: Evidence from Firm-Level Panel Data." *Review of Industrial Organization* 25 (2): 175–203.

Berthon, P., J. Hulbert, and L. Pitt. 1999. "To Serve or Create? Strategic Orientations towards Customers and Innovation." *California Management Review* 42 (1): 37–58.

Brandt, L., J. Van Viesebroeck, and P. Schott. 2012. "Creative Accounting or Creative Destruction? Firm-Level Productivity Growth in Chinese Manufacturing." *Journal of Development Economics* 2: 339–51.

Buddelmeyer, H., P. H. Jensen, and E. Webster. 2010. "Innovation and the Determinants of Company Survival." *Oxford Economic Papers* 62 (2): 261–85.

Carlin, W., M. Schaffer, and P. Seabright. 2004. "A Minimum of Rivalry: Evidence from Transition Economies on the Importance of Competition for Innovation and Growth." *Contributions to Economic Analysis & Policy* 3 (1): 1284–327.

Chen, J., and W. Qu. 2003. "A New Technological Learning in China." *Technovation* 23 (11): 861–67.

Cheung, K.-Y., and P. Lin. 2004. "Spillover Effects of FDI on Innovation in China: Evidence from the Provincial Data." *China Economic Review* 15 (1): 25–44.

Child, J., and D. Tse. 2001. "China's Transition and its Impact on International Business." *Journal of International Business Studies* 32 (1): 8–21.

Clerides, S., S. Lach, and J. Tybout. 1998. "Is Learning by Exporting Important? Micro-Dynamic Evidence from Colombia, Morocco and Mexico." *Quarterly Journal of Economics* 113 (3): 903–48.

Cohen, W., and D. Levinthal. 1989. "Innovation and Learning: The Two Faces of R&D." *Economic Journal* 99: 569–96.

———. 1990. "Absorptive Capacity: A New Perspective on Learning and Innovation." *Administrative Science Quarterly* 25: 128–52.

Crépon, B., E. Duguet, and J. Mairesse. 1998. "Research and Development, Innovation and Productivity: An Econometric Analysis at the Firm Level." *Economics of Innovation and New Technology* 7 (2): 115–85.

Ellison, G., and E. Glaeser. 1997. "Geographic Concentration in US Manufacturing Industries: A Dartboard Approach." *Journal of Political Economy* 105(2): 889–927.

Evenson, R., and L. Westphal. 1995. "Technological Change and Technology Strategy." In *Handbook of Development Economics*, edited by T. Srinivasan and J. Behrman. Amsterdam: North Holland, 3rd edition.

Fujita, B. M., and J.-F. Thisse. 2003. "Does Geographical Agglomeration Foster Economic Growth? And Who Gains and Loses from It?" *Japanese Economic Review* 54 (2): 121–45.

Geels, F. 2004. "From Sectoral Systems of Innovation to Socio-Technical Systems: Insights about Dynamics and Change from Sociology and Institutional Theory." *Research Policy* 33 (6–7): 897–920.

Geroski, P., S. J. Machin, and J. van Reenen. 1993. "The Profitability of Innovating Firms." *RAND Journal of Economics* 24 (2): 198–211.

Ghemawat, P., and A. M. Spence. 1985. "Learning Curve Spillovers and Market Performance." *Quarterly Journal of Economics* 100: 839–52.

Glaeser, E. L. 2008. *Cities, Agglomeration, and Spatial Equilibrium*. Oxford University Press.

Griffith, R., E.Huergo, J. Mairesse, and B. Peters. 2006. "Innovation and Productivity across Four European Countries." *Oxford Review of Economic Policy* 22 (4): 483–98.

Griffith, R., S. Redding, and J. Van Reenen. 2004. "Mapping the Two Faces of R&D: Productivity Growth in a Panel of OECD Industries." *Review of Economics and Statistics* 86 (4): 883–95.

Griliches, Z. 1958. "Research Cost and Social Return: Hybrid Corn and Related Innovations." *Journal of Political Economy* 66 (5): 419–31.

Gruber, H. 1998. "Learning by Doing and Spillovers, Further Evidence from the Semi-Conductor." *Industry Review of Industrial Organization* 13: 697–711.

Guan, C. J., R. C. Yam, E. P. Tang, and A. K. Lau. 2009. "Innovation Strategy and Performance during Economic Transition: Evidences in Beijing, China." *Research Policy* 38: 802–12.

Guo, K. 1997. "The Transformation of China's Economic Growth Pattern – Conditions and Methods." *Social Sciences in China* 18 (3): 12–20.

Hall, P. 1995. *Innovation, Economics and Evolution, Theoretical Perspectives on Changing Technology in Economic Systems*. New York: Harvester Wheatsheaf.

Hashi, I. and N. Stojcic. 2010. *The Impact of Innovation Activities on Firm Performance Using a Multi-Stage Model: Evidence from the Community Innovation Survey 4*. CASE Network Studies and Analyses Working Paper (410).

He, C. 2009. "Industrial Agglomeration and Economic Performance in Transitional China." In *Reshaping Economic Geography in East Asia*, edited by Y. Huang and A. M. Bocchi, chapter 16, 258–81. Washington, DC: World Bank.

He, X., and M. Qing. 2011. "How Chinese Firms Learn Technology from Transnational Corporations: A Comparison of the Telecommunication and Automobile Industries." *Journal of Asian Economics* 23 (3): 270–87.

Heckman, J. 1976. "The Common Structure of Statistical Models of Truncation, Sample Selection and Limited Dependent Variables and a Simple Estimator for such Models." *Annals of Economic and Social Measurement* 5: 475–92.

Henderson, V. 2003. "Marshall's Scale Economies." *Journal of Urban Economics* 53 (1): 1–28.

———. 2005. "Urbanization and Growth." In *Handbook of Economic Growth*, edited by S. Aghion and N. Durlauf, 1543–91. North Holland: Elsevier.

Howell, A. 2015. "'Indigenous' Innovation with Heterogeneous Risk and New Firm Survival in a Transitioning Chinese Economy." *Research Policy* 44 (10): 1866–76.

———. 2016. "Firm R&D, Innovation and Easing Financial Constraints in China: Does Corporate Tax Reform Matter?" *Research Policy* 45 (10): 1996–2007.

———. 2017. "Picking 'Winners' in China: Do Subsidies Matter for Indigenous Innovation and Firm Productivity?" *China Economic Review* 44: 154–65.

Hu, A., G. Jefferson, and J. Qian. 2005. "R&D and Technology Transfer: Firm-Level Evidence from Chinese Industry." *Review of Economics and Statistics* 87 (4): 780–6.

Huang, Y. 2003. *Selling China: Foreign Direct Investment during the Reform Era*. New York: Cambridge University Press.

Jefferson, G. H., B. Huamao, G. Xiaojing, and Y. Xioyun. 2002. "R&D Performance in Chinese Industry." *Economics of Innovation and New Technology* 15 (4/5): 345–66.

Jefferson, G. H., and T. G. Rawski. 1994. *How Industrial Reform Worked in China: The Role of Innovation, Competition and Property Rights*, 129–56. Washington, DC: World Bank.

Johansson, B., and H. Lööf. 2009. *Innovation, R&D and Productivity: Assessing Alternative Specifications of CDM-Models*. CESIS Working Paper Series 159.

Jovanovic, B. 1982. "Selection and the Evolution of Industry." *Econometrica* 50 (3): 649–70.

Keller, W. 2010. "International Trade, Foreign Direct Investment, and Technology Spillover." In *The Economics of Innovation*, edited by B. Hall and N. Rosenberg. North-Holland: Elsevier.

Kemp, R., M. Folkeringa, J. de Jong, and E. Wubben. 2003. *Innovation and Firm Performance*. Scientific Analysis of Entrepreneurship and SMEs, Report H200207.

Kesidou, E., and H. Romijn. 2008. "Do Local Knowledge Spillovers Matter for Development? An Empirical Study of Uruguay's Software Cluster." *World Development* 36 (10): 2004–28.

Kim, L. 2001. "The Dynamics of Technological Learning in Industrialisation." *International Social Science Journal* 53 (168): 297–308.

Lall, S. 1992. "Technological Capabilities and Industrialization." *World Development* 20: 165–86.

Li, H., and K. Atuahene-Gime. 2001. "Product Innovation Strategy and the Performance of New Technology Ventures in China." *Academy of Management Journal* 44 (6): 1123–34.

Liu, F.-C., D. F. Simon, Y.-T. Sun, and C. Cao. 2011. "China Innovation Policies: Evolution, Institutional Structure, and Trajectory." *Research Policy* 40 (7): 917–31.

Liu, X., and T. Buck. 2007. "Innovation Performance and Channels for International Technology Spillovers: Evidence from Chinese High-Tech Industries." *Research Policy* 36 (3): 355–66.

Lööf, H., and A. Heshmati. 2006. "On the Relationship between Innovation and Performance: A Sensitivity Analysis." *Economics of Innovation and New Technology* 15 (4/5): 317–44.

Lööf, H., and P. Nabavi. 2013. *Learning and Productivity of Swedish Exporting Firms: The Importance of Innovation Efforts and the Geography of Innovation*, CESIS Working Paper Series No. 296. 1–25.

Love, J. H., and S. Roper. 2009. "Organizing the Innovation Process: Complementarities in Innovation Networking." *Industry and Innovation* 16: 273–90.

Lu, J., and Z. Tao. 2009. "Trends and Determinants of China's Industrial Agglomeration." *Journal of Urban Economics* 65 (2): 167–80.

Miguel Benavente, J. 2006. "The Role of Research and Innovation in Promoting Productivity in Chile." *Economics of Innovation and New Technology* 15 (4–5): 301–15.

Nahm, J., and E. S. Steinfeld. 2012. *Reinventing Mass Production: China's Specialization in Innovative Manufacturing*. SSRN Working Paper 2012-25.

Naidoo, V. 2010. "Firm Survival through a Crisis: The Influence of Market Orientation, Marketing Innovation and Business Strategy." *Industrial Marketing Management* 39: 1311–20.

Noble, C., R. Sinha, and A. Kumar. 2002. "Market Orientation and Alternative Strategic Orientations: A Longitudinal Assessment of Performance Implications." *Journal of Marketing* 66 (3): 25–39.

Olley, G. S., and A. Pakes. 1996. "The Dynamics of Productivity in the Telecommunication Equipment Industry." *Econometrica* 64 (6): 1263–97.

Pakes, A., and R. Ericson. 1998. "Empirical Implications of Alternative Models of Firm Dynamics." *Journal of Economic Theory* 79 (1): 1–45.

Pakes, A., and Z. Griliches. 1980. *Patents and R and D at the Firm Level: A First Look*. NBER Working Paper 0561.

Peng, M., and P. Heath. 1996. "The Growth of the Firm in Planned Economies in Transition: Institutions, Organizations, and Strategic Choice." *Academy of Management Review* 21 (2): 492–528.

Porter, M. 1990. *The Competitive Advantage of Nations*. New York, NY: Free Press.

Qian, Y., and C. Xu. 1993. "Why China's Economic Reforms Differ: The M-Form Hierarchy and Entry/Expansion of the Nonstate Sector." *Economics of Transition* 1 (2): 135–70.

Rapping, L. 1965. “Learning and World War II Production Functions.” *Review of Economics and Statistics* 47 (1): 81–6.

Rhee, Y., B. Ross-Larsen, and G. Pursell. 1984. *Korea’s Competitive Edge: Managing the Entry into World Markets.* Baltimore: The Johns Hopkins University Press.

Rodriguez-Pose, A., and R. Crescenzi. 2008. “Research and Development, Spillovers, Innovation Systems, and the Genesis of Regional Growth in Europe.” *Regional Studies* 42 (1): 51–67.

Roper, S., J. Du, and J. Love. 2008. “Modelling the innovation value chain.” *Research Policy* 37: 961–77.

Salomon, R., and J. Shaver. 2005. “Learning by Exporting: New Insights from Examining Firm Innovation.” *Journal of Economics and Management Strategy* 14 (2): 431–60.

Shea, D. 2012. “The Impact of International Technology Transfer on American Research and Development.” In *Committee on Science, Space, and Technology Subcommittee on Investigations and Oversight, United States House of Representatives*.

Sheshinski, E. 1967. “Tests of the ‘Learning by Doing’ Hypothesis.” *Review of Economics and Statistics* 49 (4): 568–78.

Silva, A., O. Afonso, and A. P. Africano. 2012. “Learning-by-Exporting: What We Know and What We Would Like to Know.” *International Trade Journal* 3 (1): 255–88.

Steinfeld, E. S. 2004a. “China’s Shallow Integration: Networked Production and the New Challenges for Late Industrialization.” *World Development* 32 (11): 1971–87.

Steinfeld, E. S. 2004b. “Chinese Enterprise Development and the Challenge to Global Integration.” In *Global Production Networking and Technological Change in East Asia*, edited by S. Yusuf, M. Altaf, and K. Nabeshima, 255–96. Washington, DC: World Bank and Oxford University Press.

Sun, Y. 2002. “Sources of Innovation in China’s Manufacturing Sector: Imported or Developed In-House?” *Environment and Planning A* 34 (6): 1059–72.

Tan, J. 2001. “Innovation and Risk-Taking in a Transitional Economy: A Comparative Study of Chinese Managers and Entrepreneurs.” *Journal of Business Venturing* 16 (4): 359–76.

Thompson, P. 2009. “Learning by Doing.” In *Handbook of Economics of Technical Change*, edited by B. Hall and N. Rosenberg. October. Amsterdam: Elsevier, North-Holland.

Thornton, R. A., and P. Thompson. 2001. “Learning from Experience and Learning from Others: An Exploration of Learning and Spillovers in Wartime Shipbuilding.” *American Economic Review* 91: 1350–68.

UNIDO. 2011. World Manufacturing Production: Statistics for Quarter IV. Vienna.

US–China Economic and Security Review Commission. 2011. 2011 Report to Congress of the US–China Economic and Security Review Commission. Washington, DC.

Wakelin, K. 2001. “Productivity Growth and R&D Expenditure in UK Manufacturing Firms.” *Research Policy* 30: 1079–90.

Wang, C., and C. Lin. 2008. "The Growth and Spatial Distribution of China's ICT Industry: New Geography of Clustering and Innovation." *Issues & Studies* 44 (2): 145–92.

Wang, C. C., and G. C. Lin. 2013. "Emerging Geography of Technological Innovation in China's ICT Industry: Region, Inter-Firm Linkages and Innovative Performance in a Transitional Economy." *Asia Pacific Viewpoint* 54 (1): 33–48.

Wang, J., and K. Tsai. 2003. *Productivity Growth and R&D Expenditure in Taiwan's Manufacturing Firms*. NBER Working Paper Series 9724.

Wooldridge, J. M. 1995. "Selection Corrections for Panel Data Models under Conditional Mean Independence Assumptions." *Journal of Econometrics* 68: 115–32.

Young, S., and P. Lan. 1997. "Technology Transfer to China through Foreign Direct Investment." *Regional Studies* 31 (7): 669–79.

Zahra, S. A., and G. George. 2002. "Absorptive Capacity: A Review, Re-conceptualization, and Extension." *Academy of Management Review* 27: 195–203.

Zhou, K. Z. 2006. "Innovation, Imitation, and New Product Performance: The Case of China." *Industrial Marketing Management* 35: 394–402.

Zhou, Y. 2008. *The Inside Story of China's High-Tech Industry: Making Silicon Valley in Beijing*. Lanham, MD: Rowman & Littlefield.

APPENDIX

Table A1: Summary Statistics and Pearson's Correlation Coefficients

Panel A: Summary Statistics

Variable	Mean	St. Dev.	Min	Max
TFP	2.685	0.978	0.0002	12.610
Innov	12.566	77.933	0.000	3,701.362
RDint	0.489	3.613	0.000	214.857
RDch	0.102	0.302	0	1
mktshr	0.280	0.365	0.001	4.672
DistP	347.587	308.231	0.000	2,732.400
age	6.716	3.511	1	17
Exp	0.094	0.244	0.000	1.000
Subs	0.005	0.026	0.000	0.355
Levg	0.035	0.096	0.000	0.763
HCap	0.012	0.078	0.000	3.242
EG3	0.016	0.017	–0.014	0.151
Den	0.754	1.093	0.002	11.196
Glob	0.162	0.194	0.000	18.755
IndPr	175.633	127.422	2.939	1,850.756
RegPr	0.000	1.000	–1.956	22.122
InstQ	0.000	1.000	–0.961	10.130
LrnDo	10.571	3.070	1.118	23.658

Panel B: Correlations

	TFP	Innov	RDint	RDch	mktshr	DistP	age	Exp
TFP								
Innov	0.07*							
RDint	0.05*	0.28*						
RDch	0.03*	0.18*	0.40*					
mktshr	0.22*	0.05*	0.01*	0.10*				
DistP	–0.06*	0.01	–0.02*	0.02*	0.00			
age	0.06*	0.02*	0.03*	0.07*	0.10*	–0.02*		
Exp	0.03*	0.03*	–0.01*	0.03*	0.09*	–0.11*	0.06*	
Subs	–0.04*	0.03*	0.05*	0.05*	0.00	0.03*	0.03*	–0.01*
Levg	–0.05*	0.00	–0.01	0.01*	0.03*	0.08*	0.01*	–0.04*
AbsCap	0.05*	0.08*	0.17*	0.14*	0.02*	0.02*	0.02*	–0.03*
EG3	–0.01*	0.02*	0.01*	0.03*	0.01*	0.02*	0.03*	0.07*
Den	0.04*	–0.02*	–0.02*	–0.01*	0.03*	0.09*	0.00	–0.03*
IndPr	–0.11*	0.03*	0.05*	0.06*	–0.06*	0.11*	–0.01*	–0.14*
RegPr	–0.03*	–0.01	–0.05*	–0.02*	–0.03*	0.05*	–0.07*	0.05*
InstQ	–0.04*	0.01	0.01*	0.02*	–0.03*	0.45*	–0.10*	–0.13*

continued on next page

Table A1 *continued*

	Subs	Levg	AbsCap	EG3	Den	IndPr	RegPr
TFP							
Innov							
RDint							
RDch							
mktshr							
DistP							
age							
Exp							
Subs							
Levg	0.01*						
AbsCap	0.02*	0.00					
EG3	0.00	–0.01*	0.00				
Den	–0.03*	0.02*	–0.02*	–0.03*			
IndPr	0.11*	0.07*	0.05*	0.06*	0.00		
RegPr	0.00	0.02*	–0.08*	0.01	0.18*	0.02*	
InstQ	0.03*	0.07*	0.02*	–0.03*	0.06*	0.14*	0.04*

[1] Correlations are Pearson. [2] * *p*<0.001.
[2] * *p*<0.001.